

SFM-MVS to Mesh

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Abstract—Structure From Motion (SFM) and Multiview Stereo (MVS) are computer vision algorithms commonly found in a wide range of domains and use cases, one of the most prevalent being photogrammetry. In this project, we investigate the ideal methodology and object properties for photogrammetry of specific objects using SFM, and explore an altered approach to the feature extraction and feature matching steps in the algorithm. Additionally, we evaluate the effectiveness of two algorithms for surface reconstruction on our SFM-MVS (point cloud) outputs.

1. Introduction

One of the most common applications of Structure From Motion (SFM) and Multiview Stereo (MVS) is in photogrammetry. These two techniques are complementary to each other, and result in a dense point cloud reconstruction of an object (or environment) from image data. However, in many fields where photogrammetry is used, a 3D mesh is likely more useful than a point cloud is. As such, time is often spent cleaning resultant point clouds and converting them to meshes, when the brunt of this process could be automated and simplified. Furthermore, SFM can be relatively slow for many datasets. The general outline of SFM algorithms involves feature extraction, feature matching, triangulation and bundle adjustment. Each of these steps can take considerable time, however there is not much to change with regards to triangulation and bundle adjustment. On the other hand, feature extraction (SIFT [1] based) and feature matching can be altered to be computationally faster at a minimal cost to accuracy. In a nutshell, this project report will explore proposed alterations to feature extraction and feature matching in SFM, investigate the ideal methodologies and object types for this altered approach, and evaluate algorithms relating to point cloud processing and mesh reconstruction. The source code for the project can be found on GitHub.

2. Theory and Technical Details

This project largely focuses on alterations to SFM and post processing SFM-MVS output for mesh construction. The general workflow and steps taken in this project can be seen in Figure 1 and are the following:

1. We implement a custom BRISK-SIFT feature extraction stack for SFM

2. We implement feature matching using approximate nearest neighbors for speed, with outlier removal from Lowe's Ratio Test [1] and MAGSAC++ [2]
3. We implement a feature processing method to further simplify key point matches
4. Our features and matches are used to build sparse and dense reconstructions via COLMAP [3]
5. Resultant point clouds are processed and used to generate meshes

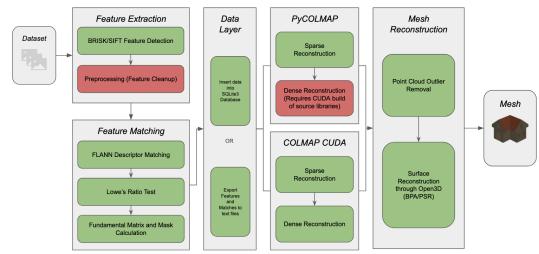


Figure 1. Pipeline/Project Workflow

2.1. SFM-MVS

SFM algorithms generally consist of the following steps: feature extraction, feature matching, triangulation, and bundle adjustment.

Traditionally, feature extraction in SFM algorithms use Lowe's SIFT approach for both feature detection and description [1]. Detection in SIFT involves a Gaussian pyramid-like structure of octaves for scale space representation. Each octave of scale space contains a set of Gaussian convolved images separated by a scale factor, and each octave uses a down-sampled image relative to the previous octave. The extrema (within a given window) of a difference-of-Gaussian (DoG) (Figure 2) function applied to adjacent Gaussian images within octaves is used to detect stable key points in scale space. Mathematically, the scale space is defined as a function $L(x, y, \sigma)$, produced from a variable-scale Gaussian, $G(x, y, \sigma)$ and the input image $I(x, y)$ [1]:

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y)$$

where $*$ is the convolution operation. The DoG function takes the form:

$$\begin{aligned} D(x, y, \sigma) &= (G(x, y, k\sigma) - G(x, y, \sigma)) * I(x, y) \\ &= L(x, y, k\sigma) - L(x, y, \sigma) \end{aligned}$$

with some constant multiplicative scale factor k . DoG ap-

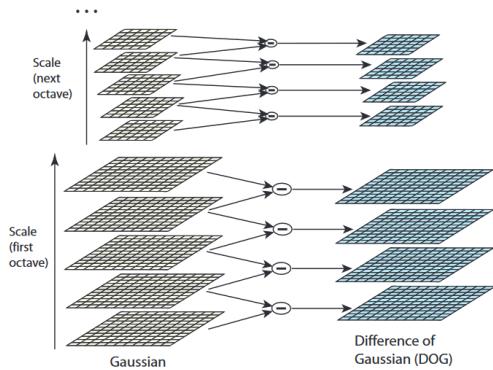


Figure 2. Difference of Gaussians and Sift Scale Space

Source: Adapted from [1]

proximates the normalized Laplacian of Gaussian [4], whose local extrema was shown to correspond to stable key points/blobs. SIFT descriptors [1] take the gradient directions over a spatial region around feature points. A histogram of these gradient directions (orientations) is normalized and invariant against rotation, scale, and brightness. The descriptors are stored as a 128-dimensional vector containing these histogram values corresponding to the gradient magnitudes and are known for their distinctiveness. BRISK feature detection [5] builds on a computationally optimized version of FAST 9-16 adapted for scale invariance via a simplified representation of scale space (compared to SIFT [1]). Due to the simplified scale space representation and use of a computationally efficient FAST 9-16 detection algorithm, BRISK is considerably faster than SIFT while still detecting high quality key points. The set of detected points with BRISK is similar to many SIFT detected points. Additionally, since both approaches revolve around scale, rotation, and illuminance invariance, and since description is independent of detection, SIFT descriptors can be easily applied to BRISK key points. For the purposes of this project, we rely on OpenCV's implementation of both SIFT [6] and BRISK [7]. Feature matching in SFM (with SIFT descriptors) is done by identifying a nearest neighbor (based on L2 distance) between descriptors in 2 views [1]. This is efficiently approximated through [8].

Lowe's ratio test [1] compares the distance measures of the 2 nearest neighbors and rejects matches where the ratio between the distances from these neighbors is greater than or equal to some value l (ie. $d_1 \geq l \cdot d_2$), eliminating false matches. [9]'s MAGSAC++ [2], an improved version of RANSAC, further refines these matches by finding inliers during a fundamental matrix estimation between randomly sampled matches. Two view geometry estimation, triangula-

tion and bundle adjustment, as well as multiview stereo, are handled through COLMAP [3] [10] [11], resulting in sparse and dense point cloud reconstructions (with estimated surface normals).

2.1.1. Image Capturing. Image capturing for SFM was primarily focused on small objects with three things in mind:

1. Brightness constancy (via controlled lighting)
2. Angle variety and image overlap
3. Limited background noise (via. lightboxes/backdrops as shown in Figure 3) (*note: this is not present for some earlier datasets*)



(a) Black backdrop

(b) White backdrop

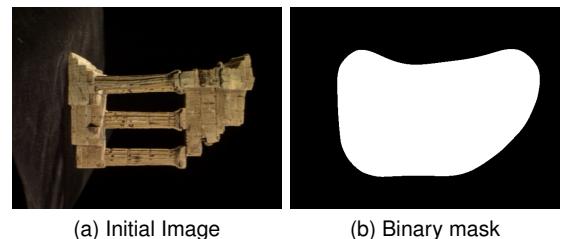
Figure 3. Lightbox-like backdrops

Angle variety and image overlap was achieved by taking images in short intervals, between either camera motion or object motion (ie. physical rotation). Overlap for large objects (ie. buildings) was achieved through capturing every 3-5 steps.

The overall methodology for capturing smaller objects throughout the project was based on [12] and [13].

2.2. Feature Preprocessing

During feature extraction, further processing can be done to isolate key points on objects. We apply a combination of image filtering, blurring, and canny edge detection to build a binary mask (show in Figure 4) covering the object of interest. This mask is used to discard key points which



(a) Initial Image

(b) Binary mask

Figure 4. Binary Mask. Dataset from [12]

are determined to be background noise. Preparation for canny edge detection involves noise reduction through a gaussian blur for effective detection [14]. Though OpenCV's

implementation [15] applies a 5×5 Gaussian kernel, further reduction is often necessary. Additionally, we apply a DoG (shown in Figure 5) based approach to accentuate edges and blobs for lower texture objects and noisier datasets. Sobel

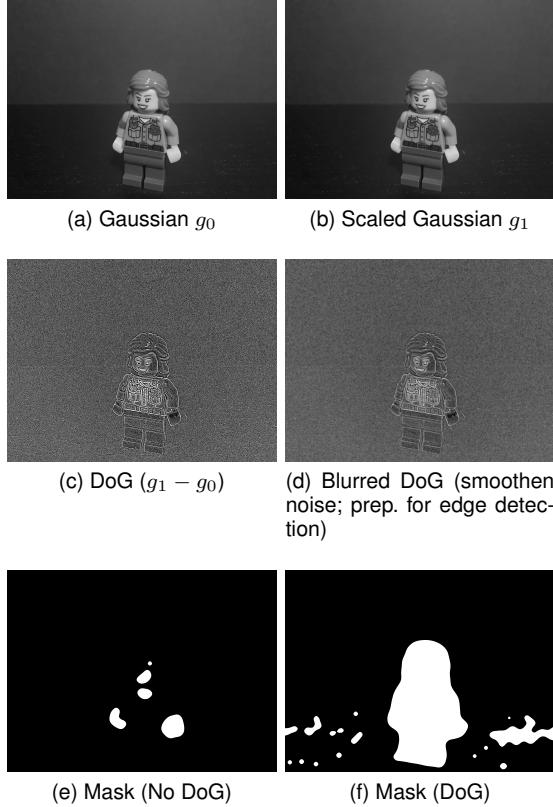


Figure 5. Difference of Gaussian based preprocessing approach. (σ -scale factor $k = 2$) Inspired by [1].

filters applied in the horizontal and vertical directions allow us to obtain edge gradients and directions [15] as follows:

$$G = \sqrt{G_x^2 + G_y^2}, \quad \theta = \arctan \left(\frac{G_y}{G_x} \right)$$

where G is the edge gradient and θ is the edge direction. Non-maximum suppression removes unwanted pixels that may not be part of an edge [15]. Hysteresis thresholding determines edge criterion via a user defined lower-upper bound (l, u) :

- i $G > u \rightarrow$ edge
- ii $G < l \rightarrow$ not an edge
- iii $G \in [l, u] \rightarrow$ classified based on connectivity to edge pixels

We use the edge image, $E(x, y)$, to build a mask by:

1. Convolving a Gaussian kernel on E
2. Binary thresholding is applied to the convolved image (forming the initial mask M)
3. Apply two median blur filters to M

We can apply our mask to the source frame and exclude key points that are irrelevant to the image. Though this does

not directly affect the dense point cloud reconstruction from MVS, it can decrease matches from background noise, thus improving match performance and the accuracy of two view geometry. A general outline of our feature preprocessing approach is shown in Figure 6 and an example is how in Figure 7

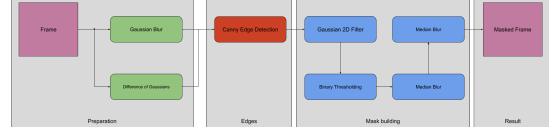


Figure 6. Feature preprocessing pipeline.

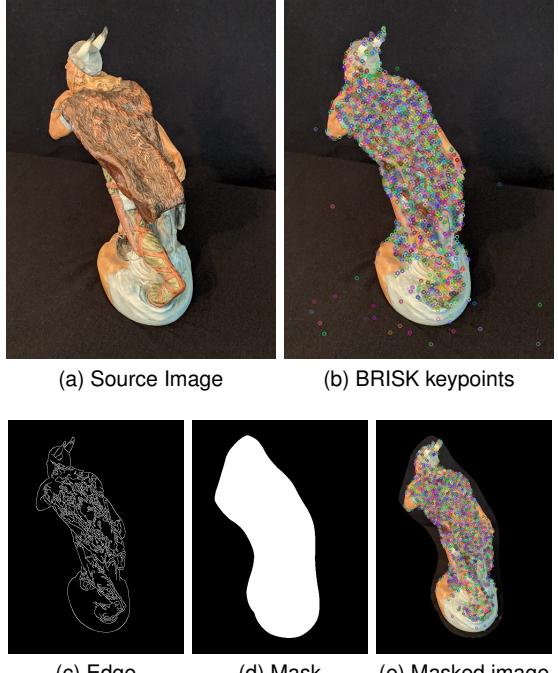


Figure 7. Feature preprocessing example. Dataset from [13]

2.3. Point Cloud Processing

This project uses Open3D’s implementation of the Ball-Pivot Algorithm (BPA) [16] [17] and Poisson Surface Reconstruction (PSR) [18] [17], two widely used mesh reconstruction techniques. BPA involves a “ball” with a user-defined radius, r , which pivots along a manifold surface of the 3D object. Triangles are formed when the ball touches 3 points without “falling through”, eventually leading to a triangle mesh once all points are considered [16]. This process can be repeated with various different radii to improve accuracy. An implementation trick we discovered with radii tuning was defining them as an array of scaled average neighbor distances. This approach often gave the best results with respect to BPA. PSR [18] formalizes surface reconstruction as a poisson problem and creates very

smooth surfaces that robustly approximate noisy data using a point cloud, its normals, and an octree of a user specified depth. However, PSR assumes the point cloud represents an object rather than the environment surrounding it, as such its robustness to noise is limited when background points are introduced. Additionally, BPA [16] is generally not as robust as PSR for noise in an object point cloud, however it handles background noise well (given enough separation between points). To alleviate the effect of noise, we use Open3D’s radial and statistical point cloud outlier removal algorithms to automate background noise removal [19], improving overall mesh quality for both approaches.

3. Results

3.1. Initial Evaluation

Initial evaluation involved a direct benchmark of BRISK and SIFT feature detectors for various datasets. (Benchmarks were collected on the same Ryzen 9 5900HS 16GB RAM system on six datasets) Both Figures 8 and 9, as well

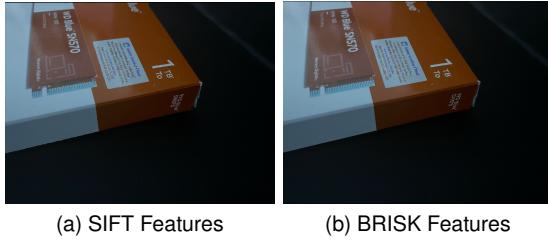


Figure 8. SIFT vs BRISK detected features (ssd box)

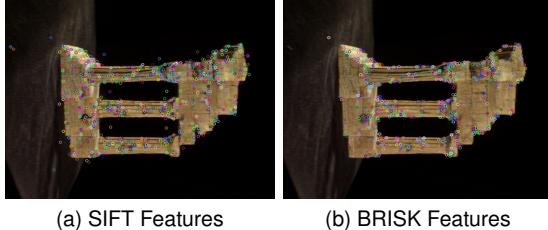


Figure 9. SIFT vs BRISK detected features (templeRing [12])

as Table 1, demonstrate a substantial difference in overall ability. Referring to Figure 8, we see that SIFT detection is able to find nearly all the points BRISK detection finds, as well as more subtle features like the entire edge of the box (which BRISK largely fails to detect). In cases where these types of low-texture, subtle features are important, our BRISK-SIFT SFM may not be viable compared to traditional SIFT-SIFT. However, figure 9 suggests that the more “nuanced” feature points may also be more akin to noise (detections on black background) and unneeded. Furthermore, BRISK is considerably faster than SIFT ($\sim 2.3x$ faster) as seen in Table 2 and still produces a large number of high quality points in textured regions (ie. areas with text

in Figure 8) (surprisingly, BRISK yields 29% more points than SIFT does on average).

TABLE 1. KEYPOINT EXTRACTION (NO. OF KEYPOINTS EXTRACTED)

Dataset	SIFT	BRISK
Temple Ring [12]	39945	42789
Viking [13]	58604	145037
Lego5	60767	53192
Keyboard	219924	204750
Ace Coffee Building	164260	212897

TABLE 2. KEYPOINT EXTRACTION (TIME (s))

Dataset	SIFT	BRISK
Temple Ring [12]	3.8003	1.2922
Viking [13]	5.3268	3.2936
Lego5	87.4832	16.2658
Keyboard	44.5370	12.0966
Ace Coffee Building	18.0179	7.2542

3.2. COLMAP Comparison

We evaluate the results of BRISK-SIFT feature extraction against both traditional SIFT-SIFT (on our SFM stack) and results from COLMAP on the “templeRing” [12] dataset. In Figure 10, we see that our SFM stack (for

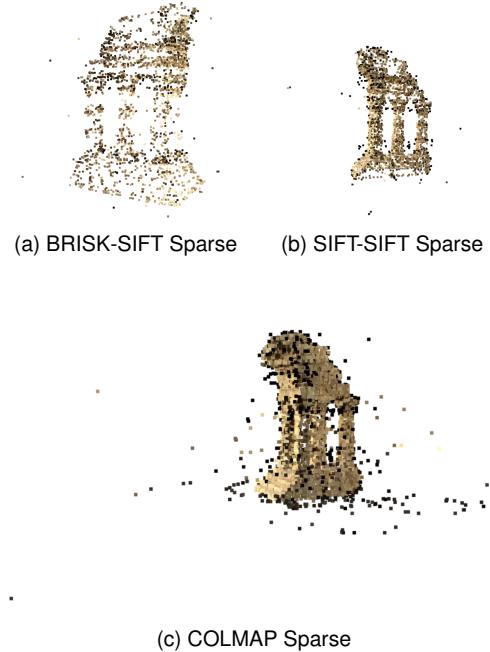


Figure 10. Sparse Reconstruction of our SFM stack (with BRISK-SIFT and SIFT-SIFT) and full COLMAP and both BRISK-SIFT and SIFT-SIFT) results in a sparser point

cloud compared to pure COLMAP, however considerably less visible noise as well. With BRISK-SIFT in particular, our SFM stack results in a sparser point cloud compared to other methods (likely due to less detections), however it also contains the least amount of noise in the reconstructed points. In Figure 11, we see that the dense reconstruction from COLMAP’s MVS [11] with our BRISK-SIFT SFM stack is nearly identical to both our SIFT-SIFT and COLMAP with the exception of a small gap. This is likely due to the difference in matched features, causing slightly different camera and pose estimation. Nonetheless, all these point clouds provide a reasonably accurate 3D representation of the object.

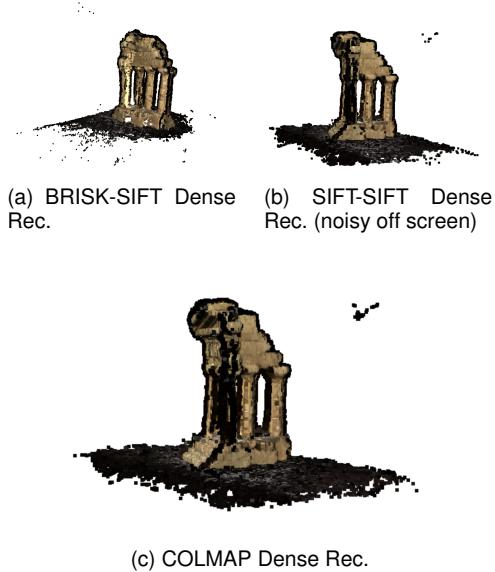


Figure 11. Dense Reconstruction of our SFM stack (with BRISK-SIFT and SIFT-SIFT) and full COLMAP

3.3. Feature Preprocessing Evaluation

We evaluate our feature preprocessing (a method of key point cleanup during feature extraction) with a benchmark test (same as Table 1 and Table 2) and a visual test on the “lego5” dataset.

TABLE 3. FEATURE PREPROCESSING (FT. EXTRACTION TIME (S))

Dataset	No Img Preproc.	Image Preproc.
Temple Ring [12]	1.2922	2.3747
Viking [13]	3.2936	4.6455
SSD Box	5.8452	9.6800
Lego5	16.2658	30.7978
Keyboard	12.0966	22.5780
Ace Coffee Building	7.2542	12.3442

TABLE 4. FEATURE PREPROCESSING (FT. MATCHING TIME (S))

Dataset	No Img Preproc.	Image Preproc.
Temple Ring [12]	23.600	22.989
Viking [13]	88.046	87.223
SSD Box	38.348	36.611
Lego5	104.346	101.194
Keyboard	178.749	178.099
Ace Coffee Building	77.786	72.757

3.3.1. Benchmarks. Table 4 shows that feature preprocessing provides a marginal benefit for matching (~2% reduction in time on average). However, Table 3 shows that it also causes a ~70% increase in feature extraction time (on average), significantly lengthening the overall search process for a slight refinement (~5% less matches on average). Still, it is worth noting that the increased feature extraction times (Table 3) are still faster than using SIFT (Table 2)

3.3.2. Visual Test. To further evaluate feature preprocessing, we apply our DoG implementation to the “lego5” dataset. The resulting reconstructions are shown in Figures 12 and 13. From Figure 12, we see that there is much more

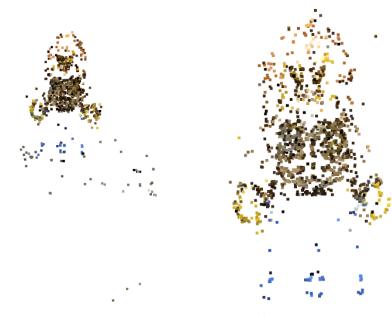


Figure 12. Sparse Reconstruction without vs with ft. preprocessing

noise in the non-feature preprocessed sparse reconstruction.

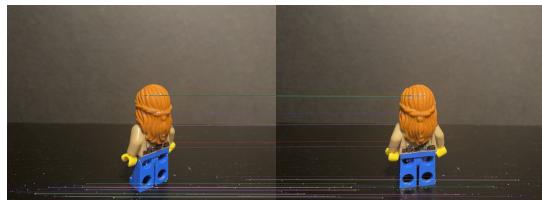
The dense reconstruction of the feature preprocessed dataset (shown in Figure 13) also appears to be denser than the non-preprocessed dataset (note the legs). Feature match refinement from preprocessing is shown in Figure 14. This is especially useful in cases where the object moves independent of the environment (ie. user rotates object rather than using camera motion).

3.4. Noisy Data

We evaluated our methodology on two “noisy” datasets, “lego” and “can.” The dense reconstruction from the lego dataset via our BRISK-SIFT SFM-MVS stack, as well as



Figure 13. Dense Reconstruction without vs with ft. preprocessing



(a) No Ft. Preproc.



(b) With Ft. Preproc.

Figure 14. Feature Matches without vs with Feature Preprocessing on lego5 sample image

a sample image are found in Figure 15. The reconstruction shown is relatively accurate with regards to the lego figure, although it does fail to capture certain features (likely due to its flat texture and glossy finish). However, there is a significant amount of background noise, likely from elements such as the metal picture frame in the background. Reconstructions for the "can" dataset are shown in Figure 16, and a sample image is shown in Figure 17. Unfortunately, our BRISK-SIFT based SFM pipeline was unable to create sufficient matches for this object, and thus could not create a reconstruction. We believe this is due to a lack



Figure 15. Logo dataset reconstruction.



(a) SIFT-SIFT (b) COLMAP

Figure 16. Can dataset reconstruction



Figure 17. Sample image from "can"

of viable edges as well as the can's glossy and reflective surface, making it difficult to satisfy the 9/16 condition [5]. We believe the resultant point cloud representations shown in Figure 16 are look poor for similar reasons (ie. glossy surface).

3.5. Point Cloud Processing Evaluation

We evaluate our point cloud processing methodologies by applying them to the resultant point clouds of four datasets (via our SFM-MVS workflow). These datasets are "lego", "templeRing" [12], "Viking" [13], and "ace." As mentioned in the previous section, the "lego" dataset results in a rather noisy reconstruction. Applying our outlier removal strategies, however, appear to significantly improve it (Figure 18).



Figure 18. Outlier Removal on lego

Similarly, we find that outlier processing can be applied to other, less noisy datasets to eliminate some unnecessary structure (refer to Figure 20).



Figure 19. Raw point cloud reconstructions

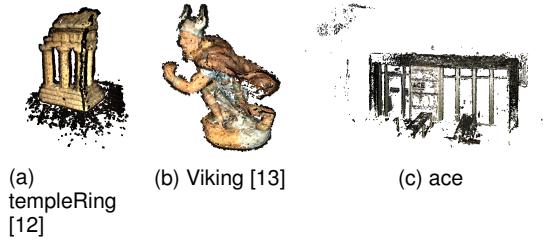


Figure 20. Outlier removal

We can then apply our mesh reconstruction algorithms, shown in Figures 22 and 24.

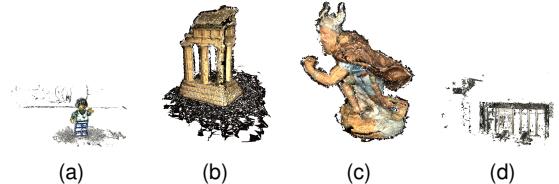


Figure 21. BPA on raw reconstructions

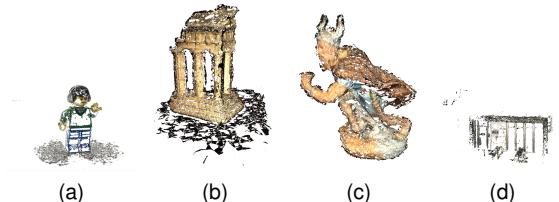


Figure 22. BPA on outlier removed reconstructions

We can see that PSR is often times a better alternative to BPA as it provides a cleaner, higher quality mesh compared to BPA. However, significant environmental noise, as in Figure 23, can cause diminished results.

4. Conclusion and Future Work

This paper presents improvements to existing SFM-MVS pipelines. We proposed an alternative approach to feature extraction, by implementing BRISK features as a faster

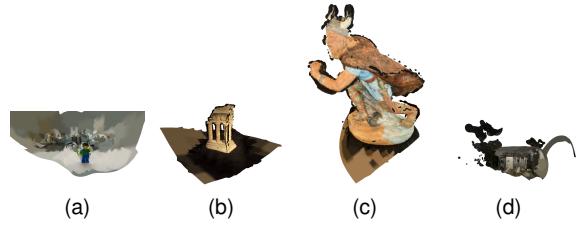


Figure 23. PSR on raw reconstructions

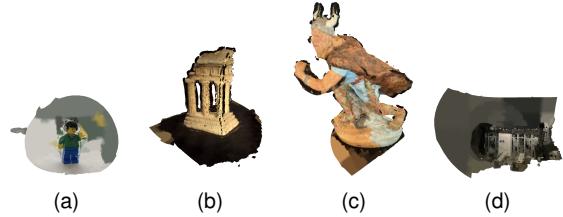


Figure 24. PSR on outlier removed reconstructions

alternative to the SIFT features commonly used in existing systems. Although there exist situations where BRISK features are not as performant as SIFT, we believe that our SFM-MVS pipeline can still be effective in most cases. Furthermore, we presented a feature preprocessing pipeline, which has shown to be effective at clearing background noise, and masking the object of interest. Additionally, we improved feature matching by implementing approximate nearest neighbor searches and match refinement through MAGSAC++. Visual analysis of different surface reconstruction techniques leads us to believe that PSR is superior for reconstructing meshes. We found throughout testing and evaluation that ideal image datasets require well textured objects, constant illumination conditions, smooth backdrops, a high quantity of images with sufficient visual overlap and sufficient parallax. Our versatile system has proven to be capable of reconstructing high quality meshes in reasonable time, for datasets of varying complexity.

4.1. Future Work

There is significant room for future work to improve and extend our SFM-MVS system. One crucial improvement would be implementing CUDA libraries to increase the efficiency of feature extraction, matching, incremental mapping, and surface reconstruction. Additionally, we would like to explore the implementation of a BRISK-like algorithm on top of a DoG octave, with the goal of creating a pseudo SIFT-BRISK detection algorithm for more robust keypoints at similar speeds to BRISK.

Author Contributions

Roderick Lan implemented the BRISK-SIFT feature extraction stack, feature matching, the Difference of Gaussian method in feature preprocessing, point cloud outlier

removal, and poisson surface reconstruction.

Abdullah Khadeli implemented the feature preprocessing algorithm, interaction with PyCOLMAP and COLMAP, and the ball pivot algorithm. Additionally, he handled benchmarking.

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