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A Machine Learning-Based Method for Parking Slot Feature Detection at Extreme Conditions

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ABSTRACT

With the rapid development of self-driving cars, automatic parking technologies have been widely concerned. However, extreme conditions such as different illuminations and incomplete features bring huge challenges for the parking slot detection, which is a key to automatic parking systems. To accurately and quickly detect parking slot features in such unfavorable conditions, an efficient park slot feature detection method based on the Convolutional Neural Network (CNN) is proposed in this paper. We collect simulated parking slot images under various extreme conditions which are taken as the input of the network as dataset. For each image in dataset, the parking slot feature points are carefully labeled. The YOLO v3 is applied as the basic neural network framework and the transfer learning is employed to train the network so as to accurately detect the parking slot features. Experimental results show that the parking slot feature recognition accuracy of the proposed method exceeds 96%, and the detection speed reaches 26 Frames per Second (FPS).

Keywords: Parking slot feature detection, Transfer learning, Convolutional neural network.

1. INTRODUCTION

Due to the complex environments of parking spaces, drivers could not see surroundings of the vehicle clearly, leading to difficulties to them for parking correctly. Furthermore, wireless charging vehicles require precise parking to improve charging efficiency [1]. These have raised active demands for automatic parking technologies. However, the parking slot environment varies inevitably with illumination and climate conditions, bringing big challenges to automatic parking. Thus, a robust method to recognize parking spaces at extreme conditions (e.g. lack of light, reflect light, bad weather, water logging, as shown in Fig. 1) is imperative. At present, automatic parking can be roughly categorized into two types: ultrasonic sensor-based methods and image-based methods.

An ultrasonic sensor-based automatic parking system measures the distance by time of flight (TOF) that means the travel time of ultrasonic waves from a sensor to an object [2, 3]. With multiple ultrasonic sensors, the system itself can determine the direction of measurement distance with right angle [4]. Satonaka et al [3] got the parking space with modeling in the rounded edge side of vehicles, but this method needs a lot of calculations and cannot be applied to an underground parking slot with right angle structure. P Degerman et al [5] used ultrasonic sensors for environment mapping and utilized the Hough Transform to pick up the right angle for parking. S Rahman et al [6] designed a parking slot marked with a circle so that the Hough transform can work well in detecting parking spaces. But these methods also need huge calculations and they cannot satisfy the required accuracy for automatic parking, especially for electric vehicle wireless charging.

Later, since computing abilities of the hardware have rapidly developed, image-based methods are more favorable because they are much more reliable, safer and cheaper compared with ultrasonic sensor-based methods. Most importantly, they can detect more complex scenes with a camera. In early image-based automatic parking systems, traditional machine vision algorithms [7] were used to assist to reconstruct parking space model. Hough Transform, as a method of machine vision, can also be used to image and detect the edge of parking spaces [8]. Other systems detect the corner points of parking spaces, and then complete the missing corner points according to the relationship between image plane and 3D space to reconstruct the parking space. Y Tang et al [9] revealed that the result of data fusion of multiple sensors is more accurate than that of a single sensor in parking data acquisition. C Unger et al [10] used real-time computing of environmental information around vehicles to build depth maps for parking assistance systems. This method was demonstrated in different applications for flexibility and robustness. However, these approaches have a common shortcoming that they have strict requirements for the environment and cannot be used in some natural environments with dramatic changes.

Fig 1 Examples of parking slot corners at extreme conditions: lack of light, reflect light, water-logging, partial occlusions, physical damages and out-of-focus blur.

More recently, deep learning technologies, especially CNN, have shown unique advantages in resolving high-dimensional feature extraction from images [11-14]. In 2015, J Redmon et al [15] proposed the YOLO detection algorithm, which is a brand-new end to end neural network. In the video test, it achieved 45 FPS, which satisfies the speed requirement of real-time detection. Although YOLO improves the detection speed, it sacrifices accuracy compared with Faster RCNN [16], which is a two-stage object detection algorithm. In 2016, J Redmon et al [17] proposed an updated version based on the YOLO algorithm named YOLO v2, whose detection speed was 67 FPS and the mean Average Precision (mAP) reached 76.8%. In 2018, J Redmon et al [18] updated YOLO v2 again and got YOLO v3, improving both accuracy and speed for object detection.

Based on the advanced research results of YOLO network on target detection, this paper proposes a real-time method for feature point detection of parking spaces. First, feature extraction network is designed. Then, datasets are collected to train and validate the designed neural network. Finally, recognition accuracy and speed of the network are evaluated using the collected datasets. Results show that the YOLO v3 deep learning algorithm can well realize the parking feature point detection even at extreme conditions such as lack of light, strong reflective light, water-logging, partial occlusions, physical damages, out-of-focus blur and so on. The image-level recognition accuracy exceeds 98% and the recognition accuracy for parking slot corner is higher than 96%.

2. METHODOLOGY

Algorithms based on machine vision for parking feature points detection require both high recognition accuracy and real-time detection. Compared with the traditional machine vision algorithms which have poor adaptabilities to various environments, deep learning methods exhibit strong generalization abilities. Given specific application scenarios, deep learning can conduct targeted learning and constantly improve performance through iterative system in practice [19, 20]. Among the deep learning network algorithms, YOLO v3 algorithm is featured with strong real-time detection and high accuracy, which is suitable for feature point detection. In real applications, a self-parking system is required to recognize classification of parking slot's surrounding objects and the precise location of parking slot. Since the feature points of parking slot are distinguished from surrounding environment characteristics, they can be used as the major character for locating the parking slot. Therefore, here the YOLO v3 network is employed to extract the parking slot features from images and give the precise pixel-level location.

2.1 Feature Extraction Networks

The basic model of YOLO v3 is Darknet-53, containing 53 convolution layers and 5 pooling layers [18]. It applies shortcut-connection technique [21] between layer and layer, so that the output of the underlying layer jumps every few layers into a higher layer as input, avoiding decrease in effective information. Besides, inspired by the idea of MobileNet [14], this network contains a lot of 3×3 convolutions and 1×1 convolutions, which can increase the depth of the network with low cost. YOLO series networks are built up by this basic model. It is worth mentioning that images can be directly input into this network without separating the specific object from images while training or testing because the labels (including class and location) of training samples or test samples can be distinguished by the network itself, reducing the time-consuming and tedious image preprocessing. During the training process, each input image is divided into a grid structure of S×S [15], and the network would predict which grid cell the center of an object will fall into. For each grid, the network predicts B bounding boxes and the confidence of each box. Confidence indicates the confidence of the bounding box to the detected object, and it is formulated as

$$Confidence = P_r(object) \times IOU \tag{1}$$

where IOU (Intersection-Over-Union) is defined as

$$IOU = \frac{A\bigcap}{A\bigcup} \tag{2}$$

where A is the area of detection result, B is the reference Ground Truth(GT) area of the input image. Each detected bounding box contains *x*, *y*, *w*, *h* and *confidence*, where (*x*, *y*) is the center of the detected bounding box in its original image coordinate, *w* and *h* are the width and height of the detected bounding box, respectively. The network also predicts the probability belonging to *C* class of each grid

$$P_r(C) = P_r\left(Class_i \mid Object\right) \tag{3}$$

which represents the probability of the center of a class *i* object falling into the current grid. The final output layer outputs dimensional tensor as follows

$$S \times S \times (B \times 5 + C) \tag{4}$$

2.2 Anchor Box

YOLO v3 is inspired by the idea of Faster-RCNN and introduces the concept of anchor box. Anchor box is an initial candidate box with fixed size and ratio in terms of width and height, and YOLO v3 chooses the anchor size and ratio based on the actual size of a specific detected object. During training process, sum of squared error is used as loss function. If the GT's value for the coordinate is $\hat{t}_*$, then the gradient towards the loss value could be easily computed, that is the ground truth value minus the prediction value $\hat{t}_* - t_*$.

The anchor of YOLO v3 is determined by the data aggregation classes of VOC 2007 and VOC 2012, whose categories are rich and the fixed anchors are universal. However, it is not suitable for specific detection tasks. When it comes to the self-made parking feature detection dataset, it is suggested to carry out an additional clustering operation for determining the size of anchor box and a method called K-means is adopted in this paper. K-means is a clustering algorithm in non-supervised learning field. The basic K-means algorithm has a simple idea. First, the constant value *k*, which means the final clustering category number, is determined in advance. Second, initial points are randomly selected as the center points corresponding categories. Then the Euclidean distances between each sample and the center points are computed and organized in numerical order as well. The smallest one means this sample possibly belongs to the center point's corresponding category. So we get a rough classification based on the Euclidean distance. Finally, we recalculate the center points of different categories and repeat above processes until the center points of different categories are no longer to change. Then the category of each sample and the center point of each class can be determined. The loss function of K-means is defined as the sum of square distance between each sample point and its clustering center $\mu_c(i)$:

$$J(c,\mu) = \sum_{i=1}^{m} \| x^{(i)} - \mu_{c^{(i)}} \|^2 \tag{5}$$

To maximize the efficiency of K-means algorithm, the loss values of K-means with different *k* are separately tested for the training set of parking slot features. K-means algorithm is used to cluster the width and height of the target box in the dataset. The change of the loss function corresponding to different *k* in the clustering process is shown in Fig. 2.

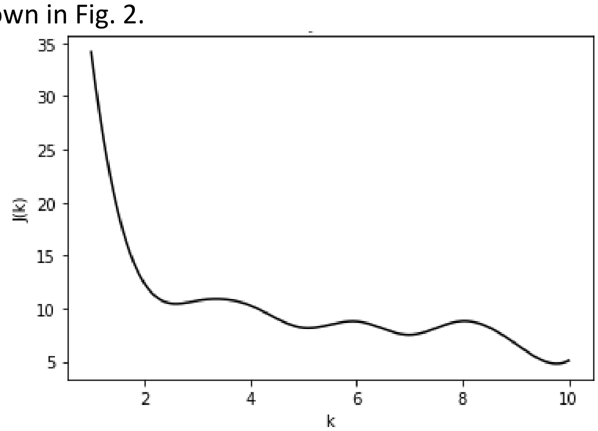


Fig 2 Loss function curve towards different *k*.

It can be seen that smaller the *k* is, faster the algorithm is. Therefore, we select *k*=5 considering the accuracy and computation cost simultaneously. In experiments, anchor sizes are set to (2.75, 3.49), (2.30, 3.14), (1.98, 2.97), (4.22, 4.63) and (2.31, 2.84).

3. EXPERIMENTS

Experiments were implemented using the open source framework of darknet-53 network. During the training procedure, the transfer learning technique was applied to redistribute the learning weight of the proposed deep convolution neural network.

3.1 Dataset

Experimental dataset is collected according to the simulation of the real parking model based on the regulations of Code for design of parking garage building JGJ 100-2015 [22]. The resolution of collected images is 640 pixel × 480 pixel, and 425 images containing 436 feature corner points of parking slots are used as the training dataset, while 117 images containing 140 feature corner points of parking slots are used as the test dataset. Images as shown in Fig. 3 are collected in different environments, such as different illumination (Fig3. a, b, i), different smooth surface reflection (Fig3. g, h, j, l), fuzzy images (Fig3. g, h), different background color (Fig3. c, e, f, k), different parking line color (Fig3. e, f), covered feature points (Fig3. d) and gathered water (Fig3. k). If the feature points of images are recognized, then the labels of detected feature points are marked as characteristic angular "inflection".

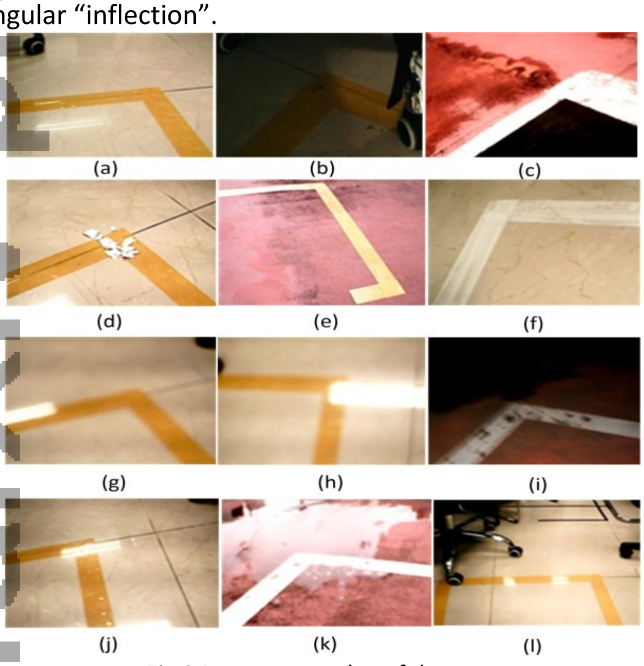


Fig 3 Image examples of dataset.

The framework of the proposed neural network is illustrated in Fig. 4. It consists of two stages, namely training stage and recognition stage. The training stage firstly uses extreme learning machine algorithm [23] to estimate output weights of the Darknet-53 by giving training images in a batch, which means 64 image and label pairs are read every training step. The label includes *w, h, d, name, xmin, ymin, xmax, ymax*, which represent width, height, depth, image name, upper-left and lower-right coordinates of the bounding box of target, respectively. In the recognition stage, the trained model outputs the class label, class number, confidence, upper-left and lower-right coordinates of objects in tested images.

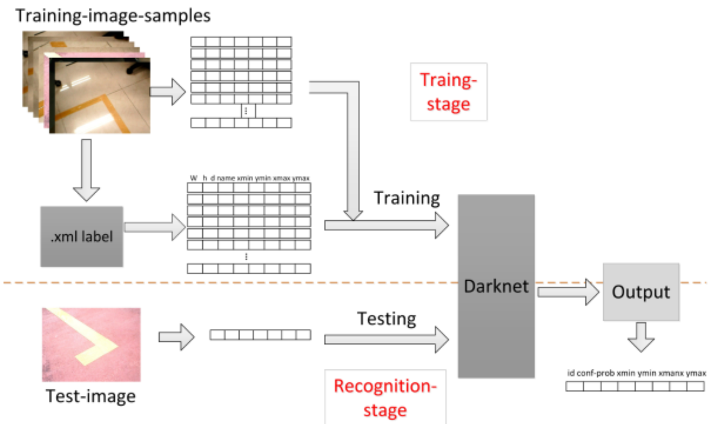


Fig 4 Framework of the proposed method for parking slot feature detection.

3.2 Experimental Configuration

A personal computer equipped with Intel Core i7, TATAN XP 1080P, 12 GB video memory, Ubuntu 64-bit operating system was used as the platform. 80% of the dataset are set as the training set and the rest are served as the test dataset. By applying the idea of transfer learning, we used the pre-trained parameters from YOLO v3 website as the initial network parameters to make the network converge rapidly.

Learning rate is one of the hyper-parameters in deep learning method, and the loss value would converge slowly if it is too small while the loss value could not achieve the optimum point if it is too large. Therefore, a variable learning rate strategy as shown in Fig. 5 was designed in this paper. Initial learning rate is 0, then the learning rate increases as the batch step increases until 0.001 so that the training process could converge faster. When the number of batch steps is greater than 1000, the loss value fluctuates around a specific value so the learning rate should be set smaller to keep loss value descending. In particular, the learning rate is reduced 10 times at 8000 step and 15000 step, respectively.

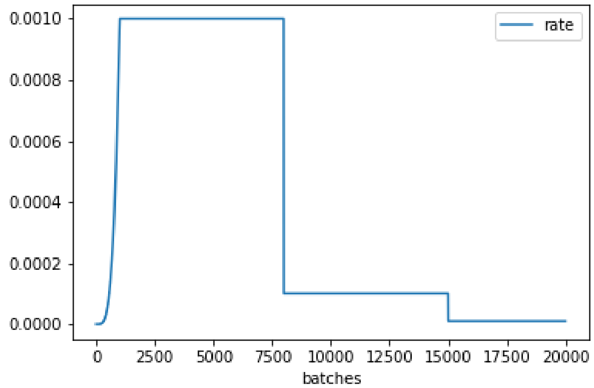
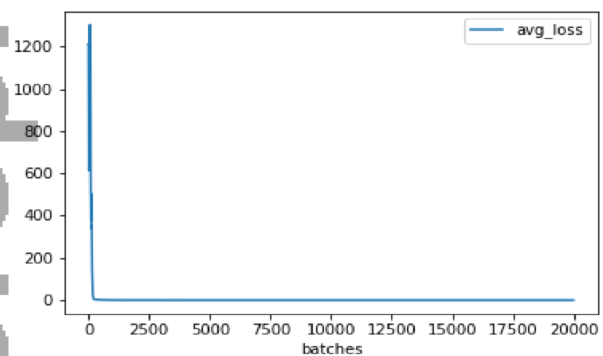


Fig 5 Learning rate curve.

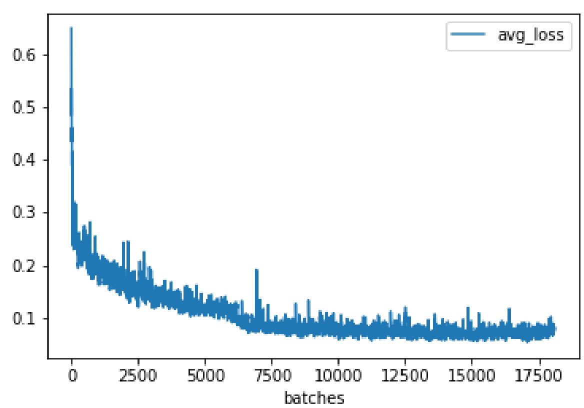
4. RESULTS AND ANALYSIS

4.1 Analysis on Training Process

The training dataset has been trained for 20,000 iterations on the YOLO v3 network and the entire training process has been monitored. Fig. 6(a) shows the change of average loss in the whole process.



(a)



(b)

Fig 6 Loss value curve in the (a) whole training procedure and (b) local view.

It is clear that from Fig. 6(a), as the number of iterations increases, the average loss decreases rapidly. After about 500 iterations, it keeps stable and converges to a very small value. To further detail the change of average loss, locally enlarged view from 1000 to 20000 iterations is shown in Fig.6 (b). It is worth mentioning that the start batch point marked as 0 actually equals to 1000 in Fig. 6(b). It can be seen that the average loss value reduces to about 0.1 at 10000 step. Considering the number of iterations and the convergence factor of average loss, batch 10000 is selected as the final training output parameter of the neural network model.

4.2 Evaluation on Test dataset

In the paper, we used two test datasets to evaluate the performance of the designed neural network for parking slot feature detection. One test dataset consists of 117 images, which totally contain 119 target corner points. The other includes 89 images, which contain 89 target cornet points in total. Examples of detection results at different conditions are presented in Fig. 7. It is clear that the designed neural network model can accurately recognize and locate the bounding box of parking slot feature points even at extreme environments. Among the first 117 test images, 115 images and all of the second 89 test images are correctly recognized for containing parking slot corners. That is to say, image-level recognition accuracy based on the two test datasets reaches 98% and 100%, respectively. More details are summarized in Table 1. Herein, if the confidence is equal or greater than 0.5, then the corresponding parking slot corner is considered to be recognized accurately; otherwise, it is wrongly recognized. Based on this criterion, it is indicated that recognition accuracy for parking slot corner exceeds 96%.

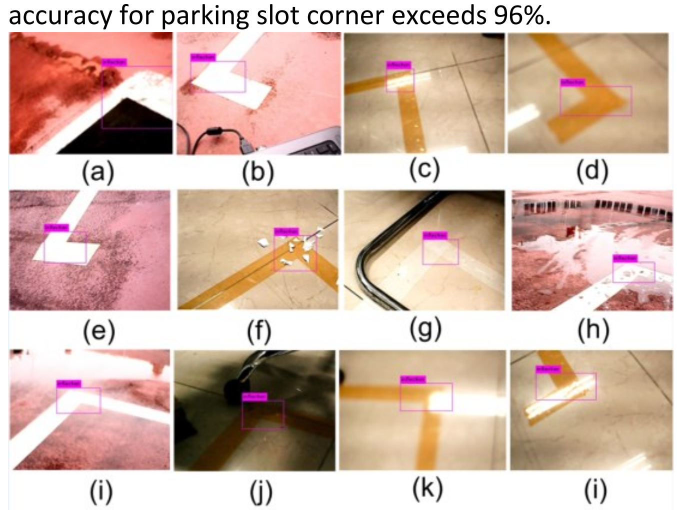


Fig 7 Detection results of feature points of parking slot under extreme environments.

Table 1 Recognition accuracy by different test dataset.

Dataset No.	Image number	Detected corners	Probability (thresh=0.5)		Correct recognition number	Total target number	Target recognition rate	Images recognition rate
			>=0.5	<0.5				
1	117	140	115	25	115	119	115/119=96.64%	115/117=98.29%
2	89	107	89	18	89	89	89/89=100%	89/89=100%

Based on the experimental platforms described above, a camera was applied to real-time acquire images, and the designed neural network achieved detection speed of 26 FPS, satisfying the requirements of real-time detection. In addition, the detection confidence is high and recognition results are stable. Fig. 8 shows examples of screenshot images in video of real-time test process. It is illustrated that multiple features appearing in the field of vision can be also accurately recognized.

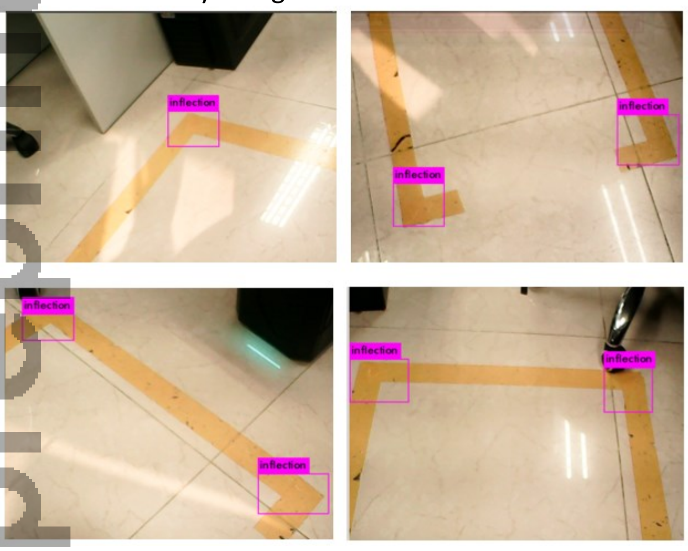


Fig 8 Examples of real-time recognition results.

5. CONCLUSION

In the paper, a deep learning method using transfer learning technique based on YOLO v3 neural network has been proposed for detecting feature points of a parking slot at extreme conditions. Because it is difficult to acquire abundant datasets in real situation, we have simulated the parking slot based on the regulations of Code for design of parking garage building JGJ 100-2015. After acquiring simulated dataset, a clustering method called K-Means has been applied for determining the size of anchor boxes so that the feature points of parking slots can be more easily recognized by the neural network. Additionally, a flexible learning rate strategy has been adopted to keep the loss value descend. With these strategies, the loss value fluctuates slightly at the end stage of the training process. Two test datasets have been used to verify the efficiency of the proposed method. Results indicate that the recognition accuracy for parking slot feature is higher than 96%, and the detection speed reaches 26 FPS, which can meet the requirement of real-time detection.

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REFERENCE

[1] S. A. Birrell, D. Wilson, C. P. Yang, G. Dhadyalla and P. Jennings, “How driver behaviour and parking alignment affects inductive charging systems for electric vehicles,” Transportation Research Part C, vol. 58, pp. 721–731, 2015.

[2] W. J. Park, B. S. Kim, D. E. Seo, D. S. Kim and K. H. Lee, “Parking space detection using ultrasonic sensor in parking assistance system,” IEEE Intelligent Vehicles Symposium, pp. 1039-1044, 2008.

[3] H. Satonaka, M. Okuda, S. Hayasaka, T. Endo, Y. Tanaka, and T. Yoshida, “Development of parking space detection using an ultrasonic sensor,” Proceedings of 13th World Congress, pp. 1–10, 2006.

[4] J. L. Crowley, "Dynamic world modeling for an intelligent mobile robot using rotating ultrasonic ranging device", IEEE International Conference Robotics and Automation, pp. 128-135, 1985.

[5] P. Degerman, J. Pohl, and M. Sethson, “Hough transform for parking space estimation using long range ultrasonic sensors,” SAE World Congress & Exhibition, Paper 2006-01-0810, 2016.

[6] S. Rahman, M. Ramli, F. Arnia, R. Muharar, M. Luthfi and S. Sundari, “Analysis and Comparison of Hough Transform Algorithms and Feature Detection to Find Available Parking Spaces”, International Conference on Computing and Applied Informatics, vol. 1566, 012092, 2020.

[7] X. Zeng, “The Algorithm of CFNN Image Data Fusion in Multi-sensor Data Fusion”, Sensors & Transducers, vol. 166, no. 3, pp. 197–202, 2014.

[8] H. Deng, D. Jiang, and Y. Wei, “Parking cell detection of multiple video features with PCA-and-bayes-based classifier”, 2006 IEEE International Conference on Information Acquisition, pp. 655–659, 2006.
[9] Y. Tang and X. Wu, “Scene Text Detection and Segmentation Based on Cascaded Convolution Neural Networks,” IEEE Transactions on Image Processing, vol. 26, no. 3, pp. 1509–1520, 2017.
[10] C. Unger, E. Wahl, and S. Ilic, “Parking assistance using dense motion-stereo: Real-time parking slot detection, collision warning and augmented parking,” Machine Vision and Application, vol. 25, no. 3, pp. 561–581, 2014.
[11] A. S. Razavian, H. Azizpour, J. Sullivan, and S. Carlsson, “CNN features off-the-shelf: An astounding baseline for recognition,” 2014 IEEE Conference on Computer Vision and Pattern Recognition Workshops, pp. 512–519, 2014
[12] E. Haber, L. Ruthotto, E. Holtham, and S.-H. Jun, “Learning across scales - A multiscale method for Convolution Neural Networks,” AAAI Conference on AI, pp. 1-8, 2017.
[13] H. Yoo, “Deep Convolution Neural Networks in Computer Vision : a Review”, arXiv, vol. 4, no. 1, pp. 35–43, 2015.
[14] A. G. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand, M. Andreetto, and H. Adam, “Mobilenets: Efficient convolutional neural networks for mobile vision applications.”, arXiv:1704.04861, 2017.
[15] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, “You Only Look Once: Unified, Real-Time Object Detection,” The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 779–788, 2016.
[16] S. Ren, K. He, R. Girshick, and J. Sun, “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 6, pp. 1137–1149, 2017.
[17] J. Redmon and A. Farhadi, “YOLO9000: Better, faster, stronger”, 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 6517–6525, 2017.
[18] J. Redmon and A. Farhadi, “YOLOv3: An Incremental Improvement”, arXiv:1804.02767, 2018.
[19] H.T.Vu and C. Huang, “A multi-task convolutional neural network with spatial transform for parking space detection”, 2017 IEEE International Conference on Image Processing (ICIP), pp. 1762-1766, 2017.
[20] L. Zhang, J. Huang, X. Li and L. Xiong, “Vision-Based Parking-Slot Detection: A DCNN-Based Approach and a Large-Scale Benchmark Dataset”, IEEE Transactions on Image Processing, vol. 27, no. 11, pp. 5350-5364, 2018.
[21] K. He, X. Zhang, S. Ren, J. Sun. “Deep Residual Learning for Image Recognition”, 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 770-778, 2016.
[22] Code for design of parking garage building JGJ 100-2015, Urban-Rural Development of the People’s Republic of China.
[23] Z. Huang, Y. Yu, J. Gu, and H. Liu, “An Efficient Method for Traffic Sign Recognition Based on Extreme Learning Machine,” IEEE Transactions on Cybernetics, vol. 47, no. 4, pp. 920–933, 2017.