Igor Martinelli: Assignment 7 Report

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1 Structure from Motion

Introduction

This section presents the results of the 3D reconstruction process as part of the Structure from Motion (SfM) pipeline implemented in this project. The aim is to critically analyze the reconstructed 3D scene in relation to the effectiveness of the various SfM steps undertaken, including feature matching, camera pose estimation, and point triangulation.

Methodology

The 3D reconstruction was achieved through a series of systematic steps integral to the SfM process. Initially, key features were extracted from a set of 2D images and correspondences between these features across multiple images were established. Subsequent steps involved estimating the pose (orientation and position) of each camera and triangulating these feature points to reconstruct a 3D representation of the scene. This process was incrementally repeated as more images were added to the reconstruction, enhancing the depth and detail of the 3D model.

Results and Discussion

The resulting plot from the SfM process is depicted in Figure 1. This visual representation showcases a cloud of 3D points that collectively form the structure of the scene captured in the 2D images. Notably, the following observations are made:

- **Spatial Distribution**: The density and distribution of the 3D points vary across the plot, with certain regions exhibiting a higher concentration of points. This variation reflects the feature-rich areas in the original images where key points were more successfully detected and matched.
- **Challenges and Limitations**:
  - Areas with sparse point clouds were observed, likely due to regions in the images lacking distinct features or having insufficient overlap between images.

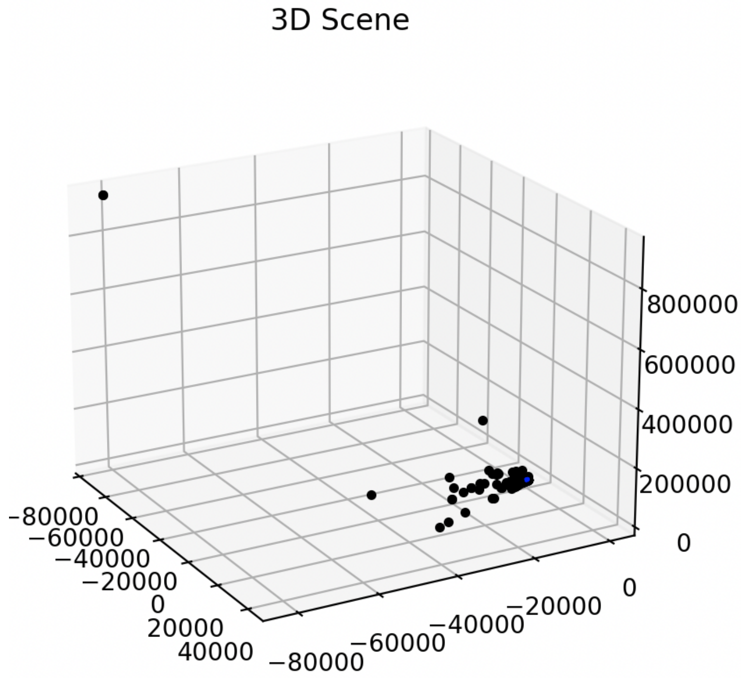

Figure 1: 3D Reconstruction of the Scene

2 Model Fitting

Introduction

This section discusses the implementation and results of the line fitting task, utilizing both least-squares and RANSAC methods. The objective was to estimate the parameters of a linear model in the presence of noise and outliers.

Methodology

The task was approached by generating a synthetic dataset based on a ground truth linear model $y = kx + b$. The dataset included noisy data points and intentional outliers to challenge the robustness of the fitting algorithms.

3.1.1 Least-squares Solution

The least-squares solution was implemented in Python using the 'numpy.linalg.lstsq' method. This approach provided an estimate of the line parameters k and b by minimizing the sum of squares of residuals.

3.1.2 RANSAC

The RANSAC algorithm was implemented to robustly estimate the line parameters in the presence of outliers. The algorithm iteratively selected a random subset of the data points, computed a least-squares solution for this subset, and then determined the number of inliers based on a predefined distance threshold. The best model was chosen based on the maximum number of inliers.

Results and Discussion

The line fitting results are visually represented in Figure 2, which includes the inliers, outliers, and the fitted lines from both the least squares and RANSAC methods.

The data points classified as inliers are marked in green, while the outliers are marked in yellow. The linear regressor, derived from the least-squares fitting, is indicated by the dark blue line. Conversely, the RANSAC regressor is represented by the light blue line. It is evident from the figure that the RANSAC regressor is less affected by the presence of outliers and closely follows the trend of the inliers, aligning more accurately with the ground truth model than the least squares fit.

The results highlight RANSAC's robustness to outliers, fitting a model well-aligned with inliers, unlike the least-squares method which is more outlier-sensitive, as the dark and light blue lines in Figure 2 illustrate.

Ground Truth (k, b): The actual values of k and b used to generate the synthetic dataset were $k_{\text{gt}} = 1$ and $b_{\text{gt}} = 10$.

Estimation from Least Squares (k_ls, b_ls): The least-squares fitting method estimated the values as $k_{\text{ls}} = 0.6159656578755457$ and $b_{\text{ls}} = 8.96172714144364$.

Estimation from RANSAC (k_ransac, b_ransac): The RANSAC fitting method provided more robust estimates, closer to the ground truth, with $k_{\text{ransac}} = 0.9643894946568986$ and $b_{\text{ransac}} = 9.98292129496683$.

The results demonstrate the effectiveness of RANSAC in handling outliers compared to the least squares method, especially in terms of adherence to the ground truth values.

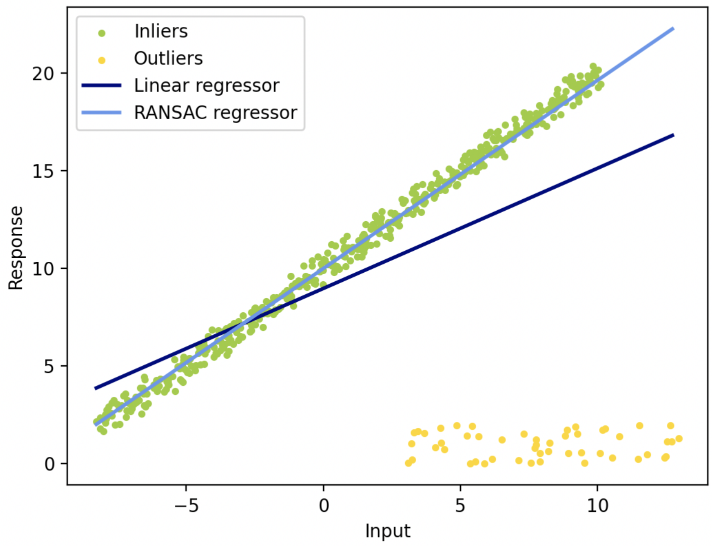

Figure 2: Comparison of Line Fitting using Least Squares and RANSAC