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Fisheye Visual Inertial Odometry for Indoor Mobile Robots Localization

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Introduction

The indoor mobile robots in one study mostly operate in artificial environments, such as corridors with white walls. The intensity changes and sparse features in indoor environments are challenging factors for indoor mobile robot localization. To ensure that robots can be operated stably in indoor environments, their localization systems must handle such scenes. The feature-based visual-inertial odometry (VIO) or simultaneous localization and mapping (SLAM) algorithm assumes that there is a large overlapping area between the two images. Once the camera moves rapidly, the robot walks to a corner and faces white walls. The number of inline features is reduced, which eventually causes a decrease in the accuracy of the systems pose estimation and even failure. This is a major factor limiting the performance and operating scenarios of the VIO system.

Research Questions

The most excellent VIO system in two studies is based on the pinhole camera model. However, images collected by the fisheye camera are seriously distorted, so the traditional SLAM and VIO systems cannot be directly used with fisheye camera images. In addition, the fisheye camera projection model is highly nonlinear, which causes difficulties with feature tracking, stereo matching, and triangulation.

Methodologies

A. Feature Tracking

To improve feature tracking robustness for fisheye images, we assume that the speed and direction of feature *j* are consistent, as shown in Figure 1. So the speed of the feature *j* at time *k - 1* and k are defined as

$$\mathbf{v}_{\mathbf{p}_j}^{k} = \frac{\mathbf{p}_j^{k} - \mathbf{p}_j^{k-1}}{\triangle t}, \quad \mathbf{v}_{\mathbf{p}_j}^{k-1} = \frac{\mathbf{p}_j^{k-1} - \mathbf{p}_j^{k-2}}{\triangle t} \tag{1}$$

where p_j^k is position of feature *j* at time *k*. So, the feature *j* is an outlier, if

$$\frac{\| \mathbf{v}_{\mathbf{p}_j}^{k} \|_2}{\| \mathbf{v}_{\mathbf{p}_j}^{k-1} \|_2} > n_{th}, \frac{v_{\mathbf{p}_j}^{k\ T} * \mathbf{v}_{\mathbf{p}_j}^{k-1}}{\| \mathbf{v}_{\mathbf{p}_j}^{k} \|_2 \| \mathbf{v}_{\mathbf{p}_j}^{k-1} \|_2} < \arccos(\theta_{th}). \tag{2}$$

where n_{th} and θ_{th} are the features speed and direction increment thresholds, respectively. Finally, the features that have been tracked more than two times are transformed into normalized coordinates with the EUCM for publication.

The back-end receives the IMU measurements and feature positions, triangulates the features that have been tracked multiple times, updates the feature depths with the Gaussian filter, and updates the system state with the error-state Kalman filter. The error state of the IMU is defined as a 15 × 1 vector, which includes the increments of attitude, position, velocity, acceleration bias, and gyroscope bias.

$$\tilde{\mathbf{x}}_{imu} = \begin{bmatrix} \delta\boldsymbol{\theta}_{\mathbf{wb}} & \delta\mathbf{p}_{w} & \delta\mathbf{v}_{w} & \delta\mathbf{b}^{a} & \delta\mathbf{b}^{w} \end{bmatrix} \tag{3}$$

The system error state is defined as follows

$$\tilde{\mathbf{X}} = \begin{bmatrix} \tilde{\mathbf{x}}_{imu} \mid & \tilde{\mathbf{x}}_{c_1} & \tilde{\mathbf{x}}_{c_2} & \dots & \tilde{\mathbf{x}}_{c_i} \end{bmatrix}^{T}. \tag{4}$$

Finally, the pose estimation of the robot is realized on the basis of the classic EKF-VIO algorithm [3].

Figures

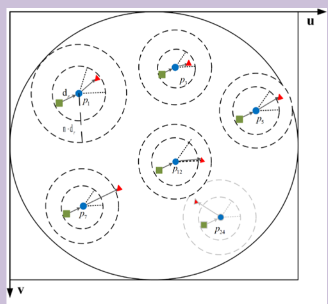

Figure 1. Feature outlier elimination strategy with velocity consistency

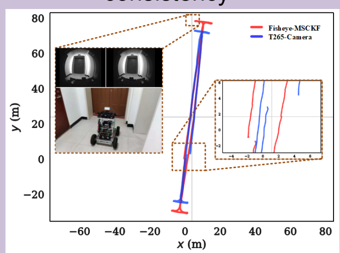

Figure 2. The trajectory of the mobile robot on the indoor environmental

Conclusion

This paper presents a fisheye VIO to improve the pose estimation accuracy of indoor robot. To improve the stability of feature tracking in distorted images collected by the fisheye camera, a feature tracking and outlier elimination strategy based on the consistency constraints is introduced. Furthermore, a Gaussian filter is used to iteratively update the feature depths to improve the robustness and flexibility of the system. This study is an extension of the MSCKF-VIO [3], and it can be further extended to applications involving indoor autonomous robots.