Improvement of 3D and Dense Reconstruction for Moving Object and Comparative Study on 3D Reconstruction Algorithms

Mohammad Nooruddin, Md. Maruf Hossain Shuvo

Abstract— In computer vision 3D reconstruction is a popular method for the measurement of figures and appearance of real substances. It denotes the reverse process of finding 2D images from 3D scenes which helps in image investigation and understanding. However, in 3D reconstruction due to the presence of moving object in the images, it creates some confusing questions like: whether the object is moving or the camera is moving or both are moving. This misperception leads to inaccurate camera motion when the structure from motion algorithm reconstructs the path of the camera with respect to a moving object. Moreover, faulty camera positions, wrongly placed map objects problems like this happens because of 3D reconstruction with moving object. For the 3D reconstruction from multiple 2D images using robust estimators are mandatory. Random Sample Consensus (RANSAC) and M-Estimator Sample Consensus (MSAC) are the popular robust estimator in computer vision field. So, for understanding what robust estimator can perform better in which situation for the 3D reconstruction, having idea about robust estimators is important. This work attempts to implement a way to resolve this reconstruction problem for most moving and momentary objects. This work also attempts to make a comparison between two robust estimators: RANSAC and MSAC by their performance analysis on reconstructed 3D scene. By building the cloud model using both of the algorithm a comparison between their performances can easily be made with the help of cloud model. In case of moving object on an image, by using semantic understanding of the captured scene, it is thinkable to accomplish the problem of most objects which are moving and temporary. Using only key points on static object classes we can do the reconstruction. Using binary masking of the semantically segmented image we can classify the semantic segmented image as excluded segmentation and included segmentation class which are considered to be black and white part of the binary masked image respectively. The consequence is a 3D reconstruction of binary masked image that shows the significant non-moving portions of the scene and the camera motion with respect to them and solves the problem of 3D reconstruction for moving objects.

Index Terms— 3D reconstruction, Random Sample Consensus (RANSAC), M-Estimator Sample Consensus (MSAC), Semantic segmentation, Binary masking, Structure from motion (SfM), 3D cloud model

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1 Introduction

The topic of obtaining 3D models from images is a fairly new research field in computer vision.

In photogrammetry, on the other hand, this field is well established and has been around since nearly the same time as the discovery of photography itself [1]. Three-dimensional data sensing and reconstruction is eagerly demanded by the communities of multimedia, virtual reality, robotics, medical imaging, etc., and it usually serves as a core ingredient of many applications [2]. In 3D reconstruction we can have the fundamental 3D data of the 2D images in different views and in different angles. The precision of observed surface 3-D reconstruction is critical for solving navigation tasks, automatic guidance and control tasks, and pattern recognition tasks. It is supposed that limitation in weight and dimensions allows equipping moving object with only single monocular multispectral sensor. So information about 3-D scene structure must be extracted from sequence of images, made from moving object in different moments of time [3].

The limitation of 3D reconstruction is that after the reconstructions process the lacking of cloud points on the 3D model. Thus, increasing the cloud in the 3D reconstructed model is our ultimate goal. In case of moving object, reconstructions of outdoor and indoor environments using stereo cameras are confronted with harmful effects caused by moving objects [4]. In 3D reconstruction, the moving object gets many feature correspondences along the whole arrangement and becomes substantial in the reconstruction [5]. In 3D reconstruction the moving object prevails over the reconstruction of the non-moving object and it is perceived as a static object, which results in faulty camera position and wrongly placed map objects.

With the development of 3D imaging technique and different methods 3D reconstruction has received increased attention recently. A framework for 3D reconstruction, examination, reproduction and dynamic activity of the heart and the coronary corridors was produced on an IBM/PC perfect PC, utilizing pictures from MRI Cine-CT Ultrasound or Angiography for the geometry of the heart [6]. Binocular stereo method and photometric stereo technique were the methods that were used early to acquire information from multiple images [7]. Since then many experiments and measurements are made on 3D reconstruction to improve the field of computer vision. In 3D reconstruction, registration of point sets is a fundamental problem. Researchers proposed a non-rigid registration method based on the Random Sample Consensus (RANSAC) and the local structure information to improve the result of registration between point sets with shape difference [8]. RANSAC is a robust estimator which continues by over and again creating arrangements evaluated from negligible set of correspondences assembled from the information, and afterward tests every answer for support from the entire arrangement of putative correspondences. Because of the continuous event of befuddles in RANSAC the support is the quantity of correspondences with mistake beneath a given edge [9]. That's why the MSAC was introduced to overcome the problems of RANSAC. Specifically MSAC is appropriate to evaluating complex surfaces or more broad manifolds from point information. It is connected here to the estimation of a few of the numerous view relations that exist between pictures related by unbending movements [10]. So, the best way to analyze the performance of these two methods is to observe the 3D models obtained by these two methods and then make a comparison with the important and significant parameters of these two methods. To cope with many or unknown moving object it is desirable to build models on the fly, such as bottom-up, feature-based Structure from Motion (SfM) estimation techniques [11]. Assigning a semantic label to each of the pixels of an image containing moving object and recovering the dense 3D geometry from a dataset of multiple input images, have reached a level of maturity where good results can robustly be acquired from well-conditioned input data. Difficulties also arise in 3D reconstruction when there are more number of outliers in an image then inliers and that's why a robust estimator is needed for robust matching. By introducing a well-established robust estimator in 3D reconstruction process, the efficiency of the 3D reconstruction process increases significantly.

In this research, at first we build a dense 3D reconstructed model of 2D images using two robust estimated algorithms: RANSAC and MSAC which are discussed later then we measure important properties of the 3D cloud model formed by both of the algorithm. We compared two 3D cloud model formed with RANSAC and MSAC algorithm and showed whose efficiency is better from both of them. We also changed number of images to see the effect on both of the algorithm and we noted down the change we find in RANSAC and MSAC algorithms after changing the number of images during experiment. In case of moving object contained in a scene the images were reconstructed using structure from motion method which showed the cameras were not following a random pattern then the images were semantically segmented and binary masked and then reconstructed and we observed the 3D points of the moving objects are gone and cameras are placed in a straight line. In this study, we have used different simulation software's like Visual SfM, Cloud Compare, and MATLAB. To build 3D reconstructed model from multiple 2D images by matching features of different images we have used Visual SfM. We found the inliers between multiple 2D images; SIFT features and dense reconstructed model of 2D images by using Visual SfM. Cloud Compare was used here for the comparison of different 3D dense model. For two view reconstruction and binary masking MATLAB was used.

- *Mohammad Nooruddin completed his B.Sc. in Electronics and Communication Engineering degree from Khulna University of Engineering & Technology, Bangladesh, E-mail: emonnmoz@gmail.com*
- *Md. Maruf Hossain Shuvo is currently working as a lecturer in the Department of Electronics and Communication Engineering at the Khulna University of Engineering & Technology, Bangladesh, E-mail: maruf.shuvo1@yahoo.com*

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2 MATERIALS AND METHODS

2.1 Scale Invariant Feature Transform (SIFT) Algorithm

To provide a feature description of the object, interesting points on the object in an image can be extracted. Descriptions extracted from a training image can then be used to identify the object when attempting to locate the object in a test image containing many other objects. The features extracted from the training image needs to be detectable under changes in image scale, noise and illumination in order to perform reliable recognition. Such points usually lie on high-contrast regions of the image, such as object edges. The relative positions between features in the original scene shouldn't change from one image to another. Typically, features in the articulated or flexible objects does not work in any change of the internal geometry between two images in the set under consideration. The SIFT algorithm detects and uses a large number of features from the image that reduces the average errors [12]. As the SIFT feature robust estimator is invariant to uniform scaling, orientation, illumination changes, and partially invariant to affine distortion, it can identify objects robustly even among clutter and under partial occlusion [13].

2.2 Random sample consensus (RANSAC) Algorithm

Random sample consensus (RANSAC) is an iterative method which is also known as robust estimator used to estimate parameters of a mathematical model from a set of observed data that contains outliers, when outliers are to be accorded no influence on the values of the estimates. Therefore, it also can be interpreted as an outlier detection method [14]. RANSAC is a non deterministic algorithm because it produces a reasonable result only with a certain probability. With this probability increases more iterations are allowed. It is a learning technique to estimate parameters of a model by random sampling of observed data. RANSAC uses the voting scheme to find the optimal fitting result from a dataset having data elements with both inliers and the outliers. Data elements in the dataset are used to vote for one or multiple models.

2.3 M-Estimator Sample Consensus (MSAC) Algorithm

In particular, MSAC is another well suited robust estimator for estimating complex surfaces or more general manifolds from point data. It is applied here to the estimation of several of the multiple view relations that exist between images related by rigid motions. These are relations between corresponding image points in two or more views and include epipolar geometry and projectivities. These image relations are used for several purposes: (a) matching, (b) recovery of structure (c) motion segmentation and (d) motion model selection.

2.4 Structure from Motion (SfM) Algorithm

Structure from motion (SfM) is a photogrammetric range imaging technique used to estimate 3D structures from 2D image sequences represented in figure 1. In human vision, SfM is a phenomenon that can recover 3D structure from the projected 2D motion field of a moving object. The feature trajectories over time are then used to reconstruct their 3D positions and the camera's motion. In direct approaches the geometric information is directly estimated from the images without any intermediate abstraction to features. The Structure from Motion algorithm combines all the above algorithm and builds 3D reconstructed model.

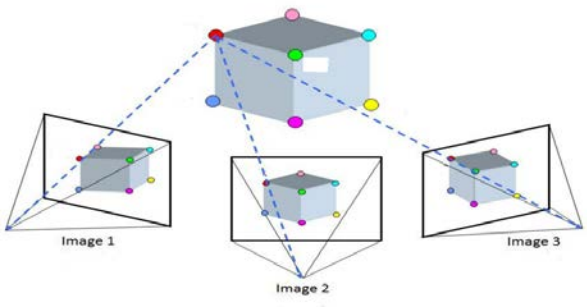

Fig. 1 3D reconstruction from 3 images using Structure from Motion.

2.5 3D Reconstruction procedures

Every 3D reconstructed model follows the same procedure unless to reduce computation time or complexity it has been modified for special cases the procedures are modified. In figure 2 we see that in general 3D reconstruction procedure for robust matching between multiple images RANSAC was used as robust estimator. In our study we will also use MSAC and will make a comparison between both of the algorithms. For 3D reconstruction of some 2D images we first need to extract the key features from an image using SIFT algorithm. Then those key features get matched by the robust estimator. RANSAC and MSAC are two robust estimators. So, after matching the key features in the image we get an image with pairwise 2D matches. Then depending on camera motion and calibration structure from motion algorithm is applied to those pairwise 2D matched images. After applying structure from motion with the help of triangulation the 3D reconstructed model is formed therefore. In case of 3D reconstruction there may be one image, two images or multiple images may present. In our study, we worked with different number of images to compare RANSAC and MSAC algorithms. So, for different number of images different reconstruction methods are used which are discussed here.

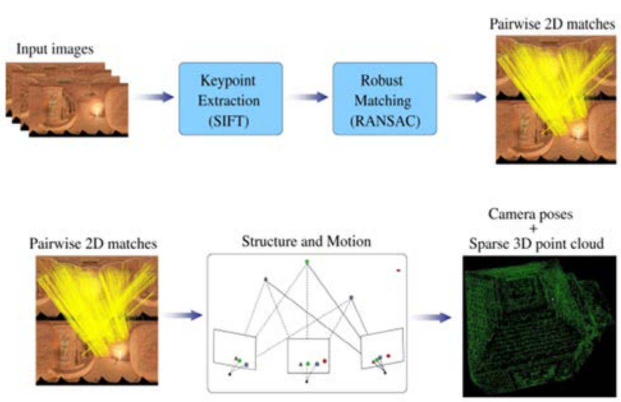

Fig. 2 Overview of General 3D reconstruction procedure

2.6 Semantic Segmentation and Binary Masking of images having moving object

In an image there are several objects who dominate over the image. So, to identify the each object efficiently semantic segmentation is used. Basically, semantic segmentation enables to allot a clear cut tag to every pixel in a picture. In our study, with the help of semantic understanding of the captured scene, it is possible to resolve the problem 3D model reconstruction of most moving and temporary objects. By making use of semantic segmentations, we can determine which key points belong to potentially moving objects. The result is a 3D reconstruction that depicts the important non-moving parts of the scene and the camera motion with respect to them. Binary masking is done mainly for one reason and that is to change specific bits in the original image. It can change one or more bits from 1 to 0 or 0 to 1. A binary mask is normally known as matrix of binary numbers in T-F (Time-Frequency) domain. In our work we binary masked the semantically segmented image and divide them into two classes to create a difference between the static and moving parts. In the binary masked image, the white part is defined as included segmentation class which defines non-moving or static objects and the black part is defined as excluded segmentation class which defines moving objects in the image.

3 SIMULATION RESULTS AND DISCUSSIONS

In our research work we covered two things: (1) Comparison between RANSAC and MSAC Algorithms (2) Created a 3D reconstructed scene for images having moving object by fixing the camera positions of reconstructed scene. The performance analysis shows the better robust estimator between RANSAC and MSAC. We obtained the two 3D cloud models by using both of the algorithms and compared the properties of those 3D clod models. We also have built a 3D reconstructed model for the images containing moving objects which successfully overcomes the problem of randomly located camera positions in a 3D reconstructed model built from the images containing moving object. In this work we build two 3D reconstructed models. One model is created using RANSAC algorithm and another one is created with the help of MSAC algorithm. At first we built the 3D models and dense reconstructed model. Then we compare these two 3D cloud models in cloud compare software. At last we give a comparison of computation time for different number of images for these two algorithms. We take two images of wine bottle for our experimental purpose as shown in figure 3.

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Fig. 3 Two images of wine bottle.

Now having these two images we build the 3D and dense reconstructed model using RANSAC algorithm which is shown in figure 4. As we are experimenting with two images so in 3D reconstructed model we can see that there are only two cameras present there. Figure 5 shows the 3D dense reconstructed model of wine bottle images which is built with help of RANSAC algorithm and keeps the shape of main wine bottle image. But in case of dense reconstructed model in figure 5 for RANSAC algorithm we can observe that many cloud points are lost because one cloud point cannot build a corresponding relationship with another cloud point.

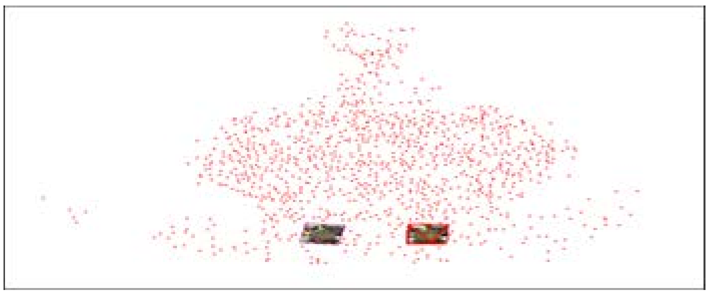

Fig. 4 3D reconstructed model of wine bottle images using RANSAC algorithm.

The shape from the 3D reconstructed model is lost in the dense reconstructed model. But in dense reconstructed model of wine bottle which is shown in figure 5 we can see that RANSAC algorithm fails to keep the shape of the wine bottle images. The dense reconstructed file is a polygon file which is saved to the drive and later it can be used for any type of analysis. Now, we are going to build the 3D and dense reconstructed model of those wine bottle images with MSAC algorithm. In figure 6 we can see the 3D reconstructed model of those experimental images build MSAC algorithm. We can see the shape of 3D reconstructed model is same as the shape of wine bottle. The density of 3D model cloud is high here.

Fig. 5 Dense reconstructed model of wine bottle images after using RANSAC algorithm.

We applied MSAC algorithm in the 3D reconstruction procedure to the two wine bottle images. The robust estimator MSAC build the 3D reconstructed model after having the SIFT features of those images. In figure 7 we can see the dense reconstructed model of those two images after applying MSAC algorithm. We can clearly see here that, in figure 5.5 the dense reconstructed model shows much better cloud model than

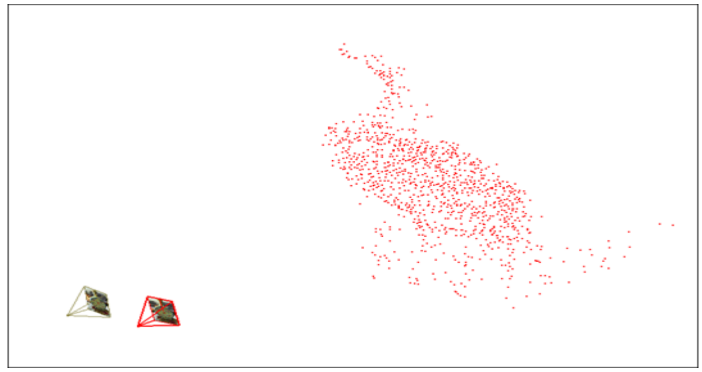

figure 5.3. Here the relationship between each cloud was established clearly and thus we can see a better dense reconstructed model here and thus we can see a better reconstructed model here.

Fig. 6 3D reconstructed model of wine bottle images after using MSAC algorithm.

In cloud compare we upload both of the cloud models which are shown in figure 8. The left cloud model is built with MSAC algorithm and the right cloud model is built with RANSAC algorithm.

Fig. 7 3D cloud models built by MSAC and RANSAC algorithm in cloud compare.

It is clearly seen that, the number of clouds in the left one is more than the right one. It is also clearly visible to anyone that the cloud model built with MSAC algorithm has more cloud density.
From table I we can see different properties of cloud model that we obtained from cloud compare software for RANSAC and MSAC algorithm. Total number of cloud points after 3D reconstruction in 3D cloud model created using MSAC algorithm is more than the 3D cloud model which was built using RANSAC algorithm. The 3D cloud model built using MSAC algorithm contains higher values of cloud density, roughness and octree level than the 3D cloud model in RANSAC algorithm. Which indicates that the 3D cloud model created using

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MSAC algorithm is more perfect than 3D cloud model built using RANSAC algorithm. It indicates that the level connected components should be more in the 3D cloud model built using MSAC algorithm. The volume indicates that how many cloud points has spared in how much space. The 3D cloud model built using MSAC algorithm possess more volume than the cloud model built using RANSAC algorithm. So, the cloud points in 3D model spares more in space in case of MSAC algorithm. The percentage of matching cells signifies that how many matching features have been reconstructed after 3D reconstruction and how many of them are visible to show the main shape of input image properly. In this case also MSAC has more percentage of matching cells. The term average neighbor per cell also indicates the density of 3D cloud model around an individual cell. We can see in table I that 3D cloud model constructed using MSAC algorithm holds around 5.8 average neighbor cells around a cell on the other hand the 3D cloud constructed using RANSAC algorithm holds this value around 4.0. So, the comparison made from table I shows us that the 3D cloud model built using MSAC algorithm proves to be better structured and efficient model than the 3D cloud model constructed using RANSAC algorithm.

TABLE 1
PROPERTIES OF 3D CLOUD MODEL FOR RANSAC AND MSAC ALGORITHM

Properties of 3D cloud model	RANSAC	MSAC
Total number of cloud points	1642	7793
Cloud density	0.261145	0.236439
Roughness	0.25321	0.23512
Octree level	0.0143963	0.0361322
Volume of 3D cloud model	34.600	173.764
Surface density	8	19
Matching cells	53.3%	54.3%
Non matching cells	46.7%	45.7
Average neighbor per cell	5.8/8.0	4.0/8.0

We have made an analysis of 3D cloud models created by RANSAC and MSAC algorithm by increasing the number of images for reconstruction which is shown in table II.

TABLE II
TOTAL NUMBER CLOUD POINTS IN TERMS OF INCREASING IMAGES IN RANSAC AND MSAC ALGORITHM

RANSAC		MSAC	
No. of images	Total number of cloud points	No. of images	Total number of cloud points
2	1642	2	7793
5	3893	5	7811
8	7579	8	7882
10	7801	10	7894

In table II we observe that the reconstruction process of RANSAC algorithm becomes better when the number of images increases as the cloud point increases in the 3D cloud model. MSAC shows the same performance for increasing the number of images which it showed for lower number of images. After observing the cloud points for increasing the number of images for both of the algorithm we made a graphical representation of the relation between number of images and number of point cloud in figure 8 and in figure 9 for both RANSAC and MSAC algorithm respectively. From graphical representation of RANSAC algorithm in figure 8 we observe that with the increase of image the graph is linear as the cloud points are increasing. From graphical representation of MSAC algorithm in figure 9 we observe that its curve remains almost same for increasing the number of images.

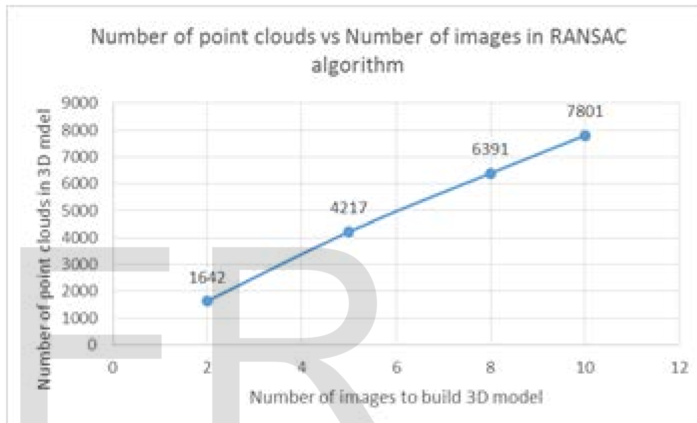
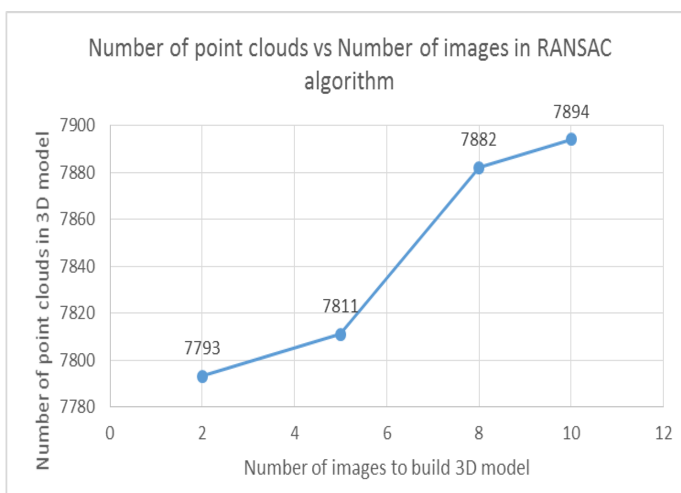


Fig. 8 Comparison between numbers of point clouds in 3D model vs number of images to build 3D model in RANSAC algorithm.

In figure 8 we show the comparison between total number of images versus total number of cloud points in the 3D models constructed by RANSAC and MSAC algorithm graphically. Now, in case of MSAC algorithm we show the same comparison on figure 9.



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ISSN 2229-5518

Fig. 9 Comparison between numbers of point clouds in 3D model vs number of images to build 3D model in MSAC algorithm.

We can clearly see from figure 8 and figure 9 that in case of RANSAC algorithm when the images are increasing the number of cloud points are increasing and in case of 10 images its cloud point becomes nearly equal to cloud point of MSAC algorithm for 10 images. So, we can say that when the number of images increases the efficiency of RANSAC algorithm increases and becomes nearly equal to MSAC algorithm. But when there are less number of images to reconstruct a 3D model it performance is poor. So, we can finally say that for low number of images MSAC algorithm can build a better 3D model and for more number of images RANSAC and MSAC both algorithms are suitable to use.

3 Simulation Results for 3D Reconstruction of Images Having Moving Object

At first we semantically segment the input images which means we give a tag to the image which can identify the objects in images. Then we apply binary masking to the images. Applying binary masking creates two classes in an image. In the binary masked images, the white part is defined as included segmentation class which defines non-moving or static objects and the black part is defined as excluded segmentation class which defines moving objects in the image. Then we reconstruct those binary masked images and the result is 3D reconstructed scene for the images which have moving object. At first we took some aero plane images which are moving continuously. Continuous images show that they are moving from one position to another position. In figure 10 we can see the images of moving aero plane. These are the experimental images.

Fig. 10 Images of moving aero plane.

In figure 10 we can see that the aero plane gets many feature correspondences along the whole sequence and becomes significant in the reconstruction. For a human, it is easy to see that we are following an aero plane along a road but for the 3D reconstruction algorithm it is ambiguous. Now this images on figure 10 are semantically segmented which are shown in figure 11. In figure 11 we can see that aero plane was detected with a red mark with the help of semantic segmentation.

Fig. 11 Semantically segmented moving aero plane images.

In figure 11 we can see that aero plane was detected with a red mark with the help of semantic segmentation. This semantically segmented images on figure 11 are binary masked which is shown in figure 12. In figure 13 we can see that we have binary masked those images and now there are only two colors, white and black. So, these two colors are divided into two classes, white for included segmentation classes and black for excluded. Excluded classes are the moving objects.

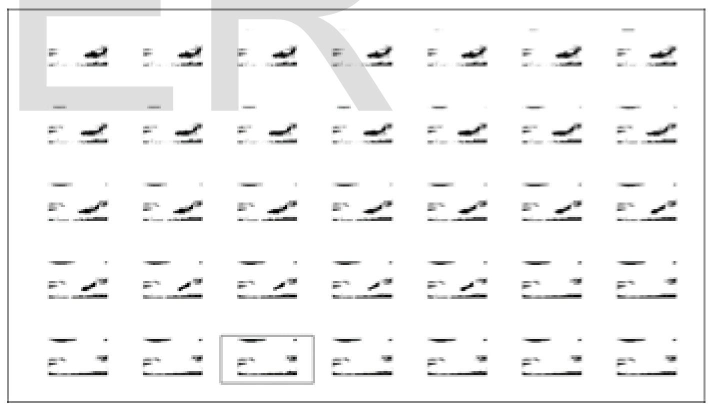

Fig. 12 Binary masking of semantically segmented images.

Now, we create 3D reconstruction model using those binary masked image and the result is shown below in figure 14 and in figure 15. In figure 14 and 15 we can see that the 3D reconstructed contains significantly low number of cloud points because having no matching features in the images. As the object was moving, it was tough to reconstruct the scene for the moving object. Because no significant feature can be matched because of the movement of the object. So there is only way left to say that the reconstruction has happened or not and that is the position of camera. If the camera positions are formed in a straight line it indicates that the scene is reconstructed properly. So, our focus for building the 3D reconstructed model for the images having moving object is to fix the camera position of the reconstructed scene.

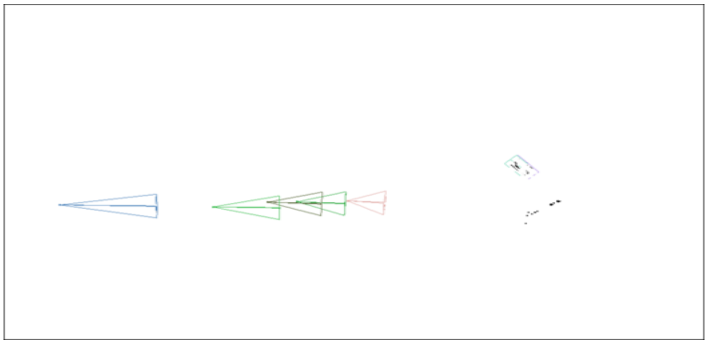

Fig. 13 3D reconstructed scene of binary masked images.

We have made a comparison with the conventional Structure from Motion to build 3D model for the images having moving object. We build the 3D model of those images using Structure from Motion algorithm using Visual SFM software which is shown in figure 15. In figure 16 we can see that, reconstruction of the moving aero-plane images from front. The camera positions are not forming a straight line as expected but instead positioned in a somewhat random pattern. Some 3D points representing environmental things on the left and right of the cameras can be seen, but the significant structure is the reconstruction of the moving aero-plane at the far end of the scene.

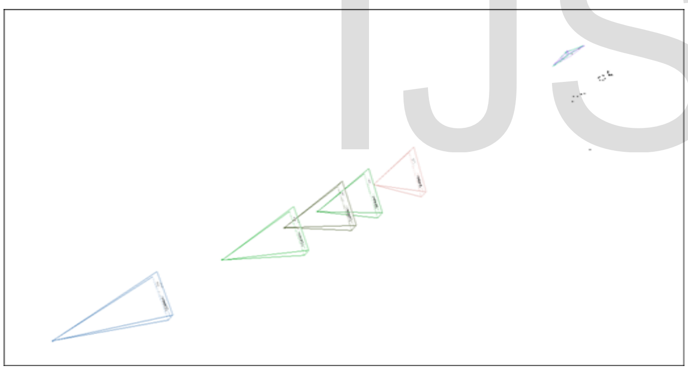

Fig. 14 Side view of 3D reconstructed scene of binary masked image

We also can see that, the camera positions have seemingly random altitudes, which is not expected in a 3D model. If we compare 3D model built we can see reconstruction after masking feature points for excluded classes, the cameras are correctly placed along a straight line with roughly the same distance between them. The 3D points representing the aero-plane are gone and as there were no such major things without aero-plane to detect so those things were not reconstructed and the camera maintained a straight line but in figure 16 the 3D model is not properly reconstructed because here the cameras are positioned in a random pattern. We performed this simulation by varying the number of images for each method and made a comparison with conventional procedures. However, MSAC algorithm showed better performance than RANSAC algorithm. This simulation results shows that RANSAC and MSAC both algorithms are suitable for higher number of images and for lower number of images MSAC algorithm is suitable. The simulation results for 3D model of the images containing moving object also shows that the method proposed here performs better that conventional Structure from Motion algorithm.

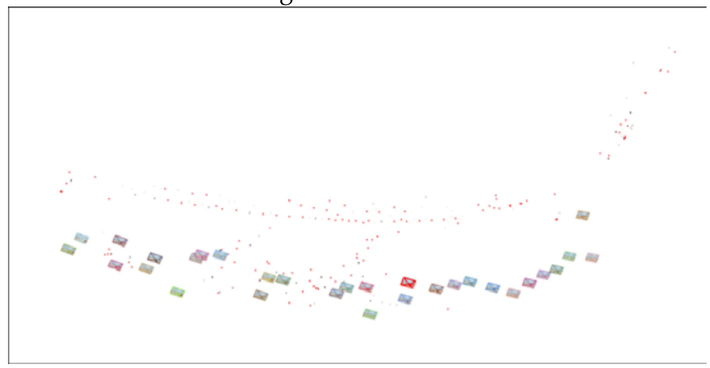

Fig. 15: 3D reconstructed model of aero plane images using SFM algorithm

4 Conclusion

It is desirable to improve the performance of robust estimator to increase the matching of features between the images. So this work focuses on showing the better performed algorithm to build a 3D reconstructed model. For the improvement of 3D cloud model both methods: RANSAC and MSAC were compared to show which should be used to get better result and output in case of reconstructing 3D model. It is essential to know the performance of these algorithm to have a better 3D model. In case of image having moving object it was a problematic matter to build a 3D reconstructed model. In this research this problem was reduced using semantic segmentation and binary masking. The camera positions plays a vital role during the 3D scene reconstruction and at last by camera position it was make sure that the images having moving object were reconstructed properly. So, MSAC algorithms appears to be more efficient as the cloud model built with MSAC algorithms shows better performance in every case than RANSAC. However, in case of higher number of images any of the algorithm shows nearly same proficiency. Semantic segmentation and 3D reconstruction can be combined to resolve the problem of 3D reconstruction for images containing moving object. However, if the environmental things are the major part of the image in the images having moving object, then those things will also reconstruct and moving object will always be gone after reconstruction.

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