Marker-Based Mapping and Localization for Autonomous Valet Parking

Zheng Fang, Yongnan Chen, Ming Zhou, Chao Lu
Presenter: Ming Zhou E-mail: zhouminganhui@qq.com

Robotic Environmental-perception and Autonomous-navigation Lab
Faculty of Robotic Science and Engineering, Northeastern University, China

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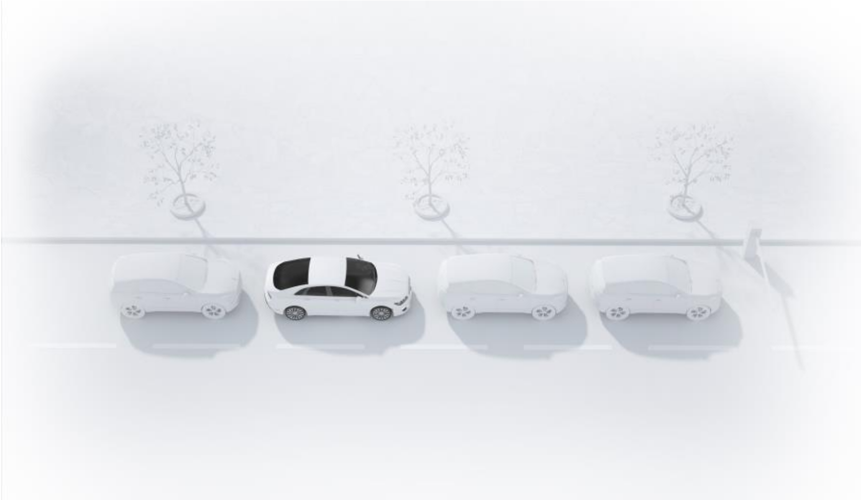
What is AVP?

Traditional valet parking

Auto valet parking

Benefits & Challenges

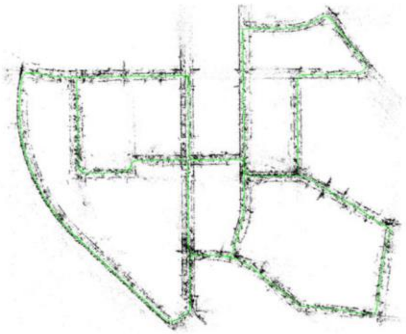


- Driver-friendly
- Enable high density parking
  - (1.6 million parking spaces for 4.37 million vehicles in Beijing for 2014)
- Reduce accidents caused by human errors during parking
  - (40% Accidents occur during parking related maneuvers)

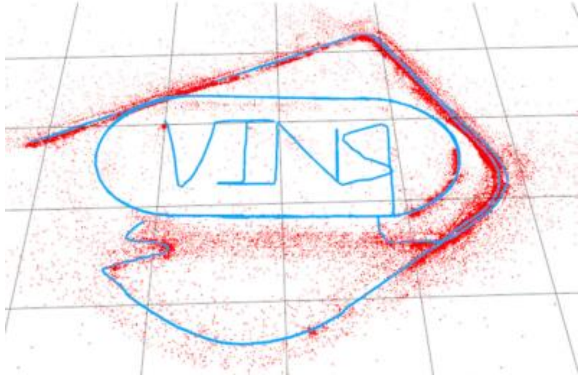
- No GPS signals available
- Vehicle movements will change the appearance of the same place
- Illumination condition is complicated in such scenes

Related Works

• Geometric SLAM Methods



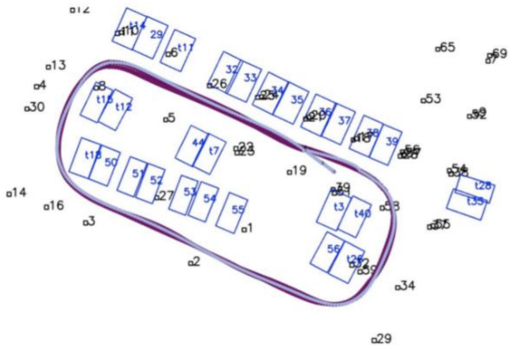
ORB_SLAM2
（IEEE Transaction on Robotics 2017）



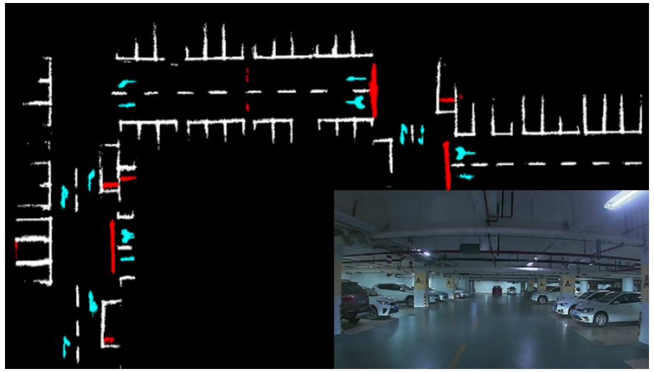
VINS MONO
（IEEE Transaction on Robotics 2018）

- Feature-based maps lack long-time stability

• Semantic SLAM Methods



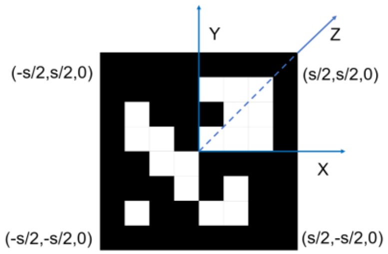
Detect ground parking slots (IV 2018)

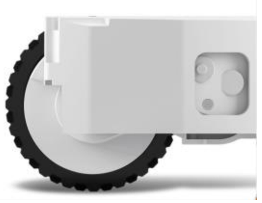


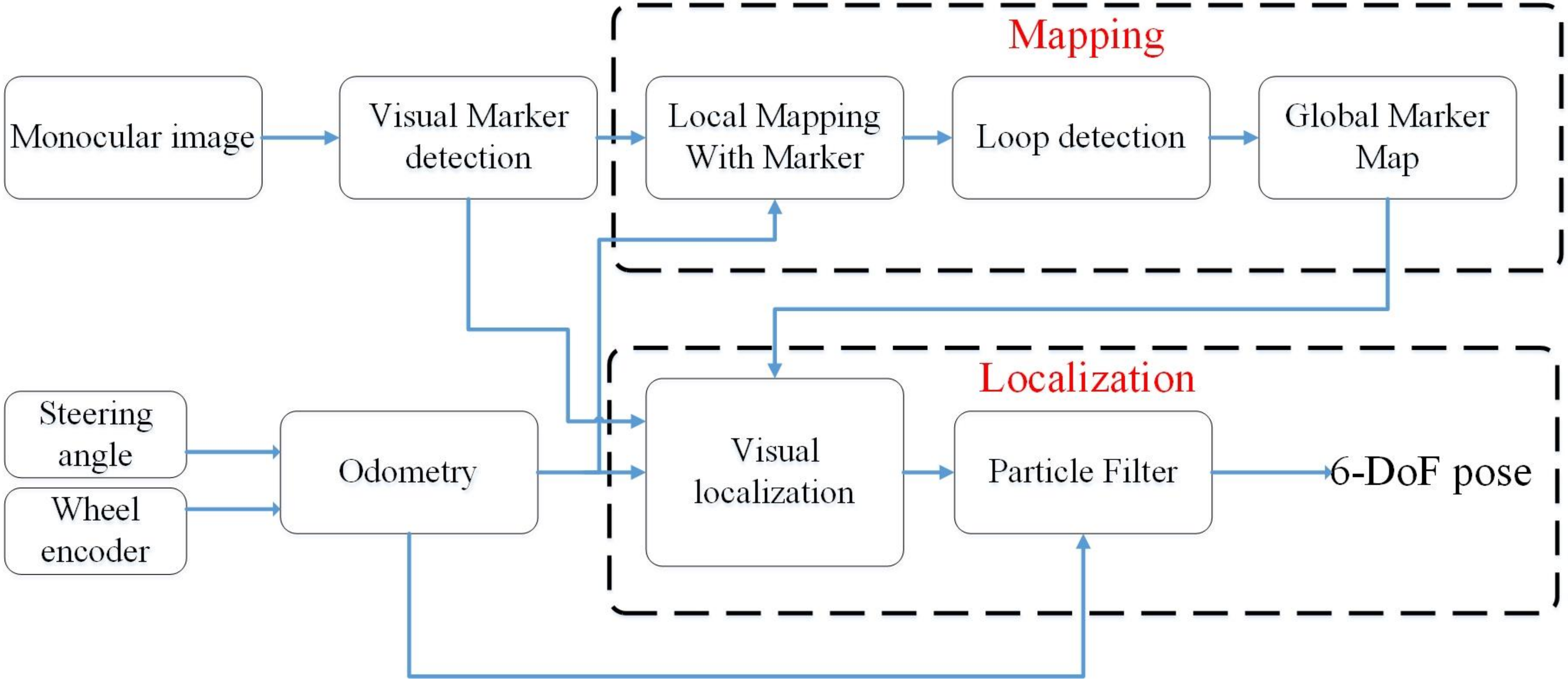
AVP-SLAM (IROS 2020)

- Resource-demanding
- Ground information may suffer from occlusion or wearing

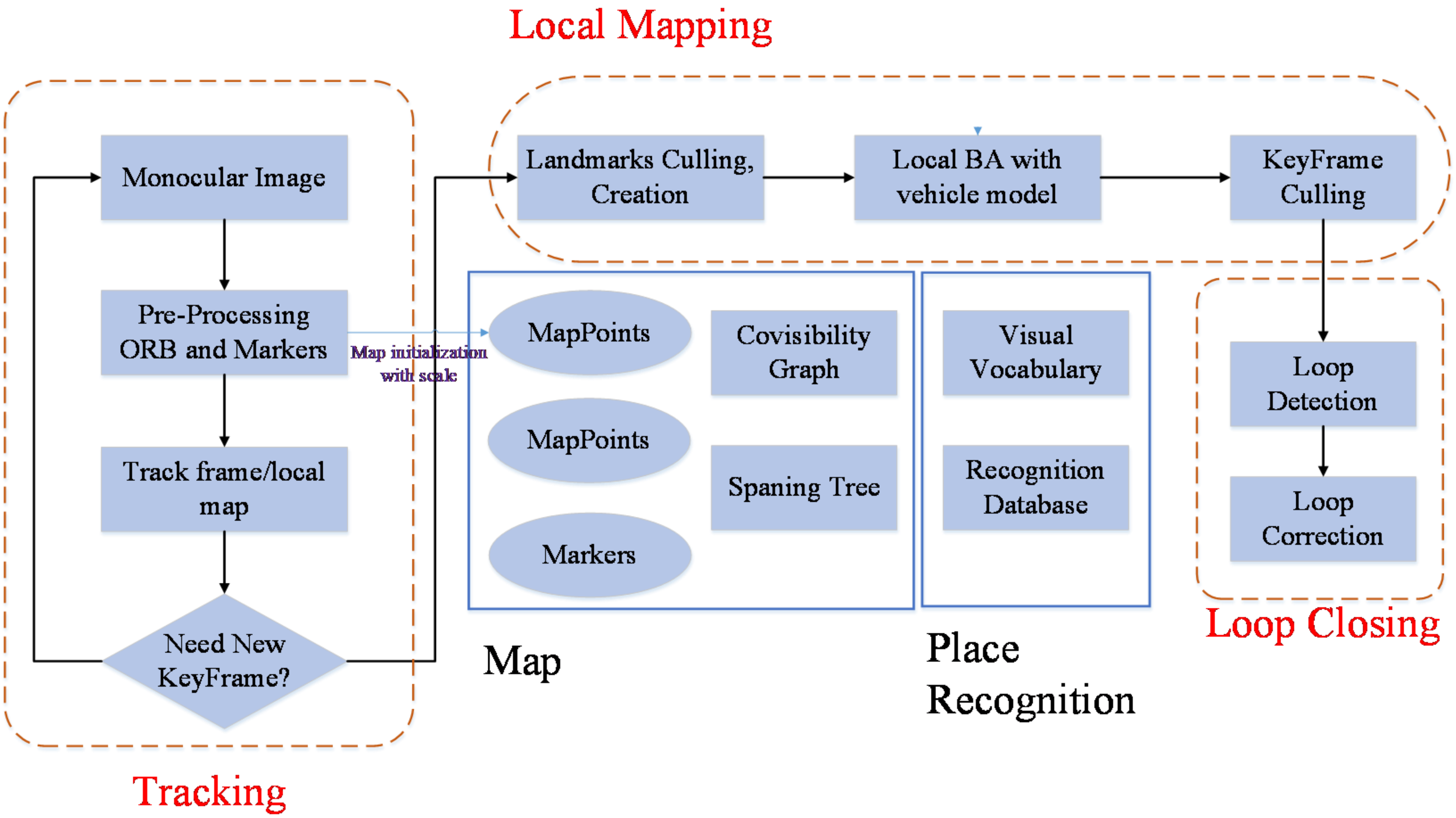
Algorithm Pipeline







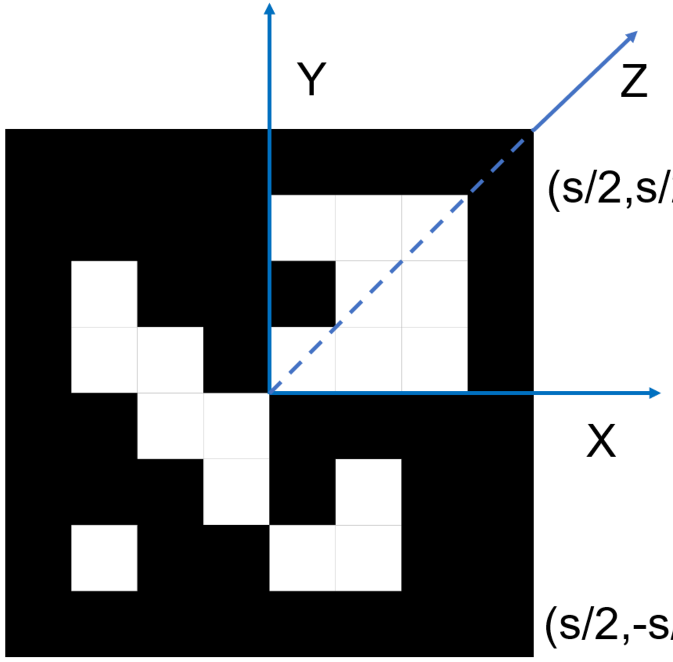
Mapping Algorithms



Mapping Algorithms

• Scale Recovery From Visual Fiducial Markers

1.Get the side length of the printed markers
2.According to the hypothetical 3D marker coordinate, get the corresponding corner point coordinate.
3.Extract markers from monocular image
4.Solve the PnP problem to get the relative pose of marker
5.Given the poses of the same marker in two images, we can recover the scale of monocular slam

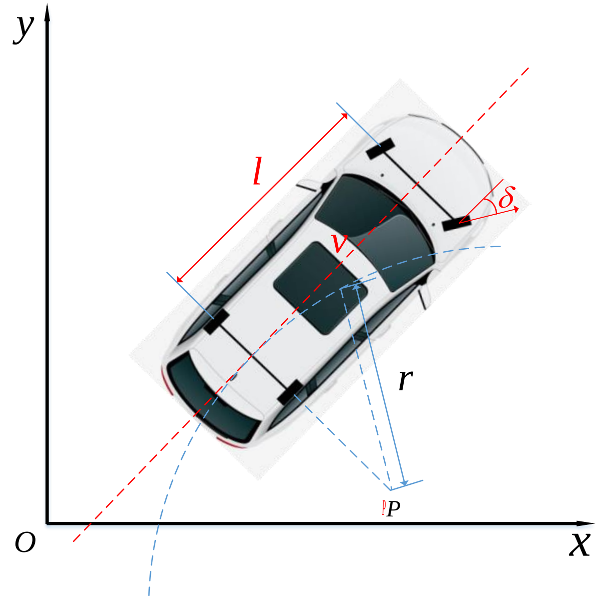


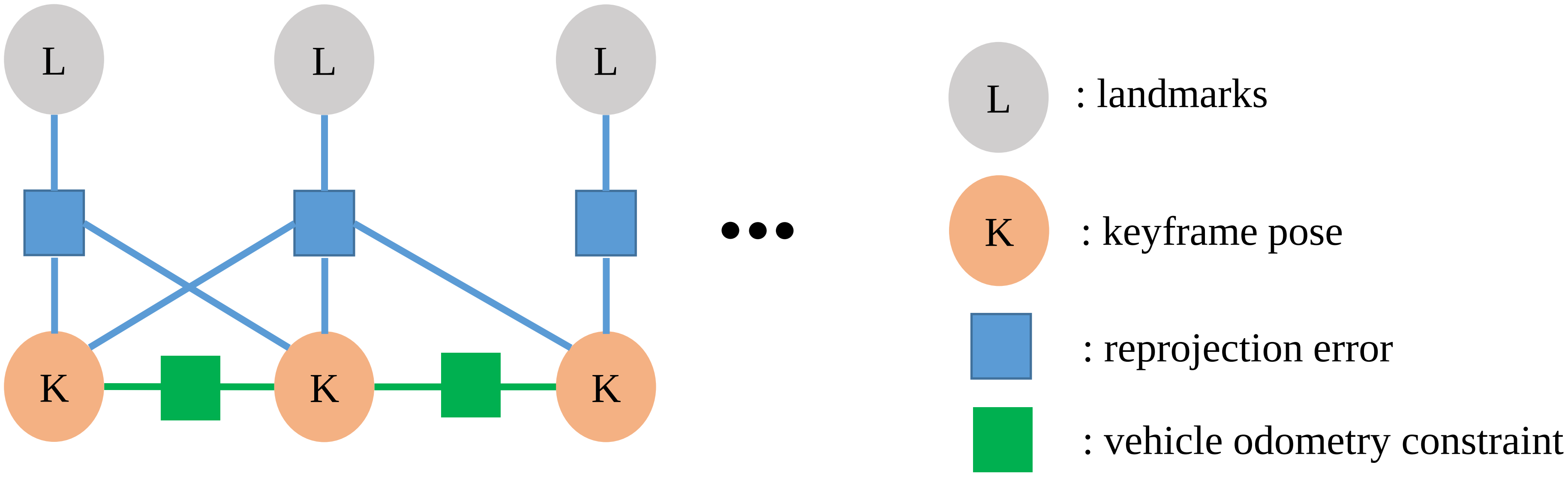
$$\boldsymbol{R}_{WC}^{k+1}\boldsymbol{R}_{CM_i}^{k+1}\boldsymbol{p}_{M_iC}^{k+1}-\boldsymbol{R}_{WC}^{k}\boldsymbol{R}_{CM_i}^{k}\boldsymbol{p}_{M_iC}^{k}=\boldsymbol{s}(\boldsymbol{p}_{WC}^{k+1}-\boldsymbol{p}_{WC}^{k})$$

Mapping Algorithms

- Pose Optimization with Vehicle Odometry Constraints

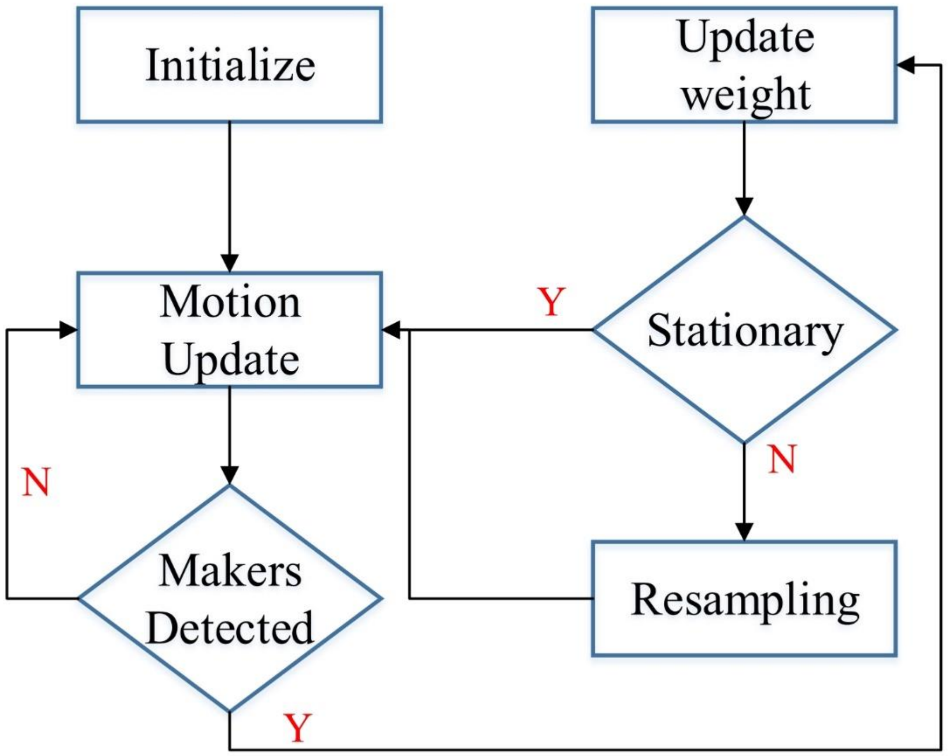
1. Fuse wheel speed and steering angle to form vehicle odometry
2. Add the vehicle odometry constraint edge to pose optimization





Localization Algorithms

• Structure



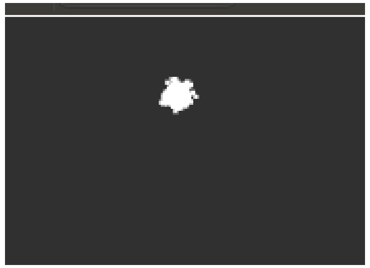
• Initialization

- Data Association(Using Marker ID)
- Coordinate Transform

$$\begin{bmatrix} x_0 \\ y_0 \\ \theta_0 \end{bmatrix} = \begin{bmatrix} x_k - x' cos\theta' + y' sin\theta' \\ y_k - x' sin\theta' + y' cos\theta' \\ \theta_k - \theta' \end{bmatrix}$$

- Distribute Particles

$$\begin{bmatrix} x_n \\ y_n \\ \theta_n \end{bmatrix} = \begin{bmatrix} N(x_0, std_x^2) \\ N\left(y_0, std_y^2\right) \\ N\left(\theta_0, std_\theta^2\right) \end{bmatrix}$$



Localization Algorithms

• Motion Update

$$p(X_t|z_t, u_t, X_{t-1}, m) = p(X_t|u_t, X_{t-1})$$

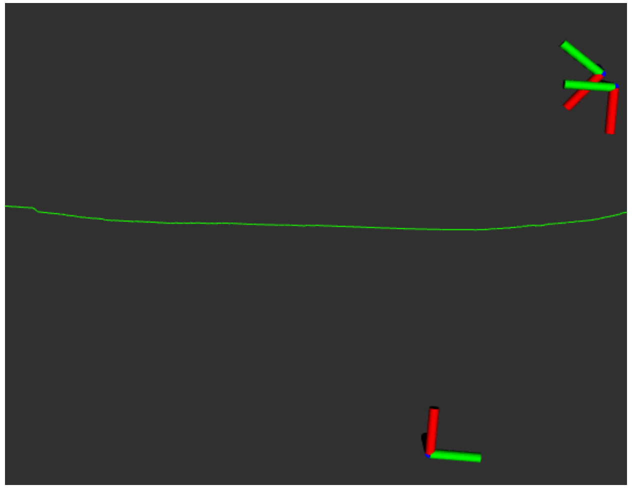
$$\begin{bmatrix} x_t^n \\ y_t^n \\ \theta_t^n \end{bmatrix} = \begin{bmatrix} \mathrm{N}\left(0, x_\sigma^2\right) \\ \mathrm{N}\left(0, y_\sigma^2\right) \\ \mathrm{N}\left(0, \theta_\sigma^2\right) \end{bmatrix} + \begin{bmatrix} x_{t-1}^n + \cos\left(\theta_{t-1}^n + \Delta\theta\right)\Delta x - \sin\left(\theta_{t-1}^n + \Delta\theta\right)\Delta y \\ y_{t-1}^n + \sin\left(\theta_{t-1}^n + \Delta\theta\right)\Delta x \\ \theta_{t-1}^n + \Delta\theta \end{bmatrix}$$

• Observation Update

$$p(X_t|z_t, u_t, \widehat{X}_t, m) = p(X_t|z_t, m, \widehat{X}_t)$$

- Marker Filtering
- Data Association & Coordinate Transform

$$\begin{bmatrix} x_{ob\_map} \\ y_{ob\_map} \\ \theta_{ob\_map} \end{bmatrix} = \begin{bmatrix} x_{ob}\cos\theta_n - y_{ob}\sin\theta_n + x_n \\ x_{ob}\sin\theta_n + y_{ob}\cos\theta_n + y_n \\ \theta_{ob} + \theta_n \end{bmatrix}$$



Localization Algorithms

• Observation Update

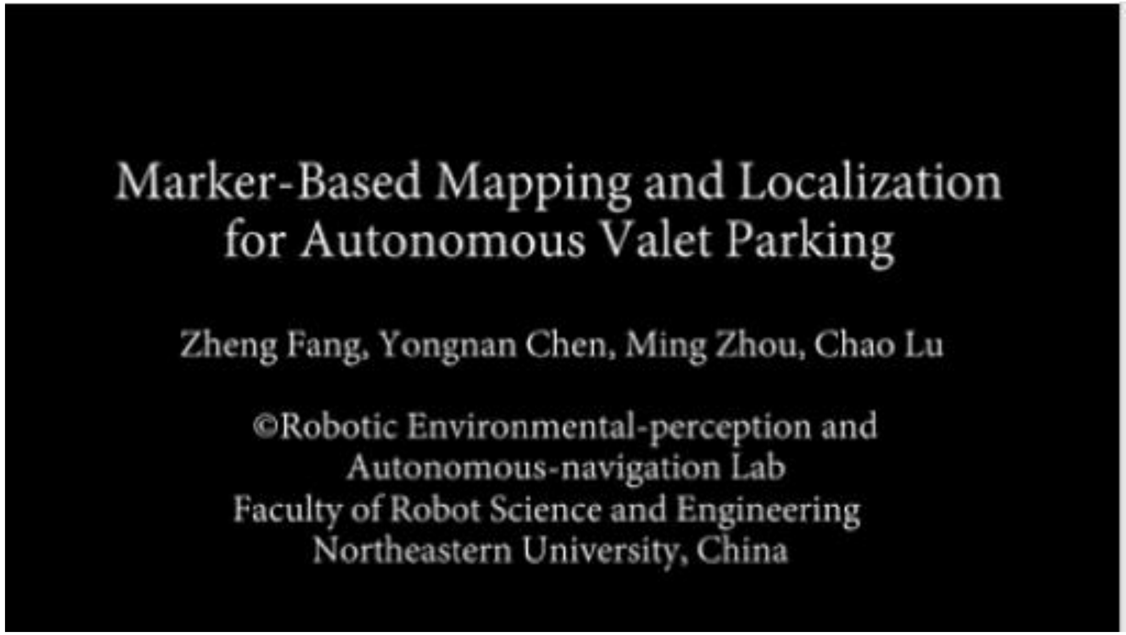
- Update Particle Weights

$$w_n = \frac{e^{-\left(\left(\left(x_{ob\_map}-x_{ob}\right)^2/\sigma_x^2\right)+\left(\left(y_{ob\_map}-y_{ob}\right)^2/\sigma_y^2\right)\right)/2}}{2\pi\sigma_x\sigma_y}$$

- Resampling
  - No resampling while stationary

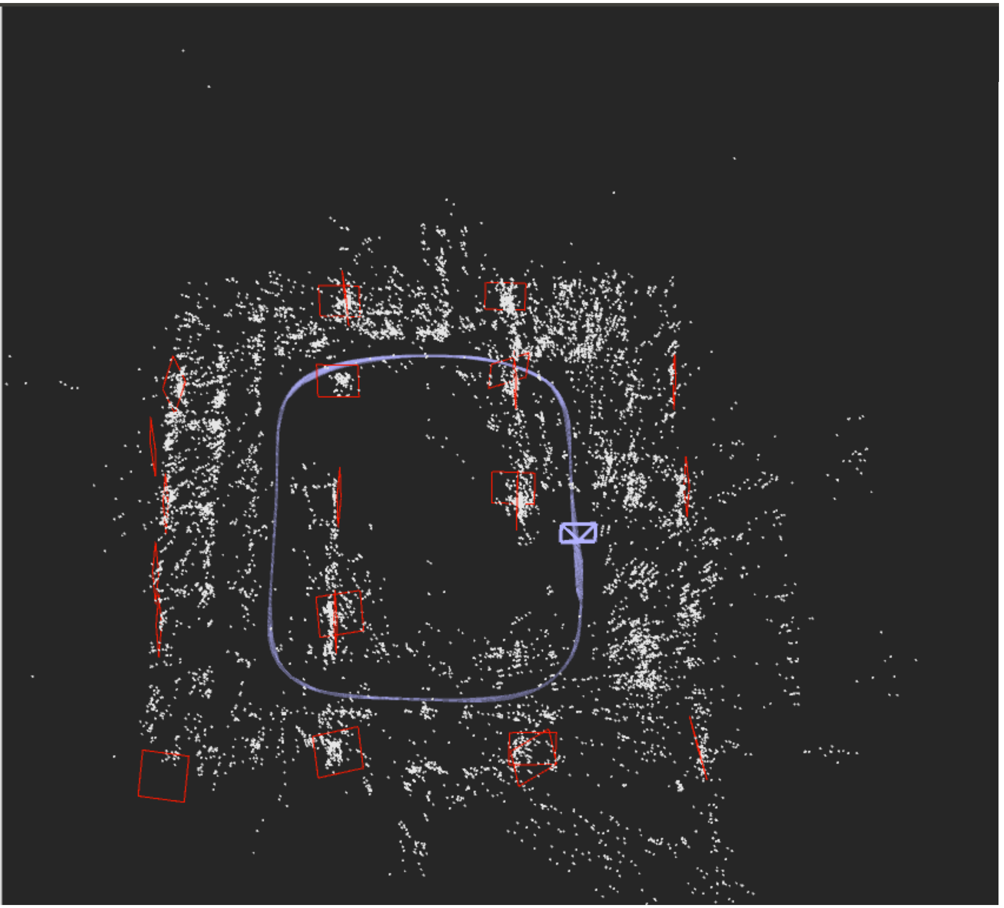
- Output Vehicle Pose
  - Get average particle state rather than highest weighted

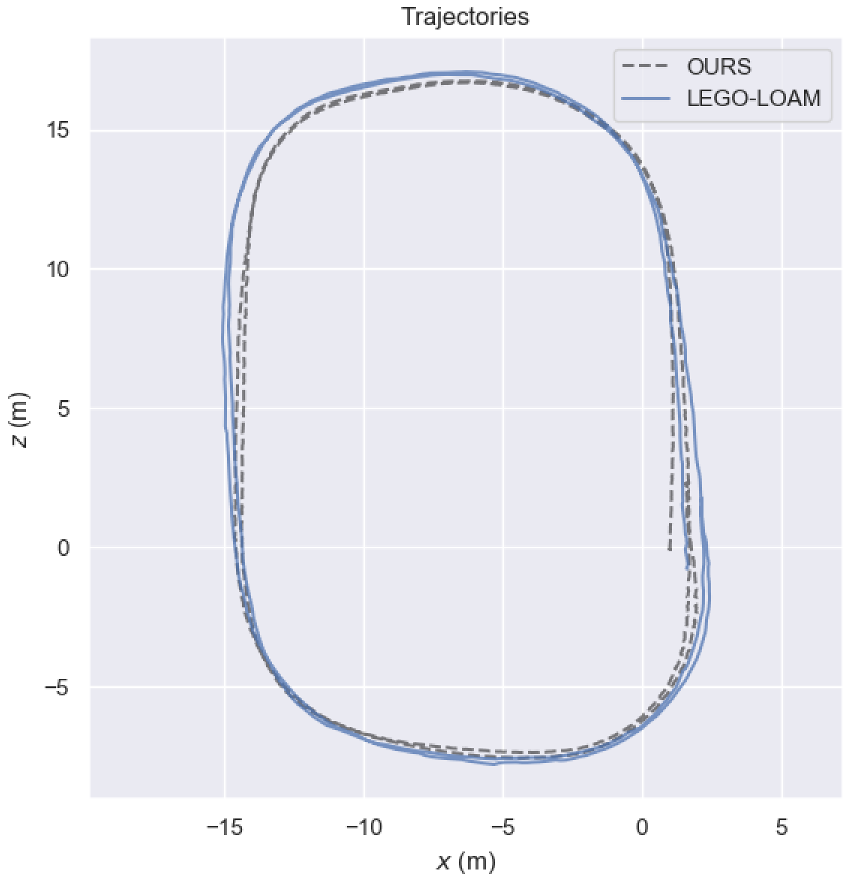
• Visualization



Experiments

• Mapping Metric Evaluation





Environment:

- Underground garage about $500m^2$
- Marker size is 0.552m
- Average interval between markers is 8m
- Total trajectory length is 143m

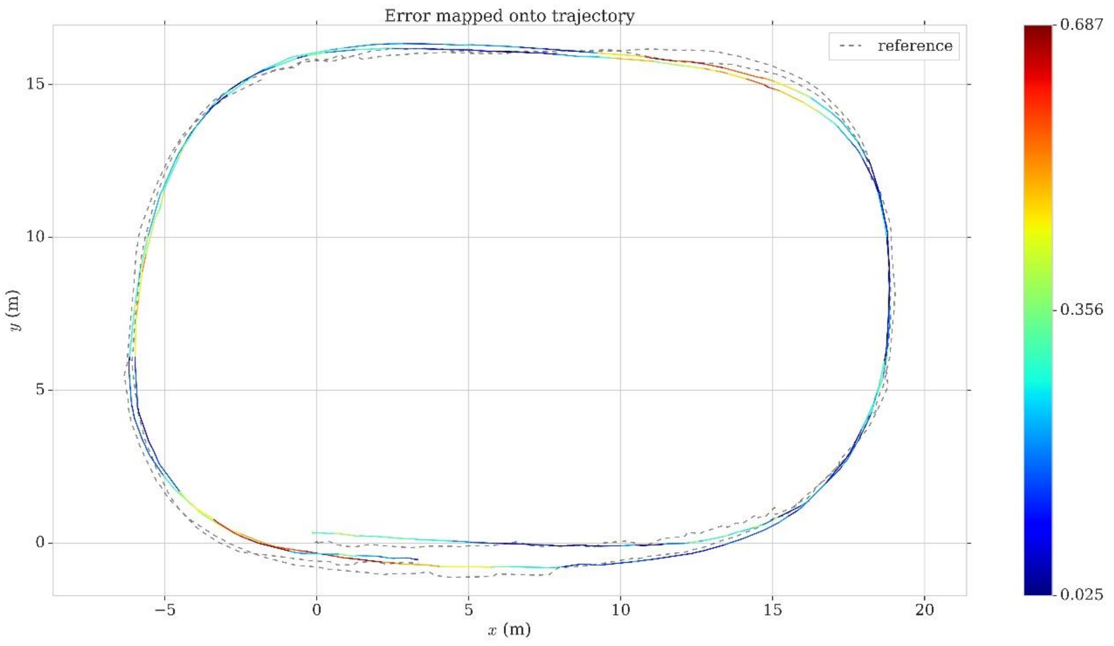
Results:

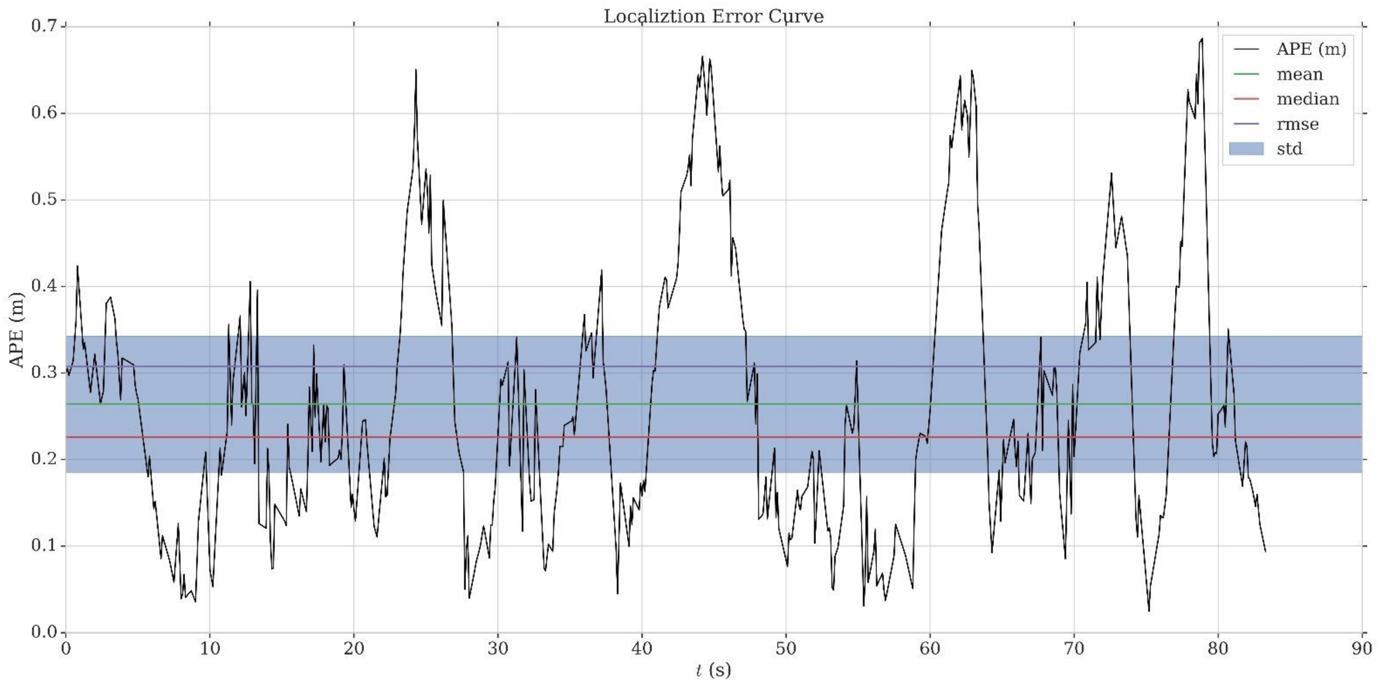
RMSE is 0.438m

NESS is 0.306%

Experiments

• Localization Accuracy Evaluation





Error(m)	Mean	Max	Min	Std	Median	RMSE
Experiment 1	0.301586	0.775068	0.015272	0.171292	0.259017	0.346836
Experiment 2	0.263982	0.686745	0.024782	0.157513	0.225755	0.307403

Experiments

- Computational Resources

	CPU occupation	Memory used[MB]	Frequency[Hz]
i7 laptop	14%	500	100
A53 embedded	25%	510	100

- System Robustness

- False matches due to environment appearance changes

- Marker detections not affected

Conclusions

- Pros

  - Long-term usable map & High environmental robustness
  - Low computational resource consumption

- Cons

  - Limited scene of application

THANK YOU