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A New Fast 3D Reconstruction Approach using Multiple View Images

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Abstract – **The extract key points and matching the pictures are the most paramount reconstruction 3D factors. They almost two-thirds the time of reconstruction. This paper presents a method to extract the most paramount key points, through the use of GrabCut algorithm that elimintes considerable parts of images that does not have its prominence in the reconstructio. Moreover, the proposed algorithm uses siftGPU algorithm that runs parallel to any process more than one image at a time to extract key points and carry out matching process. The experiments show that the proposed system increase the speed of reconstruction and thoroughly good.**

Keywords – **3D Reconstruction, Structure From Motion (SFM), Mash Reconstructionand Multi-View Stereo (MVS).**

I. INTRODUCTİON

3D reconstruction is one of the classical and difficult problems in computer vision, and finds its applications in a variety of different fields. In recent years, large scale 3D reconstruction from community photo collections has become an emerging research topic, which is attracting more and more researchers from academy and industry. However, 3D reconstruction is extremely computationally expensive. For example, it may cost more than a day in a single machine to reconstruct an object with only one thousand pictures. In the Structure from Motion (SfM) model [1, 2], 3D reconstruction pipeline can be divided into various steps: feature extraction, image matching, track generation and geometric estimation, etc. Among them, image matching occupies the fundamental computational cost, even more than half of all in some case. Moreover, inexact matching results might lead to washout of reconstruction. Therefore, fast and accurate image matching is critical for 3D reconstruction.

There are various ways to build reconstruction For example Reconstruction manually is most Statute method to reconstruct a 3D model for an object real world. but is a method ponderous and very intensive. Level of realism can be achieved [3]. The other way tried to eliminate the voltage on the user . 3D Scanner Variant Guide to reconstruction is to let computers to take some work, and is a well-established method of 3D scanning. The 3D the scanner is the device that apprehends the detailed information for shape and appearance[4]. Modern developments in techniques scanners and Laser able to apprehend point clouds of scenes the real world, And also Automatically can reveal scene planes and create 3D models without the help of the user which can generate Points dense cloud from total images by photogrammetry tools [5].To create a point clouds typically sharing the same problems from noisy and lost data. Makes it very hard to apply the methods of surface reconstruction the direct [6,7], Points cloud doesn't contain the specific edges and borders.

Last method offered by the this paperPhotogrammetry reconstruction regains 3D information from a single or more of images. Mainly focused on rebuilding Photos multi view called stereo vision. Epipolar geometry describes the features and the linkages between the scene and the 3D geometric projections on two or more images of 2D. Figure 1 shows the idealistic workflow for photogrammetric reconstruction. The first step of photogrammetric reconstruction includes the registration of all input images. This procedure is called structure-from-motion and includes the computation of intrinsic and extrinsic camera parameters. For registered images, it is possible to compute 3D positions from two or more corresponding image points. Multi-view stereo algorithms use these conditions and compute dense point clouds or triangulated meshes from the input scene.

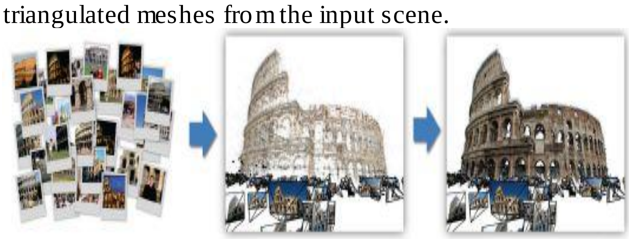


Fig.1. Reconstruction Photogrammetry are recording multiple images (A): is created by the structure from motion (B) and 3D geometry by dense multi view stereo [8].

The terms Multi-view Stereo (MVS) simulates the sense of human sight distance and 3D objects. It uses two or more images from various points of view to get the 3D structure of the scene and distance information. Many algorithms stereo multiview [9, 10] used all the images at the same time to rebuild the 3D model. It requires a high expense and also lacks scalability. Furukawa [10] suggested PMVS (multiple stereoscopic vision correction) and took multiple pictures of various views of the body to extract feature points. It is then expanded abroad to find more of the interview points. Furukawa CMVS also suggested (Views compilation of multiple stereo) [12] in 2010, has been used to ameliorate the image combines numerous susceptibility in order to see the stereo, and sustainable forest management PMVS broker contacts.

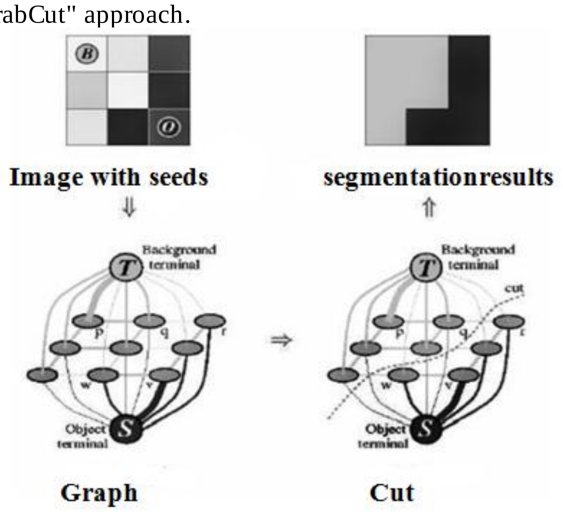
RGB-D systems have been developed due to the advent of RGB-D sensors, such as the Microsoft Kinect.

Steinbruecker et al. [13] introduced a fast energy-based approach to stiffly stratify the RGB-D images for a static scene. Khoshelham et al. [14] presented an epipolar search method to gain more precise 3D correspondences and defined adaptive weights for the 3D points based on their theoretical random error to mend registration accuracy of RGB-D data. By combining both low level feature correspondences and high level plane primitives from an RGB-D camera, Dou et al. [14] improved indoor 3D reconstruction in challenging cases with incomplete image features or geometry information.

The remainder of this paper is as follows. Section 2 presents GrabCut algorithm Segmentation Images. Section 3 presents the method and work Structure from motion. Section 4 goes further into the implementation details, with Section5 showing the experimental results. Section 6 discusses our conclusions

II. GrabCut Algorithm Segemantation Images

The GrabCut technique is one of such graph based technique which may be performed using Cut techniques as a part of its refining process of initial user segmentation between foreground and background of image. GrabCut algorithm is primarily developed at Microsoft Research Cambridge. There are many segmentation methods Among them graph theoretical techniques have more characteristics in practical applications. These techniques assort the image into mathematically well-defined structures, making the formulation of image segmentation problem more precise and the computations more efficient. In these techniques the image is treated as a weighted and undirected graph [15] . Graph cut techniques can be used efficiently to resolve image segmentation problems which can be formulated in terms of energy minimization which in turn can be formulated as max-flow problem in a graph [16] . Figure 2 shows the diagram of "GrabCut" approach.



Fg.2. Cut, Graph, image with seeds, segmentation results A simplified diagram of the "GrabCut" approach[17]

Results have been better if the the algorithm repeated more than once. Figure 3 shows the results according to the repeated one . The goal of the implementation of this algorithm, is to eliminate the number of key points, in order to eliminate the time in the extraction stage of key points.

(a) **(b)** **(c)** **(d)**

Fg.3. (a) Enter image, (b) Repeat algorithm once, (c) Repeat algorithm three times, (d) Repeat five times the algorithm.

III. Structure From Motion

3.1 Over view

Relative motion between two cameras and the object to be reconstructed by Structure from motion is a stereo-based method, to make hypotheses about the 3D object's shape. Different contributions and several approaches, e.g Chiuso et al. 2002 and Hui et al. 2006 in [18] [19] are done for this method.

Recent methods for structure from motion are described by Christof Hoppe et l. (2013) in [20], who proposed a new method for incrementally extracting a triangular surface mesh from an increasingly growing sparse SfM (structure from motion) point cloud in real-time. And Christof Hoppe et al. (2012) in [21] also proposes an online SfM approach that permits the checking of the reconstruction result on site. To guide the user throughout the acquisition, they envisage the existing Ground Sampling Distance (GSD) and image redundancy as quality indicators on the surface model.

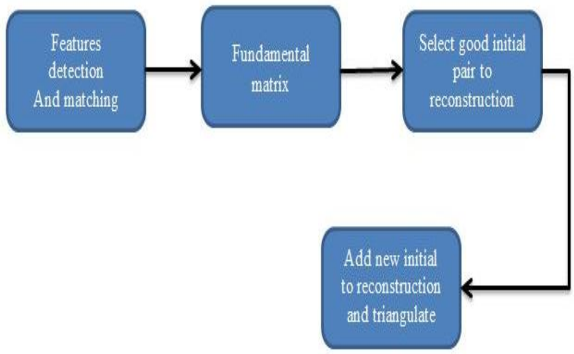


Fig.4. SfM system Architecture

3.2 Feature detection and the matching

Feature detection of key points is part of the preprocessing step. The concept of feature detection refers to methods which aim to calculate the abstractions of image information and local decision-making in each image point whether there is an advancein Q, then all of the corresponding points are removed. After the correspondences in P and Q are obtained, the RANSAC algorithm is used to assess the fundamental matrix. Theoutlier threshold in RANSAC is set to 0.6% of the maximum image size. The computation of fundamental matrix using the Levenberg-Marquardt method [22] to optimize the parameters, so the error is minimized. If the remaining amount is less than 20 after outlier removal, thenredo all of the correspondence matching. There are more than algorithm (to detect features. Matching) in the image, for example, (sift. surf)We use (sift). We'll show comparison between Sift Cpu and Sift Gpu.In fact, Used (Sift) because it extracted a big number of key points, and after the first step we need a lot of number of key points, and the variation between the number of points extracted up to about twice what is in the (surf)[23] .

3.3 Methodology Structure from motion

1-First, we choose two locations very far from the object and use the overlapping image regions to assess a set of camera parameters. Therefore, the initial reconstruction will provide a quite good result. Let RANSAC outlier threshold equals 0.004*maximum image size, and use at least 100 point correspondences of the lowest proportion of the inliers for the homography computation. This group coincide with the camera parameter estimation using five-point relative pose algorithm [24]. The bundle adjustment is then carried out using the two initial images.

2-The next step is to add additional cameras. We picked from the 3D locations of the three largest amount of track to subjoin camera. In the RANSAC process, we used Hartley et al. [25] (direct linear transform, DLT) is a method of determining the three dimensionallocation of an object (or points on an object) in space and to initialize the new camera external parameters. In addition to providing an upper triangular matrix K used to estimation the camera internal parameters, we use K to commence the new camera's focal length. We execute the steps of the bundle adjustment to add the new cameras and supervise the alterations, while keep the rest of the model intact.

3-In the last step, we add a new camera observation point in order to optimize the whole process. If the additional camera can observe this point, then join it. If the maximum angle is greater than a threshold (2.0 degrees), then perform the Delaunay triangulation, which can eliminate the points at infinity. Once the new points are added, we carry out the entire bundle adjustment to create an integral model. Keep adding new cameras and reiterate these steps until the point observed in the remaining images are not adequate for the reconstruction. (We used 20 point as the stop threshold.)

In this work, we use bundler [26], a SfM system to implement this part. The bundler can assort the disordered photo collection to a structured set, and thus can be used for afficacious implementation of many computer vision algorithms. The output is used for PMVS or other redevelopment tools. The system flow chat of the SfM is shown in Figure 4.

IV. 3D MODEL RECONSTRUCTION

As shown in Figure 5, the system takes diverse images from various angles for two various poses of the object in the first stage.

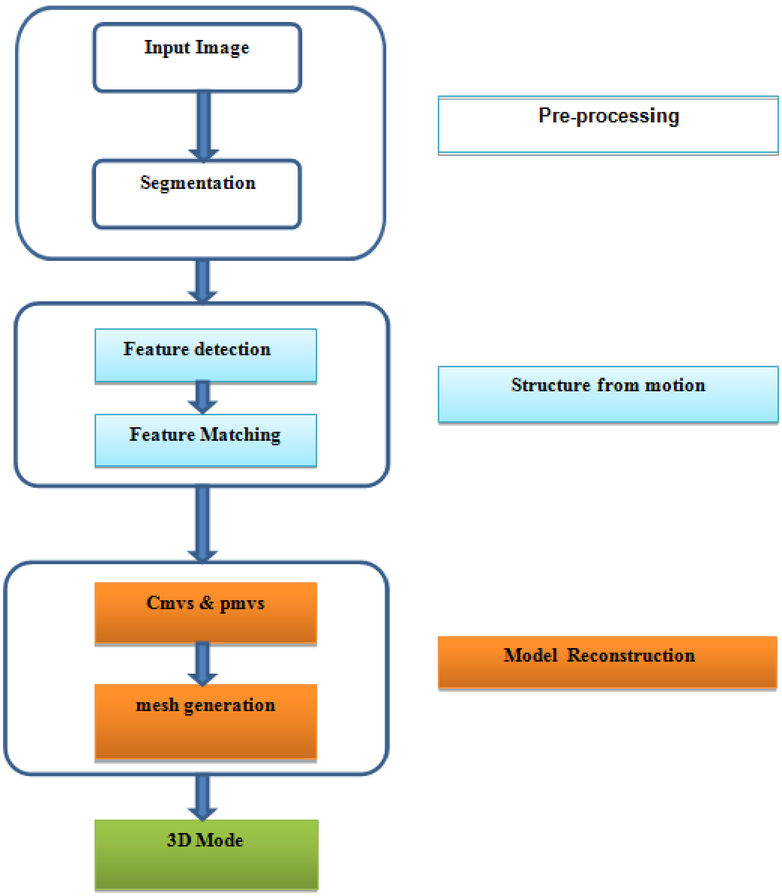


Fig.5. Flow chart of 3D reconstruction approach

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Then, feature detection and correspondence matching. The relation of the correspondence features is used for SfM and self-calibration of the camera parameters and scene geometry. When the camera parameters and the corresponding 3D points are gained, they are used for the reconstruction of the 3D model.

4.1 Block Reconstruction

When we use (SFM) images to assess the parameters, it is specific image recognition that can deal with them for reconstruction, and we do this procedure before application (CMVS) .We use (CMVS) (Clustering Views for Multi-view Stereo) Furukawa proposed to ameliorate the capability of the display multiple stereo vision started. PMVS (Patch-based Multi-view Stereopsis) Provides information which can be counted faster and more precisely .

4.2 3D mesh generation

We have a 3D point cloud. To re-surface of the body building, and we need to combine 3D points in the grid to form a more complete 3D model. Thus, we use the PSR (Poisson surface reconstruction) [27] to establish network link. Often this algorithm adopted for 3 D surface reconstruction. Can use assess analogy directional 3D surface point, and effectively deal with the noise, and the network user adjustable density.

V. EXPERMETAL SETUP AND RESULTS

In this paper we use the algorithm (GrabCut algorithm Segmentation Images) on multiple set of images about (28) image show in figure (6), and the goal of this algorithm to minimize feature detection to increase the speed matching), as shown in Figure 7.

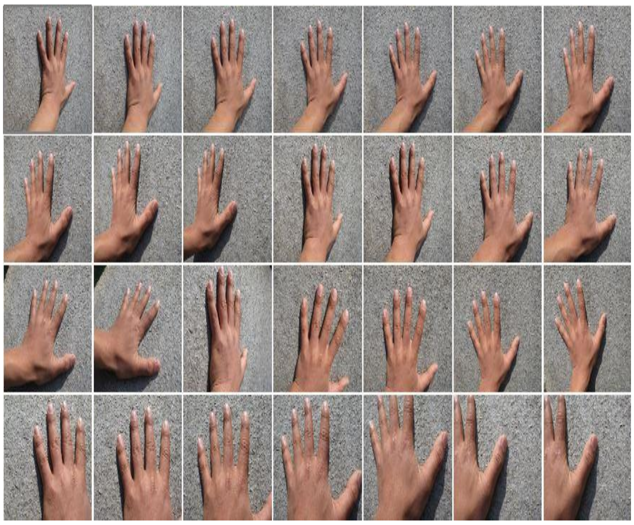

Fig.6. Input Images

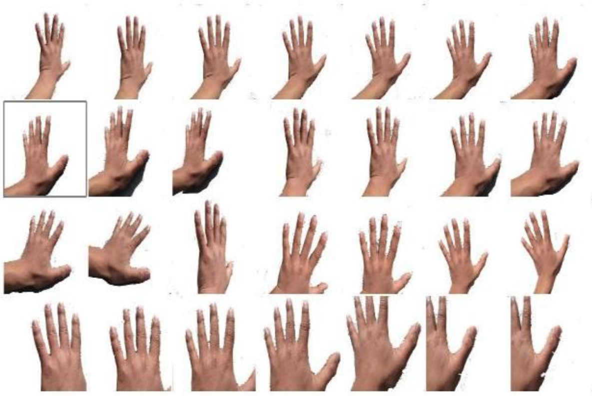

Fig.7. The result after Per-Processing method

Then we use (SFM) to get the point cloud 3D. In steps (PMVS) we get the color point information (3D). The use of (CMVS) in order to make the work (PMVS) faster and more precisely. As shown in the results it's much faster than the preceding and contain very few holes. As shown in Figure 8 and table 1.

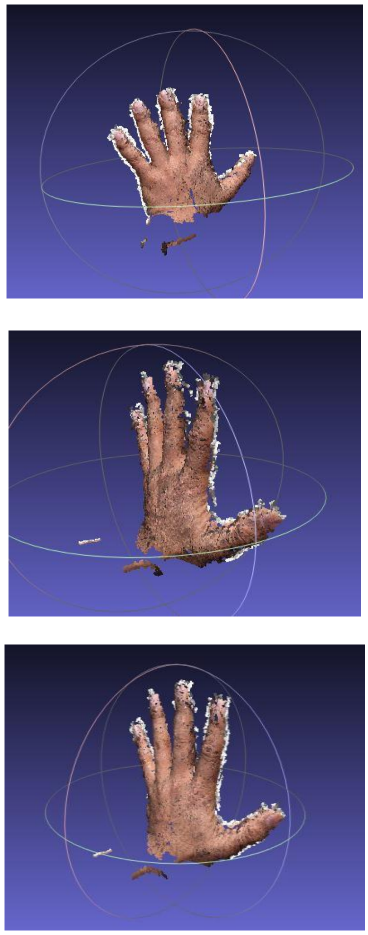

Fig.8. 3D Reconstruction using SFM and PMVS

Table 1: Simulation results after preprocessing

Image Size	Number of images	Feature Detection timing	Image Match		3D reconstruction
2000x1500	28	11 sec	Number	timing	28.000 seconds used
			378	47 sec	

As for the results before Pre-processingstep. The results were as shown in the table below

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Table 2: Simulation results before preprocessing

Image Size	Number of images	Feature Detection timing	Image Match		3D reconstruction
			Number	timing	
2000x1500	28	20 sec	378	362 sec	63.000 seconds used

In Table 1, we used 28 input images, it consumed time to extract the fundamental points of 11 seconds, and thus become a matching number 378 was fulfilled in 47 seconds. Bringing the time of reconstruction 28 seconds.
In Table 2, we have used the same number of images in Table 1 and it was time to extract the main points of 20 seconds and was the congruent number as in Table 1, but was done in 362 seconds. Bringing the time of reconstruction 63 seconds.

The big variation is due at the time of reconstruction between the two tables in the prime treatment step, which we added in Table 1.

Comparison between CPU and GPU

GPU always have a startup overhead time, which can be mentioned by calling at the beginning of the program, this startup time is subtracted in the final GPU run time as it is a one-time cost. The CPU/GPU run time with various image sizes is shown in Figure (9). For small images, CPU runs faster than GPU. However, as the image size increases, the CPU run time increases basically while the GPU run time stays comparatively steady. With image size 2592x1936, the GPU implementation runs almost 4x faster than CPU implementation.[28]

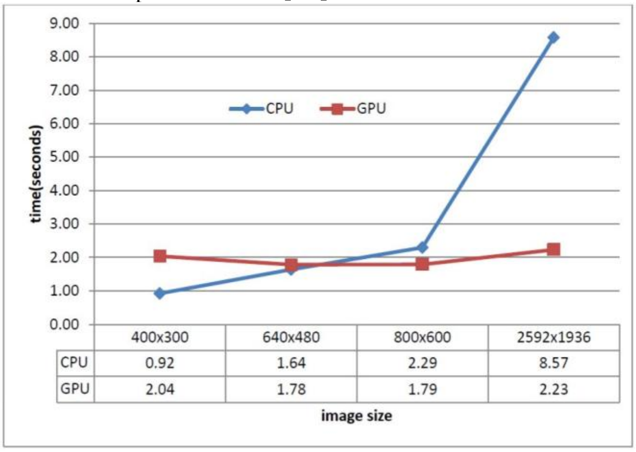

Fig.9. A comparison between CPU and GPU implementation of SIFT algorithm

SiftGPU is an application of SIFT [29] for GPU. SiftGPU processes pixels parallely to build Gaussian pyramids and reveal DoG Keypoints. Based on GPU list generation[30], SiftGPU then uses a GPU/CPU mixed method to exepditously build compact keypoint lists. Finally keypoints are addressed parallely to get their orientations and descriptors.

VI. Conclusion

A new fast 3D reconstruction approach has been presented. This has been done by taking out the paramount points and the image matching system. Experiments show that we have attained an increase in speed in the extraction of the primary points and image matching. Through the system that we have suggested. The GrabCut algorithm has played a fundamental role in the achieved speed rate. The proposed approached has increased the speed of matching process ten times or faster while maintaining accuracy.

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