

# Vision based Semantic Mapping and Localization for Autonomous Indoor Parking

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**Abstract**—Autonomous indoor parking without human intervening is one of the most demanded and challenging tasks of autonomous driving system. The key point to this task is real-time precise indoor localization. However, most indoor parking lots are composed of monotonous texture-less scenes and thus, are hostile to traditional visual feature-based SLAM methods. In this paper, we proposed a novel and practical solution of real-time indoor localization for autonomous driving in parking lots. High level landmarks, the parking slots, are extracted and enriched with labels to avoid the instability of low-level visual features. We then proposed a robust method for detecting incorrect data associations between parking slots and further extended traditional optimization framework by dynamically eliminating suboptimal data associations. Visual fiducial Tags are also introduced to improve the overall precision. Their number and distribution are also analyzed and compared. As a result, a semantic map of parking lot can be established fully automatically and robustly. We experimented the performance of real-time localization based on the map using our autonomous driving platform TiEV and the average accuracy of 0.3m tracking tracing can be achieve at a speed of 10kph.

**Index Terms**—Indoor, ParkingLot, Semantic landmark, Robust SLAM

## I. INTRODUCTION

AUTONOMOUS driving has been witnessed great progress in recent years, breakthrough has been made in several harsh fields, including obstacle detection, real-time motion planning and high precision localization (mostly based on differential GNSS). Recently, testing self-driving car can already drive safely in urban and suburban areas[? ]. However, parking in a large indoor parking lot without human interfere is still an unsolved problem. One critical reason is the lack of robust high precision localization mean in these GNSS forbidden area. Traditional indoor localization methods require pre-equipment sensors, such as WiFi, Bluetooth or UWB. Wireless signal suffers from occlusion and decays while users distance to signal sources increases, so a significant number of stations are needed for stability, let alone their relative low precision[? ]. Laser-based SLAM system is eligible for localization an unmanned vehicle in environments such as a factory or a warehouse[? ]. However, these range based representation is of high data volume and is vulnerable to dynamic scenes. As a result, visual SLAM (VSLAM) built on low-cost cameras became one of the most favorable localization method.

VSLAM is known to be effective in texture-rich environment[? ]. Nevertheless, they can easily fail in monotonously textured scene such an indoor parking lot. ? ] adopted sparse feature point based SLAM method with panorama images to localize a car in parking lots. But the extracted sparse feature can be unstable when the ground floor is stained with tire markings or water spots. The distortion presented in the stitched panorama images can also disturb the feature extraction. Recently, ? ] employ DSO method with forward looking camera for mapping and localization in indoor parking lot. The direct methods estimate camera poses directly based on photometric error derived from the whole image, thus are more robust than sparse methods in ?? area [ ]. However, they often require high frame rate and are susceptible to global illumination change, which restrict their usage in unevenly illuminated indoor parking lot[ ]. Moreover, the re-localization based on pre-built dense map is not trivial (to verify). Therefore, more stable, legible and light weighted visual landmarks which are immune to the above shortcomings are demanded.

As a typical kind of semantic landmarks in parking lots, parking-space is now a favour for researchers [1] [2] [3]. Recently, deep learning-based method show its capability of accurate and robust detection of such kind of meaningful objects [? ]. Inspired by these methods, we present an robust VSLAM system based on the recognition of high level landmarks for parking, i.e. parking-spaces and their IDs. Limited visual fiducial markers are introduced for improving overall accuracy and robustness. Facing the visual aliasing problem of parking slots, we proposed a robust outliers detection and elimination strategy in the optimization stage. Finally, a two dimensional map of parking slots can be robustly established which is distinguished from the traditional feature-based or point-cloud map for its stability, re-usability, light weight and human readable. Our system is implemented on an autonomous driving vehicle and tested in real parking lots.

## II. RELATED WORKS

SLAM has long been a classic topic in the robotics field and recently became heated in the autonomous driving[ ]. (author?) [4] (author?) [5] and (author?) [6] use Extended Kalman Filter(EKF) to simultaneously optimize the sensor and landmarks positions in real-time. These methods modeled the optimization problem as a Markov Chain, thus can provided promising localization results with high efficiency. However, the computation grows quadratically with the number of landmarks[7], so these methods are bounded in room-sized domains when regarding visual features as landmarks.

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Probability filters have many further extensions such as UKF [1], Information filter [2], particle filter [3] etc. However, they all assume the conditional independence of the current measurement with the historical states, which restricts the SLAM into a predict-update iteration loop. Inspired by the bundle adjustment research [4], a factor graph based optimization framework (known as Graph SLAM) was proposed [5]. The graph-based optimization method is closely related to a Markov random field model, thus can involve the influence of all historical measurements, which together with its flexibility enable the Graph SLAM became the most popular SLAM method [6].

Generally VSLAM methods fall into two groups, so called feature-based methods (the indirect methods) and direct methods. In feature-based methods, low-level features are detected and treated as landmarks. To prevent integrating all the features into the factor graph (John: should use correct expression from PTAM), PTAM [8] separates tracking and mapping into two sub-tasks, keyframes are extracted and used in optimization, but because of what?? it still works in small areas (a desk or a room corner). [9] and [10] build city-scale sparse maps using G2O, a graph optimization framework [11]. Nevertheless, the optimization of sparse 3D point cloud is time-consuming, so the off-line mapping procedure is a must. Built on the idea of PTAM [8], ORB-SLAM [12] offers stable and efficient graph-based VSLAM system. With the keyframe detection and the BoW-empowered fast loop closure detection, ORB-SLAM performs well in various indoor and outdoor environments. However, ORB-SLAM is still easy to fail in texture-less environments.

Because feature-based methods are only capable of creating sparse feature-based mapping, they cannot be directly used in applications where full reconstruction is demanded, e.g. AR or structure from motion. Direct methods based on photometric error and utilize all image pixels are proposed [13]. Comparing to sparse feature-based methods, direct methods can output a semi-dense point cloud with higher quality at a real time speed. But in practice, direct methods require high rate of overlapping between consequent frames and high frame rate is also necessity since (to be filled) to estimate the depth accurately. Direct methods are also known to be vulnerable to motion blur, camera defocus and global illumination changes [14]. SVO [15] and DSVO [16] combine advantages of feature-based method and direct method, and runs extremely fast (100 Hz). However, lacking of loop closure detection, these odometric methods drifts as time increases and gets lost easily.

Traditional SLAM methods do not incorporate human understandable meanings (semantics) associated with landmarks into the method, which now is recognized to be crucial for construct a human readable map and strengthen the descriptive power of landmarks [17]. [16]. [17] added semantic labels to a LSD-SLAM framework to construct a dense map with classes attached to geometric entities, but semantic labels helps little in the optimization or localization stages. SLAM++ [18] and Semantic Fusion [19] employed semantic labels in the RGBD SLAM framework to aid the loop closure. However, both methods...

(!!should be very clear about the defects of these methods, i.e. 3D objects? not precise regarding to the localization of ob-

jects? can be confusing when multiple objects are searched?)

In [20], shop names and shop facades are recognized as labels in large indoor shopping spaces. [1] detects parking lots from the (fixed IP camera?) top view image, and use detected lots to estimate camera poses (is this a slam?).

[2] and [3] reconstruct the metric map and the semantic map of parking lot, which helps the route planning and parking task. (!!semantics in VW paper(2015) is not used in SLAM at all, not sure about the second one )

In a short conclusion, existing VSLAM methods generally could not perform robustly in texture-less area like an indoor parking lot. Therefore, more descriptive landmarks, especially landmarks attached with semantics should be used instead of low level feature in such a scenario.

### III. APPROACH

Our semantic VSLAM system includes four fisheye cameras and one monocular camera. Four fisheye cameras are fixed at two reflectors, and at the front and rear bumpers, which consist a surround-view system. A top-view image is thus fused from the surround-view inputs after intrinsic and extrinsic calibration, as shown in Fig. 2. In the top-view image, who indicates ground textures, parking slots are detected. The monocular camera is installed to the left of the real-view mirror to capture front scenes. The change of steering wheel angle, as well as the vehicle speed and heading direction collected by IMU are also used in our system.

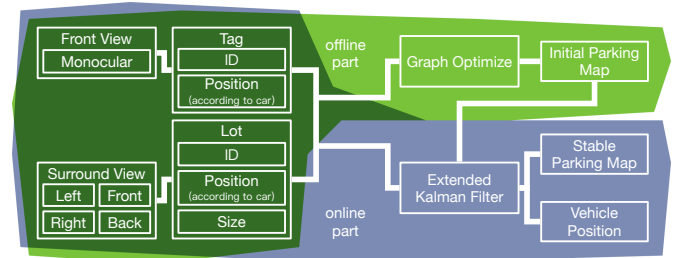


Fig. 1. Pipeline of the method

We choose parking slot as the landmark since parking slots are the most distinguishable objects in a parking lot, and the precise locations of parking slots are informative for localization and navigation during autonomous parking. Our parking slot detector is based on [21], in which corner points of parking slots are detected and classified (Fig. 4). Afterwards, parking slots are assembled according to the corner points (Fig. ??). Although the CNN-based method is capable of detection all kinds of corner points fast and robust, the exact shape of the parking slot cannot be known due to the limited visible range of the surround vision system. As a result, we have to optimize the shape of the parking slots in our SLAM system. Furthermore, the ID of each parking slot should be detected for facilitating data association between parking slots.

Another kind of landmark used in our system is visual fiducial markers. Fiducial markers are introduced as an aid for the constancy of localization since few parking lot is detected near the entrances and exits (but we put the markers

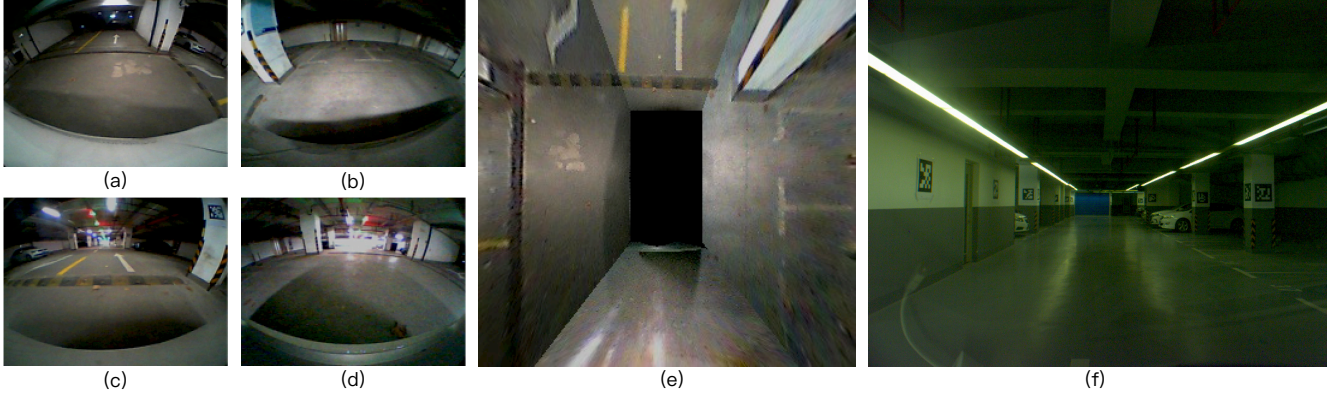


Fig. 2. (a)(b)(c)(d) are images from left, right, front, back fisheye cameras. (e) shows the top-view image fused from (a)(b)(c)(d). The image from the monocular camera is (f).

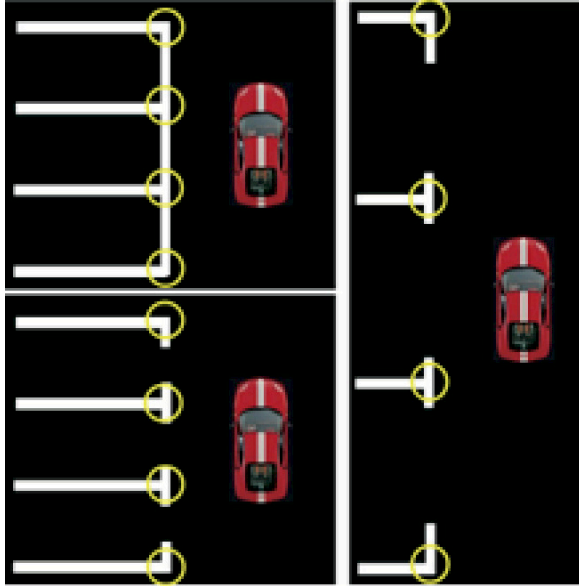


Fig. 3. In this graph, yellow circles show the image patterns to be detected.[21]

in the inner path of two rings?). Later in the experiments, we show that fiducial markers may not be fully prohibited but their number can be limited. We select AprilTags as visual markers for its robustness and high efficiency (a frame rate of 10 Hz)[24].

#### A. CNN based Parkinglot Recognition

Most traditional parking lot recognition methods use low-level features, such as corners and edges, which result in unstable and imprecise detections. CNN based method uses high-level features and offers stable and robust result. In our system, a learning based lot detection method [21] is applied.

First, marking-point patterns are detected by a binary classifier. Marking-point pattern refers to a image patch at the intersection of two parking-lines. [21] The popular AdaBoost framework is used. A boosted classifier is made up of several

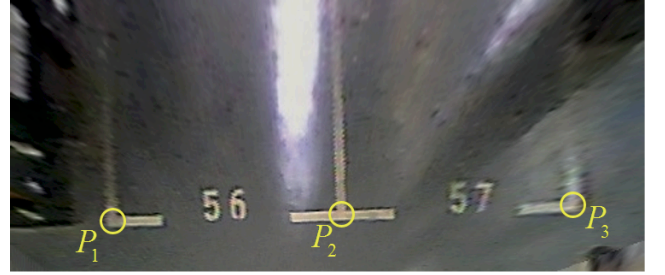


Fig. 5. 1

n this figure,  $\overrightarrow{P_1P_3}$ ,  $\overrightarrow{P_1P_2}$  and  $\overrightarrow{P_2P_3}$  consist three lots, but  $\overrightarrow{P_1P_3}$  is a false positive detection.[21]

weak classifiers, which, in our case, are shallow decision tree. Three types of feature the normalized intensity, the gradient magnitude and the oriented gradient histograms are used. Also, the constant soft-cascade strategy[21] is introduced for acceleration. Since there are five kinds of marking point patterns, there are five classifiers rather than one. Once a marking-point pattern is detected, it is rotated to fit the standard pattern.

Parking lots are then recognized based on the marking-point patterns. In this method, the entrance-line is especially focused. We use the entrance-line rule to make preliminary detections. A further decision is made by conforming the preliminary detection to the parking lot model.

The final step is to remove the miss-detected entrance-line, like  $\overrightarrow{P_1P_3}$  in Fig 5. We remove the entrance-line candidate who has more than two marking-point patterns on it to avoid this situation. Once a parking-line is detected, the direction of a lot is determined as well. And the depth of a parking lot is known a prior knowledge.

Since the relative car coordinate overlaps the top-view image coordinate, the lot coordinate in the top-view image is the same as that in the vehicle relative coordinate. Lot IDs are also recognized basing on the priori knowledge of parking lots since IDs are always located in the center of the entrance-line. We fine tuning the PVANet[22] to detect IDs. However, the IDs are so small on the top view image, only limited

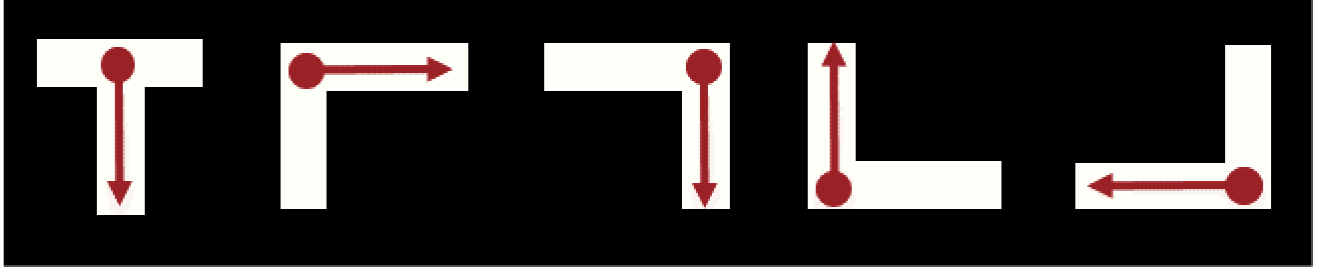


Fig. 4. Examples of marking point patterns, the red arrow indicates the direction of each patterns.[21]

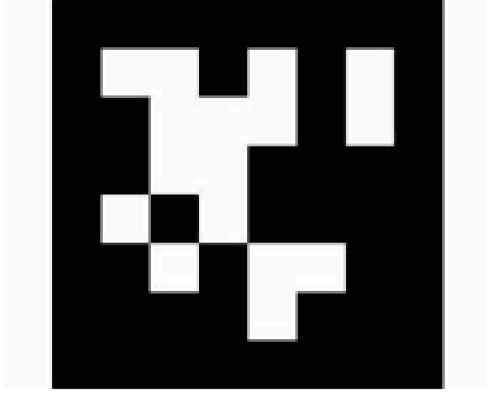


Fig. 6. An example of AprilTag

number of ID are detected, others are initially associated by Nearest Neighbor Method. Finally, all the detected ID and measurement of parking lots are added to the graph as max mixture [23] edges with multiple hypothesis including null hypothesis.

#### B. Visual markers/fiducial detection and Pillar wall inference

The surround view system offers an intuitional ground observation at a high frame rate, however it has limitations. The resolution of the top-view image is far from satisfactory, limiting the lot detection performance. Most part of the surround view images are discarded, only downward parts are available. And the calibration information for image fusion becomes inaccurate as time goes.

Pillar-walls are part and crucial in parking slots. They can be used for localization, indoor structure inference and obstacle avoidance. However, pillar-wall detections using image segmentation cost much time and still offer unstable results. Though RGBD camera like Kinect can captures walls easily, they do cost a lot. Visual markers, which present pillar-walls are introduced for its robustness and high efficiency.

We use a 2D bar code style visual marker AprilTag. The detection work is completed by AprilTag C source Open Library(<https://april.eecs.umich.edu/wiki/AprilTags>)[24], and the relative position between visual markers and the vehicle is solved by the PnP model [25]. Every tag texture indicates a unique ID, so tag data association is always correct.

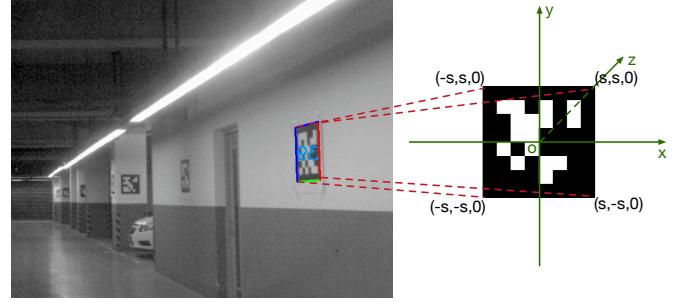


Fig. 7. An example of the relationship between a detected tag in the image plane(left figure) and its corresponding hypothetical 3D tag coordinate(right figure)

In the PnP model, we assume four corner points of the tag always lie on the same plane, and thus define the hypothetical 3D tag coordinate( whose origin is a tags geometrical center, x axis and y axis are both parallel to tags edge, pointing rightward and upward respectively, and z axis is perpendicular to the tag plane, pointing inward). So the relationship between the tag corner in the image and that in the hypothetical 3D tag coordinate can be described as,  $R_{3 \times 3} \cdot K_{3 \times 3}^{-1} \cdot x_{3 \times 1} + t_{3 \times 1} = X_{3 \times 1}$

where  $R_{3 \times 3}$  and  $t_{3 \times 1}$  is the relative rotation and translation vector,  $K_{3 \times 3}$  is the intrinsic camera matrix,  $X_{3 \times 1}$  is the coordinate in the hypothetical 3D tag coordinate and  $x_{3 \times 1}$  is the homogeneous coordinate in the image plane.  $X_{3 \times 1}$  and  $K_{3 \times 3}$  are prior knowledge, and  $x_{3 \times 1}$  has already been detected. Only  $R_{3 \times 3}$  and  $t_{3 \times 1}$  are unknown parameters with 6 DOF, more than 3 corresponding points are needed for iteration.

Once  $R_{3 \times 3}$  and  $t_{3 \times 1}$  is calculated, the Rodrigues transformation is performed on  $R_{3 \times 3}$  to separate the angle( $\alpha$ ) bonded by the array starts from the tag to the north and the array starts from the tag center to the vehicle. The distance( $d$ ) is the 2-norm of  $t_{3 \times 1}$ . So the tag locates at  $(x = \sin(\alpha) \cdot d, y = \cos(\alpha) \cdot d)$  in the vehicle relative coordinate.

#### C. Optimization

At every frame, the relative car-landmark position, together with the speed and angular changes of vehicle should be added to the parking map incrementally. These values are archived from a Kalman-based extrapolater with the steering wheel, car speed and the compass readings from a cheap IMU



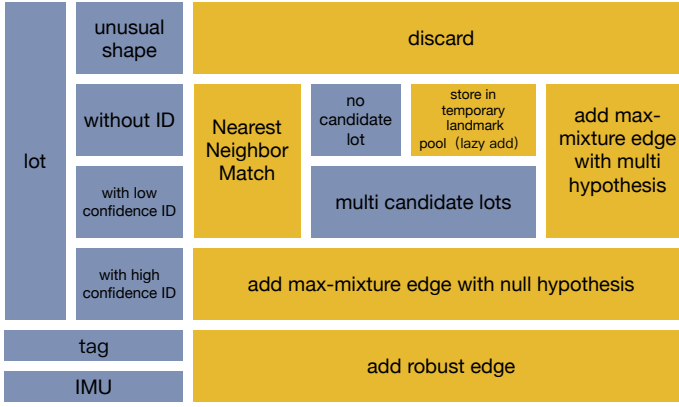


Fig. 8. The overall pipeline of the offline optimization stage

as the input. During the mapping stage, the popular graph optimizer G2O is used, some experimental designed rules are also introduced for outlier detection. Thus, the offline part outputs a 2D parking map and an optimized vehicle trajectory. During the online stage, the former parking map acts as the initial map, and is updated simultaneously with the extended Kalman filter(EKF). This results in a smoother trajectory, which helps the further control task.

In this section, a 2D map is built by fusing all the observation datum collected in the former sections. The accumulated error of IMU may cause drifting in localization. Due to imprecise detection of tags or lots, there will be ambiguities in the map. To avoid these problems, we use the popular g2o[11] framework together with the max-mixture model [23] to optimize both car and landmarks positions and ensure correct data association in the offline section, the figure above give the overall view of the optimization step.

During the offline stage, we use [11] to build the initial parking map. All the observations are treated as edges in the graph. Observations from vehicle to tag or vehicle are presented by G2O standard edges. However, observations from vehicle to parking lot sometimes contain miss data association causing by lot ID detection error and lead to great residual error in the graph. ID detection error is inevitable, so max mixture models [23] are introduced to eliminate the mistaken associations.

1) *G2O Optimization Framework*: [11] offers a global framework for nonlinear least square problems. Under the G2O framework, all the elements to be optimized are regarded as vertices, while all the observation constraints are known as edges who connect vertices. The least square problem of graph optimization in SLAM field can be expressed by the following equation:

$$F(x) = \sum_{k \in C} e_k(x_k, z_k)^T \Omega_k e_k(x_k, z_k) [11]$$

$$x^* = \underset{x}{\operatorname{argmin}} F(x) [11]$$

where  $k$  denotes the  $k$  Th vertex in the graph(either a vehicle or a landmark position);  $C$  denotes the total ID group;  $x_k$  is the parameter block of each vertex(containing the vertices location and direction), while  $z_k$  and  $\Omega_k$  is the mean and covariance of the  $k$  Th edge;  $e_k(x_k, z_k)$  is the error function of  $x_k$  and  $z_k$ ,

it measures how well  $x_k$  matches  $z_k$ . These elements consist the global error function  $F(x)$ , and  $x^*$  denotes the global optimal solution. To find the solution  $x^*$ ,  $F(x)$  is rewrite as  $F(\tilde{x} + \Delta x) \simeq c + 2b^T \Delta x + \Delta x^T H \Delta x$ , while  $c = \sum_{k \in C} e_k^T \Omega_k e_k$ ;  $b = \sum_{k \in C} e_k^T \Omega_k J_k$ ;  $H = \sum_{k \in C} J_k^T \Omega_k J_k$ ;  $\tilde{x}$  indicates the initial value of  $x$ .  $\Delta x$  is the residual between  $\tilde{x}$  and  $x^*$ , and  $J_k$  is the Jacobian Matrix of each  $e_k$ . Then we can get the global optimal solution  $x^*$  by solving the linear function  $H \Delta x^* = -b$  and add  $\Delta x^*$  to  $x^*$  iteratively.

2) *Max-Mixture Model*: Max-Mixture Model [23] aims to detect loop closure errors in the back-end part of a pose graph. Traditionally, all distributions in a back-end graph system are considered as unimodal Gaussians, thus wrongly associated datum result in great global errors. When sum-mixture model replaces unimodal Gaussian, wrongly associated data can be suppressed by other mixture elements. To simplify the problem, the sum is substituted by a max operator. When an uncertain loop closure occurs, a max-mixture of several elements is thus added to the graph: several possible loop closure alternatives and a null hypothesis indicating that all the former alternatives are wrong. A null hypothesis is quite effective even with a extremely small weight.[23] This method works well in pose graphs[26][27][16], and we will prove its effectiveness in landmark association in the experiment section.

Since there is no wrongly associated data in IMU and tag observations, they are considered as robust edges in the graph, while the parking lot observations are always with high uncertainty, and several steps are added to guarantee the robustness. Once parking lots are detected, they are re-examined using some prior knowledge. Unusual lots(too small, too large or with abnormal length-width ratio) will thus be discarded. The rest lots are classified by the confidence level of lot IDs. Lot observations with high confidence IDs are added to the graph as Max-Mixture edges with null hypothesis. Due to the existence of false positive IDs with high confidence, a null hypothesis indicating the wrong edge association is essential. The location of lot observations with low confidence IDs and without ID are matched with all the excited lot landmarks by nearest neighbour method. As several candidate lots are detected, these candidate lot association together with the original association obtained by lot detection are add to the graph as a Max-Mixture edge with multi hypothesis. If no candidate detected, the lot observation will be pushed into the temporary landmark pool. In case the certain number(M) of same landmark is collected in the pool, the M observations are added to the graph as a max-mixture edge with multi hypothesis. The best car lot association will be selected as the initial landmark observation. Information matrix of landmark edges are shifted according to their detection confidence level.

The vertices collection of the graph includes vehicle position at every time stamp and all landmark(tags and lots) positions. The graph is optimized by Gauss-Newton Method once a new landmark edge is added. All the optimized landmarks consists of the initial 2D map.

In the online part, the well-known Extended Kalman Filter(EKF)[7] is introduced to filter the inconsistency in

localization results from various observation.

3) *Extended Kalman Filter*: Extended Kalman Filter[7] is a classical back-end choice in SLAM field. Since there are errors in all the observations, EKF is used to determine to which extent the observations can be believed. The following equations express the whole optimization procedure:

$$\begin{aligned}\hat{x}_{k|k-1} &= f(\hat{x}_{k-1|k-1}, u_{k-1}) \\ P_{k|k-1} &= F_{k-1}P_{k-1|k-1}F_{k-1}^T + Q_{k-1}\end{aligned}$$

$$\begin{aligned}\tilde{y}_k &= z_k - h(\hat{x}_{k|k-1}) \\ S_k &= H_k P_{k|k-1} H_k^T + R_k \\ K_k &= P_{k|k-1} H_k^T S_k^{-1} \\ \hat{x}_{k|k} &= \hat{x}_{k|k-1} + K_k \tilde{y}_k \\ P_{k|k} &= (I - K_k H_k) P_{k|k-1}\end{aligned}$$

$x$  is the state matrix (containing real-time car pose and positions of all landmarks);  $\hat{x}_{k|k-1}$  denotes the calculated from the former state,  $\hat{x}_{k-1|k-1}$  while denotes the former state matrix.  $z_k$  denotes the observations at  $k$  time stamp, and  $u_{k-1}$  is the control matrix (indicating IMU datum and real-time control of the vehicle control system).  $P$  is the corresponding covariance matrix of  $x$ , while  $F_{k-1}$  and  $H_k$  are the Jacobian matrix of  $f(\hat{x}_{k-1|k-1}, u_{k-1})$  and  $h(\hat{x}_{k|k-1})$ . Both  $Q$  and  $R$  are pre-given noise matrix. Once updated, the state and covariance matrix are switched to fit current time stamps observations.

We discard the graph optimization method to attain a smoother vehicle localization trace, which is meaningful for the later control part. Except for lot and tag observations, the car direction and speed from both IMU and vehicle control system (the steering wheel) are also added to the filter. This combination enables a more robust localization performance in various harsh situations (etc. long term localization under limited tags or lots with large direction drifting in IMU, which is discussed in the Experiments part). Since the covariance matrix increases quadratically with the number of landmark[7], local map is introduced to achieve real-time performance. Those landmarks who has not been observed for a period of time is removed from the local map. The online localization can start from either an empty map or the initial parking map built in the offline stage. However, due to the local map strategy, the online lot map starting from an empty map is to improved.

#### IV. EXPERIMENTS

In this section, we test our method both online and offline, and discuss several questions about the usage of visual markers. All the parking lot datasets are collected by Roewe E50 in Jiading Campus of Tongji University.

##### A. Online real-time mapping and localization

During the online part, the vehicle is first operated by human to initialize the parking map. Once the map stabilizes, a car trace is recorded. Then the vehicle drives automatically at the speed of 3 km/h following this pre-recorded trace and fixes its direction constantly according to real-time localization record. The automatic driving procedure is repeated 10 times,

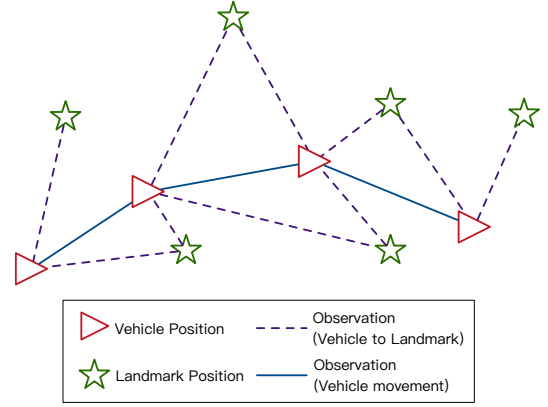


Fig. 9. The connection between the vehicle at each time stamp and the landmarks.

automatic driving traces are also recorded and compared to the pre-recorded one. Fig 11 shows the traces of both manual and automatic driving trace. Quite a number of visual markers (60 tags) are used to cover the lot-free parts near the entrance and to guarantee a fully stable and credible localization result. Each tag is printed on a A2-size paper with 48.8 cm side length. While observing, those tags who are 20 meters or farther than the vehicle are discarded since the accuracy decreases as tags become smaller in the image. However, observations with dip-angle are reliable constraints as long as they are within 20 meters.

Fig. 10. The dip-angle doesn't affect the accuracy while the distance makes great influence.

Fig. 11. A comparison between the human-driving and automatic driving trace

##### B. Offline mapping test

As to the offline part, several datasets with different starting points are collected. Each dataset is processed independently. The covariance of each edge shifts from 0.1 to 0.25 according to its confidence level. Fig 12 shows the map result for two of these datasets. Map blocks with more tags have higher precision as tags are ideal landmarks who will never be wrongly associated. The low detection rate of parking ID also affects the mapping result, as shown in fig 13.

In one dataset, there is a no-tag map block (marked in fig 12), where wrongly associated data always occurs. However, once a loop is detected, all landmark-positions are corrected. Then, duplicate landmarks are merged.

##### C. How many tag is needed?

As described in the previous section, tags are ideal landmarks promising a robust localization and mapping result. In this part, we discuss which tags are indispensable while others are not a must.

Fig. 12. toDo

Fig. 13. toDo

We think several factors may affect the importance of each tag: the visibility rate, the distribution and the distance to the nearest rate. Considering the factors above, we make several tag combinations and test their performance. The final result is shown in fig 14, both visibility and distribution play an important role. The crucial tags should be separated in the lot, and have a good visibility rate. In our parking lot case, at least 3 tags are needed, while 10 evenly distributed tags offer the best result.

a statistic result of the rightly located lots in each graph give the tag position solution based on the visibility of cameras based on visibility of the front camera (put tags at where there are multi visibility) be separated in the lot compare the solution to the statistic result very similar

(john: should add Tags can be replaced by instruction arrows or parkinglot ids on the pillar, here restricted by the goal and the environment tags are required )

## V. CONCLUSION

The conclusion goes here.

## APPENDIX A

### PROOF OF THE FIRST ZONKLAR EQUATION

Appendix one text goes here.

## APPENDIX B

Appendix two text goes here.

## ACKNOWLEDGMENT

The authors would like to thank...

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