

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

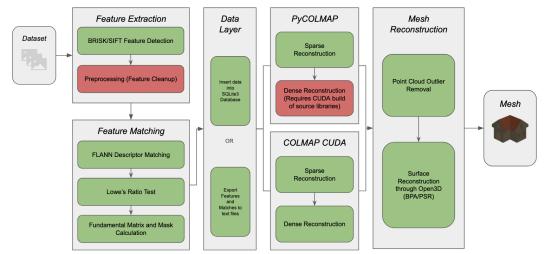


Figure 1. Pipeline/Project Workflow

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-

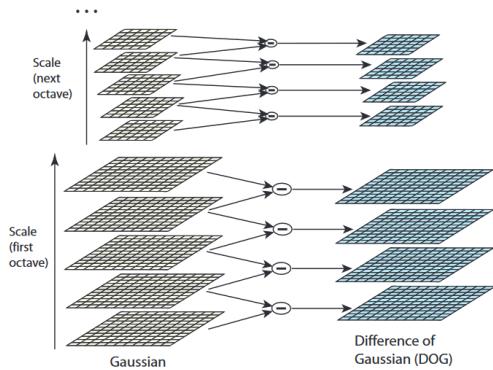


Figure 2. Difference of Gaussians and Sift Scale Space

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

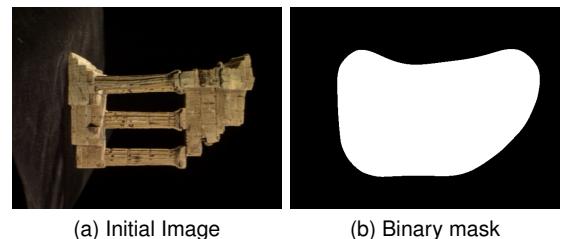
Figure 3. Lightbox-like backdrops

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

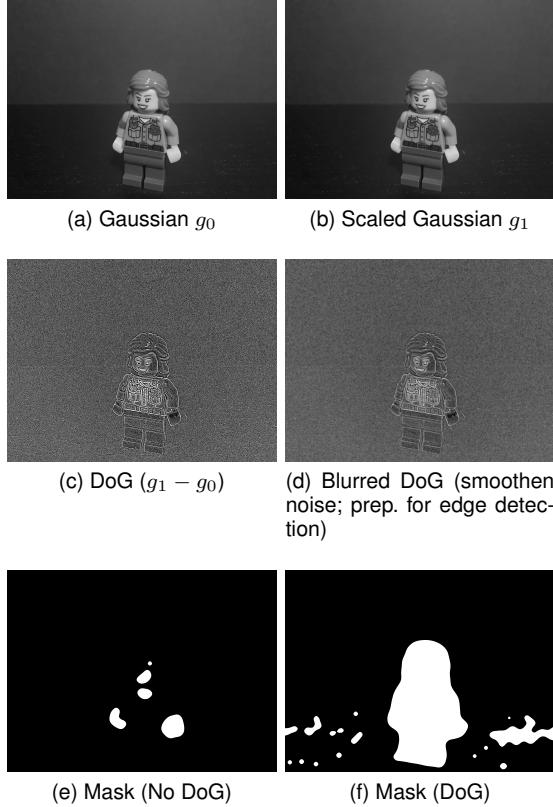


Figure 5. Difference of Gaussian based preprocessing approach. (σ -scale factor $k = 2$) Inspired by [1].

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

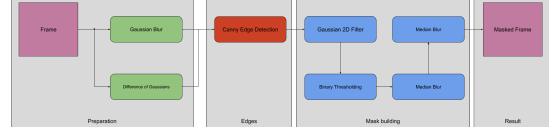


Figure 6. Feature preprocessing pipeline. Dataset from [13]

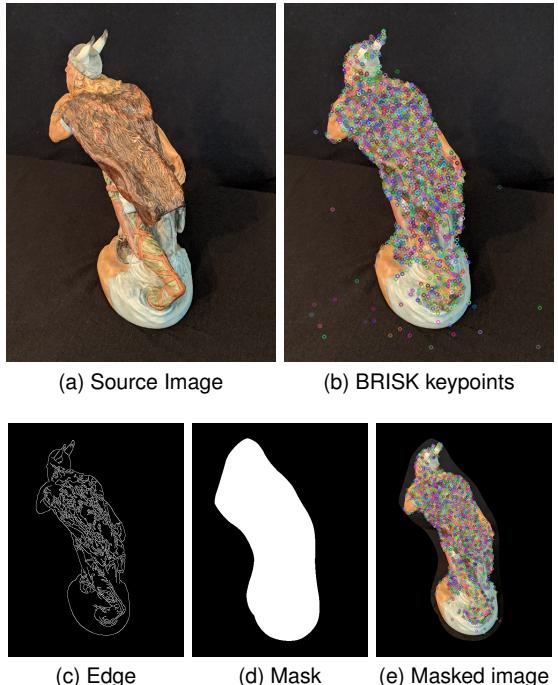


Figure 7. Feature preprocessing example

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

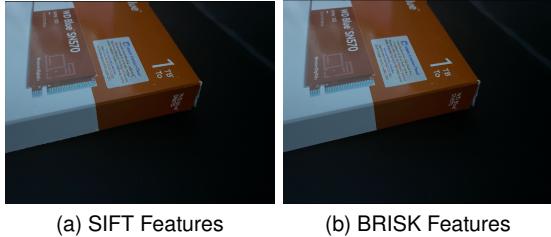


Figure 8. SIFT vs BRISK detected features (ssd box)

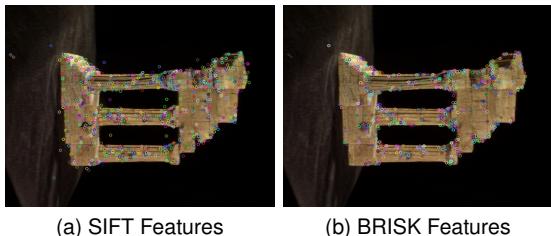


Figure 9. SIFT vs BRISK detected features (templeRing [12])

as Table 1, demonstrate a substantial difference in overall ability. Referring to Figure 8, it is clear 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). However, Figure 9 suggests that these more “nuanced” feature points may be more akin to noise (detections on black background) and are unneeded. Furthermore, BRISK is also considerably faster than SIFT 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).

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

Acknowledgments

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