Robust Visual Odometry On SE(3):Design and Verification

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Introduction:

Visual odometry estimates the robotic vehicle's trajectory based on the kinematic model and image captured by the onboard camera when the vehicle's attitude cannot be directly retrieved. However, ***modeling uncertainty, measurement noise, feature mis-identification, and switching output*** can hinder accurate estimations. This paper proposes a robust visual odometry design and algorithm in a sampled-data structure. Comprehensive simulations and experiments demonstrate the relationship between design parameters and estimation performance under various uncertainties. Tuning guidelines are provided for visual odometry parameters to address these uncertainties.

Preliminary:

The Special Euclidean Group is defined as

$$SE(3) := \{X = \begin{bmatrix} R & T \\ 0 & 1 \end{bmatrix} \in \mathbb{R}^{4\times4} | R \in SO(3), T \in \mathbb{R}^3, \det(X) = 1\}$$

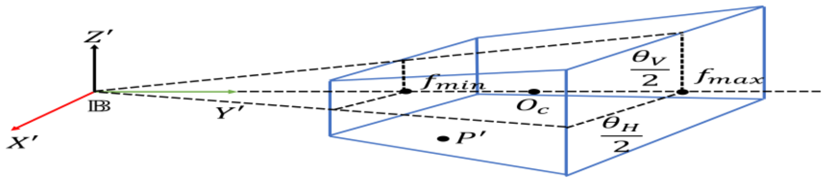
where R is the rotation matrix and T is the translation vector of the rigid body in Inertial Coordinate $\mathbb{I}$.
The Lie Algebra of the Special Euclidean Group is defined as

$$se(3) := \{A = \begin{pmatrix} \omega_\times & v' \\ 0 & 0 \end{pmatrix} \in \mathbb{R}^{4\times4} | \omega_\times \in so(3), v' \in \mathbb{R}^3\}$$

where $\omega_\times$ is the skew-symmetric matrix of the angular velocity $\omega \in \mathbb{R}^3$ and v' is the linear velocity. Both ω, v' are in the body coordinate $\mathbb{B}$.
For any point in $\mathbb{I}$ having the form of $P = [x \quad y \quad z]^T$, its relative position $P' = [x' \quad y' \quad z']^T$ in $\mathbb{B}$ can be obtained as:

$$P' = R^T(P - T), \begin{bmatrix} P' \\ 1 \end{bmatrix} = X^{-1} \begin{bmatrix} P \\ 1 \end{bmatrix}$$

Geometrical Constraint of the Sensor:



The parameter of a general camera can be implemented as

$$\boldsymbol{\theta} = \{\theta_H, \theta_V, f_{min}, f_{max}\}$$

where θ_H, θ_V are the horizontal and vertical field of view, and f_{min}, f_{max} are the minimum and maximum distance for an standard selected feature mark to be recognized by the camera.

For any point with relatice potition $P' = [p_x' \quad p_y' \quad p_z']$, it has to satisfy:

$$f_{min} \le p_y' \le f_{max}, |p_x'| \le p_y' \tan\left(\frac{\theta_H}{2}\right), |p_z'| \le p_y' \tan\left(\frac{\theta_V}{2}\right)$$

Visual Odometry Design:

A. Mathematical Model of the System
The kinematical model of the system is

$$\dot{X} = X(U + D)$$

where $X \in SE(3)$ is the state of the robotic vehicle, $U \in se(3)$ is the control input to the robotic vehicle, and $D \in se(3)$ is the unknown lumped match uncertainty.

The output from the camera is implemented as

$$Y_i = \begin{cases} \begin{cases} X^{-1}C_i + \Lambda_i, & i \in \mathbb{G}(X, \bar{Y}) \\ [0_3^T \quad 1]^T + \Lambda_i, & i \in \mathbb{G}^c(X, \bar{Y}) \end{cases}, & i \in \mathbb{O}(\bar{Y}) \\ 0_4, & i \in \mathbb{O}^c(\bar{Y}) \end{cases}$$

Here the $\mathbb{O}(\bar{Y})$ and $\mathbb{O}^c(\bar{Y})$ denote the identified and unidentified feature marks, and $\mathbb{G}(X, \bar{Y})$ and $\mathbb{G}^c(X, \bar{Y})$ denote the correctly identified and mis-identified feature marks. The $C_i = [P_i^T \quad 1]^T$ includes the information position vector of i^{th} feature mark in $\mathbb{I}$, and $\Lambda_i = [\lambda_i^T \quad 0]^T$ represents the measurement noise and position of the mis-identified points in $\mathbb{G}(X, \bar{Y})$ and $\mathbb{G}^c(X, \bar{Y})$ respectively.

B. Odometry Design
The visual odometry estimating state of the robotic vehicle X is proposed:

$$\dot{\hat{X}} = \hat{X}(U - \Psi - Q)$$
$$\hat{Y}_i = \hat{X}^{-1}C_i$$

where

$$\Psi = \hat{X}^{-1}\mathbb{P}(\ell \sum_{i \in \hat{\mathbb{G}}(\hat{X}, \bar{Y})} \hat{X}(Y_i - \hat{X}^{-1}C_i)C_i^T)\hat{X}$$

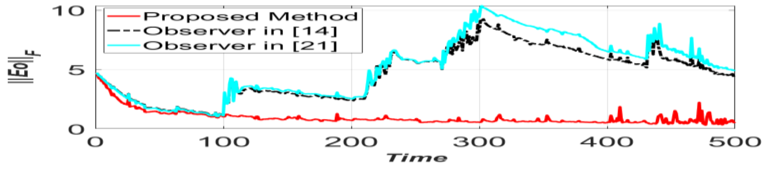
$$Q = \hat{X}^{-1}\mathbb{P}(K_o \cdot \hbar \sum_{i \in \hat{\mathbb{G}}^c(\hat{X}, \bar{Y})} \hat{X}(Y_i - \hat{X}^{-1}C_i)(Y_i - \hat{X}^{-1}C_i)^T \hat{X}^T)\hat{X}$$

and $\ell, \hbar \in \mathbb{R}_{>0}, K_o = K_o^T \ge k_o^* \cdot I_{4\times4}$ are the design parameters. $\hat{\mathbb{G}}(\hat{X}, \bar{Y})$ and $\hat{\mathbb{G}}^c(\hat{X}, \bar{Y})$ are the estimate of the set $\mathbb{G}(X, \bar{Y})$ and $\mathbb{G}^c(X, \bar{Y})$ based on the information of $\hat{X}$ and the geometrical constraint.

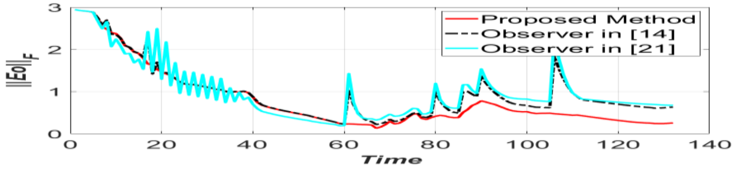
Selected Simulation and Experiment Results:

Due to the space limitation, only the selected simulation and experiment results are presented here.

Simulation Result:



Experimental Result:



Comparative simulation and experiments are presented here, where the red line represent the proposed visual odometry and the other lines represent the existing visual odomtery (observer). It can be seen that the proposed method has better estimation. More simulation and experiment results can be found in the full version of the Manuscript.