Review of Research on Vision-Based Parking Space Detection Method

Yong Ma, Jiangxi Normal University, China
Yangguo Liu, Jiangxi Normal University, China
Shiyun Shao, Université de Montréal, Canada*
Jiale Zhao, Chongqing University, China

https://orcid.org/0000-0002-5895-9148
Jun Tang, Changhong Network Technologies Co., Ltd., China

ABSTRACT

Parking space detection is an important part of the automatic parking assistance system. How to use existing sensors to accurately and effectively detect parking spaces is the key problem that has not been solved in the automatic parking system. Advances in artificial intelligence and sensing technologies have motivated significant research and development in parking space detection in the automotive field. Firstly, based on extensive investigation of a lot of literature and the latest research results, this paper divides parking space detection methods into methods based on traditional visual features and those methods based on deep learning and introduces them separately. Secondly, the advantages and disadvantages of each parking space detection method are analyzed, compared, and summarized. And the benchmark datasets and algorithm evaluation standards commonly used in parking space detection methods are introduced. Finally, the vision-based parking space detection method is summarized, and the future development trend is prospected.

KEYWORDS

Artificial Intelligence, Automatic Parking, Deep Learning, Parking Space, Traditional Vision

INTRODUCTION

Due to the surge in the number of cars in our country, the number of urban parking spaces is far from meeting the requirements of the existing number of cars. The limited parking space makes roads, streets and parking lots congested. On the other hand, more and more novice drivers are on the road, aggravating this situation and increasing the probability of traffic accidents. In the current complex traffic environment, there are higher requirements for the driver’s driving skills.

For the driver, it is a difficult thing for the old driver and the novice driver to park the car. During the parking process, it is not only necessary to move the vehicle back and forth repeatedly, so that the car can park in the parking space accurately, and in the process of parking, always pay attention to the obstacles and passers-by around the vehicle to avoid collision, which is a very difficult problem for the driver, which also puts forward a more difficult problem for the driver’s driving level and reaction time. high demands. Through the analysis of the causes of traffic accidents and the accumulation of parking experience in life, it is concluded that there are the following difficulties in the parking process:
(1) The blind spot of the driver’s field of vision. In the car, the driver can only observe the obstacles around the vehicle through the rear-view mirror. Due to the limited information observed in the rear-view mirror, there are blind spots of vision behind the left and right sides of the vehicle, and the image displayed through the rear-view mirror will appear to some extent. The degree of distortion leads to the driver’s unclear understanding of the outside environment of the car, which increases the difficulty of parking in place.

(2) The fault tolerance rate of the driver operating the vehicle is low. Reversing is an essential step in parking, but it is often difficult for novice drivers with inexperienced drivers, and it is necessary to control the steering, accelerator and brake pedal of the vehicle while reversing. Mentioned the difficulty of parking in place.

(3) The limitation of parking space size. In the limited urban space, the space left for parking spaces is getting smaller and smaller. In addition, the parking positions of some adjacent parking spaces are not standardized, which will further compress the limited parking space, making it even more difficult to park in the space.

A large number of traffic accidents caused by parking and consumers’ demands for car safety in the process of parking and warehousing, and with the proposal of automatic driving, automatic parking assistance system has attracted extensive attention of researchers (Frank, 2014; Kageyama, 2004), it is imminent to develop an automatic parking assistance system to reduce the difficulty of parking and improve the safety of the car. In the process of parking in place, the system first uses various sensors to sense the environmental information around the vehicle, eliminates blind spots in the field of vision, and provides real-time early warning when encountering dangerous situations, so as to build a safe parking space for the driver; secondly, the system can replace the driver to control the steering wheel for automatic steering operation, improve driving safety; finally, according to the different parking spaces detected, the corresponding parking strategy will be selected to achieve fast and accurate parking. In the process of developing an automatic parking system, a key issue that needs to be solved is how to use the onboard sensors to correctly detect and locate the parking space. The solutions to this problem can generally be divided into two types, free-space-based parking space detection method and vision-based parking space detection method (Wan et al., 2009).

The free-space-based method mainly uses the reflection principle of the ranging sensor, such as ultrasonic radar (Jeong et al., 2010; Pohl et al., 2006), laser scanner (Ibisch et al., 2013; Zhou et al., 2012), short-range radar (Dubé et al., 2014; Loeffler et al., 2015; Schmid et al., 2011), etc., to accurately calculate the distance between the vehicle and surrounding obstacles, and judge the status between adjacent vehicles to determine the location of the target parking space size, as shown in Figure 1. However, the free-space-based method requires adjacent vehicles around the target parking space to detect parking spaces, and the accuracy of its detection depends on the poses of adjacent vehicles. At the same time, there are shortcomings such as a small detection range and detection blind spots.

Figure 1. Free-space-based approach
In order to overcome these shortcomings, more and more researchers are turning their attention
to the vision-based method in the hope of finding a more versatile and robust solution. The working
principle of the vision-based method is fundamentally different from that of the free-space-based
method. The vision-based detection method is to determine the parking space by identifying and
locating the parking line segment drawn on the ground. Obviously, the performance of this method
does not depend on the presence or the posture of the adjacent vehicle. Vision-based parking space
detection methods generally realize the detection and recognition of parking space marking lines by
using traditional technology () or deep learning technology (), then perform geometric reasoning to
determine the final parking space based on the detected parking line. The vision-based parking space
detection method is more reasonable than the free-space-based parking space detection method, and
it is more in line with the perception of human drivers. Therefore, the vision-based parking space
detection method has been extensively studied by researchers, and this is also the focus of this article’s
research and analysis.

Xu et al. (Xu et al., 2000) are the first to start the study of vision-based parking space detection
method. This method makes use of the characteristic that the color of the marking line of the parking
space in the image is significantly different from the background color to detect the parking space.
However, this method is easily affected by the external environment such as different lighting
conditions. After systematically sorting out and summarizing the related literature on vision-based
parking space detection methods, this paper divides vision-based parking space detection methods
into two categories, as shown in Figure 2. One is the parking detection method based on traditional
visual features. The traditional visual features in this method include the line feature and corner
feature of the parking space marking line. The line segments and corner points are detected by the
traditional detection method, and then geometric reasoning is performed on the detected features to
determine the effective parking space. Another type is to use deep learning technology to determine
the nodes and patterns of the parking space marking lines, and then pair the nodes according to the
manually designed geometric rules, and generate candidate parking spaces according to the pattern
of the nodes. Compared with the traditional method, this method has stronger robustness and higher
detection performance. The main contributions of this paper are as follows:

(1) Carry out pretty systematic and comprehensive research and classification of the vision-based
parking space detection methods since 2000, detailed elaboration and analysis of each type of
method;
(2) The public datasets of parking space detection and the evaluation indexes of parking space
detection method performance are introduced;
(3) The main indicators and characteristics of representative parking space detection methods are
analyzed, compared, and summarized;
(4) Discuss the main problems and future development trends in the vision-based parking space
detection method.
Section 1 of this paper introduces the research background and current research status of parking space detection methods; Section 2 introduces parking space detection methods based on traditional visual features; Section 3 introduces parking space detection methods based on deep learning; Section 4 introduces the public datasets and performance evaluation indicators of parking space detection; Section 5 summarizes the whole paper and looks forward to the future research direction and development trend.

2. TRADITIONAL-VISUAL-FEATURES-BASED METHODS

Traditional-visual-feature-based parking space detection methods are mainly based on pre-designed features, by detecting traditional visual features in the input image, and then performing geometric reasoning based on the detected features to determine the final parking space. Among them, according to the difference of detect parking space features, the traditional visual feature-based parking space detection methods are divided into corner feature-based methods and line feature-based methods, as shown in Figure 3.
2.1. Corner-Feature-Based Methods

Corner feature-based methods are mainly based on hand-designed features, using traditional feature detection methods, such as Harris corner detection (Harris & Stephens, 1988) and Fast corner detection (Rosten & Drummond, 2006), to detect the corner points of the parking space in the image, as shown in Figure 4. Then it matches the corners according to the geometric rules of parking spaces to determine whether the matched corner pairs can form an effective parking entrance.

Jung et al. (Jung et al., 2009) proposed a semi-automatic parking space detection method, which is based on the corner features of the parking space. The user initiates the recognition of the parking space corner point by specifying the seed point of the target parking space entrance in the user interface, and then, the neural network-based classifier is used to recognize the connection pattern of the corner points of the parking space around the seed point, and the final parking space is determined according to the connection pattern of the corner points. Finally, the location of the target parking space is displayed in a unified user interface. Using such a user interface method can greatly reduce the search area, thereby greatly reducing the calculation load and the error recognition rate.

Suhr et al. (Suhr & Jung, 2013) proposed a method to automatically recognize marking lines of sparking space. This method recognizes different types of parking space marking lines by modeling parking space markings as a hierarchical tree structure, Figure 5 shows the detection process of the method, which is mainly divided into two processes: bottom-up and top-down.
Before detecting parking spaces, the method first removes the radial distortion of the obtained fisheye image through a quintic polynomial model, and then transforms the undistorted image of the real-world ground plane into a bird’s-eye image of the ground plane through projective transformation. Figure 6 shows the result of bird’s-eye view transformation.

Figure 6. Transformation of fisheye image to bird’s eye image

(a) Original fisheye image  (b) Undistorted image  (c) Bird's-eye image

Then, through a bottom-up hierarchical tree structure to over-generate parking space candidates so as not to lose the correct parking space. The process includes Harris corner detection, node and parking space generation, and type selection process. After that, according to the nature of the parking space marking type, through the top-down hierarchical tree structure, the falsely generated parking spaces, nodes and corners are eliminated to determine the final parking space, as shown in Figure 7. Although the method is fully automatic, it also outperforms previous semi-automatic methods with a small amount of computation.

Figure 7. Detection results of hierarchical tree structure
On the basis of (Suhr & Jung, 2013), Suhr et al. (2012) proposed a new method of automatic recognition of parking space marking lines, which can recognize many kinds of parking space marking lines from the surrounding panoramic view. The method first uses a hierarchical tree structure-based method to detect parking spaces in the current image, and then uses the transformation between consecutive images to predict the position of the previously detected parking space in the current image, and combine the parking spaces detected in the current image with the parking spaces predicted in the previous image. Finally, cluster the detected parking spaces according to the type and direction, and select the cluster that contains more than a predetermined number of parking spaces as the final parking space.

Hsu et al. (2019) proposed a visual detection algorithm for available parking spaces, which aims to solve the problem that the detection performance of the free-space-based method depends on the existence and pose of adjacent vehicles. This method uses visual technology in both parking space recognition and parking space occupancy classification. The parking space recognition stage includes four steps: feature extraction through fast corner detector; feature classification based on the ratio of parking space marking line and road surface; using random sample consensus (RANSAC) algorithm (Fischler & Bolles, 1981) to detect the line width of the guide line and marking line, separating line generated according to the width of the parking space. The parking space occupancy classification stage includes three steps: parking space selection; parking space feature extraction, including the road surface features extracted by the region growing algorithm and the non-road surface features extracted by the Canny edge detector (Canny, 1986). The classification of parking space available through the naïve Bayes classifier (Thrun, 2002).

Although corner feature-based parking space detection methods have good performance, these methods still have certain limitations. First, the corner features cannot always provide an accurate target position and course angle. In addition, because the corner feature is difficult to maintain robustness and contains too many constraints in most complex scenes, for example, when it is necessary to make a decision about a parking space in multiple frames, the entrance line of the parking space should be visible and there should be no change in the type of parking space angle feature caused by vehicle movement.

### 2.2. Line-Feature-Based Methods

Different from the corner-feature-based parking space detection methods, line-feature-based detection methods detect the marking line of parking space in the image, which can be divided into separating line and entrance line, as shown in Figure 8. Then use Sobel filter, segmented neural network, Canny edge detector, segment detector (Von Gioi et al., 2012) and cone-hat filter to detect line segments, and linear fitting algorithms to predict the marking line of parking spaces, such as Hough Transform (Illingworth & Kittler, 1988), Radon Transform, RANSAC (Random Sampling Consensus) and customized row clustering algorithm. After the parking space marking lines are detected, the geometric relationship of the parking space marking lines is analyzed to determine the final parking space.

**Figure 8. Types of parking space marking lines**

![Figure 8. Types of parking space marking lines](image-url)
Jung et al. (2006a) proposed a vision-based parking space detection method, which converts the detected edge image into peak-pair detection and clustering in Hough space. Peak-pair detection assumes that in the edge image, a marking within a fixed width range becomes a parallel line pair, and forms a feature pattern in the Hough space. Combined with prior knowledge, the one-dimensional filter can detect the marking. It has similarities with many newly developed methods. These methods focus on the geometric structure of the Hough space peak and use the corrected point-to-line segment distance to reflect the geometric structure of the parking space marking line. Once the guide line of the parking space marking lines is successfully recognized, the T-shaped template matching is used to determine the final parking space.

Jung et al. (2006b) proposed a parking space detection method based on monocular vision, that is, the driver designates the seed point through the touch screen in the target parking space to recognize the parking space marking line. The method uses homography to construct a bird’s eye view image. In the bird’s eye view image, adjacent vehicles are projected from the camera in the outer direction. If the marking line segment dividing parking spaces and their front ends are observed, the method can successfully recognize the target parking space marking line. Directional intensity gradient uses the width of the marking line and the direction of seed point related to the camera position as the prior knowledge to detect parking space marking line segment, which is not affected by noise and light changes. This method effectively uses the structure of the marking line in the bird’s eye view image to quickly recognize the target parking space.

Wang et al. (2014) proposed a parking space detection method based on Levenberg-Marquardt image stitching (Moré, 1978). This method combines four images from a fisheye camera into an Omni-directional bird’s eye image. On this basis, a parking space detection method based on Radon transform is proposed. The main idea of this method is to complete the detection of the bright spot in the Radon space. Through clustering and filtering based on the shape feature of the parking space, it can effectively alleviate the influence of noise, so as to detect effective parking spaces, as shown in Figure 9. Moreover, Radon transform has better anti-noise ability and robustness, and has better accuracy for the detected line segment with gray information.

Figure 9. Results of parking space detection after cluster filtering
parking space pattern recognition method based on a decision tree classifier to analyze line segment is proposed. Multiple types of parking spaces can be recognized by following the geometric features between corresponding pattern line segments. Parking space pattern recognition uses the individual characteristics of the parking space type to eliminate non-parking spaces and outliers at the edge of object lines. This parking space detection method has stronger robustness.

In previous studies, only the occupants of large objects in the parking space were considered, and the presence of internal markings with information or small objects, such as traffic cones, garbage bags, and pedestrians, were ignored. In order to overcome these limitations, Lee et al. (2016) proposed an available parking space detection method based on context analysis. The method includes two stages: parking space recognition and parking space occupancy classification. Firstly, in the parking space recognition stage, a cone-hat marking line filter and entropy-based line segment marking clustering are used to detect parking space marking lines. The cone-hat marking line filter can extract straight line features well even in the case of reduced visibility. The entropy-based line marking clustering algorithm can quickly and efficiently allocate the extracted markings to each parking line. Compared with other line segment detectors, this detection method has faster detection speed and stronger robustness in the case of distortion or ambiguity of parking lines. Then, the detected parking lines are used to generate candidate parking spaces. Secondly, the parking space occupancy classification stage verifies the parking space availability based on the detected parking spaces. For each detected parking space, the context features of the visual parking space are collected by extracting the Histogram of Gradient (HOG) (Dalal & Triggs, 2005) and frequency amplitude characteristics of the parking space. Based on these visual features, Support Vector Machines (SVM) (Suthaharan, 2016) are used to classify the availability of parking spaces.

Similarly, in order to solve the problem that most of the existing methods only focus on the occupancy of typical parked vehicles, and fail to distinguish the availability of small obstacles within the parking space. Li et al. (2017) proposed a parking space detection method that uses an image segmentation algorithm and stereo vision algorithm to calculate the height of small obstacles in the parking space marking line. This method detects various parking space marking lines through the Around View Monitor system (AVM) composed of four fish-eye cameras around the vehicle. This method uses a line segment detector (LSD) to detect a pair of parallel lines with a fixed distance in a parking space marking with edge information, and then uses an image segmentation algorithm and a stereo vision algorithm to calculate the height of small obstacles within the parking marking line. Compared with other line segment detection methods such as Hough transform and Radon transform, the proposed detection method has a faster and stronger detection ability in the case of severely damaged or weak marking lines in parking space.

In order to realize automatic recognition of multiple types of parking space marking lines and have stronger robustness to various lighting conditions, Suhr et al. (2018) proposed a method of parking space marking line to recognize multiple types of parking spaces under various lighting conditions, such as daytime, night and underground, etc. The method first extracts parallel line pairs from AVM images to detect the separating lines of parking space marking lines. Then, the separating lines detected in the current image are combined with the separating lines detected in the previous image, and then the separating line is paired to generate a candidate parking space according to the geometric constraints of the parking space. Next, use the line feature and corner feature of the parking space to determine the entrance position of the parking space, and use the ultrasonic sensor to classify the candidate parking spaces and confirm the availability of these candidate parking spaces. Finally, the vacant parking spaces recognized in the current image and that in the previous image are combined to determine the final parking space. In order to achieve more reliable recognition, the method not only uses the separating lines and the parking space in the current image, but also uses the vehicle odometer based on the on-board motion sensor to track the location of the parking space.

Li et al. (2018) proposed a parking space detection method based on geometric features to realize automatic parking space detection under various lighting (dark, strong) and ground conditions.
(brick, curved, blurred, marking). The method first uses the line clustering method based on the LSD algorithm to detect the separating lines, then pairs the separating lines according to the geometric features of the parking spaces to generate candidate parking spaces. Finally, uses line-based and learning-based methods to detect parking space entrances. Compared with the previous line segment detection methods such as distance transform and Hough transform, the proposed method has a more robust detection ability under different lighting conditions.

Due to the great difference between indoor and outdoor parking environments, it is very difficult to train the learning-based classifier or make use of template matching methods to achieve parking space detection. Zong et al. (2018) proposed a vision-based in-door and outdoor vacant parking space detection method. It is divided into the parking space detection stage and the parking space tracking stage. In the parking space detection stage, first, an improved line extractor based on the line segment detector (LSD) is used to obtain the candidate parking space line edge, and then the parking space corner extractor is used to extract the parking space rotation angle L-Type structured information to realize the detection of parking spaces. In the parking space tracking stage, in order to achieve the tracking of the parking space in the previous frame, a search method is proposed to obtain candidate parking spaces, and the real position of each parking space is updated using an algorithm based on Kalman filtering, and confidence is given. Finally, with the help of ultrasound and reconfirmation scheme, most of the false positives, including locations that cannot be parked, will be deleted to obtain the final parking space detection results.

Compared with the corner feature-based detection method, the line feature-based parking detection method is more accurate and has fewer constraints. In addition, it is more robust to occlusions caused by vehicles or objects.

3. DEEP-LEARNING-BASED METHODS

Parking space detection methods based on traditional visual features have a common limitation: these methods are based on hand-designed visual features, and as a result, the performance of these methods is often very poor outside the specific conditions with these designed visual features. With the continuous research on deep learning technology, deep learning technology has also been applied to parking space detection tasks and has achieved positive results. According to the different application technologies of parking space detection, the parking space detection methods are divided into object-detection-based methods, image-segmentation-based methods and regression-based methods, as shown in Figure 10.

Figure 10. Classification of parking space detection methods based on deep learning
3.1. Object-detection-based Methods

The parking space detection method based on object detection is to detect the marking points of the parking space through the deep neural network applied to the object detection task. The marking point refers to the local image block centered on the intersection of two parking lines, as shown in Figure 11. Then it analyzes the geometric relationship between the marking points according to the rule constraints of the parking space marking line to determine the final parking space.

Zhang et al. (2018) proposed a parking-space detection based on the learning method (PSDL). Given a surround-view image, PSDL first uses a pre-trained detector to detect marking points, then infers effective parking spaces based on these marking points. Compared with the traditional visual feature-based parking space detection method, PSDL has many differences. Firstly, PSDL is based on the marking-point pattern. The marking-point pattern is easier to recognize and more stable than the original visual features, such as lines or corners. Secondly, for the detection of marking points, PSDL adopts a data-driven learning strategy, which is more robust to the changes in imaging conditions than low-level visual algorithms.

In fact, for parking space detection, there are various unfavorable factors, such as the diversity of the ground material, multiple changes of lighting conditions, and the unpredictable shadow caused by nearby trees, which make the vision-based parking space detection method more difficult. In order to
solve these problems to a certain extent, Zhang et al. (2018) proposed a parking space detection method based on Deep Convolution Neural Network (DCNN), namely DeepPS, which takes the surrounding view image as input, uses a pre-trained model based on the You Only Look Once Version 2 (YoloV2) to detect the marking-points in the input image. Then, according to the two detected marking-points, DeepPS determines whether the marked points can form a valid entry line, if “yes”, DeepPS will also determine the type of parking spaces. Through a standard pre-trained DCNN model, the local image pattern defined by the pair of marking points is classified to complete the detection of parking spaces. DeepPS can handle many types of parking spaces, and this method is the first time that deep learning technology is applied to parking space detection.

In the vision-based parking space detection method, although the information provided by the visual image is much richer than that of the distance sensor, it is also accompanied by the complexity of processing this information. The parking space detection must be based on high-quality visual cue features and the input data with high variabilities, for example parking spaces can have different shapes, parking space marking lines can have different colors, observation conditions may change, there may be noise, etc. In addition, it’s almost impossible to manually design a set of feature patterns suitable for various conditions. On the other hand, the task of learning the most appropriate feature set directly from the data has stronger robustness and adaptability to different conditions. Therefore, Zinelli et al. (2019) proposed an end-to-end deep neural network parking space detection method to achieve parking space detection and occupancy classification in the input image. The network used in this method is an anchor-free variant based on the Faster Region-based Convolutional Neural Network (Faster-RCNN) framework (Ren et al., 2015), which can detect multiple types of parking spaces at the same time.

Suhr et al. (2021) proposed an end-to-end single-stage parking space detection method, which uses Convolutional Neural Network (CNN) to simultaneously obtain global information (the location of parking space entrance, the type of parking space, parking space occupancy) and local information (intersection position, direction), and combined them with the attributes of the parking space to detect the parking space. This method divides the input AVM image into multiple grids and extracts CNN features for each grid unit, then global and local information of parking space are obtained by convolutional filtering of extracted feature images. In the final process, non-maximum suppression (NMS) (Neubeck & Gool, 2006) is used to integrate global and local information of the parking space to obtain the final parking space detection, as shown in Figure 12.

Figure 12. Information integration based on non-maximum suppression

In order to solve the problems of low recognition rate, sensitivity to environmental changes, and weak generalization ability brought by vision-based parking space detection methods, Xu et al. (2020) proposed a deep convolutional neural network-based parking space detection method. This method takes a fish-eye image collected by a four fish-eye camera installed on the vehicle body as input, and
uses the improved fish-eye image to directly detect the parking spaces in the fish-eye image through the YoloV3 network structure (Redmon et al., 2016).

Due to the complex visual environment, such as lighting changes, shadows and visual limitations, the accuracy of parking space detection needs to be improved urgently. To solve this problem, Li et al. (2020) proposed a deep learning-based vacant parking space detection method, namely VPS-Net. The detection framework of this method is shown in Figure 13, VPS-Net splits vacant parking space detection into two stages: parking space detection and parking space classification. In the parking space detection stage, a detector based on YoloV3 is used to simultaneously detect marking points and parking space heads. Then geometric cues are used to match pairs of marking points and determine the direction of the parking space. Finally, two invisible vertices are inferred based on the type, direction and paired marking points of the parking space, so as to obtain a complete parking space. Compared with the previous method based on the marking-points, requiring complex steps to match the paired marking-points of parking space, VPS-Net simplifies the process of parking space detection, and it can detect various parking spaces quickly and robustly. In the parking space occupancy classification stage, the detected parking spaces are first regularized, the size of the parking space images is unified, and then the images are input into the designed DCNN model to classify the parking spaces, and the detection results are displayed in the image.

**Figure 13. Framework of VPS-Net parking space detection**

For vehicles equipped with automatic parking systems, the accuracy and speed of parking space detection are critical, but high-precision accuracy is obtained at the price of expensive computing equipment, which is sensitive for many car manufacturers. Yu et al. (2020) proposed a detector using Convolutional Neural Network (CNN) to obtain faster speed and smaller model size, while maintaining the detection accuracy of parking spaces. In order to achieve the optimal balance, a strategy is formulated to select the best receiving domain, (an extensible and customizable training strategy is developed for the pre-training of the model, in which the candidate scores are selected during training and the channels of selected cores are pruned during fine-tuning). The redundant channels are automatically pruned after each training iteration. Moreover, the model combining the corner features and line features of the detected parking space runs efficiently in real-time on a general-purpose processor.
3.2. Image-segmentation-based Methods

The image segmentation-based parking space detection method is to segment the parking space marking lines through the deep neural network used for semantic segmentation, and then use these segmented marking lines to infer the target location of the parking space.

The lighting variation of the outdoor parking lot and the high reflection of the indoor parking lot reduce the reliability of parking space detection. Jang et al. (2019) proposed a parking space detection method based on semantic segmentation and vertical grid coding. This method consists of semantic segmentation and parking space detection. Firstly, the semantic segmentation based on deep neural networks classifies the visual objects in the AVM image, such as free space, parking markings, vehicles and other objects, without using distance sensors or 3D reconstruction algorithms. Semantic segmentation based on deep learning can provide robust marking data in different parking environments, including different outdoor light conditions and indoor high-reflection conditions. Secondly, the parking space detection based on a vertical grid is to encode the marking data in the regions of interest (ROI) of the parking space, and to recognize the areas formed by the parking space marking and the empty space surrounded by static objects. The vertical grid coding method can quickly and effectively detect parking spaces in complex environments without fusing sensor data.

In the process of automatic parking, to perform robust detection of parking spaces and road structures, Wu et al. (2018) proposed a parking space and lane marking line segmentation method based on High Fusion Convolutional Network (HFCN). The method uses HFCN as the base network and adds extra efficient VH-stages to better segment the various parking space markings, the network structure is shown in Figure 14. The VH-stage consists of two independent linear convolution kernels, which are a vertical convolution kernel and a horizontal convolution kernel. This improvement enables the network to extract the linear features of parking spaces robustly and accurately, the detection results are shown in Figure 15.

---

**Figure 14. VH-HFCN network structure**

---

**Figure 15. Results of VH-HFCN detection**

(a) Original image  (b) GT  (c) VH-HFCN
Due to the too large model size, (Wu et al., 2018) cannot meet the requirements of embedded and mobile platforms. Jiang et al. (2019) proposed a parking space detection method for semantic segmentation, namely DFNet. The DFNet network model can be divided into three parts: basic module, feature extraction module, and refinement module. For the base module, it uses Densenet as the base network. Compared with many Resnet applied to semantic segmentation models, Densenet has a smaller model size and faster training speed, and the accuracy is similar. In the feature extraction module, the pyramid pooling module proposed by Pyramid Scene Praising Network (PSPNet) is used, and bilinear interpolation is used for upsampling. After these two modules, the feature map is magnified to the same size as the input image, but when the magnification factor is large, it will bring noise, making it difficult to classify the pixels at the boundary of the two regions. Therefore, a refinement module is added at the end of the model to refine the segmented region. For the refinement module, a Residual Fusion Block (RFB) composed of a convolutional layer and a pooling layer is proposed. The RFB is used to refine the segmented area of each class and reduce the impact of noise caused by the magnification layer. RFB mainly focuses on the classification of pixels at the boundary of two regions. Since these pixels are difficult to classify, RFB can reduce the false prediction of these pixels and improve the accuracy.

Jian et al. (2020) proposed a semantic segmentation model of lines and points based on multi-task learning. The model can simultaneously detect lines and points, and then use the output results of the model for post-processing to determine the location of parking spaces. At present, most visual algorithms are based on the vision features—corner features and line features, through some low-level visual algorithms (such as fast detector, Harris detector, Hough transform, Radon transform, RANSAC transform), which are sensitive to light and difficult to maintain robustness. Therefore, in order to solve the above problems, Jiang et al. (2020) proposed a parking space marking detection method based on deep learning. This method uses the mask-RCNN algorithm (He et al., 2017) to generate the mask of marking points, and then uses the line segment detection (LSD) algorithm to detect the mask and filter the interference lines, and to find the guide line and the separating line to determine the final candidate parking space.

3.3. Marking-point-regression-based Methods

The parking space detection method based on the marking point regression is to establish a regression model to determine the position of the marking points of the parking space, predict the pattern of the marking points, and then use geometric inference to determine the final parking space.

Previous researches in this field are mostly based on general off-the-shelf models, which had various limitations in solving specific problems. Huang et al. (2019) proposed a parking space detection method based on the regression of directional marking-point, namely DMPR-PS, the detection flow of this method is shown in Figure 16. Instead of using multiple off-the-shelf models, DMPR-PS uses a new CNN-based model specifically designed for the regression of direction marking points. Given a surround-view image, the model can predict the position, shape, and orientation of each marking point. Then the parking space can be easily inferred by applying geometric rules based on the detected marking points.

![Figure 16. DMPR-PS parking space detection method process framework](image)
Although DMPR-PS improves the detection speed, it can only detect parallel parking spaces or vertical parking spaces. Therefore, in order to overcome the limitations of the above method, Li et al. (2020) divided parking space detection into the directional regression and entrance line classification, so as to achieve rapid and robust detection of various parking spaces. This method makes the detection of parking spaces robust and simple through the regression and classification of the direction entrance line. For parking spaces of different shapes and different angles, the parking space represents as a directional entrance line, and a DCNN detector is designed to obtain the type, position, length and direction of the entrance line at the same time. Finally, the complete parking space can be easily inferred through the detection results and the prior geometric information.

DeepPS uses a rectangle descriptor to extract the types of marking points in a rectangular area composed of parking space vertices. However, the rectangular descriptor is sensitive to changes in direction. The directional descriptor uses the T/L template in DMPR-PS to describe the vertex pattern. Although the descriptor is more robust to directional changes, it can only extract the vertex patterns of T/L type parking spaces, and it is not suitable for describing complex non-T/L type scenes, such as tilting parking spaces and trapezoidal parking spaces. There are no fixed patterns for the marking points of different types of parking spaces, which makes it difficult to find a general method to describe the different parking space vertex patterns. In order to solve this problem, Wu et al. (2020) proposed a variable circular descriptor parking space detection method, which enables the network model to learn the feature patterns of different types of parking space vertices. For different types of parking space vertices, the feature patterns of the corresponding types are used as the descriptors of the parking space vertices. Therefore, the descriptor can be compatible with different types of parking space detection tasks and has a good generalization ability. In addition, because the computational cost of the network model severely limits the application of deep learning algorithms in practical engineering, this method uses a coarse-to-fine method to solve this problem to reduce the complexity of the network model. The algorithm decomposes the task into two stages. In the first stage, the coarse position of the regression marking-point is learned. The optimization of the first stage has a fast convergence speed due to its simplicity. In the second stage, the image is cropped with the predicted coarse position as the center, and the model outputs the fine position of the marking point, which further refines the offset between the coarse position and the true position on the ground.

4. ANALYSIS AND COMPARISON OF PARKING SPACE DETECTION METHODS

4.1. Common Datasets
In order to scientifically and consistently evaluate the performance of various parking space detection methods, it is necessary to use standard image data sets for testing and comparison. At present, the commonly used image data sets are Tongji Parking-slot Dataset 2.0 and PSV dataset, as shown in Table 1.
(1) Tongji Parking-space Dataset 2.0: The images in this dataset are surround-view images synthesized by four low-cost fisheye cameras. A variety of parking space types are considered, including vertical parking spaces, parallel parking spaces and inclined parking spaces, and different lighting conditions and weather conditions are considered when collecting outdoor samples. The dataset contains 9827 training images and 2338 test images. In order to test the performance of the parking space detection algorithm under different special conditions, the test images are divided into 6 categories, as shown in Table 2.

Table 1. Common dataset for parking space detection.

| Dataset               | Literature                | Number of samples | Training set | Test set | Scenes                                                                 | Parking space type                                      |
|-----------------------|---------------------------|-------------------|--------------|----------|------------------------------------------------------------------------|---------------------------------------------------------|
| Tongji Parking-space  | Zhang et al. (2018)       | 12165             | 9827         | 2338     | Indoor parking space, outdoor normal light, outdoor rain, outdoor shadow, outdoor street lamp, outdoor tilt | Vertical parking space, parallel parking space and inclined parking space |
| Dataset 2.0           |                           |                   |              |          |                                                                        |                                                         |
| PSV dataset           | Wu et al. (2018)          | 4249              | 2550         | 1699     | Indoor, outdoor, bright light, shadow                                  | Horizontal, vertical and diagonal grooves, different colors |

(2) PSV Dataset: This dataset contains PSV datasets of various surrounding environments, including indoor, outdoor, strong light, shadow, etc. Vague and clear parking spaces and lane markings are collected. The type of parking spaces includes vertical parking spaces, parallel parking spaces and inclined parking spaces, as well as parking spaces with different color marking lines, such as yellow and white.

4.2. Parking Space Detection Performance Evaluation Metrics

At present, the detection performance of parking spaces mainly includes two evaluation indicators: recall (R) and precision (P). Precision is the proportion of the correct predictions that are positive to the total predictions. The recall is the proportion of the correct prediction that is positive to all actually positive. The specific calculation method is shown in equation 1 and equation 2.

Table 2. Sample number of parking spaces in different conditions.

| Subset             | Number of samples |
|--------------------|-------------------|
| indoor parking lot | 226               |
| outdoor normal daylight | 546          |
| outdoor rainy     | 244               |
| outdoor shadow    | 1127              |
| outdoor street light | 147            |
| outdoor slanted   | 48                |
\[ P = \frac{TP}{TP + FP} \]  

\[ R = \frac{TP}{TP + FN} \]

Among them, TP represents the set of positive samples with correct predictions, FP represents the set of positive samples with incorrect predictions, and FN represents the set of negative samples with incorrect predictions.

### 4.3. Analysis and Comparison of Parking Space Detection Methods

The analysis and comparison results of the research on vision-based parking space detection methods are shown in Table 3. The main comparison factors include method classification, method name, publication year, method evaluation index, and method characteristics.

Parking space detection methods based on traditional vision are divided into corner feature-based methods and line feature-based methods. In parking space detection methods based on corner features, classic algorithms such as Harris and Fast are usually used to detect corner features of parking spaces. However, since the detected corner features are low-level features of parking spaces, the detection of parking spaces is not robust. In the parking space detection method that is line-features-based, the commonly used methods are: Hough transform, Radon transform, LSD straight line detection, etc., Hough transform is not robust in detecting parallel line pairs due to the influence of noise, clutter, lighting and weather conditions, etc., Moreover, the Hough transform cannot detect multiple parking spaces at the same time, while the Radon transform can not only detect multiple parking spaces simultaneously, but also improve the robustness and detection accuracy of straight line detection significantly. Compared with the Hough transform method, the LSD straight line detection method has stronger robustness under the conditions of different lighting or blurred parking space marking lines on the ground. When Hough transform and Radon transform detect parallel straight lines, they ignore the opposite nature of the color gradients of the two straight lines, while Random Sample Consensus (RANSAC) line detection method takes this into consideration and greatly improves the detection performance of straight lines. However, the RANSAC straight line detection method is highly dependent on the lines. In the case that the parking space marking lines are blocked or partially damaged, its performance will be significantly reduced.

The parking space detection method based on deep learning can be divided into the method based on target detection, the method based on image segmentation and the method based on marked point regression according to the difference of the deep model used in the parking space detection method. In methods based on target detection, target detection models and improved models are often used to detect parking space, such as Yolo, Faster-RCNN, etc. In the method based on image segmentation, according to the in-consistency between the parking space marking line and the ground background color, the image segmentation model is used to segment the parking space marking line. In the method based on marked-point regression, the regression model is mainly used to detect the marking point of the parking space. The parking space detection methods based on target detection and the marking point regression both detect the marking points of the parking space through the model, then infer the parking space on the basis of the geometric constraints of the detected marking points and the parking space marking line.
Nowadays, vision-based parking space detection methods have become the main-stream of parking space detection methods. Especially since 2010, with the great success of deep learning networks in the field of computer vision, the image feature extraction methods based on convolution neural network have made breakthrough progress, bringing image feature extraction to a new level. This paper has carried out a more detailed combing and classification of vision-based parking space detection methods. The vision-based parking space detection methods are divided into traditional visual features-based methods and line-feature-based methods.

### Table 3. Comparison of various parking space detection methods.

| Classification                  | Literatures           | Characteristics                                                                 | Published year | Precision | Recall |
|--------------------------------|-----------------------|---------------------------------------------------------------------------------|----------------|-----------|--------|
| Corner-feature-based methods   | Suhr et al. (2013)    | This method recognizes multiple types of parking space markings by modeling parking space markings as a hierarchical tree structure. | 2013           | 96.3      | 95.3   |
|                                | Hsu et al. (2019)     | This method uses a Fast corner detector for feature extraction, and the extraction speed is faster. | 2017           | 99.3      | 98.4   |
| Traditional-visual-features-based methods | Jung et al. (2006a)  | This method converts the detected edge image into peak pair detection and clustering in Hough space, and the recognition is more accurate. | 2006           | -         | -      |
|                                | Wang et al. (2014)    | This method can complete the detection of bright spot pairs in the radon space. The Radon transform has good anti-noise ability and robustness and has good accuracy for the detection lines with gray information. | 2014           | 97.1      | 81.5   |
| Line-feature-based methods     | Lee et al. (2016)     | This method uses the D-DBSCAN to detect parking space line segments. Compared with other line segment feature detectors, the D-DBSCAN algorithm can robustly extract lines even in the case of short and weak lines. | 2016           | 97.9      | 95.1   |
|                                | Li et al. (2017)      | This method uses LSD to detect a pair of parallel lines with a fixed distance. Compared with other line segment detection methods such as Hough transform and Radon transform, the LSD detection method has a faster and stronger detection ability in the case of severe damage or weak parking space marking line. | 2017           | 94.4      | 93.2   |

### 5. SUMMARY AND PROSPECT OF PARKING SPACE DETECTION METHODS

Nowadays, vision-based parking space detection methods have become the main-stream of parking space detection methods. Especially since 2010, with the great success of deep learning networks in the field of computer vision, the image feature extraction methods based on convolution neural network have made breakthrough progress, bringing image feature extraction to a new level. This paper has carried out a more detailed combing and classification of vision-based parking space detection methods. The vision-based parking space detection methods are divided into traditional visual features-based methods and line-feature-based methods.
feature-based methods and deep learning-based methods. And because of the different technologies used in parking space detection, the parking space detection methods based on traditional visual features are divided into corner-based parking space detection methods and line-based parking space detection methods. The parking space detection methods based on deep learning are divided into object-detection-based parking space detection methods, image-segmentation-based parking space detection methods and marking-point-regression-based parking space detection methods. This article elaborates, analyzes and compares each parking space detection method in detail, and summarizes the characteristics of each parking space detection method.

Based on the existing research results, we believe that there are following research points in the field of vision-based parking space detection.

(1) Multi-sensor fusion method.

The parking space detection methods mentioned in this paper are based on the premise of a single sensor, but in the practical aspect of detection, the detection with only a single sensor has inherent limitations. For example, the parking space is not easy to track under the rapid movement of the camera, it is difficult to deal with dynamic obstacles, etc., Therefore, the fusion of different sensor data to complement each other can make the detection performance of parking spaces more robust and more accurate. For example, Iner-tial Measurement Units (IMU) can measure the acceleration and angular velocity of the sensor body and is complementary to the camera sensor. After the fusion of the two, a more perfect performance of the parking space detection can be obtained. However, how to effectively integrate multiple sensors is a problem worthy of in-depth discussion.

(2) Establishment of large standard dataset

In the field of parking space detection, there are few datasets used for parking space detection. At present, the only large dataset comes from the PS2.0 Dataset constructed by Tongji University. The dataset contains a variety of conditions, different types of parking spaces. However, since all the images are stitched together from the images taken by four cameras during the construction of the dataset, as a result, the images are deformed or blurred, which seriously affects the performance of parking space detection. Therefore, it is very important to construct a large and reliable dataset.

(3) Closer combination with deep learning

Among the existing parking space detection methods, the detection of parking spaces is realized through multi-stage methods. For example, the DeepPS uses two different CNN to extract image features and classify them. However, given the strong correlation between these two problems, the CNN in the feature extraction process of these two problems is highly repetitive. Therefore, DeepPS can be further improved. How to design a single-stage network model to directly predict the available parking space is one of the hotspots in current research. Some methods have been listed in this paper. For example, DMPR-PS tries to use a single CNN to obtain the information needed for parking space inference. There is still room for further improvement in the construction of deep network models.

(4) Parking space detection method applied to real-time video

At present, the researches on the parking space detection methods mainly focus on a static image, and there are few researches on video. In order to achieve the optimal balance of detection speed and detection accuracy, Select and Prune the Fully Convolutional Net-works (SPFCN) (Yu et al., 2020) has developed a strategy to select the best receiving domain, and it is a useful attempt to automatically
trim redundant channels after each training iteration. However, these methods are still based on the two-dimensional static image and do not make good use of the time sequence relationship between the frames in the video. Therefore, in terms of video parking space detection methods, some new and pioneering work is urgently needed to lead the future research direction.

**FUNDING AGENCY**

The Open Access Processing fee for this article was covered in full by the authors.
REFERENCES

Canny, J. (1986). A computational approach to edge detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence, PAMI-8*(6), 679–698. doi:10.1109/TPAMI.1986.4767851 PMID:21869365

Dalal, N., & Triggs, B. (2005). Histograms of oriented gradients for human detection. 2005 IEEE computer society conference on computer vision and pattern recognition, 886-893. doi:10.1109/CVPR.2005.177

Dubé, R., Hahn, M., Schütz, M., Dickmann, J., & Gingras. D. (2014). Detection of parked vehicles from a radar-based occupancy grid. *2014 IEEE Intelligent Vehicles Symposium Proceedings*, 1415-1420. doi:10.1109/IVS.2014.6856568

Fischler, M. A., & Bolles, R. C. (1981). Random sample consensus: A paradigm for model fitting with applications to image analysis and automated cartography. *Communications of the ACM*, 24(6), 381–395. doi:10.1145/358669.358692

Frank, R. (2014). Sensing in the ultimately safe vehicle. *Convergence International Congress and Exposition on Transportation Electronics*, Paper No 2004-21-0055.

Harris, C. G., & Stephens, M. (1988). A combined corner and edge detector. *Alvey Vision Conference*, 15. doi:10.5244/C.2.23

He, K., Gkioxari, G., Dollár, P., & Girshick, R. (2017). Mask r-cnn. *Proceedings of the IEEE international conference on computer vision*, 2961-2969.

Hsu, C.-M., & Chen, J.-Y. (2019). Around View Monitoring-Based Vacant Parking Space Detection and Analysis. *Applied Sciences (Basel, Switzerland)*, 9(16), 3403. doi:10.3390/app9163403

Huang, J., Zhang, L., Shen, Y., Zhang, H., Zhao, S., & Yang, Y. (2019). DMPR-PS: a novel approach for parking-slot detection using directional marking-point regression. *2019 IEEE International Conference on Multimedia and Expo (ICME)*, 212-217. doi:10.1109/ICME.2019.00045

Ibisch, A., Stümper, S., Altinger, H., Neuhausen, M., Tschentscher, M., Schlipsing, M., & Knoll, A. (2013). Towards autonomous driving in a parking garage: Vehicle localization and tracking using environment-embedded lidar sensors. *2013 IEEE Intelligent Vehicles Symposium (IV)*, 829-834. doi:10.1109/IVS.2013.6629569

Illingworth, J., & Kittler, J. (1988). A survey of the Hough transform. *Computer Vision Graphics and Image Processing, 44*(1), 87–116. doi:10.1016/S0734-189X(88)80033-1

Jang, C., & Sunwoo, M. (2019). Semantic segmentation-based parking space detection with standalone around view monitoring system. *Machine Vision and Applications, 30*(2), 309–319. doi:10.1007/s00138-018-0986-z

Jeong, S. H., Choi, C. G., Oh, J. N., Yoon, P. J., Kim, B. S., Kim, M., & Lee, K. H. (2010). Low cost design of parallel parking assist system based on an ultrasonic sensor. *International Journal of Automotive Technology, 11*(3), 409–416. doi:10.1007/s12239-010-0050-0

Jian, D. H., & Lin, C. H. (2020). Vision-Based Parking Slot Detection Based on End-to-End Semantic Segmentation Training. *2020 IEEE International Conference on Consumer Electronics (ICCE)*, 1-4. doi:10.1109/ICCE46568.2020.9043164

Jiang, S., Jiang, H., Ma, S., & Jiang, Z. (2020). Detection of Parking Slots Based on Mask R-CNN. *Applied Sciences (Basel, Switzerland)*, 10(12), 4295. doi:10.3390/app10124295

Jiang, W., Wu, Y., Guan, L., & Zhao, J. (2019). Dfnet: Semantic segmentation on panoramic images with dynamic loss weights and residual fusion block. *2019 International Conference on Robotics and Automation (ICRA)*, 5887-5892. doi:10.1109/ICRA.2019.8794476

Jung, H. G., Kim, D. S., Yoon, P. J., & Kim, J. (2006a). Parking slot markings recognition for automatic parking assist system. *2006 IEEE Intelligent Vehicles Symposium*, 106-113. doi:10.1109/IVS.2006.1689613

Jung, H. G., Kim, D. S., Yoon, P. J., & Kim, J. (2006b). Structure analysis based parking slot marking recognition for semi-automatic parking system. In *Joint IAPR International Workshops on Statistical Techniques in Pattern Recognition (SPR) and Structural and Syntactic Pattern Recognition (SSPR)* (pp. 384–393). Springer. doi:10.1007/11815921_42
Jung, H. G., Lee, Y. H., & Kim, J. (2009). Uniform user interface for semiautomatic parking slot marking recognition. *IEEE Transactions on Vehicular Technology, 59*(2), 616–626. doi:10.1109/TVT.2009.2034860

Kageyama, Y. (2004). *Look, No Hand! New Toyota Parks Itself*. Available online: https://www.goupstate.com/article/NC/20040115/news/605146346/SJ

Lee, S., Hyeon, D., Park, G., Baek, I. J., Kim, S. W., & Seo, S. W. (2016). Directional-DBSCAN: Parking-slot detection using a clustering method in around-view monitoring system. *2016 IEEE Intelligent Vehicles Symposium (IV)*, 349–354. doi:10.1109/IVS.2016.7535409

Lee, S., & Seo, S. W. (2016). Available parking slot recognition based on slot context analysis. *IET Intelligent Transport Systems, 10*(9), 594–604. doi:10.1049/iet-its.2015.0226

Li, L., Li, C., Guo, T., & Miao, Z. (2018). Geometric Features-Based Parking Slot Detection. *Sensors (Basel), 18*(9), 2821. doi:10.3390/s18092821 PMID:30150539

Li, W., Cao, L., Yan, L., Li, C., Feng, X., & Zhao, P. (2020). Vacant Parking Slot Detection in the Around View Image Based on Deep Learning. *Sensors (Basel), 20*(7), 2138. doi:10.3390/s20072138 PMID:32290183

Loeffler, A., Ronczka, J., & Fechner, T. (2015). Parking lot measurement with 24 GHz short range automotive radar. *2015 16th International Radar Symposium (IRS)*, 137-142.

Moré, J. J. (1978). The Levenberg-Marquardt algorithm: implementation and theory. In Numerical analysis. Springer. doi:10.1007/BFb0067700

Pohl, J., Sethsson, M., Degerman, P., & Larsson, J. (2006). A semi-automated parallel parking system for passenger cars. *Proceedings of the Institution of Mechanical Engineers. Part D, Journal of Automobile Engineering, 220*(1), 53–65. doi:10.1243/095440705X69650

Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You only look once: Unified, real-time object detection. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 779-788*. doi:10.1109/CVPR.2016.91

Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster r-cnn: Towards real-time object detection with region proposal networks. arXiv preprint arXiv:1506.01497.

Rosten, E., & Drummond, T. (2006). Machine learning for high speed corner detection. *Proceedings of the 9th European Conference on Computer Vision, 430–443*. doi:10.1007/11744023_34

Schmid, M. R., Ates, S., Dickmann, J., von Hundelshausen, F., & Wuensche, H. J. (2011). Parking space detection with hierarchical dynamic occupancy grids. *2011 IEEE Intelligent Vehicles Symposium (IV)*, 254-259. doi:10.1109/IVS.2011.5940476

Suhr, J. K., & Jung, H. G. (2012). Fully-automatic recognition of various parking slot markings in Around View Monitor (AVM) image sequences. *2012 15th International IEEE Conference on Intelligent Transportation Systems, 1294-1299.*

Suhr, J. K., & Jung, H. G. (2013). Full-automatic recognition of various parking slot markings using a hierarchical tree structure. *Optical Engineering (Redondo Beach, Calif.), 52*(3), 037203. doi:10.1117/1.OE.52.3.037203

Suhr, J. K., & Jung, H. G. (2018). A Universal Vacant Parking Slot Recognition System Using Sensors Mounted on Off-the-Shelf Vehicles. *Sensors (Basel), 18*(4), 1213. doi:10.3390/s18041213 PMID:29659512

Suhr, J. K., & Jung, H. G. (2021). End-to-end trainable one-stage parking slot detection integrating global and local information. *IEEE Transactions on Intelligent Transportation Systems.*
Suthaharan, S. (2016). Support vector machine. In Machine learning models and algorithms for big data classification (pp. 207–235). Springer. doi:10.1007/978-1-4899-7641-3_9

Thrun, S. (2002). Probabilistic robotics. Communications of the ACM, 45(3), 52–57. doi:10.1145/504729.504754

Von Gioi, R. G., Jakubowicz, J., Morel, J. M., & Randall, G. (2012). LSD: A line segment detector. Image Processing On Line, 2, 35–55. doi:10.5201/ipol.2012.gjmr-ld

Wan, T., Jiang, D., Bin, Z., & Fang, W. (2009). Overview of parking space detection methods based on video. Proceedings of the 7th National Conference on information acquisition and processing.

Wang, C., Zhang, H., Yang, M., Wang, X., Ye, L., & Guo, C. (2014). Automatic parking based on a bird’s eye view vision system. Advances in Mechanical Engineering, 6, 847406. doi:10.1155/2014/847406

Wu, Y., Yang, T., Zhao, J., Guan, L., & Jiang, W. (2018). Vh-hfcn based parking slot and lane markings segmentation on panoramic surround view. 2018 IEEE Intelligent Vehicles Symposium (IV), 1767-1772. doi:10.1109/IVS.2018.8500553

Yu, Z., Gao, Z., Chen, H., & Huang, Y. (2020). SPFCN: Select and Prune the Fully Convolutional Networks for Real-time Parking Slot Detection. 2020 IEEE Intelligent Vehicles Symposium (IV), 290-297.

Zhang, L., Huang, J., Li, X., & Xiong, L. (2018). Vision-based parking-slot detection: A DCNN-based approach and a large-scale benchmark dataset. IEEE Transactions on Image Processing, 27(11), 5350–5364. doi:10.1109/TIP.2018.2857407 PMID:30028704

Zhou, J., Navarro-Serment, L. E., & Hebert, M. (2012). Detection of parking spots using 2D range data. 2012 15th International IEEE Conference on Intelligent Transportation Systems, 1280-1287.

Zinelli, A., Musto, L., & Pizzati, F. (2019). A deep-learning approach for parking slot detection on surround-view images. 2019 IEEE Intelligent Vehicles Symposium (IV), 683-688. doi:10.1109/IVS.2019.8813777

Zong, W., & Chen, Q. (2018). A Robust Method for Detecting Parking Areas in Both Indoor and Outdoor Environments. Sensors (Basel), 18(6), 1903. doi:10.3390/s18061903 PMID:29891826
Yong Ma received the M.S. degree in computer science from Xidian University, in 2003, and the Ph.D. degree in computer science from Wuhan University, in 2006. In 2018, he worked on the integrated control and dispatching of energy in microgrid with Malardalens University, Sweden. He is now a professor with the School of Computer Information Engineering, Jiangxi Normal University. His current research focuses on cloud computing, edge computing, and data science.

Yangguo Liu studied at Jiangxi Normal University, majoring in edge computing and computer vision.

Jiale Zhao received the B.Eng. degree from Huaibei Normal University in 2017. He graduated from Jiangxi Normal University with a master’s degree in engineering in 2021. Now he is a doctoral student in The School of Computer Science, Chongqing University. His research interests include cloud computing, cryptography, data security, and verifiable computation.