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Original article

Development of Classification Technique of Point Cloud Data Using Color Information of UAV Image

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Abstract

This paper indirectly created high density point cloud data using unmanned aerial vehicle image. Then, we tried to suggest new concept of classification technique where particular objects from point cloud data can be selectively classified. For this, we established the classification technique that can be used as search factor in classifying color information in point cloud data. Then, using suggested classification technique, we implemented object classification and analyzed classification accuracy by relative comparison with self-created proof resource. As a result, the possibility of point cloud data classification was observable using the image's information. Furthermore, it was possible to classify particular object's point cloud data in high classification accuracy.

Keywords : Unmanned Aerial Vehicle, Point Cloud Data, Classification, Color Information

1. Introduction

In recent spatial information technology, speed, accuracy and high dimensionality are represented as keywords. Keeping up with the pace where technology in acquiring spatial information is rapidly developing, especially, the aerial photogrammetry technique and aerial LiDAR (Light Detection and Ranging) are the main techniques. Recently, UAV (Unmanned Aerial Vehicle) is introduced in measuring and spatial information field, being the means to acquire spatial information. UAV, having the possibility of autonomic fly, has relative freedom in spatial limitation for taking and landing off, and time limitation for flying. Furthermore, there is an advantage of image shooting due to the possibility of hovering flight and shooting through low altitude flight and hovering (Lee *et al*., 2012; Colomina *et al*., 2008).

3 dimensional spatial resource acquired from UAV image is established by computer vision interpretation. As image dealing through computer vision interpretation, there are representatively SIFT (Scale Invariant feature Transform) algorithm and SfM (Structure from Motion) technique (Snavely *et al*., 2007). Dealt resource by algorithm can produce various 3 dimensional spatial resource with high accuracy as 3 dimensional modeling resource, point cloud data, and ortho imagery. Such established information can be applied as the basis for 3 dimensional spatial information resource. Point cloud data that is expressed by 3 dimensional points containing all topography and planimetric features is used as the main resource for establishing spatial information (Haala and Brenner, 1999). As point cloud data is composed of all objects in 3 dimensional points, massive amount of resource is saved. Therefore, in order to use point cloud data as various spatial information, classification of object is necessary (Hutton and Brazier, 2012). Previously, the studies were focused on directly establishing point cloud data according to aerial LiDAR survey method, eventually classifying the data. In recent years, new techniques have been proposed for classification such as extracting a forest

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area by applying ortho-image to point cloud data classification technique (Kim, 2013). Thus, there were many study in developing classification technique in various aspects. Such classification technique uses the laser information included in LiDAR system (Hutton and Brazier, 2012). At this point, the core principle for the classification technique is 3 dimensional location information of point cloud data, additional pulse information, and reflection intensity information, of which are used as classifying the object's data (Edward and Jason, 2007; Lee *et al*., 2009). While indirectly established point cloud data from UAV image is saved in the same structure LAS format as directly acquired point cloud data, there is difference in the attribute data provided. Thus, when implementing the classification by applying previous point cloud data classification technique from indirect method, there will be very low accuracy in classification result. Therefore, further development in classification method allowing object classification from indirectly established point cloud data is necessary.

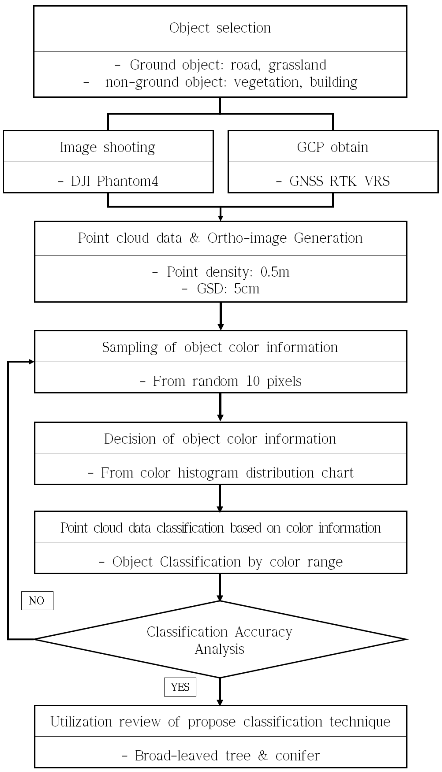


Fig. 1. Study flow

So, this study uses UAV image for improving point cloud data classification and the accuracy. And thus will use R.G.B color information as search factor, eventually suggesting selective classification technique that is effective for particular object point cloud data. Also, regarding ground and non-ground object classification result, classification accuracy was tested to observe the possibility of applying new classification technique. Fig. 1 describes the study flow diagram.

2. Point Cloud Data Classification Technique Based on Image Color Information

2.1 Characteristic of computer vision point cloud data

Point Cloud data established by the image from UAV has the same information structure with the point could data directly measured from LiDAR system. Yet, there is difference in the attribute data of point cloud data. Attribute data of point cloud data, directly collected, generally includes the measuring point's 3 dimensional location information, pulse information in which sent laser reflects back, and reflection intensity according to surface and texture as attribute data which will be provided to the user. Then, using attribute information based on statistical theory, vector information based or raster information based classification is implemented (Kim and Cho, 2012; Jeon and Choi, 2013; Yoo and Lee, 2016). Therefore, for previous point cloud data classification technique, it is impossible to classify point cloud data on particular object or there is a problem of classification accuracy decline. On the other hands, point cloud data from UAV image has advantage in reducing time and spatial limitation compared to LiDAR system. However, the point cloud data established by UAV image is the data established indirectly through computer vision interpretation, thus 3 dimensional location information and color brightness from image is saved as the attribute information. So, the amount of attribute information that can be used for point cloud data classification is relatively lacking. So, the development of new classification technique for effectively classifying point cloud data with limited amount of attribute information is required. To this, this study suggested new classification technique that can selectively classify particular point cloud data using image color information, allowing high density point cloud data classification using UAV image. When classifying using provided image color information as search factor, it is expected that the classification of both ground and non-ground object, with constant color pattern, will be possible. Therefore, improvement of previous problems including misclassification due to uniform classification based on statistical method, decline in classification accuracy, and impossibility of classification for particular objects is expected.

2.2 Point cloud data classification technique method based on color information

Point cloud data established from image, in image handling and data establishment process, automatically provides image's color information in pixel point cloud data by 1:1 composition. At this point, image's color information, as the core factor in affecting classification accuracy, may decline the accuracy when the point cloud data and image's location relationship is different. Therefore, the grant of image's color information is adjusted so that color information in which geometric correction is finished can be granted. Likewise, point cloud data granted with color information internally possesses individual color information. When using point cloud data color information describing unique color information as search factor, not only classification of indirectly established point cloud data but also selective classification using unique color pattern are possible.

In order to classify point cloud data using color information, classification technique based on color information was established. First, to classify particular object, the color brightness of the object to be classified was sampled. For image's color brightness sampling, general 8 bit image's brightness was sampled according to band for color information. For classifying object's color information, various color information was sampled other than mono pixel. Then, applying the organized color information on image histogram distribution chart, object's color information was finally decided. Using color histogram distribution chart's brightness, it was found that the decision for brightness that is to be used as search factor had higher classification accuracy when the distribution is narrow. Therefore, in this study, in order to decide on final object color brightness, color histogram was used with the distribution chart's brightness in 2% range. Then, the data was further organized by reflecting the average brightness of the sampled brightness. Table 1 illustrates the brightness within 2% range organized from color histogram, and Fig. 2 shows the concept applying color histogram distribution chart's brightness.

Table 1. Brightness value of color histogram range

Range (%)	Brightness value	Range (%)	Brightness value
2	5.12	10	25.6
4	10.24	11	28.16
6	15.36	12	30.72
8	20.48	14	35.84
9	23.04	16	40.96

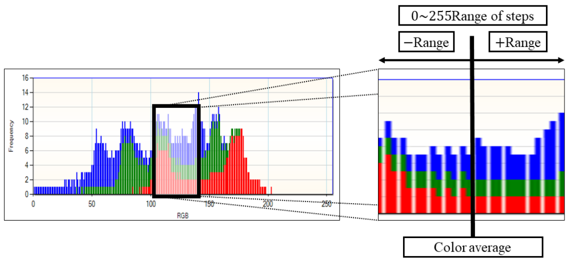


Fig. 2. Object color brightness calculation concept from color histogram range

Using color information decided from color histogram distribution, classification system based on color information for point cloud data was established. First, LAS format, the point cloud data, was input in special program for input/output, and was transformed into CSV format, the type of ASCII structure which allows free editing. Then, function able to conditionally search color brightness was established for classification implementation. Finally, classified resources were counter-transformed into LAS format, finishing the object classification. Fig. 3 illustrates the flow of classification system established.

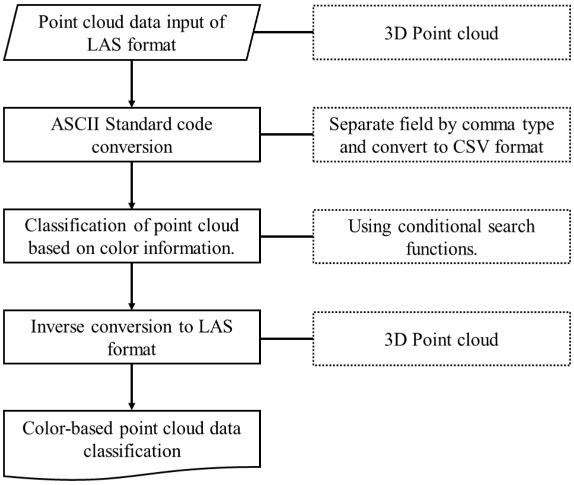


Fig. 3. Flowchart for point cloud data classification processing based on image color information

3. Point Cloud Data Classification and Accuracy Analysis

Using the point cloud data classification technique based on color information depicted in study, point cloud data about particular object was classified. Then, for the same objects, examining resources were self-established. By quantitatively analyzing the classification accuracy suggested through comparison analysis with examining resource, point cloud data classification accuracy based on this technique was examined. Furthermore, comparably higher classification accuracy was examined, and object color information evenly applicable in shooting range was established.

3.1 Classification object selection and basic source establishment

In order to implement the study, objects to be classified were selected. Then, on selected objects, the most appropriate target area was selected, thus establishing image shooting, point cloud data, and ortho imagery were established.

Table 2. Object selection for classification of point cloud data

Ground object	Non-ground object
Road	Vegetation
Grassland	Building

3.1.1 Object selection

For classification on particular point cloud data, objects to be classified in firsthand were selected. For objects, they were divided into ground and non-ground object (Table 2). Then, for the proof of established classification technique's methodology, classification accuracy and efficacy test are necessary. Therefore, objects with classification limitation based on previous technique were selected.

3.1.2 Image acquisition and basic source formation

(1) Image acquisition

Fig. 4. DJI Phantom4

The most appropriate objects with selected objects were selected. Then, in order to implement classification, point cloud data and ortho imagery, the basic sources, were formed. First, image of the objects to form the data was formed. For image acquisition, DJI phantom4 (Fig. 4) was used, and percent of end and side laps for shooting channel were set based on IOS Pix4D capture application for image acquisition. Image's percept of lap was set 80%, and percept of side lap was set 70%. In addition, considering the UAV's camera specification, shooting took place at above 100m from ground, so that GSD (Ground Sample Distance) of 5cm could be guaranteed. Finally, there were 150 images of acquisition. Table 3 shows the main data of Phantom4 applied in image shooting.

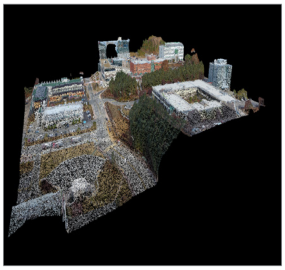
Table 3. DJI Phantom4 main specification

Machine		Camera	
Weight	1,380g	Sensor	1/2.3″
Max speed	20m/s	Lens	FOV:94°
Elevation limit altitude	6,000m	ISO Range	100~3,200
Maximum flight time	28 minutes	Shutter speed	1/8,000sec.
Satellite	GPS/GLONASS	Image Size	12MP

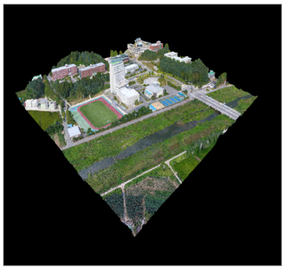
(2) Point cloud data and ortho imagery formation

In order to form point cloud data, Bentley Corporation's

3 dimensional modeling program ContextCapture program was used. By the input of 150 image collected from UAV into the system, unique characteristics that can be commonly observed from images were extracted for implementation of AAT (Auto Aerial Triangulation). Then, by the input and acquire of additionally gotten ground control point, AT (Aerial Triangulation) was implemented. Through this, absolute coordinates were given to all ground points from image, eventually forming point cloud data and ortho imagery. Fig. 5 illustrates the ortho imagery and point cloud data formation result according to road object, the ground object, and vegetation object, the non-ground object.



(a) Ortho-image (road object) **(b) Point cloud data (road object)(3D view)**



(c) Ortho-image (vegetation) **(d) Point cloud data (vegetation)(3D view)**

Fig. 5. Generation of ortho-image & point cloud data for ground & non-ground object classification

3.2 Point cloud data classification of objects based on image color and accuracy analysis

In order to classify selected objects, object's color information was used as search factor for point cloud data classification and classification accuracy analysis. Fig. 6 illustrates the flow for object's point cloud data classification and accuracy analysis.

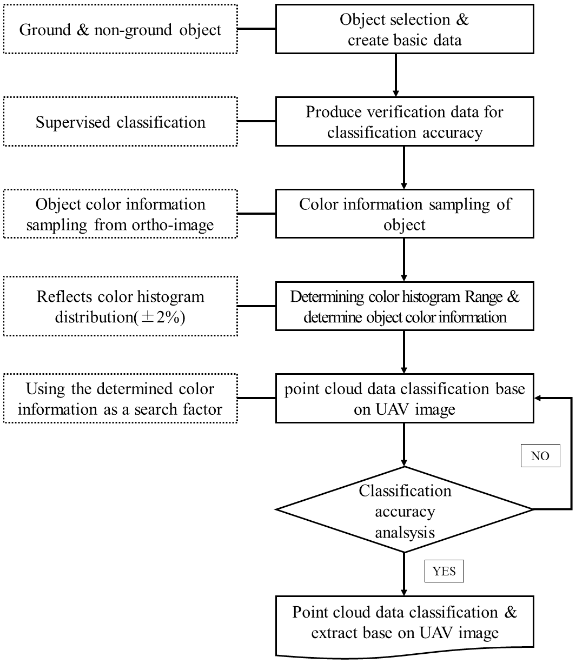
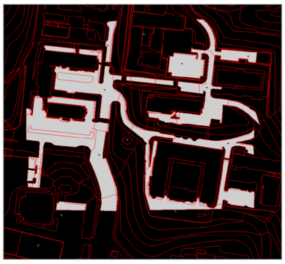
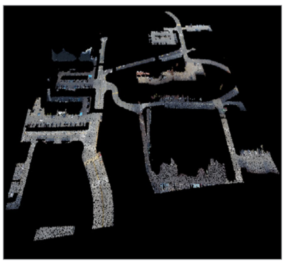


Fig. 6. Flow chart of point cloud data base on color information

(1) Road object

Classification for road object, the non-ground object, was implemented. First, in order to analyze the accuracy on classification result, road object's examination resource was produced. For examination resource, ortho imagery and national base map 1:5000 digital map was took as reference, and Autodesk corporation's AutoCAD 2016 program and Microstation V8 2004 Edition's module were used together for self-production. As a result, the ratio of total object's point cloud data to road object's point cloud data was 18.1%. Fig. 7 and Table 4 illustrates the classification result produced for examination for classification accuracy analysis.





(a) Creating a boundary file **(b) Classification result (3D view)**

Fig. 7. Create and classification verification data for road object classification accuracy analysis

Table 4. Classification result of verification data for road object classification accuracy analysis

Object	Total point	Classification point	Ratio (%)
Road	547,669	99,151	18.1

In order to selectively classify road object, object's color information were randomly selected based on 10 brightness values sampling. Then, from their brightness, the average brightness was calculated, and road object's color information standard was decided from color histogram distribution chart for color decision (Table 5).

Table 5. The color brightness value & average brightness value of the road object

Object	R	G	B	R	G	B
Road	75	79	88	66	66	74
	62	65	74	48	56	67
	29	36	52	48	56	69
	22	29	37	89	89	97
	73	76	85	53	55	67
Average	R		G		B	
	56.5		60.7		71	

Then, the average brightness that can be recognized as road object was reflected as 2% range, finally deciding on road object color brightness to be used as final search factor. At then, in order to maintain higher classification accuracy, the maximum brightness for search factor was 2% range and minimum brightness was -2% range. Table 6 shows the calculated minimum and maximum brightness to classify road object.

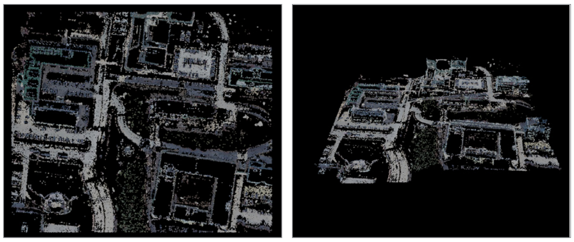
Using the decided brightness as search factor, classification suggested on this study was implemented. Table 7 shows the classification result based on road object's point cloud data, illustrating deviation analysis per road object color range. The ratio of examination resource and classified object was calculated, and the deviation was calculated on the basis of 100%. From this, classification deviation of ±3.8%~±325.7% was observable. Then, the classification deviation was ±3.8%, showing the highest classification accuracy within 6% color range. Fig. 8 illustrates the road object classification result in 6% range of the highest classification accuracy.

Table 7. Classification deviation analysis of road object

Range (%)	Total point	Road point	Classification point	Classification ratio (%)	Classification deviation (%)
2	547,669	99,151	14,354	14.5	±85.5
4	547,669	99,151	47,500	47.9	±52.1
6	547,669	99,151	95,373	96.2	±3.8
8	547,669	99,151	146,395	147.6	±47.6
10	547,669	99,151	210,500	212.3	±112.3
12	547,669	99,151	281,031	283.4	±183.4
14	547,669	99,151	353,415	356.4	±256.4
16	547,669	99,151	422,097	425.7	±325.7

Table 6. Min & max brightness value of the road object with color histogram brightness value applied

Range (%)	R.G.B brightness value					
	MIN			MAX		
	R	G	B	R	G	B
2	51.38	55.58	65.88	61.62	65.82	76.12
4	46.26	50.46	60.76	66.74	70.94	81.24
6	41.14	45.34	55.64	71.86	76.06	86.36
8	36.02	40.22	50.52	76.98	81.18	91.48
10	30.9	35.1	45.4	82.1	86.3	96.6
12	25.78	29.98	40.28	87.22	91.42	101.72
14	20.66	24.86	35.16	92.34	96.54	106.84
16	15.54	19.74	30.04	97.46	101.66	111.96

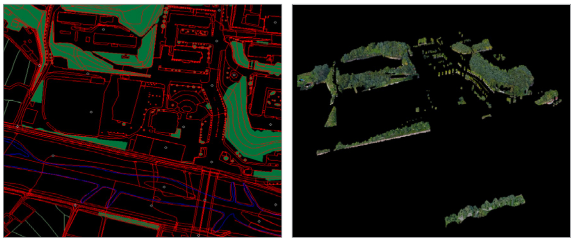


(a) Range 6% classification (2D view) (b) Range 6% classification (3D view)

Fig. 8. Result of road object classification using image color histogram

(2) Vegetation object

Classification for vegetation object, the non-ground object, was conducted. First, for objects classification accuracy analysis, examination source was established as the same way as above. As a result, the vegetation object showed ration of 22.8% when compared with the point cloud data. Fig. 9 and Table 8 describes the result of established examination source.



(a) Creating a boundary file (b) Classification result (3D view)

Fig. 9. Create and classification verification data for vegetation object classification accuracy analysis

Table 8. Classification result of verification data for vegetation object classification accuracy analysis

Object	Total point	classification point	Ratio (%)
Vegetation	1,485,824	339,467	22.8

Then, the decision procedure of color brightness for vegetation object's point cloud data classification was the same as what was proceeded with road object procedure. Table 9 describes 10 brightness and the average brightness of those in category of vegetation object. Table 10 describes the minimum and maximum brightness calculated by reflecting histogram range to the average of 10 brightness data.

Table 9. The color brightness value & average brightness value of the vegetation object

Object	R	G	B	R	G	B
Road	19	35	24	66	85	63
	64	78	29	18	33	28
	59	79	30	89	106	88
	17	29	29	61	81	46
	29	43	26	95	109	60
Average	R		G		B	
	45.6		64.4		43.7	

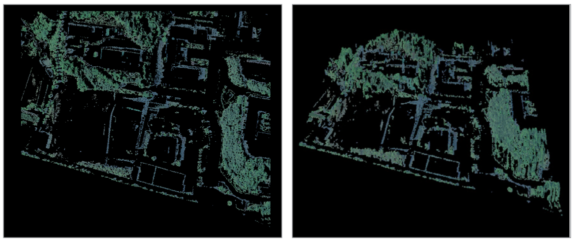
Table 10. Min & max brightness value of the road object with color histogram brightness value applied

Range (%)	R.G.B brightness value					
	MIN			MAX		
	R	G	B	R	G	B
2	48.88	83.88	73.88	59.12	94.12	84.12
4	43.76	78.76	68.76	64.24	99.24	89.24
6	38.64	73.64	63.64	69.36	104.36	94.36
8	33.52	68.52	58.52	74.48	109.48	99.48
9	30.96	65.96	55.96	77.04	112.04	102.04
10	28.4	63.4	53.4	79.6	114.6	104.6
11	25.84	60.84	50.84	82.16	117.16	107.16
12	23.28	58.28	48.28	84.72	119.72	109.72
14	18.16	53.16	43.16	89.84	124.84	114.84
16	13.04	48.04	38.04	94.96	129.96	119.96

Using decided brightness as search factor, classification was conducted based on classification system. Table 11 illustrates deviation analysis of vegetation object's color range after comparison analysis of classification result and examination source. From this, classification deviation of $\pm 0.9\%$~$\pm 96.4\%$ could be observed, and within color range 11%, classification deviation was the highest with $\pm 0.9\%$. Fig. 10 illustrates the classification result of those 11% highest range in classification accuracy of vegetation object.

Table 11. Classification deviation analysis of vegetation object

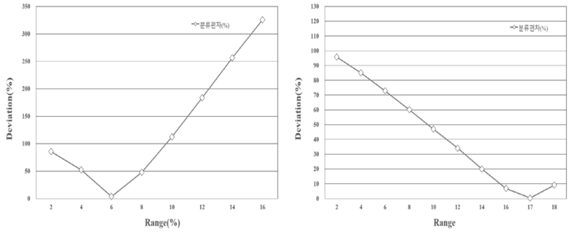
Range (%)	Total point	Vegetation point	Classification point	Classification ratio (%)	Classification deviation (%)
2	1,485,824	339,467	12,076	3.6	±96.4
4	1,485,824	339,467	61,054	18.0	±82.0
6	1,485,824	339,467	136,418	40.2	±59.8
8	1,485,824	339,467	214,577	63.2	±36.8
9	1,485,824	339,467	258,813	76.2	±23.8
10	1,485,824	339,467	298,092	87.8	±12.2
11	1,485,824	339,467	342,358	100.9	±0.9
12	1,485,824	339,467	382,920	112.8	±12.8
14	1,485,824	339,467	457,001	134.6	±34.6
16	1,485,824	339,467	511,059	150.5	±50.5



(a) Range 11% classification (2D view) (b) Range 11% classification (3D view)

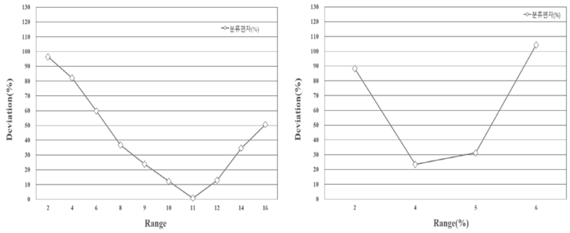
Fig. 10. Result of vegetation object classification using image color histogram

Using the provided classification technique, road and vegetation objects were classified. Also, point cloud data classifications of grassland and building object, other two selected objects, were implemented in the same procedure as done for road and vegetation objects. Fig. 11 illustrates classification deviation per color range for ground object, thus for road object, there is ±3.8% classification deviation within 6% range. For grassland object, there showed ±0.4% classification deviation within 17% range. Then, Fig. 12 illustrates color range classification deviation for non-ground objects. It illustrates ±0.9% classification deviation for vegetation object within 11% range, and ±23.4% classification deviation for building object within 4% range.



(a) Road object (b) Grassland object

Fig. 11. Classification deviation by color range (ground object)



(a) Vegetation object (b) Building object

Fig. 12. Classification deviation by color range (non-ground object)

As a result, it was possible to classify point cloud data regarding particular object by applying classification technique suggested in this study. Also, classification accuracy was observable while deciding on color brightness range to apply per object. To this, when applying classification technique suggested in this study, classification result of higher accuracy was deductible. Also, misclassification and low accuracy that was observable in previous classification technique could be improved. However, for classification deviation for building object, it was ±23.4%, showing relatively high classification deviation compared to those of other objects. This perhaps is due to the variety of roof color information of the building, thus resulting in relatively high classification deviation. Therefore, for building object, carrying out suggested technique and previous technique that uses filter size and height together, more accurate classification result is expected.

3.3 Color information establishment per object

In this study, the color information, used as search factor for selectively classifying particular object from high density point cloud data, affects classification accuracy. Therefore, securing high classification accuracy and color information per object of which can be applied to various model's point cloud data is very vital. Therefore, in this study, we tried to establish color brightness range per object based on classification accuracy analysis result so that the range can be applied to point cloud data within the same shooting range. Table 12 illustrates the histogram range that shows the highest classification accuracy among classified object's range classification deviation. Through this, establishment of the most appropriate color information was possible per object so that classification of point cloud data within shooting range is conductible.

Table 12. Color information establish of object

Category	Object	Color histogram range (%)	Classification deviation (%)
Ground object	Road	6	±3.8
	Grassland	17	±0.4
Non-ground object	Vegetation	11	±0.9
	Building	4	±23.4

4. Conclusion

In this study, through dealing with large scale image by UAV, high density point cloud data was produced. Then, applying ortho imagery's color information as search factor, the study tried to propose new point cloud data classification technique to selectively classify new point cloud data. Furthermore, through examining particular object's classification accuracy based on proposed classification technique, the technique's application possibility was analyzed.

First, point cloud data from image dealt from UAV provides different information from point cloud data directly dealt as to LiDAR. When to classify point cloud data from image, there occurs misclassification or doubt in accuracy when applying previous general classification technique. Thus, for classifying indirectly formed point cloud data from UAV image and selectively classifying particular object's point cloud data, new concept of point cloud data classification technique was suggested of which uses color information from ortho imagery as search factor.

Second, using suggested classification technique, classification for ground and non-ground object was conducted for established point cloud data. Then, classification accuracy analysis was conducted by comparing with self-created examination source. As a result, classification deviations for road, grassland, vegetation, and building were ±3.8%, 0.4%, ±0.9%, and ±23.4%, respectively. From this, the application possibility of suggested classification technique could be examined, further improving problems of previous classification techniques.

Third, for classification accuracy analysis for point cloud data, the most appropriate color information was established to classify point cloud data within the same shooting range. With established color range, by applying point cloud data from either the same or similar environment, effective application of classifying particular object point cloud data is expected.

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