

Stereo Reconstruction

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Abstract

Stereo reconstruction is the process of creating a 3D representation of a scene or an object using multiple(in this project just two) 2D images captured from different viewpoints. This report proposed a whole pipeline of stereo reconstruction that utilized several feature detectors such as SIFT, SURF and so forth at the beginning. Then feature matching algorithms including Brute-Forth matcher and FLANN were performed. After that, the eight-point or five-point algorithm was implemented to obtain the fundamental matrix and recover the pose based on the calculated matrix. Afterwards, the bundle adjustment algorithm was utilized to optimize the recovered pose mentioned above. To get desired disparity maps, image rectification and dense matching methods such as SGBM were implemented as well. Eventually, reconstructing 3D models and generating corresponding meshes were done. Experiments on several benchmark dataset showed that the proposed method performed well in terms of accuracy, speed, and robustness. The results demonstrated the effectiveness of using such algorithms for stereo reconstruction.

1. Introduction

As mentioned above, stereo reconstruction technology is utilized in different fields. And in the past few years, there has been great progress in stereo reconstruction because of advanced computer vision algorithms and available large datasets. However, the challenge of obtaining disparity maps from images based on traditional methods is still here, which is the motivation of this report as well. And this report provides a concise overview of the proposed pipeline for stereo reconstruction.

2. Related Work

2.1. Feature Detectors

What should be mention is that feature detectors play an important role in computer vision with the use of identifying distinctive points namely key points in images. And this section will introduce various feature detectors utilized in

this project.

- SIFT (Scale-invariant Feature Transform)

SIFT [1] is a popular feature detection algorithms which can detect local features in images which are invariant to scale, orientation and affine distortion. Its features can be presented by a set of key points, each of which can be described by a 128-dimension vector.

- SURF (Speeded Up Robust Features)

SURF [2] is a feature detection algorithm, which has the same principles as SIFT. However, SURF utilizes a different approach to detect key points. Besides, its features can be presented by a set of key points as well, each of which can be described by a 64-dimension vector instead of a 128-dimension vector. Therefore, SURF is faster than SIFT because of the smaller size of feature vectors. And it is more robust to noise and occlusions, but less invariant to scale and orientation.

- ORB (Orientation FAST and Rotated BRIEF)

ORB [3] is an efficient feature detection algorithm with the combination of the FAST corner detector with the BRIEF descriptor. And its features can be presented by a set of key points, each of which can be described by a 256-dimension vector. ORB is faster than SIFT and SURF and it is more robust to noise and occlusions, however, it is less invariant to scale and orientation.

- FREAK (Fast Retina Keypoint)

FREAK [4] is a binary descriptor, created to be fast and robust to affine transformations. It utilizes a binary string to represent the gradient orientation of a feature. What should be mentioned is that FREAK is just a descriptor; therefore, it should be used together with a detector such as FAST. However, FREAK is sensitive to rotations which might affect detection results in some situations.

- BRISK (Binary Robust Invariant Scalable Keypoints)

BRISK [5] is a binary feature detector and descriptor, which is designed to be fast and perform well in low-light condition. And it utilizes a binary string to represent the gradient orientation of a feature. However,

BRISK is sensitive to scale changes which might affect detection results in some situations.

- KAZE (KAnade-AEgaki-SIngh-Kosecka)

KAZE [6] is a non-binary feature detector and descriptor, which is designed to detect features in non-flat regions. KAZE utilizes a Gaussian scale space to find features. However, KAZE is slower than other feature detectors, making it not available for real-time detection.

2.2. Matching Methods

- BF Matching (Brute-Forth)

Brute-Forth Matching is a straightforward algorithm which compares every feature in one image to every feature in another image. The algorithm calculates the distance between two features and selects the closest match. And this process is repeated for all the features in the first image, while the result is a set of matches between two images.

- FLANN Matching (Fast Library for Approximate Nearest Neighbors)

FLANN Matching [7] is an efficient algorithm which utilizes an index-based method to find correspondences between features. This algorithm creates an index of the features in one image firstly and then searches for the closest match in the index for each feature in another image. It is faster than Brute-Forth matching, therefore, it is usually utilized for large datasets.

2.3. Epipolar Geometry

- Eight-Point Algorithm

The Eight-Point algorithm [8] is one of the simplest algorithms for obtaining the fundamental matrix. It utilizes eight pairwise points between given images to calculate the fundamental matrix. However, it is sensitive to noise and outliers.

- Five-Point Algorithm

The Five-Point algorithm [9] utilizes five pairwise points between given images to calculate the fundamental matrix. And it implements a non-linear optimization approach, which makes it more robust compare to the Eight-Point Algorithm.

2.4. Bundle Adjustment

Bundle Adjustment [10] aims at minimizing the reprojection error between the observed 2D coordinates and the projected 3D coordinate. And the formula is shown in figure 1.

$$E(R, T, \mathbf{X}_1, \dots, \mathbf{X}_N) = \sum_{j=1}^N |\tilde{\mathbf{x}}_1^j - \pi(\mathbf{X}_j)|^2 + |\tilde{\mathbf{x}}_2^j - \pi(R, T, \mathbf{X}_j)|^2$$

Figure 1. Formula of bundle adjustment

2.5. Dense Matching

- SGBM (Semi-Global Block Matching)

SGBM [11] is the combination of local and global algorithms, which uses a cost aggregation method to optimize the matching result for each pixel. It can generate a smoother and more accurate depth map compared to Block Matching which will be discuss later.

- BM (Block Matching)

BM [12] is a local algorithm, which is fast and efficient for real-time applications. The matching cost is calculated based on the intensity difference between pixels in two images. However, the generated depth map by using BM algorithm is less accurate compared to the SGBM algorithm.

3. Method

The method(pipeline) of this project is shown below in figure 2.

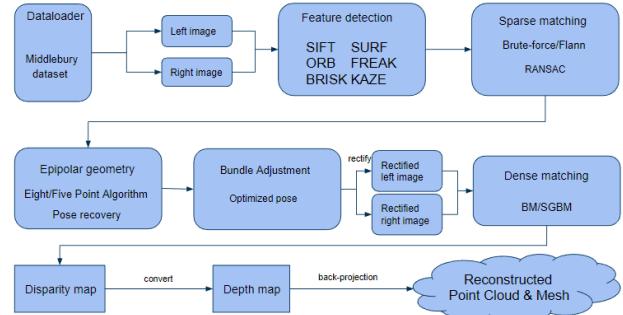


Figure 2. Pipeline of this project

4. Results

We conducted several experiments among feature detection and dense matching by incorporating different experimental settings. The corresponding results are listed below in sections.

4.1. Feature Detection and Matching

Table 1 displays the number of keypoints detected by six different detectors. Using the detected keypoints, we further obtained the paired matches for each detector as shown in Table 2. This table also includes a comparison of the results

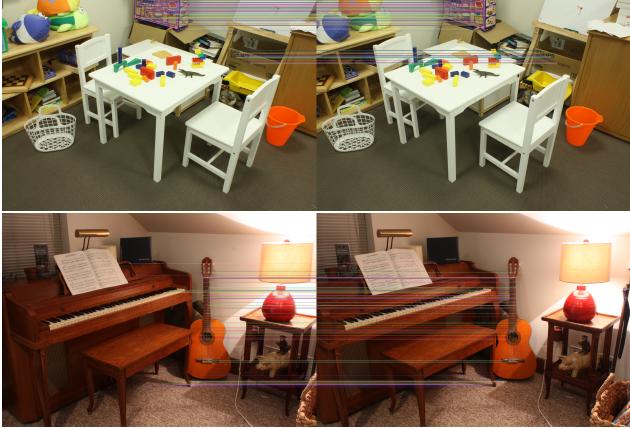


Figure 3. matches using SIFT

when using RANSAC and different sparse matching techniques, such as BF Matcher and FLANN Matcher. With the exception of FREAK, the number of matches is generally in line with the number of detected keypoints, indicating the validity of our matching results. After the application of RANSAC, only the inliers were kept for further analysis. For visualization, the matches detected by SIFT on playtable-perfect and piano-perfect can be seen in Figure 3.

detector	keypoints
SIFT	17380
SURF	18256
ORB	500
FREAK	51824
BRISK	3524
KAZE	8287

Table 1. **Number of keypoints** are recognized by six detectors on playtable-perfect.

Detector	without RANSAC		with RANSAC	
	BF	FLANN	BF	FLANN
SIFT	769	717	159	275
SURF	1065	1057	40	290
ORB	41	2	23	2
FREAK	7	115	7	37
BRISK	209	70	50	32
KAZE	311	1200	90	444

Table 2. **Number of matches** for sparse matching are compared on playtable-perfect for six detectors respectively.

4.2. Pose Evaluation

The outcome of the transformation matrix can be observed in Table 3 and Table 4 after obtaining the matched

points. It is evident that the initial results from the five-point algorithm are significantly better than those from the eight-point algorithm due to its robustness against random selections of matched points. On the other hand, bundle adjustment suffer greatly from noisy points, resulting in a deviation from the optimal direction. However, when combined with RANSAC, bundle adjustment is still crucial to optimize the poses.

	Eight-Point	Five-Point
initial	0.06073	0.00136
BA	0.11895	0.00466
RANSAC	0.00051	0.03602
BA & RANSAC	0.00044	0.00044

Table 3. **L2-distance for Rotation** {↓} in different settings considering existence of bundle adjustment and RANSAC. Initial is the direct result after five/eight-point algorithm.

	Eight-Point	Five-Point
initial	1.91453	0.11951
BA	0.30961	1.99959
RANSAC	0.02135	0.11126
BA & RANSAC	0.00319	0.00319

Table 4. **L2-distance for Translation** {↓} in different settings considering existence of bundle adjustment and RANSAC. Initial is the direct result after five/eight-point algorithm.

4.3. Block Matching

To assess the results of dense matching, we employ four metrics - BAD0.5, BAD2.0, BAD4.0, and RMS which can be seen in Table 5. The importance of bundle adjustment is again emphasized, as it significantly improves the outcome of dense matching for both BM and SGBM. Overall, SGBM outperforms BM in all metrics, making it the more suitable dense matching technique for this dataset.

Additionally, we present our results visually in the form of color disparity maps, as seen in Figure 4. When using bundle adjustment, the disparity map accurately portrays the relative position and potential 3D structure. Conversely, without bundle adjustment, the disparity map is not reliable due to the highly deviated transformation matrix, leading to noise or meaningless smooth holes. A comparison between SGBM and BM reveals that SGBM provides more solid depth information for objects close in proximity, such as the piano and piano stool, while BM offers more consistent depth information when image pixels are significantly impacted by lighting. Finally, we also verify the refined results of maps 1 in Figure 4 against the ground truth. As SGBM surpasses BM in all evaluation metrics, we will generate meshes based on its results.

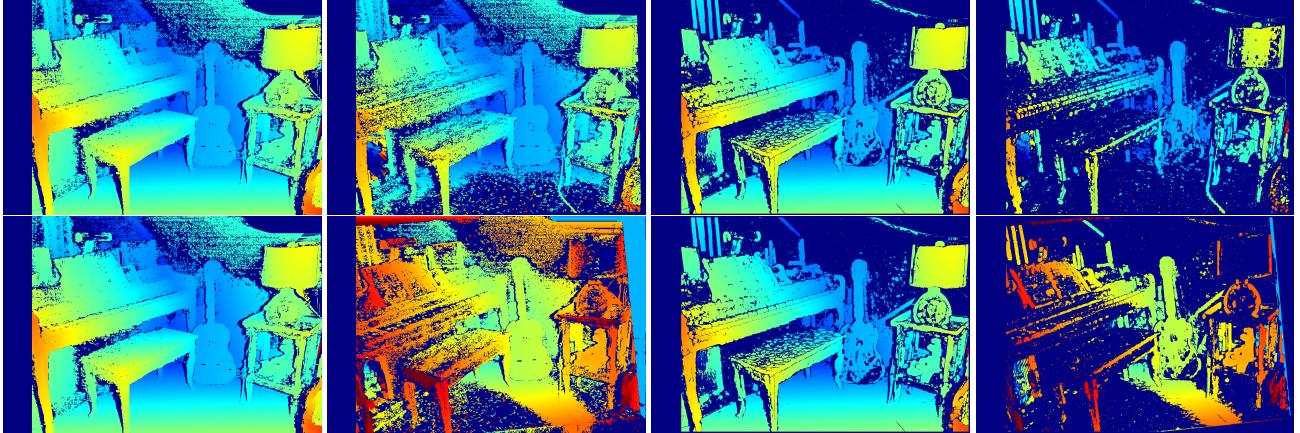


Figure 4. Color disparity map on piano-perfect. From left to right and top to bottom, **1**: 8-point+SGBM+BA, **2**: 8-point+SGBM, **3**: 8-point+BM+BA, **4**: 8-point+BM, **5**: 5-point+SGBM+BA, **6**: 5-point+SGBM, **7**: 5-point+BM+BA, **8**: 5-point+BM.

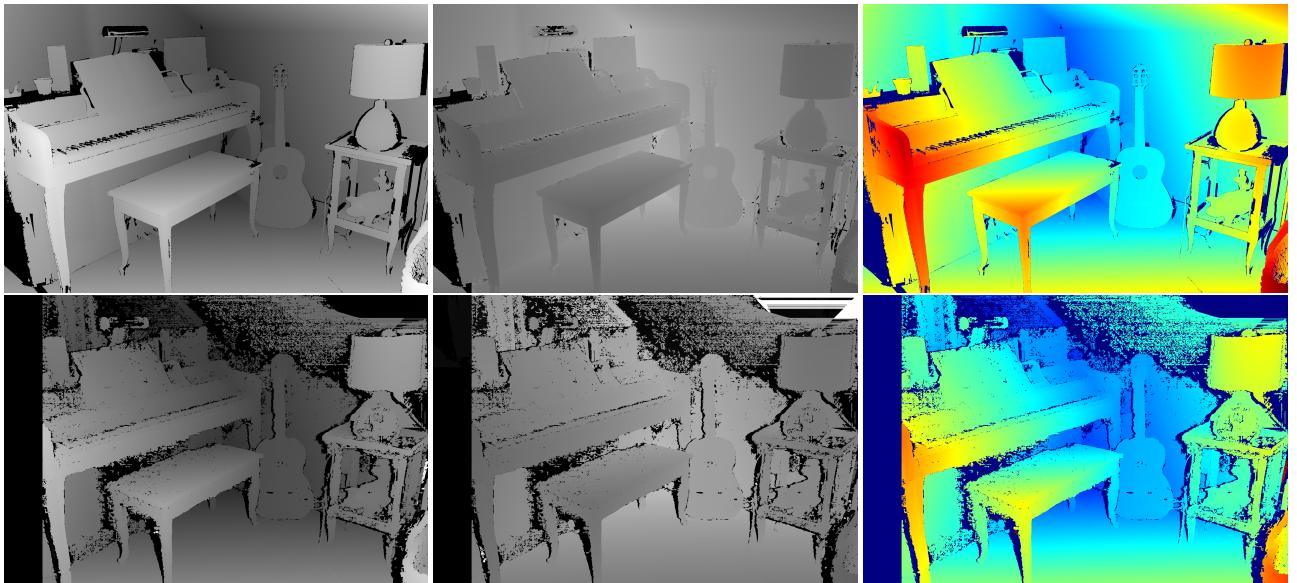


Figure 5. Disparity map and depth map. The first line shows the ground truth while the second line shows the rectified image.

	BAD0.5↓	BAD2.0↓	BAD4.0↓	RMS↓
BM	86.61	86.58	86.56	100.36
BM & BA	54.44	39.42	38.53	63.29
SGBM	86.98	86.93	86.85	92.19
SGBM & BA	50.19	27.04	24.92	45.13

Table 5. Evaluation of dense matching. We select BM and SGBM as our dense matching method, which is here based on the result of five-point algorithm. BAD0.5{↓}, BAD2.0{↓}, BAD4.0{↓} and RMS{↓} are used as the evaluation metrics.

4.4. Mesh Generation

The final reconstructed meshes are displayed in Figure 6. It is evident that the relative positioning is correct and the overall reconstruction performance is satisfactory. However, there are some missing parts in shadows and some flat slices orthogonal to the camera's capture direction, which still reveals the limitation of detectors and matching methods towards the stereo reconstruction problem.

5. Conclusion

In summary, SIFT is considered the most reliable feature detector as it can perform well in various experimental conditions, as shown in Table 2. To determine the pose, either



Figure 6. 3D meshes on piano-perfect, playroom-perfect, playtable-perfect.

the eight-point algorithm or the five-point algorithm can only provide rough estimates. On the other hand, RANSAC is able to identify and eliminate outliers, which provides a solid foundation for bundle adjustment to optimize the pose. Only after these two crucial steps, the resulting transformation matrix is sufficiently accurate compared to the ground truth based on L2-distance. Regarding dense matching methods, SGBM is superior to BM in all evaluation metrics, as indicated in Table 5. Further research can involve exploring other block matching methods since SGBM is not robust to changes in lighting conditions.

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