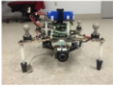


Background

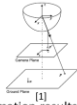


The quest to build smaller, more agile micro aerial vehicles has led to addressing cameras and IMUs as the primary sensors for state estimation. It is called visual-inertial state estimation. The minimum sensor suite only consists of a single camera and IMU.

Problem

State estimation with Visual Odometry cannot consistently achieve high performance due to [1]:

- Features' different properties
- Changing illumination conditions
- Various moving accelerated speed
- Combination of far and near objects



Solutions

Analyze exact factors affecting the accuracy of estimation results and the relationship between them. Increase the robustness of monocular visual-inertial state estimation using adaptive techniques.

Methods

Apparatus

- ARM computer
- Calibrated IMU
- Calibrated fish-eye monocular



Simulation

- Make synthetic datasets with diverse scene sizes
- Find relationship between feature depth and vehicle position estimated errors

Experiment

- Improve the algorithm
- Compare the robustness between original and adaptive programs

State Estimation Model

- Separately make models of IMU data and camera image to calculate the location of the feature
- Sliding window:

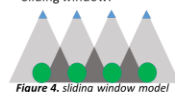


Figure 4. sliding window model

- Achieve baseline estimation
- Decrease computing cost
- Refine its solution from multi different observations

- Solve for the maximum likelihood estimation by minimizing the sum of the Mahalanobis norm of all measurement errors [2]

$$\min_x \left\{ (b_p - \Lambda_p x)^2 + \sum_{k \in \mathcal{F}} \|\hat{z}_{B_{k+1}}^{B_k} - H_{B_{k+1}}^{B_k} x\|_{P_{B_{k+1}}}^2 + \sum_{(i,j) \in \mathcal{C}} \|\hat{z}_{i,j}^{B_j} - H_{i,j}^{B_j} x\|_{P_{i,j}}^2 \right\}$$

Z : measurement H : system parameters X : states

Innovation Gate

Prerequisite

Whether the camera position should be added to the sliding window for calculation is determined by parallax, which means the displacement in the apparent position of an object viewed along two different lines of sight. And the value of threshold ϵ is 30.

$$\text{Parallax} \left(X_{B_{N-1}}^{B_N}, X_{B_N}^{B_N} \right) > \epsilon$$

Uncertainty



For a definite depth, location uncertainty is inversely proportional with baseline.



Experiments

- Set 11 scenes with size from 10m to 60m, which means the depths are ranging
- Let the features distributed in margins of the environment.
- Analyze the situations in which the monocular state estimation will fail

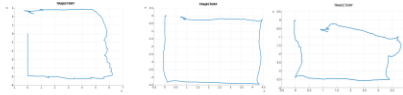


Figure 6. Estimation results (scene sizes are 10m, 30m, 50m)

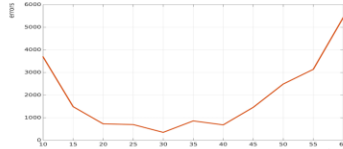


Figure 7. Errors with different depth

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Adaptation

Improve the algorithm

- Compute the mean parallax of all features
- If the parallax of l_m feature is less than mean, then add it to the list of far features
- Unless the number of far feature is more than 30% of number of all features, then eliminate them

Comparison

- Evaluate both algorithms on an environment with both far and close features

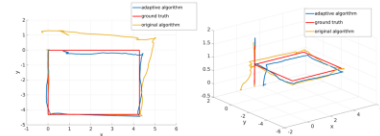


Figure 8. 2D & 3D trajectory (adaptive, original and truth)

- Calculate the errors with trajectory accumulated of both algorithms

$$\text{Errors} = \sum_{i=1}^n ((x_i - X_i)^2 + (y_i - Y_i)^2 + (z_i - Z_i)^2)$$

- Redo the previous test based on adaptive program in 11 different scenes

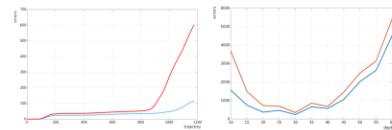


Figure 9. Cumulative errors of both algorithms

Figure 10. Errors of both algorithms in various scenes

References

- [1]. "Visual Odometry: Matching, Robustness, Optimization, and Applications", Robotics and Automation, 2012.
- [2]. "Initialization-Free Monocular Visual-Inertial Estimation with Application to Autonomous MAVs", ISER, 2014.

Acknowledgements

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