Indoor Parking Method Based on Cooperation of Intelligent Vehicle and Parking Lot

Jiwei Zhang, Baiguo Chen, LingLing Yu, Ming Cen

Automated institute, Chongqing University of Posts and Telecommunications, ChongQing, China

*e-mail: andy_zhang_w@foxmail.com, b-e-mail: 540322829@qq.com, c-e-mail: 1797251530@qq.com

d-e-mail: m_cen0104@sina.com, *Corresponding Author

Abstract—This paper designs an intelligent vehicle-parking lot cooperative indoor parking system architecture and a multi-vision sensor-based indoor vehicle detection and localization method to solve parking problems in large parking lots. The system consists of a parking lot sensor group, a parking lot server, and an intelligent vehicle terminal. The communication between the intelligent vehicle terminal and the parking lot is established through V2X technology. Sensors and parking lot servers are deployed in the parking lot to complete indoor vehicle positioning and parking space management. The intelligent vehicle terminal initiates parking/leaving requests and positioning requests to the parking lot. The parking lot server provides the parking lot real-time map, parking space information and localization information to the intelligent vehicle terminal, so as to complete the parking navigation or automatic parking in the indoor parking scene through the cooperation of the intelligent vehicle terminal and the parking lot. This paper verifies the effectiveness of the method and system developed in this paper through real parking scene experiments.

1. INTRODUCTION

With the increasing number of vehicles, more and more large and complex indoor parking lots have been built, which makes parking cruise problems no longer occur only outside the parking lot[1]. Finding parking spaces and parking in the parking lot also takes a lot of time and effort. The existing solutions generally only have a parking induction function, and the degree of information and intelligence is not enough. Therefore, this paper uses object detection and tracking technology to solve the indoor positioning problem of the vehicle, and combined with V2X technology[2], an intelligent vehicle-parking lot cooperative indoor parking system architecture is designed. This method will better solve the parking cruise problem and improve parking efficiency. Compared with other solutions[3]-[5], the object detection and tracking method based on multi-vision sensor proposed in this paper can locate the object without additional on-board equipment and identify non-vehicle targets, which has better localization accuracy. Most of the existing image object detection and tracking algorithms are directed to the case of a single vision sensor and a single object. These algorithms are not suitable for parking environments. This paper will combine other methods to improve the object detection algorithm for indoor parking lot. The intelligent vehicle-parking cooperative indoor parking system architecture designed in this paper can solve the problems of centralized server computing burden in a centralized architecture indoor collaborative parking system, and the distributed architecture has complex
deployment and high costs. The communication between the intelligent vehicle and the parking lot is established through the V2X technology. The intelligent vehicle initiates a parking / drive-out request to the parking lot. The parking lot server provides the parking lot real-time map, parking space information and localization information to the intelligent vehicle terminal. The collaboration of intelligent vehicles and parking lots completes parking navigation and automatic parking in indoor parking lot.

2. COLLABORATIVE PARKING SYSTEM ARCHITECTURE
The cloud-based collaborative parking system consists of parking lot deployment equipment, cloud server, and intelligent vehicle terminal. The system architecture is shown in Figure 1. The biggest difference between the cloud-based collaborative parking system architecture and the distributed architecture is that the node processor and the parking server are all placed on the remote cloud server, and the image data compression and decoding module is added to ensure data transmission.

Parking lot deployment equipment mainly includes vision sensor group, image data compression module and communication module. In the system, image data compression and decoding module, H.264 video codec technology is used to effectively compress the volume of image data, reduce bandwidth pressure and video transmission delay. The cloud server mainly includes an image data decoding module, an object detection module, an object tracking module, a data management module and a communication module.

![Figure 1. Cloud-based collaborative parking system architecture](image)

In the cloud-based collaborative parking system architecture, the use of multi-threads virtualizes the process of the distributed node processor processing each set of sensor data independently, thus retaining the excellent scene adaptability and algorithm flexibility of the distributed architecture.

The cloud-based collaborative parking system architecture minimizes the deployment of equipment in the parking lot and reduces the difficulty of system deployment. Data processing is centralized in the remote cloud server. The server performance can be adjusted more flexibly. The upper limit of the server's performance is not restricted by the site. The data of multiple parking lots can be completed by the one cloud server group. Reasonable load balancing is easier to maintain and more promising.

3. VISION-BASED INDOOR POSITIONING METHOD
Under the architecture of the intelligent vehicle-parking lot collaborative parking system proposed in this paper, a key issue to realize the coordinated parking navigation and automatic parking of vehicles and parking lots is how to locate the vehicle in an indoor scene. This article will design a vision-based localization method, select and improve a variety of existing technologies for parking lot scenarios, and combine these technologies to achieve the indoor localization method of this article. The image-based indoor localization method of the parking lot sensor data processing process is shown in Figure 2.
After performing data pre-processing operations such as image distortion correction, image filtering, and Perspective Transformation, a background model method to obtain foreground objects [6] is used. The shadow chroma of the foreground object is used to remove the shadow error of the object. The location information of the object is obtained by constructing a grid map. Then, the color and texture features of the object are extracted and a data association according to the features of the object is implemented.

The feature-assisted data association method used in this paper is described as follows: Let the moving object detection list at time $k$ be $D(k) = \{d_1, d_2, \ldots, d_n\}$ and the tracking track confirmation list at time $k-1$ be $T(k-1) = \{t_1, t_2, \ldots, t_m\}$, where $n$ is the number of detection objects, and $m$ is the number of tracking trajectories. Calculate the combined correlation value between the $i$-th measurement and the $j$-th trajectory based on the measurement and trajectory position and feature information, the calculation formula is as follows:

$$\lambda_{ij} = \alpha \lambda_{ij}^p + \beta \lambda_{ij}^f$$  \hspace{1cm} (1)

Among them, $\lambda_{ij}^p$ represents the correlation value calculated based on the object position information, and $\lambda_{ij}^f$ is the correlation value calculated based on the object feature information. $\alpha$ and $\beta$ are the weights of position correlation value and feature correlation value, respectively, satisfying $\alpha + \beta = 1$.

Calculate the combined correlation value matrix between all measurements and trajectories at the current moment according to formula (1) as

$$\lambda(k) = \begin{bmatrix} \lambda_{11} & \lambda_{12} & \cdots & \lambda_{1m} \\ \lambda_{21} & \lambda_{22} & \cdots & \lambda_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{n1} & \lambda_{n2} & \cdots & \lambda_{nm} \end{bmatrix}$$  \hspace{1cm} (2)

After the combined correlation value matrix is obtained, it is necessary to determine the correlation between each measurement and a specific trajectory according to the magnitude of the correlation value, to ensure that each measurement is associated with at most one trajectory, and at the same time, each trajectory is associated with at most one measurement. For a specific measurement $i$, first select the minimum combined correlation value $\lambda_{ij}^{\text{min}}$ between the measurement and all trajectories, which can be calculated by formula (3). Assuming that the minimum correlation value corresponds to trajectory $j$, then $\lambda_{ij}^{\text{min}}$ is compared with the corresponding correlation threshold $\lambda_{j}^{\text{threshold}}$. The specific $\lambda_{j}^{\text{threshold}}$ is calculated based on the ellipse area centered on the position of trajectory $j$, the length is the long axis, and the width is the short axis, as shown in formula (4).

$$\lambda_{ij}^{\text{min}} = \min(\lambda_{i1}, \lambda_{i2}, \ldots, \lambda_{im})$$  \hspace{1cm} (3)

$$\lambda_{j}^{\text{threshold}} = \frac{\pi \frac{W_j}{2} \cdot \frac{L_j}{2}}{2}$$  \hspace{1cm} (4)

Let the correlation matrix between the current measurement and the trajectory be $C(k)$:
If $\lambda^i_j < \lambda^i_{threshold}$, it means that the $i-th$ measurement originates from the $j-th$ trajectory, and the relationship between measurement $i$ and trajectory $j$ is $c_{ij} = 1$ and $c_{ij} = 0(t \neq j)$; if $\lambda^i_j \geq \lambda^i_{threshold}$, it means that measurement $i$ is not associated with any trajectory at the current moment, then $c_{ij} = 0(i=1,2,\cdots,m)$.

For the objects that have been measured and associated with the trajectory, the Kalman filter model will be used to filter and track them to estimate the optimal state of the object at the current moment.

According to the selection of the object motion model in this paper, a CV motion model is established for the vehicle, and its state vector $X = [x, \dot{x}, y, \dot{y}]^T$ contains the object position and speed information. The object in this article does not contain direction information, so the observation vector is expressed as $Z = [x, y]^T$. Therefore, the moving object state transition equation and observation equation at time $k$ can be expressed as formulas (6) and (7):

$$X_k = \Phi \cdot X_{k-1} + \omega_k$$

$$Z_k = H \cdot X_k + \nu_k$$

Among them, $X_k$ represents the object transition vector at time $k$, $\Phi$ is the state transition matrix, $\omega_k \sim N(0, Q)$ is the process noise, $Z_k$ is the observation vector at $k$, and $H$ is the observation matrix. $\nu_k \sim N(0, R)$ is the observation noise.

In the Kalman filtering framework, the object filtering process can be specifically described as follows: At time $k$, firstly predict the object state $\hat{X}(k \mid k-1)$ at time $k$ based on the object state at time $k-1$, and calculate one step prediction covariance $(k \mid k-1)$:

$$\hat{X}(k \mid k-1) = \Phi \cdot \hat{X}(k-1 \mid k-1)$$

$$P(k \mid k-1) = \Phi P(k-1 \mid k-1) \Phi^T + \Gamma \Omega \Gamma^T$$

Then calculate the filtering gain $K(k)$ based on the measurement information at time $k$, and further integrate the measurement and state prediction values with the filter gain to obtain the optimal estimate of the object state at time $k$:

$$K(k) = P(k \mid k-1)H^T[H P(k \mid k-1)H^T + R]^{-1}$$

$$\hat{X}(k \mid k) = \hat{X}(k \mid k-1) + K(k)[Z(k) - H \hat{X}(k \mid k-1)]$$

Simultaneously update the optimal estimated state covariance at time $k$:

$$P(k \mid k) = [I_s - K(k)H]P(k \mid k-1)$$

4. EXPERIMENTS

In order to verify the effectiveness of the proposed scheme, this paper first carried out a software simulation experiment based on a vision-based indoor localization method. Then, based on the collaborative parking system architecture proposed in this paper, a real experimental platform was built and the real test scenario was verified.
4.1 Simulation
In this paper, a 25-car parking lot scenario is set up in the PreScan simulation software, and multiple vehicles traveling at the same time will be set in the scenario to verify the effectiveness of the algorithm in a more complex simulation scenario. Figure3 (a) shows the initial state of the experimental scene, and Figure3 (b) records the positioning detection trajectory of the three vehicle targets in the experiment.

![Figure3 (a). Experimental scene.](image)

![Figure3 (b). Experiment end state and vehicle driving trajectory detection results.](image)

The localization error in the horizontal axis direction of the localization result and the actual running trajectory of the vehicle is shown in Figure4 (a), and the localization error in the vertical axis direction is shown in Figure4 (b).

![Figure4 (a). Horizontal localization error](image)
4.2 Parking scene experiment

In order to verify the effectiveness of the system and algorithm in real scenarios in this paper, a collaborative parking system based on cloud architecture is deployed in a small parking lot. Six DH-IPC-HFW5200R-Z network cameras are deployed in the parking lot for vehicle localization and parking space management, high-performance computer acts as a cloud server for data processing and management, and an intelligent vehicle with V2X capabilities as an experimental vehicle.

The deployment of the parking lot environment and sensors is shown in Figure 5 (a), and the intelligent vehicle used in the experiment is shown in Figure 5 (b).

The localization error in the horizontal axis direction of the localization result and the actual running trajectory of the vehicle is shown in Figure 6 (a), and the localization error in the vertical axis direction is shown in Figure 6 (b).
The experimental results verify that the system described in this article can be effectively deployed and applied in a real parking lot scenario. The vision-based indoor localization method described in this article has high localization accuracy, and the system real-time performance can also satisfy the collaborative intelligent vehicle to complete parking navigation Requirements.

5. CONCLUSIONS

In this paper, the collaborative parking system based on the cloud architecture and the vehicle indoor localization method based on multi-vision sensors are used to effectively solve the problems of vehicle localization and cooperative parking in the parking lot. The collaborative parking system based on cloud architecture proposed in this paper solves the problems of centralized server computing burden in a centralized architecture indoor collaborative parking system, high deployment costs and difficult maintenance in a distributed architecture. This method fully simplifies the equipment deployment requirements at the parking lot site, and completes the data calculation to a cloud server with sufficient computing power. The intelligent vehicle terminal only needs to communicate with the cloud server to obtain the required positioning results and parking lot information. The multi-vision sensor-based vehicle indoor localization method can more accurately achieve object detection and tracking, and the method in this paper can also accurately correlate object measurement and trajectory in multi-object scenarios. Simulation experiments and real parking lot experiments verify the effectiveness of the system and indoor localization method described in this paper. This work is supported by Chongqing Key Technology Innovation Project under Grant (cstc2020jscx-dxwtB0003).

REFERENCES

[1] Kotb A O, Shen Y C, Huang Y. Intelligent Parking Guidance, Monitoring and Reservations: A Review[J]. IEEE Intelligent Transportation Systems Magazine, 2017, 9(2): 6-16.
[2] Abboud K, Omar H, Zhuang W. Interworking of DSRC and Cellular Network Technologies for V2X Communications: A Survey[J]. IEEE Transactions on Vehicular Technology, 2016: 1-1.
[3] Henriques J F, Caseiro R, Martins P, et al. High-Speed Tracking with Kernelized Correlation Filters[J]. IEEE Transactions on Pattern Analysis & Machine Intelligence, 2015, 37(3): 583-596.

[4] Qin Y, He S, Zhao Y, et al. RoI Pooling Based Fast Multi-Domain Convolutional Neural Networks for Visual Tracking[C]// International Conference on Artificial Intelligence and Industrial Engineering. 2016.

[5] Danelljan M, Häger G, Khan F S, et al. Convolutional Features for Correlation Filter Based Visual Tracking[C]// IEEE International Conference on Computer Vision Workshop. IEEE Computer Society, 2015: 621-629.

[6] Bouwmans T. Traditional and Recent Approaches in Background Modeling for Foreground Detection: An Overview[J]. Computer Science Review, 2014: 31-66.