

A PIPELINE FOR LARGE-SCALE STRUCTURE-FROM-MOTION

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A PIPELINE FOR LARGE-SCALE STRUCTURE-FROM-MOTION

by

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Certificate

This is to certify that the thesis titled **A Pipeline for Large-scale Structure-from-Motion** being submitted by **Mr. Brojeshwar Bhowmick** for the award of **Doctor of Philosophy** in Computer Science and Engineering is a record of bona-fide work carried out by him under our guidance and supervision at the Computer Science and Engineering Department, Indian Institute of Technology Delhi. To the best of our knowledge, the work presented in this thesis has not been submitted elsewhere, either in part or full, for the award of any other degree or diploma.

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DEDICATED TO
My Parents and My Teachers.

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Abstract

In this thesis we address the problem of large-scale Structure-from-Motion (SfM) using a large set of images. The images required for Structure-from-Motion can be acquired from a site or can be downloaded from websites like *Flickr* [28]. Apart from visualization, 3D structure and camera locations obtained from SfM is also useful for a variety of applications like autonomous navigation of robots, augmented reality etc.

In Structure-from-Motion, we recover both 3D structure and camera motion parameters by minimizing the reprojection error through bundle adjustment. Incremental SfM uses bundle adjustment by seeding the reconstruction using two images and then adds cameras incrementally into the existing reconstruction. Despite significant advances in incremental SfM techniques, such pipelines suffer from several problems. Apart from requiring significant computational power to solve the large-scale computations involved, such techniques often fail to correctly reconstruct a scene when the accumulated error due to drift is large or produce partial reconstruction when the number of 3D to 2D correspondences are insufficient for adding new cameras into the existing reconstruction. Moreover, such methods are precisely dependent on the initial seed pair.

As opposed to incremental methods, global SfM methods compute 3D structure and camera motions for all the images in a set simultaneously. Such methods require a good initialization for all the camera parameters and the 3D structure for bundle adjustment. To this end, these methods use motion averaging techniques to solve for global camera

motions from pairwise epipolar geometry estimates followed by the multi-view triangulation methods to compute the initial 3D structure. Then global bundle adjustment refines the initial 3D structure and the camera motion parameters simultaneously by minimizing reprojection errors. However, obtaining good initialization for global camera motion parameters using only pairwise epipolar relationships for large number of images ($\sim 30K$ images) is difficult due to noise present in pairwise epipolar geometry estimates. Thus, incremental methods and global approaches define two prototypical extreme solutions towards the large-scale SfM with their own set of problems.

In this thesis, we propose a divide and conquer based Structure-from-Motion pipeline where the entire corpus of images is partitioned into clusters such that the images within a cluster are related to each other by dint of their viewing common parts of the 3D scene. Such an approach drastically reduces the computational load for matching image pairs without compromising accuracy. It also makes the resulting SfM problems well-conditioned. We solve the SfM problem in each cluster using motion averaging followed by global bundle adjustment. As each cluster is reconstructed independently, they may not share common 3D points to merge two reconstructions in a common frame of reference. Hence, we also propose a method for registering these individual reconstructions using the available epipolar relationships only that connect images across clusters. Our 3D registration or alignment technique works well even when the available camera-point relationships are poorly conditioned. We also selectively apply a step of global bundle adjustment on the combined clusters after successive merging. The overall result is a robust, accurate and efficient pipeline for large-scale SfM. We present extensive experimental results that demonstrate these attributes of our pipeline on a number of large-scale, real-world publicly available datasets and compare our method with the state-of-the-art. ¹

¹The code is available at <https://github.com/IITD-COMPUTER-VISION-GROUP/lsvm>

अव्स्त्रक्त

इस सिद्धांत में हम बड़े पैमाने पर स्ट्रक्चर-फ्रॉम -मोशन (एसएफएम) की समस्या का समाधान करते हैं छवियों के एक बड़ा सेट से। स्ट्रक्चर-फ्रॉम -मोशन के लिए आवश्यक छवियों को अधिग्रहित किया जा सकता है साइट से या फ़्लिकर जैसी वेबसाइटों से डाउनलोड किया जा सकता है। विजुअलाइज़ेशन के अलावा, एसएफएम से प्राप्त 3-D संरचना और कैमरा स्थान भी विविधता के लिए उपयोगी है रोबोटों की स्वायत्त नेविगेशन, बढ़ी हुई वास्तविकता आदि जैसे अनुप्रयोगों के लिए।

स्ट्रक्चर-फ्रॉम -मोशन में, हम दोनों 3D संरचना और कैमरा गति पैरामीटर पुनर्प्राप्त करते हैं बंडल समायोजन के माध्यम से पुनः प्रक्षेपण त्रुटि को कम करके। वृद्धिशील एसएफएम दो छवियों का उपयोग करके पुनर्निर्माण बीजिंग द्वारा बंडल समायोजन का उपयोग करता है और फिर जोड़ता है मौजूदा पुनर्निर्माण में कैमरे वृद्धिशील रूप से। साइनि कैट अग्रिम के बावजूद वृद्धिशील एसएफएम तकनीकों, ऐसी पाइपलाइनों कई समस्याओं से। आवश्यकता के अलावा बड़े पैमाने पर गणनाओं को हल करने के लिए साइनि कैट कम्प्यूटेशनल पावर, संचित त्रुटि के दौरान ऐसी तकनीकें अक्सर दृश्य के पुनर्निर्माण में असफल हो जाती हैं बहाव के कारण 3D से 2D डी पत्राचार की संख्या होने पर आंशिक पुनर्निर्माण का उत्पादन होता है मौजूदा पुनर्निर्माण में नए कैमरे जोड़ने के लिए अपर्याप्त हैं। इसके अलावा, ऐसी विधियां प्रारंभिक बीज जोड़ी पर निर्भर करती हैं।

वृद्धिशील तरीकों के विपरीत, वैश्विक एसएफएम विधियों की गणना 3 डी संरचना और एक साथ एक सेट में सभी छवियों के लिए कैमरा गति। इस तरह के तरीकों को एक अच्छा की आवश्यकता है बंडल समायोजन के लिए सभी कैमरा पैरामीटर और 3 डी संरचना के लिए प्रारंभिकरण। इस अंत में, ये विधियां वैश्विक कैमरे के लिए हल करने के लिए गति औसत तकनीकों का उपयोग करती हैं जोड़ीदार एपिल्लोर ज्यामिति अनुमानों से गति बहु-दृश्य त्रिभुज के बाद होती है शुरुआती 3 डी संरचना की गणना करने के तरीके। फिर वैश्विक बंडल समायोजन प्रारंभिक 3 डी संरचना और कैमरा गति पैरामीटर एक साथ फिर से रेप्रॉजेक्शन त्रुटियों को कम करना। हालांकि, वैश्विक कैमरे के लिए अच्छी शुरुआत प्राप्त करना बड़ी संख्या के लिए केवल पैरविसे एपीपोलर संबंधों का उपयोग कर गति पैरामीटर छवियों (~30K छवियां) पंथ पैरविसे एपीपोलर ज्यामिति में मौजूद शोर के कारण है अनुमान। इस प्रकार, वृद्धिशील

तरीकों और वैश्विक दृष्टिकोण डी दो प्रोटोटाइपिकल बड़े पैमाने पर एसएफएम की समस्याओं के अपने सेट के साथ चरम समाधान।

इस थीसिस में, हम एक विभाजन का प्रस्ताव देते हैं और आधारित संरचना-से-मोशन पाइपलाइन पर आधारित होते हैं जहां छवियों का पूरा कॉर्प क्लस्टर में विभाजित होता है जैसे कि छवियां एक क्लस्टर एक दूसरे से 3 डी के सामान्य भागों को देखने के संकेत से संबंधित हैं दृश्य। इस तरह के दृष्टिकोण मिलान छवि के लिए कम्प्यूटेशनल लोड को काफी हद तक कम कर देता है सटीकता समझौता किए बिना जोड़े। यह परिणामस्वरूप एसएफएम समस्याओं को भी बनाता है अच्छी तरह से वातानुकूलित। हम गति औसत का उपयोग कर प्रत्येक क्लस्टर में एसएफएम समस्या को हल करते हैं वैश्विक बंडल समायोजन के बाद। चूंकि प्रत्येक समूह को स्वतंत्र रूप से पुनर्निर्मित किया जाता है, वे आम तौर पर दो पुनर्निर्माणों को मर्ज करने के लिए सामान्य 3 डी बिंदु साझा नहीं कर सकते हैं सम्बन्ध का दायरा। इसलिए, हम इन व्यक्तिगत पुनर्निर्माणों को पंजीकृत करने के लिए एक विधि भी प्रस्तावित करते हैं उपलब्ध एपिपलर संबंधों का उपयोग केवल छवियों को जोड़ता है समूहों। हमारे 3 डी पंजीकरण या संरेखण तकनीक उपलब्ध होने पर भी अच्छी तरह से काम करती है कैमरा-बिंदु संबंध खराब स्थिति में हैं। हम चुनिंदा रूप से एक कदम भी लागू करते हैं लगातार विलय के बाद संयुक्त समूहों पर वैश्विक बंडल समायोजन का। समग्र परिणाम बड़े पैमाने पर एसएफएम के लिए एक मजबूत, सटीक और ई? सीआईटी पाइपलाइन है। हम उपस्थित है व्यापक प्रयोगात्मक परिणाम जो हमारी पाइपलाइन के इन विशेषताओं को प्रदर्शित करते हैं बड़े पैमाने पर, असली दुनिया सार्वजनिक रूप से उपलब्ध डेटासेट की संख्या और हमारी विधि की तुलना करें अत्याधुनिक के साथ।

Contents

Certificate	i
Acknowledgments	iii
Abstract	v
List of Figures	xi
List of Tables	xvii
1 Introduction	1
1.1 Camera model and epipolar geometry	3
1.2 Large-scale reconstruction	10
1.3 Our contribution	18
1.4 Thesis Outline	20
2 Related Work	23
3 Partition of Dataset	31
3.1 Creating sparse view-graph	31
3.2 Partition of dataset	34
3.3 Summary	36

4	3D Reconstruction Using Motion Averaging and Global Bundle Adjustment	39
4.1	Motion averaging	40
4.1.1	Rotation estimation	40
4.1.2	Translation estimation	41
4.2	Bundle adjustment	44
4.3	Summary	45
5	Registration of Two Independent Reconstructions Using Epipolar Relationships	47
5.1	Rotation estimation between clusters	48
5.2	Scale and translation estimation between clusters	49
5.3	Summary	51
6	Refinement of Registered Reconstruction and Re-sectioning of Cameras	53
6.1	Refinement of registered reconstruction	53
6.2	Re-section of cameras	54
6.3	Summary	54
7	Experiment Results	57
7.1	Reconstruction of base clusters	58
7.2	Epipolar registration and agglomerative clustering	64
7.3	Hierarchical merging and refinement	67
7.4	3D reconstruction results on large datasets	68
7.5	Summary	72

8	Implementation Details	75
8.1	Match-graph	75
8.2	View-graph	77
8.3	Agglomerative Clustering	78
8.4	Translation Averaging	79
8.5	Triangulation	79
8.6	Global Bundle Adjustment	81
8.7	Rotation Estimation	83
8.8	Scale and Translation Estimation	84
8.9	Re-sectioning and Final Refinement	84
9	Conclusion	85
	Bibliography	89
	Publications From the Thesis	103

List of Figures

1.1	Representation of Vitthala using 3D point cloud.	2
1.2	Representation of Central Rome using 3D reconstruction. (a) Multiple images of the Central Rome. (b) 3D reconstruction of the Central Rome (view1). (c) 3D reconstruction of the Central Rome (view2).	3
1.3	Pinhole model of a camera.	4
1.4	A 3D point (X, Y, Z) in world/object coordinate projects into an image coordinate (x, y) using perspective projection.	4
1.5	A 3D point $\mathbf{X}$ in world/object coordinate projects into an image coordinate $\mathbf{x}$. $\mathbf{R}$ and $\mathbf{t}$ are the rotation and translation of the camera coordinate system with respect to the world coordinate system.	8
1.6	For a pair of calibrated cameras, an image point $\mathbf{x}_1$ from the first camera backprojects to a ray and the projection of the ray onto the second image defines the epipolar geometry; and the intersection of the two backprojected rays from the corresponding points $\mathbf{x}_1$ and $\mathbf{x}_2$ gives the 3D reconstruction. The 3D point $\mathbf{X}$ is correct only up to a scale because the estimation of $\mathbf{t}$ is correct up to a scale.	9
1.7	Point correspondences between images.	9

1.8	(a) View-graph generated using all pair matching. Edges are present wherever there are matches in between two images. (b) Pruned view-graph created using image similarity and epipolar geometry where many edges are absent. (c) Epipolar geometry is computed using the additional edges (dashed lines) obtained by query expansion (Figure best viewed in color).	11
1.9	Camera-camera relationship on a view graph.	12
1.10	A 3D point $\mathbf{X}_i$ projects in camera $\mathbf{c}_j$. The reprojection error is the distance between the projected point ($Proj(\mathbf{c}_j, \mathbf{X}_i)$) and the observed point $\mathbf{x}_{ij}$.	15
1.11	(a)Google Earth view of Vitthala temple Hampi, Karnataka, India (b) VSFM fails to reconstruct due to insufficient 3D-2D match during resectioning.	16
1.12	Our divide and conquer approach.	21
3.1	(a) A large corpus of images are used to populate the bag of feature using the feature descriptors. The ellipses denote local feature regions, and the dots denote points in some feature space, e.g., SIFT. (b) The features are clustered in order to quantize the space into a smaller number of visual words. The visual words are the cluster centres, denoted with the large green circles. (c) Given a query image, the nearest visual word is identified for each of its features. This maps the image from a set of high-dimensional descriptors to a list of word numbers. A Bag-of-Words histogram can be used to summarize the entire image (Figures best viewed in color).	33

3.2	Our approach organises the SfM problem into a hierarchical agglomerative tree.	37
5.1	Camera-camera relationship for registration.	48
5.2	Merging of clusters in a bottom-up manner.	51
6.1	Delayed registration and re-sectioning.	55
7.1	Reconstruction of an example cluster from the Art’s Quad dataset where [107] resulted in misconfigured reconstructions but our global method succeeded.	58
7.2	Reconstruction of an example cluster from the Vitthala dataset where [107] resulted in misconfigured reconstructions but our global method succeeded.	59
7.3	Reconstruction of an example cluster from the Vitthala dataset where Zephyr [122] resulted in misconfigured reconstructions, but our global method succeeded.	61
7.4	Reconstruction of an example cluster from the Art’s Quad dataset where Zephyr [122] resulted in misconfigured reconstructions, but our global method succeeded.	62
7.5	An example base cluster from the Art’s Quad dataset where VSFM resulted in broken reconstructions but our global method method succeeded.	65
7.6	(a) VSFM fails to reconstruct due to insufficient 3D-2D match during re-sectioning. (b) Our approach correctly reconstruct using epipolar registration.	66

7.8	We evaluate the robustness of registration by successively removing edges across clusters and comparing the rotation and position error of cameras after registration against a full reconstruction (treated as ground truth). The left column plots the rotation error of cameras and the right column shows the error in camera positions as ratio of graph diameter.	66
7.7	Two examples of registration with different mean edge weight costs. Stronger cut edges yield significantly superior reconstructions.	67
7.9	Advantage of using BBA refinement: (a) shows inaccuracies in structure due to registration errors on a part of the Central Rome dataset (b) which is corrected by BBA refinement.	68
7.10	Reconstruction of Vitthala temple, Hampi.	72
7.11	Some reconstructed views from various datasets.	73
7.12	Some reconstructed views from various datasets.	74
8.1	Our pipeline starts with a set of images using which it creates a sparse view-graph. We use agglomerative clustering on this sparse view-graph to create base clusters. Each of these clusters is reconstructed using motion averaging followed by triangulation and global bundle adjustment. Two such reconstructed clusters are merged into a common frame of reference using epipolar registration method followed by a refinement (we illustrate our pipeline here using only two clusters, but the number of clusters can be many in the agglomerative tree). Finally the cameras rejected as outliers are re-sectioned.	76
8.2	Comparison of reconstructions with and without camera-point constraints in translation averaging for an example cluster from the Art's Quad dataset.	81

8.3	The apical angle at the reconstructed 3D point $\mathbf{X}$ from corresponding points $\mathbf{x}_1$ and $\mathbf{x}_2$	82
8.4	Reconstruction of an example cluster from the Art's Quad dataset using PBA [117] and Ceres Solver [2].	83

List of Tables

7.1	Dataset	57
7.2	Statistics of breaks in reconstruction for some sample clusters by VSFM	63
7.3	Statistics of breaks in reconstruction across datasets	64
7.4	Reprojection error (in pixels) analysis before and after BBA on merged clusters.	68
7.5	Camera rotation (in degrees) and translation distance (ratio of graph diameter) between our method and [20]	69
7.6	Camera rotation (in degrees) and translation distance (in ratio of graph diameter) between our method and VSFM [116].	69
7.7	# of cameras and reconstructed 3D points	70
7.8	Computational time of our method on different datasets compared with VSFM on a single processor.	71
8.1	Tools or libraries used in our pipeline.	77
8.2	Comparision of SIFT libraries available at [55], [115] and [65].	77
8.3	No. of cameras, reconstructed 3D points and time taken to reconstruct.	82
8.4	Camera rotation (in degrees) and translation distance (in ratio of graph diameter) between PBA and Ceres Solver.	83