3D Reconstruction with Multiple cameras using SIFT and Optimization

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Overview

The goal of this project is to reconstruct a 3D object using computer vision. This project found that 3D reconstruction using standard functions from Open3D leaves many outliers. These outliers can be removed using optimization techniques using statistical and radial methods.

Approach

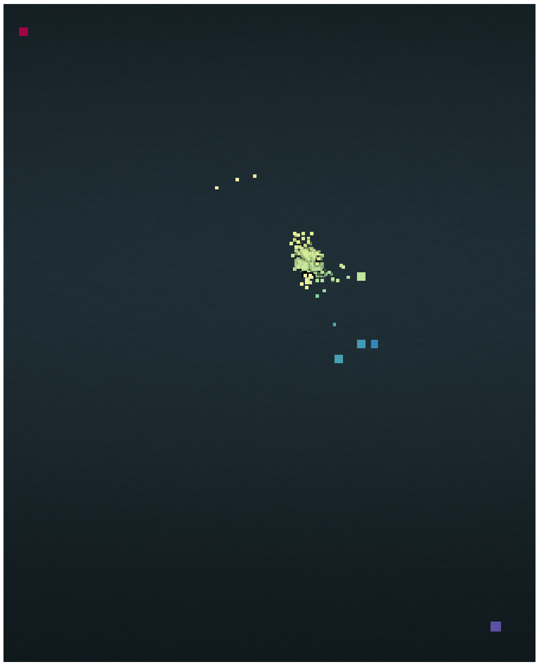
3D reconstruction was accomplished using the following steps:

1. Get multiple images of an object with known intrinsic and extrinsic camera matrices
2. Identify points of interest using the SIFT detection algorithm on gray scale versions of the images
3. Search for corresponding key points between two images using k nearest neighbors and a ratio test
4. Validate the corresponding points using the fundamental matrix to verify that corresponding points are within 1% of image's width or height
5. Reconstruct the points of interest in 3D using triangulation
6. Repeat 3-5 for multiple pairs of images
7. Optimize the image by removing outliers using statistical and/or radial methods
    a. Points are kept based on their distance from the average of their neighbors
    b. Points are kept based on the number of neighbors in a sphere around it

Results

Below is the 3D object to reconstruct.

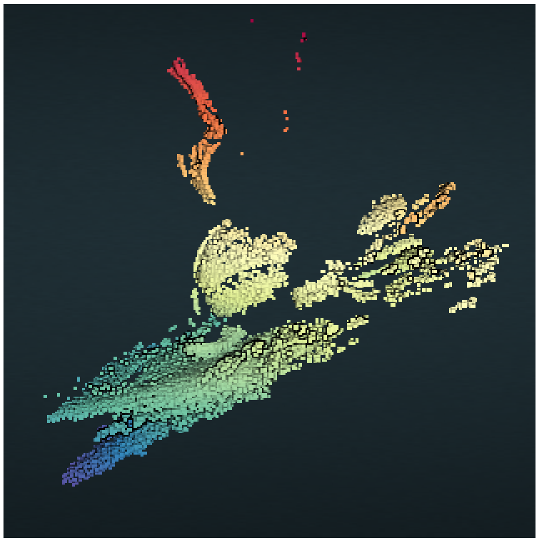
After running the steps 1 through 6, the reconstructed 3D image as shown in pypotree is below:



As shown above, the image is hard to identify due to the outliers in the point cloud. Below is a close up which better shows the reconstructed object:

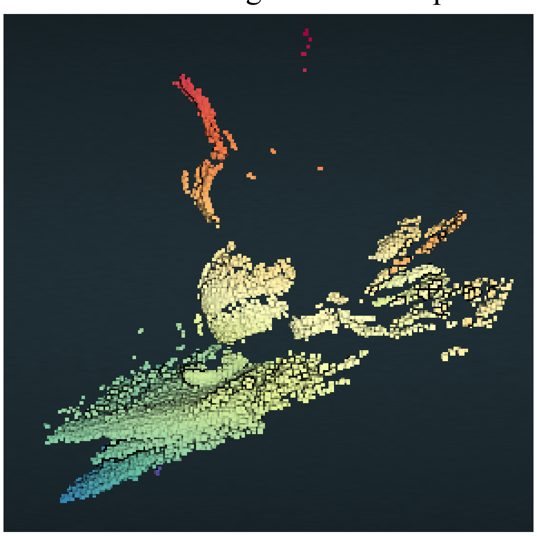
It is clear that optimization is needed in order to remove outliers. This was tested in 3 different approaches.

The first method was using statistical methods where points are removed based on the number of neighbors,"n", within "s" standard deviations. Below is the optimized image using n=20 and s=0.001.



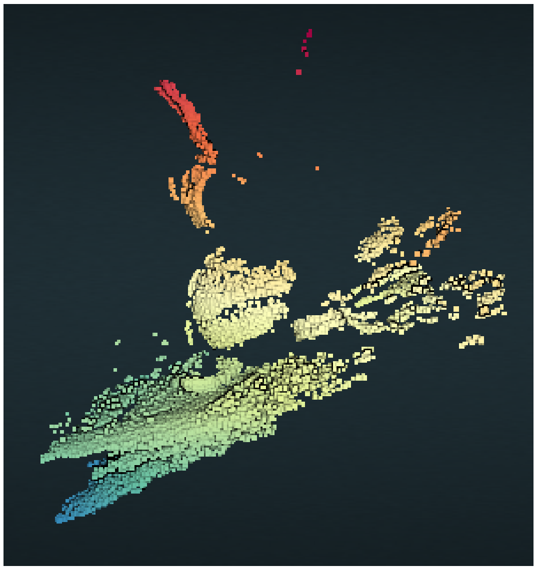
The optimized image removes the points that were far away, as well as the extra platforms that were present before optimization.

The second method removes points based on the number of neighbors, n, within a sphere with radius "r". The image below uses parameters n=16 and r=5.0.



The result for radial removal is quite similar to the previous statistical removal.

The third method combines both statistical and spherical optimization methods, respectively. Statistical inliers were found first with parameters n=20 and s=2.0, followed by radial inliers with parameters n=16 and r=5.0.



Again, the resulting 3D reconstruction is similar to the previous two methods that used a single optimization filter. This shows that differences in the optimization methods are negligible with the correct thresholds.

Conclusion

The 3D reconstruction using statistical and radial optimization can yield decent results. The differences between the methods and combinations of methods do not have any significant differences with the accuracy of the reconstruction. However, further optimization methods need to be explored in order to obtain more accurate results such as the one below. Perhaps the ratio test when grabbing corresponding tests can be tighter, or the percent of an image's width or height between corresponding points during validation can be tighter. But further experimentation is needed to find a more accurate 3D reconstruction.