Pre-processing Methodology of Image Compensation using Histogram Equalization for Generating Point-cloud of Construction Environment

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Abstract

Recently, advanced and semi-automated equipment, laser-scanner and Unmanned Aerial Vehicles (UAVs), is used for construction project. Especially, photogrammetry using image acquired from UAVs can make high accuracy data and has low cost compared with terrestrial and aerial Lidar. Unmanned Aerial Vehicles (UAVs) was considered as an important technology and using UAVs in various areas are prominent area in recent times. Unmanned Aerial vehicles (UAVs), aerial movable image sensing platform, have become the area that has been becoming notable in all industries. But in construction site, it is very hard to acquire high quality data from UAVs due to the environment changes such as diverse environment, difficulty of setting control points and post-processing. This study aims to propose the pre-processing methodology which is to compensate 2D image using image histogram in construction site. We made a variety 3D data of buildings as point-cloud using the pre-processing methods and analyzed and verified performance of results to compare with the results obtained by source data.

Keywords –

Pre-processing; UAV; Histogram equalization; point-cloud; Image compensation

1 Introduction

1.1 Background and objectives of the research

In recent years, Unmanned Aerial Vehicles (UAVs) have been widely used in a number of areas such as agriculture, civil engineering, disasters, delivery, and military sectors. The market of UAVs in the world has been increased constantly and will be expected to grow further. In particular, the expansion of spatial information portal services such as Google Earth and MS Virtual Earth is closely related to the growth of the market in UAVs. Moreover, a ratio of contribution to spatial information field by aerial monitoring is expected to grow further. Thus, much attention has been paid to the utilization of UAVs for rapid and convenience of aerial monitoring. Since photogrammetry using UAVs is efficient in terms of required time, cost, and human resources, it enables monitoring at a high frequency. Moreover, as data acquired through autonomous flight and wireless communication technology can be sent to the ground in real time, the utilization area of aerial monitoring systems based on UAVs is increasing.

Existing technologies have been concentrated on efficient algorithms using acquired data and data analysis using UAVs. In particular, various studies have been attempted to convert raw data into measurable and manageable data rather than survey purpose. Among them, most technological development of three-dimensional (3D) modeling using two-dimensional (2D) images has been underway based on point-cloud generation algorithm.

Currently, construction industry has employed not only laser scanner but also UAVs in site management and construction management variably. In particular, photogrammetry using UAVs is accurate and efficient as well as inexpensive. Thus, its utilization area and use frequency are increasing. Nonetheless, it is hard to acquire high-quality data according to various changes in environments such as diversity of shooting environment, difficulties in application of reference points, and difficulties in post-processing due to the characteristics of construction sites.

Thus, this study proposes a pre-processing method of 2D images compensated using image histogram in photogrammetry using UAVs in order to overcome the limitations of photogrammetry in the construction industry. This study generates 3D spatial information of various buildings using unmanned aerial photogrammetry and verifies and analyzes a level of improvement based on keypoint and point-cloud values. The reliability of unmanned aerial photogrammetry is determined based on the above result and applicability to various construction sites is discussed.

1.2 Research trend

The research and development of core technologies that can be indexes of photogrammetry has been conducted. The Scale Invariant Feature Transform (SIFT) developed by Lowe[1] and Structure from Motion (SfM) developed by Snavely[2] are two of the most widely used technologies in UAV image processing. Later, Furukawa[3] and Rothermel[4] proposed an algorithm that converted an initial low-density point-cloud into high-density point-cloud through recalculation using a multi-view stereo (MVS) technology. The bundle adjustment, which is a standard technology of aerial triangulation, can calculate exterior and interior orientation parameters of each photo in the digital photogrammetry filed.

The most significant drawback of photogrammetry using UAVs is low accuracy compared to that of laser scanner. Thus, if the low accuracy drawback is resolved, it can decrease cost in construction sites and construction schedule using only photogrammetry. There have been a number of previous studies on analysis on various factors that can degrade accuracy.

Snavely and Szeliski[2] studied noise occurrence in 3D information due to mismatch between corresponding pixels. Construction sites have many factors that make photogrammetry difficult through 2D images such as untidy environment, changes in lighting, sensor noise, and mismatch between pixels[7]. Since 3D photogrammetry data obtained from construction sites are likely to have a large amount of noise, data processing is needed to improve.[8] Kerdsrilek[9] removed DSM point clouds at locations where height change was severe such as buildings automatically and enabled conversion into DTM through interpolation of surrounding data by the development of SCOP++ algorithm. However, the algorithm had a weakness that heights of large or high-rise buildings had to be edited manually since heights were represented obliquely. To increase quality of photogrammetry in various construction sites, a study on main causes and resolution methods has been proposed previously. In particular, Lowe[1] extracted feature points that were not changed between different images effectively and proposed a method that produced highly reliable 3D data. The study reported that although a feature point was not affected by rotation and scale of images, a change in the number was affected by distortion, noise, and changes in lighting. Previous studies found that acquired 2D images had a significant effect on 3D data quality.

Thus, processing of acquired 2D data is the most effective way to obtain high quality 3D data to have efficient data acquisition in a poor environment such as construction sites. A number of processing methods for 2D images have been proposed to acquire high quality 3D images such as changes in illuminance, changes in contrast, and changes in sharpness. Among the above processing methods, the most efficient method is changes in illuminance and contrast of images considering algorithms to acquire photogrammetry data. Generally, this process is called histogram equalization (HE), which was studied by Pizer.[10] for the first time. This method transforms illuminance and contrast by changing image histogram of image information values displayed as a form of histogram. Kim[11] developed bi-histogram equalization (BBHE) based on existing HE methods to increase quality of illuminance and contrast values. Later, Abdullah[12] compared and analyzed Global Histogram Equalization (GHE), Local Histogram Equalization (LHE), and Dynamic Histogram Equalization (DHS) to determine strengths and weaknesses of each of HE algorithms. As shown in the previous studies, it was proven that increasing image quality itself can be closely related to 3D data quality but no direct studies have been conducted yet.

Thus, the present study aims to present a method to overcome the limitation of photogrammetry in construction sites using UAVs and prove that the use of HE algorithm on 2D images that can affect 2D images directly can give a direct effect on improvements on the quality of photogrammetry.

1.3 Research contents

UAVs have been utilized in various areas including military, agriculture, reconnaissance, and civil engineering since the first appearance. With the introduction of small unmanned aircrafts called drone, UAVs have provided various functions with high quality and low price as commercial UAVs are also available in industrial uses.

In recent years, 3D information acquired through UAVs has been widely used in various tasks such as construction supervision, verification of construction errors, and utilization as building information modeling (BIM) data in construction sites. Particularly, record of progress in construction projects can be done with photogrammetry using UAVs, which is efficient in terms of cost and time consumption. However, there are a large number of factors that degrade 3D data quality such as untidy environment of construction sites, changes in lighting, sensor noise, mismatch between pixels, diversity of shooting environment, difficulties in reference point application, and difficulties in post-processing due to the characteristics of construction industry. In addition, inaccuracy and errors can also be present due to the characteristics of photogrammetry. Thus, it is necessary to have a method that reduces inaccuracy and errors.

The present study applied a method that increases illuminance and contrast of 2D images to increase accuracy of 3D data. Among them, HE algorithm was used to acquire high quality contrast values by changing image attribute values.

UAV devices and cameras were selected first and then target buildings were shot. Point clouds of images transformed through HE algorithm and acquired original 2D images were created and 3D data values were compared. The reliability on the result values is evaluated by utilizing laser scan data. Finally, accuracy analysis was conducted with regard to data values obtained in the original image and images transformed through the HE algorithm.

2 Theoretical discussion

2.1 SFM technology

The SfM algorithm generates 3D scenes automatically using overlapped photos. It was developed by Professor Snavely in Cornell University in the USA in 2006. It is a technology that restores 3D shapes in each scene and location relationships of cameras and then restructures a number of overlapped photos shot from multiple angles using 3D. The SfM algorithm implements image registration easily despite of changes in location of cameras or scale by using the recognition of feature points in the scale-invariant feature transform (SIFT) algorithm.

Since accuracy of coordinate value (x, y, z) of target object and initially estimated camera location is degraded, it can be improved by using iterative calculations of non-linear least squares method. Each of the pixels is represented as a point cloud, which is a 3D coordinate value whose accuracy is high. However, the SfM method has no scale and orientation information, a coordinate value of point cloud has a relative spatial coordinate value between object and 2D image.

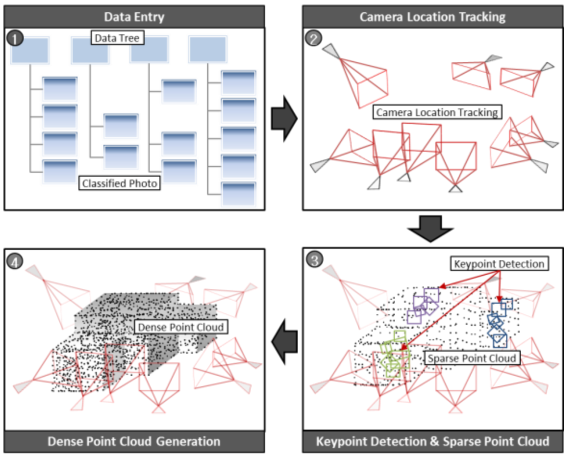

Figure 1. . Input 2D image, Calculation of camera pose, Generation of 3D point-cloud

2.2 SIFT algorithm and generation of point-cloud

The core element in the SfM is to determine a coordinate value of feature point matched with 2D image shot at multiple angles. First, feature points are extracted from 2D images of objects and then a relationship of feature points between images is determined. Next, a matrix is generated with regard to the corresponding relationship followed by factorization to estimate camera locations and coordinate value of each feature point. To do this, a factorization process is performed using bundle adjustment and bundler, which is open software. The feature point matching of 2D images is performed through random sample consensus (RANSAC) and track method. If two feature points are present in three 2D images, a point cloud is generated. If this condition is not met, it is automatically removed. In contrast with exiting aerial photogrammetry, SfM has an advantage that all processes are performed automatically. However, the precision of early point clouds was too low to represent an object accurately.

Thus, Clustering view for Multi-view Stereo (CMVS) and Patch-based Multi-View Stereo (PMVS) developed by Professor Furukawa in Washington University in the USA are employed to improve the precision. CMVS decompose overlapped 2D images into subset or cluster and PMVS is utilized to reconstruct 3D structure from the cluster independently.

In early point clouds generated by the bundler, the number of points is increased as processes of CMVS and PMVS are progressed thereby generating high-density point clouds. However, all the processing procedures in the data values are performed automatically, it is difficult for users to inspect or modify the data values. As a result, it has a problem of degrading reliability somewhat in regard to the accuracy of the output.

2.3 Image histogram

Image histogram represents color distribution in digital images as histogram. Normally, a value range in the horizontal axis is 0 to 255, which represents image histogram of the gray scale of the image. Since histogram of specific image is represented, an overall color distribution of the image can be determined at a glance. Image histogram helps users to identify the characteristic information of images such as image contrast, brightness, and color distribution easily. Various features of filtering such as decrease or increase in image contrast and changes in brightness can be done by transforming information provided by image histogram.

2.4 Histogram Equalization

HE improves image quality by making a distribution of image contrast value uniform. The objective of HE is to generate a histogram of uniform distribution. In particular, HE is effective when an image has a dark and detailed part. Thus, it can cope with poor environments in construction sites efficiently. HE is executed according to the following four phases largely. First, frequency (hist[j]) of brightness value (j) is calculated using IE. Second, cumulative histogram values based on cumulative frequency are calculated using the calculated frequency and normalized.

$$sum[i] = \sum_{j=0}^{i} hist[j] \tag{1}$$

Third, the normalized cumulative histogram is mapped to gray level values using mapping function of gray scale.

$$n[i] = sum[i] \times \frac{1}{N} \times 255 \tag{2}$$

(N = No. of total pixels in the image)

Finally, pixel value i in the input image is converted into a normalized value n[i] thereby generating a resulting image.

In the present study, each section of RGB values is converted using the above method thereby generating an image of high quality contrast.

3 Research method and experiment scope

3.1 Research process

The experimental method used in this study had three phases: data collection, experiment, and result analysis. In detail, it was divided into device selection, data acquisition, data transformation, data processing, data comparison, and reliability verification. in the data collection phase, devices were selected and a flight plan of UAV was set up before acquiring 2D image data of the specified buildings. Next, in the experiment phase, collected 2D image data were transformed using HE. After this, each of KeyPoint, Sparse Point Cloud, and Dense Point Cloud with regard to original 2D image and transformed 2D images was acquired and compared. In the result and analysis phase, final values derived based on each of the data were compared and analyzed to verify a level of quality improvement.

3.2 Experimental equipment and software

3.2.1 UAV and camera

Aircraft	
Weight	1280 g
Diagonal Size	350 mm
Max Ascent Speed	5 m/s
Max Descent Speed	3 m/s
Max Speed	16 m/
Max Service Ceiling Above Sea Level	6000 m
Operating Temperature	0°C to 40°C
GPS Mode	GPS/GLONASS
Max Flight Time	Approx. 23 minutes
Camera	
Sensor	Sony EXMOR 1/2.3" Effective pixels: 12.4 M (total pixels: 12.76 M)
Lens	FOV 94° 20 mm (35 mm format equivalent) f/2.8, focus at ∞
ISO Range	100-1600 (photo)
Shutter Speed	8s -1/8000s
Max Speed	16 m/
Image Max Size	4000×3000

Figure 2. UAV and Camera

In this study, DJI Phantom 3 professional, which was the most widely used commercial UAV, and Sony EXMOR camera were employed to suggest applicability of photogrammetry in the construction industry using commercial UAVs. This UAV model can maintain a flight for about 20 min. and its maximum speed was 16m/s. A size of camera image acquisition was 4000x3000 pixels, which was 12 Mbytes. It is an excellent device used in various areas.

3.2.2 Software

In recent years, a large number of software products of photogrammetry specialized for UAVs have been launched in the market. In particular, Pix4Dmapper or Photoscan is the most popular commercial software among them. In the present study, two products of software, Pix4Dmapper and Photoscan were used initially but Photoscan was finally selected because of its small noise produced in buildings. The study was conducted by utilizing functions of Keypoint analysis, generation of Sparse Point Cloud, and generation of Dense Point Cloud with regard to 2D images in Photoscan. Moreover, HE was implemented using Matlab. The photos before and after the transformation and their image histograms were represented visibly in each of four windows in the screen.

4 Analysis on experiment results

4.1 Target buildings for experiments

	Test 1	Test 2	Test 3
Object			
Range	100 m x 40m	45 m x 25m	50m x 30m
Distance	100 ~ 120 m	10 ~ 15 m	5 ~ 10 m
Material	Glass, Steel	Glass, Tile, Brick	Tile, Brick
Image	51	63	40
Whether	Cloudy	Cloudy	Sunny

Figure 3. Test target

In the experiment, three buildings were targeted. For experiment 1, Academic Information Center in Sungkyunkwan University was selected. Its shooting area was 100m×40m and a shooting distance was 100m–120m. The external materials were glass and steel. The weather was cloudy. For experiment 2, Suseonggwan in Sungkyunkwan University was chosen. Its shooting area was 45m×25m and a shooting distance was 10m–15m. The external materials were glass, tiles, bricks, and paint. The weather was cloudy. For experiment 3, Student Center in Sungkyunkwan University was chosen. Its shooting area was 50m×30m and a shooting distance was 5m–10m. The external materials were tiles, bricks, and paint. The weather was sunny. Experiment 1 used civil scale, which was conducted to verify the applicability in civil engineering. Experiment 2 targeted a building in which structures and changes in illuminance were diverse. It was similar to real construction sites. Experiment 3 targeted a general building.

4.2 Compensation of original 2D image using HF

Images acquired in Experiments 1, 2, and 3 were transformed using HE software. During this process, unclear images particularly in cloudy weather or many shadows were beneficial significantly, which can be seen visibly.

4.3 Comparison and analysis on KeyPoint of original 2D image and compensated 2D image

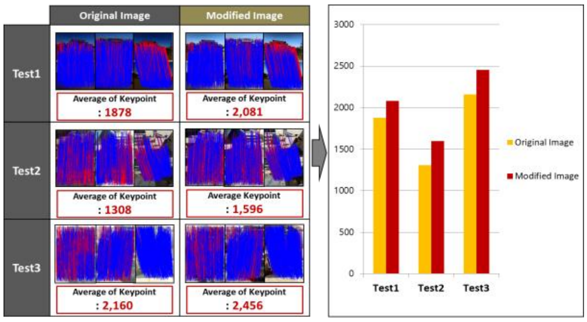

Figure 4. Result of keypoint extraction

A mean value of each KeyPoint in 2D images was acquired and compared. In Experiment 1, 1,878 Keypoint values from the original images and 2,081 Keypoint values from the transformed images were obtained. In Experiment 2, 1,308 Keypoint values from the original images and 1,596 Keypoint values from the transformed images were obtained. In Experiment 3, 2,160 Keypoint values from the original images and 2,456 Keypoint values from the transformed images were obtained. Ultimately, more Keypoint values were obtained from transformed images than from original images.

4.4 Comparison and analysis on Sparse Point Cloud of original 2D image and compensated 2D image

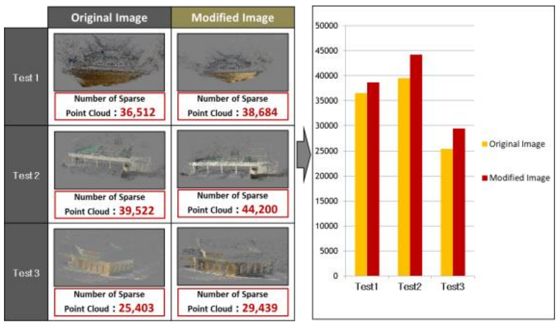

Figure 5. Result of sparse point-cloud

The results of Sparse Point Cloud acquired from original images and transformed images in Experiments 1, 2, and 3 were compared and analyzed. In Experiment 1, 36,512 Sparse Point Cloud values were obtained from original images and 38,684 Sparse Point Cloud values were obtained from transformed images. In Experiment 2, 39,522 Sparse Point Cloud values were obtained from original images and 44,200 Sparse Point Cloud values were obtained from transformed images. In Experiment 3, 25,403 Sparse Point Cloud values were obtained from original images and 29,439 Sparse Point Cloud values were obtained from transformed images. Ultimately, more Sparse Point Cloud values were obtained from transformed images than from original images. However, an increase in Experiment 1 was not that larger than that of the other two experiments.

4.5 Comparison and analysis on Dense Point Cloud of original 2D image and compensated 2D image

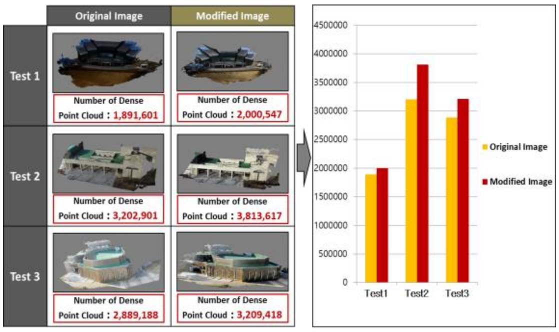

Figure 6. Result of dense point-cloud

The results of Dense Point Cloud acquired from original images and transformed images in Experiments 1, 2, and 3 were compared and analyzed. In Experiment 1, 1,891,601 Dense Point Cloud values were obtained from original images and 2,000,547 Dense Point Cloud values were obtained from transformed images. In Experiment 2, 3,202,901 Dense Point Cloud values were obtained from original images and 3,813,617 Dense Point Cloud values were obtained from transformed images. In Experiment 3, 2,889,188 Dense Point Cloud values were obtained from original images and 3,209,418 Dense Point Cloud values were obtained from transformed images. An increase in Experiment 1 was the lowest but an increase in Experiment 2 was 20%, which was higher than that in Experiment 1.

4.6 Comparison and analysis on increase rate of final results

The result values in Experiments 1, 2, and 3 were all increased. Increase rates in Key Point, Sparse Point Cloud, and Dense Point Cloud were as follows: in Experiment 1, increase by 11%, 6%, and 6%, in Experiment 2, increase by 22%, 12%, and 19%, and in Experiment 3, increase by 14%, 16%, and 11% were verified.

5 Conclusion

The present study analyzed the effect of HE on improvements on photogrammetry quality by comparing results values of Keypoint, Sparse Point Cloud, and Dense Point Cloud, which were scales that determined quality of photogrammetry. Conclusively, most values were increased as presented in this study. The present study thus presented applicability of HE that HE can be efficiently employed in construction sites where quality of 2D image was much degraded.

However, civil scale, that is, photogrammetry results on targets that were distanced 100 m or longer had a small amount of increase in the result values. It was assumed that since shooting of targets was done from a long distance, detailed information was small and approximate 3D data on shapes were formed. Thus, the present study can be suitable for buildings whereas its efficiency in photogrammetry of long distance as needed in civil engineering was lower than that of short-distance.

The limitation of the present study is as follows: since the present study targeted only three buildings, it had a lack of experimental information which should have more various types of target buildings. However, if an in-depth study on method that improves quality of 3D images using quality of 2D images continues as conducted in the present study, higher quality of values can be obtained efficiently in the future.

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