Approach

The goal of this project is to create a 3-dimensional reconstruction of an object given a dataset of images of the object from different perspectives and camera matrices for each image. This project primarily uses OpenCV and NumPy to achieve this result. We will firstly get points of interest utilizing OpenCV's built-in SIFT detection algorithm. We shall then find correspondences, 2 images at a time, using OpenCV's built-in BFMatcher and knnMatch algorithm. During this step, we shall also implement a ratio test, which compares the best match with the second-best match, to filter out bad correspondences. We tested different ratio thresholds for optimum results. We shall then validate our correspondences using the camera matrices given to us. We shall build the fundamental matrix F using the camera matrices of each pair of images and then validate each pair of corresponding points using F by comparing p1 x F x p2 (Where p1 and p2 are the points of correspondence in homogenous form) to a threshold. We tested different thresholds for optimum results. We now have a collection of validated 3D points. For further optimization, we shall use statistical approaches to remove outliers. We tested two different metrics to remove outliers, Filtering by magnitude and Filtering by distance from the center (The center was defined by the mean of each coordinate). We computed the mean and standard deviation of each metric and used those values to filter out outliers. In each approach, we used a z-test to decide which point is an outlier and which isn't. We tested out several different critical points for the z-test for optimum results. We then applied both filters to our points to achieve our final result.

Results

We tested correspondences and avoid correspondences using the first two images in our dataset.

We found that number of correspondences found was directly proportional to the ratio threshold. At higher thresholds, we encountered more noise but at lower thresholds, we encountered a sparse collection of points.

Ratio Threshold	No. of Correspondences	Noise
0.75	4802	Huge number or noisy correspondences
0.5	1617	Minimal noisy correspondences
0.6	2843	Moderate number of noisy correspondences

We settled on 0.6 as the ratio threshold to achieve less noise and a high number of correspondences.

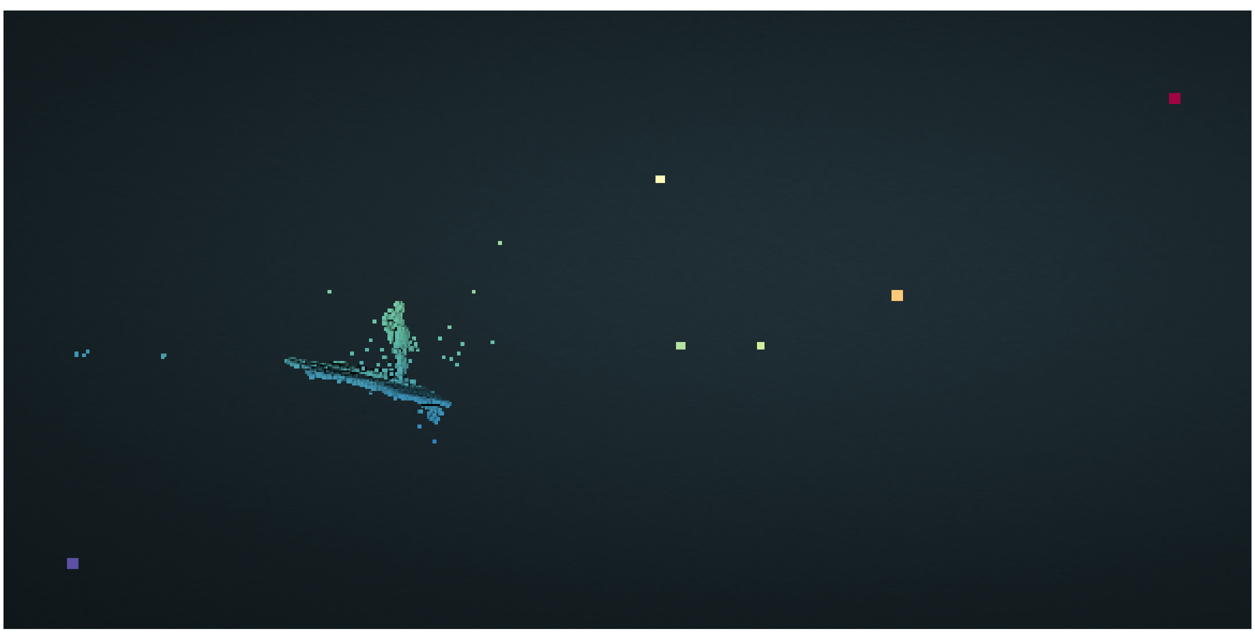
We then tested different thresholds for validation. The number of validated correspondences was directly proportional to the threshold. We initially had 2843 correspondences.

Validation Threshold	Number of valid correspondence	Noise
0.01	2731	Huge number or noisy correspondences
0.001	2274	Minimal Noise but also missed a lot of valid points
0.05	2576	Some Noise but also retains most valid points

We settled on 0.05 as our validation threshold as it led to less noise but preserved the most valid correspondences.

We proceeded to collect and validate correspondences from all 48 images, iterating the process 2 images at a time.

We compiled a total of 28696 validated points for our 3D reconstruction but this included a lot of outliers.

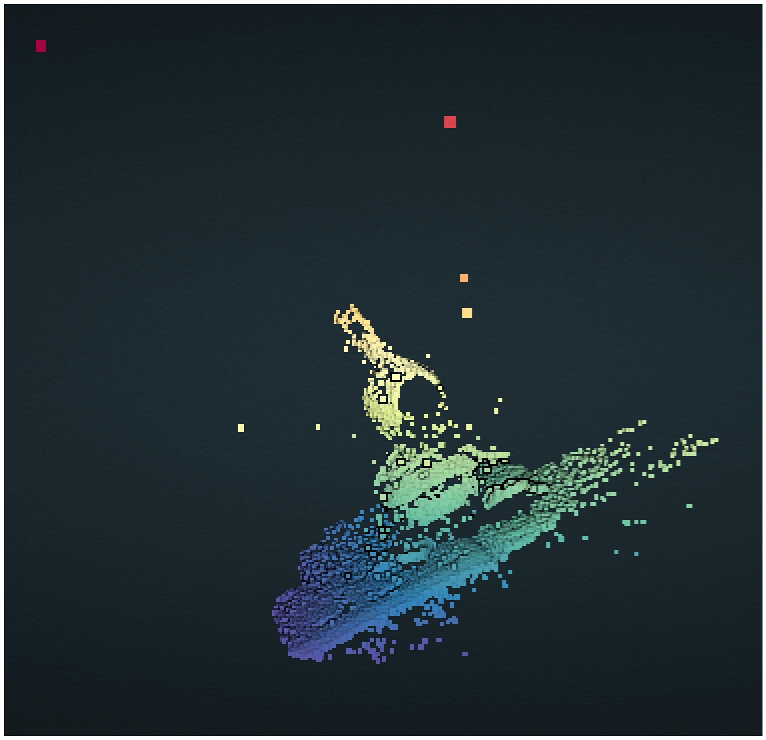


Visualization of all validated points including outliers

We filtered out outliers using a statistical approach. We first tried filtering by the magnitude of each point. We found the mean magnitude to be 720.38 units with a standard deviation of 58.15 units. We found the z score of each point in our complied dataset and compared that to a threshold critical value. The number of inliers was directly proportional to the chosen threshold.

Critical threshold (In number of standard deviations away from the mean)	Number of inliers	Notes
2	28682	Still had a high number of outliers
1.5	28218	Still had a high number of outliers
1	25911	Removed most outliers
0.5	20050	Removed a lot of inliers

We chose 1 as the optimum critical threshold for magnitude.



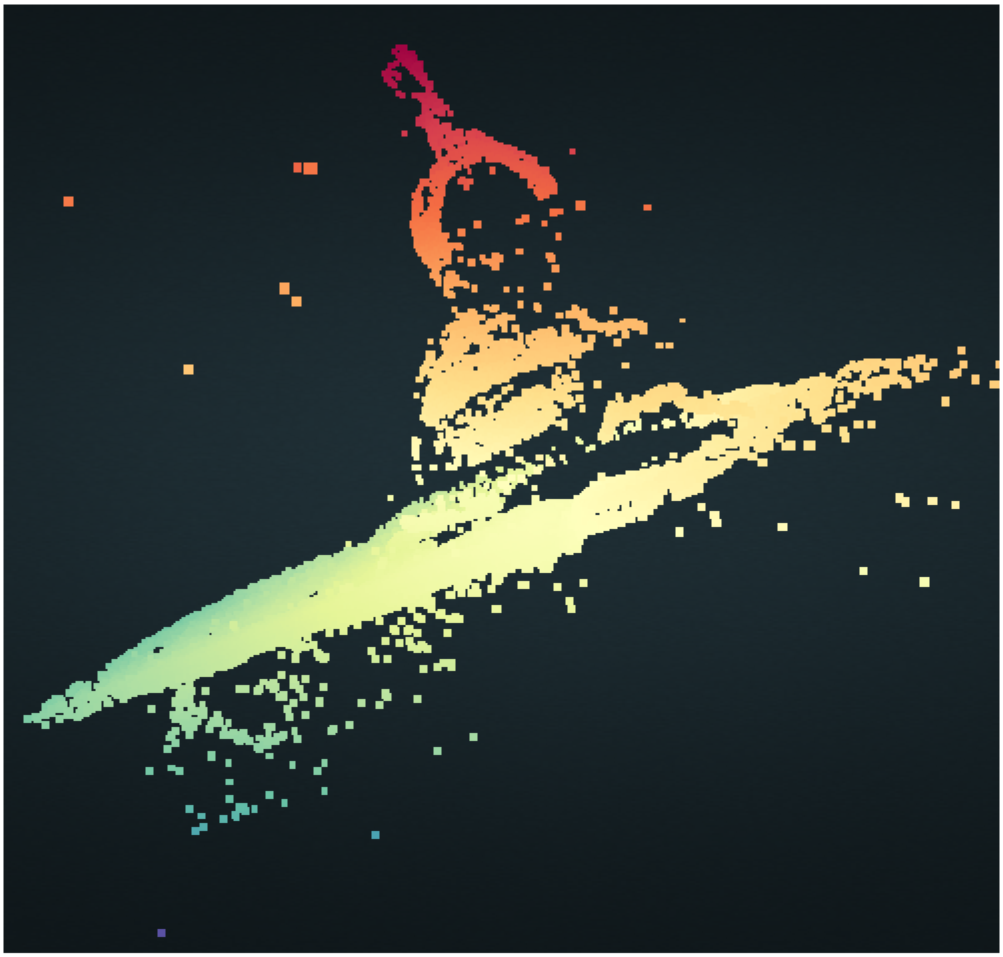
Inliers after filtering by magnitude (Z_critical = 1)

Similarly, we tried filtering by distance away from the center. We computed the center by simply finding the mean of the x, y, and z coordinates of our validated points. We found the distance away from this center for each point in our collection. We found the mean distance to be 92 units with a standard deviation of 62 units. We found the z score of the distance of each point in our complied dataset and compared that to a threshold critical value. The number of inliers was directly proportional to the chosen threshold.

Critical Threshold	Number of inliers	Notes
3	28586	Still had a lot of outliers
2	28029	Removed most outliers

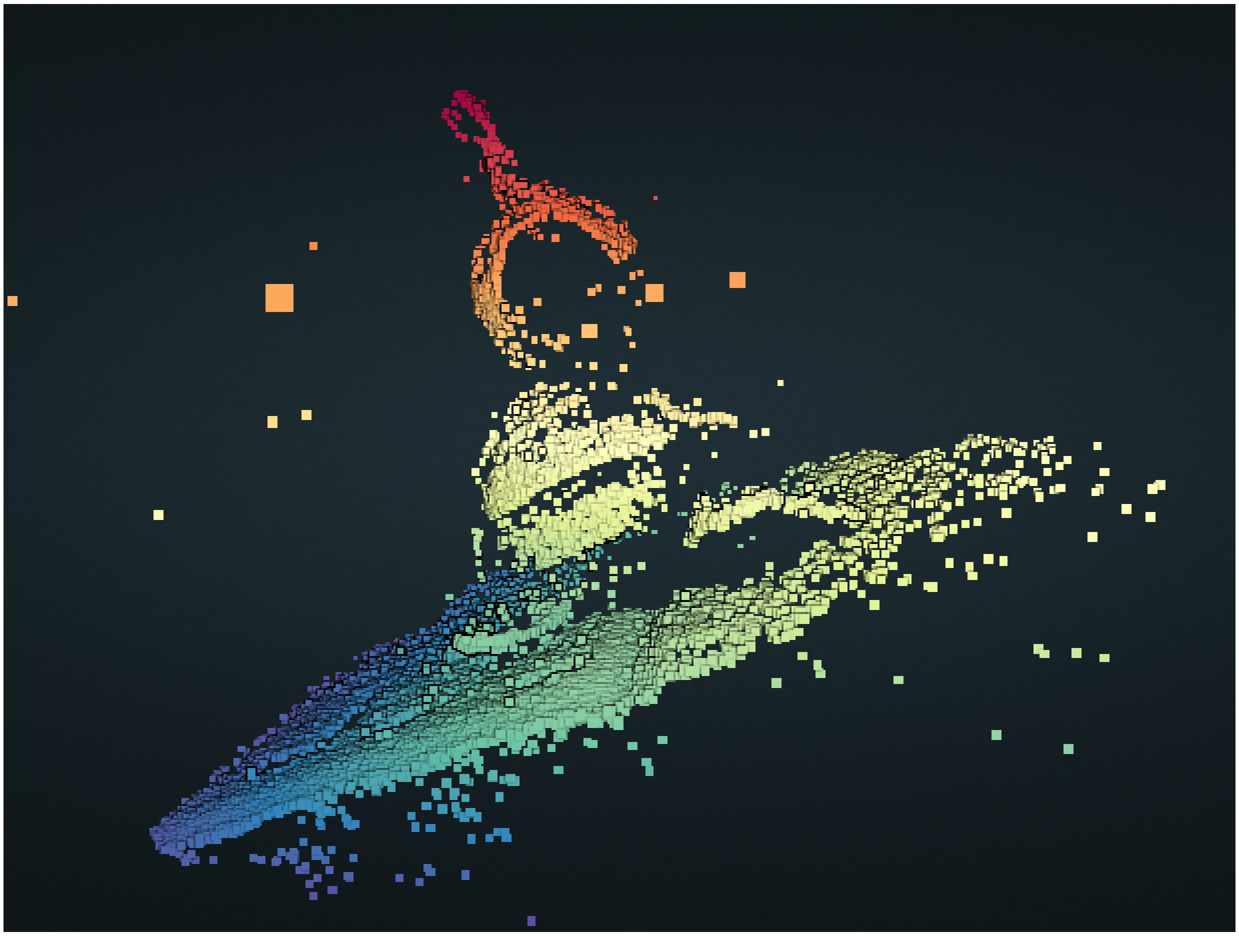
1.5	25218	Removed a lot of inliers

We found a critical threshold of 2 to be optimum.



Inliers after filtering by distance from the center (Z_critical = 2)

We applied both filters on our collection of validated points and were left with 25475 inliers.



Final 3D reconstruction after applying both filters.