A study on the classifying vehicles for traffic flow analysis using LiDAR DATA

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Abstract : Airborne laser scanning thechnology has been studied in many applications, DSM(Digital Surface Model) development, building extraction, 3D virtual city modeling. In this paper, we will evaluate the possibility of airborne laser scanning technology for transportation application, especially for recognizing moving vehicles on road. First, we initially segment the region of roads from all LiDAR DATA using the GIS map and intensity image. Secondly, the segmented region is divided into the roads and vehicles using the height threshold value of local based window. Finally, the vehicles will be classified into the several types of vehicles by MDC(Minimum Distance Classification) method using the vehicle's geometry information, height, length, width, etc

Keyword : LiDAR, vehicles classification, MDC

1. Introduction

In order to determine the LOS (Level Of Service) on a road, the road's geometry information and transportation condition is need to be known. The road's geometry information is including the parameters(linearization, designed velocity, etc) and transfortation condition is including the parameters(type of vehicle, vehicle count per lane, velocity, etc). As the technology for collecting transportation condition's parameters has greatly advanced, we are now able to obtain traffic information automatically at real-time for a wide area. Therefore, in this paper, we will evaluate whether it is possible to apply airborne laser scanning technology for recognizing the type of vehicle, which is the parameter of transportation.

2. DATA

The Lidar DATA were acquired for the Cheon-an area in South Korea using the optech ALTM 30/70 system and were processed using the commercial software package, ArcGIS and the program languages, Matlab, C.

Table 1. Overview of technical parameters of ALS system

Contents	values
Flying height	1000m(from the surface)
Scan area	1310km×1611km
Repetition Rate	70,000Hz
Scan Angle	±15°
Scan rate	30Hz
Overlay rate	75 %
Scan line	16directions
Density of point	5.17 point/㎡

3. Processing of LiDAR DATA

1) Segmentation of road region from raw LiDAR DATA

In this paper, we have used two methods for segmenting the road region, including the vehicles from raw LiDAR DATA. The first method involved using the digital map with which the TM (Transverse Mercator) is transformed into UTM (Universal Transverse Mercator) coordinate system (UTM is the same as LiDAR DATA's coordinate system). The second method was using intensity data from LiDAR DATA. In this method, we had to manually digitize the centerline

By using the transformed and the digitized centerline in a road, we were able to make a polygon by buffering width along the centerline and segmented only the points including the polygon from raw LiDAR DATA. But, the latter of the two methods was found to be better than the former. So we chose the latter.

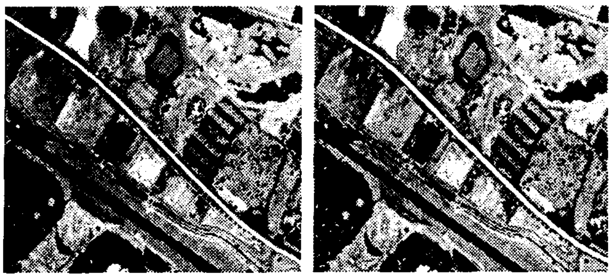

Fig 1. The region of road (L : Digital map and intensity image, R : Digitizing and Intensity Image)

2) Segmentation of vehicles points from the road region

Local threshold window

In this part, we segment vehicle points from the road region using the local threshoding window (3m * 3m)
① Search the minimum z value point of the points within window.
② Calculate the Δz between minimum point and the points within window.
③ Extract the points that Δz value is only over 0.7m and below 4.5m
Here, the thresholing value (Δz=0.7m) is considered by the surface's gradient and the thresholding value (Δz=4.5m) is considerd by the facilies' height limit on the road.

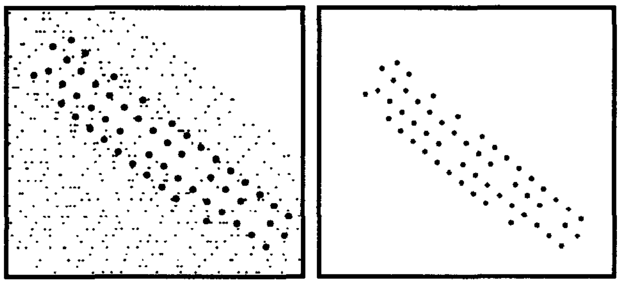

Fig 2. Segmentation vehicles points (L : road and vehicle, R : segmentation of vehicle)

Excluding the vehicles' error point

Considering the data acquired for road area, it is overlaid by the several strips. Thus, as shown in Fig 3, if the time taken for the sensor to receive the reflected signal from the vehicles on the surface is not considered, the two vehicles are recognized as a same vehicle. So, the vehicle point must be segmented by considering the time value. Through these steps, we were able to automatically extract 61 vehicles by local thresholding window and by considering the time value.

TIN and labeling

We have developed a TIN (Triagulated Irregular Network) for recognizing the vehicles initially using that segmented vehicle points, and eliminated that the length of lines is over 1.5m. Finally, we were able to initially created vehicles' polygon and labeling.

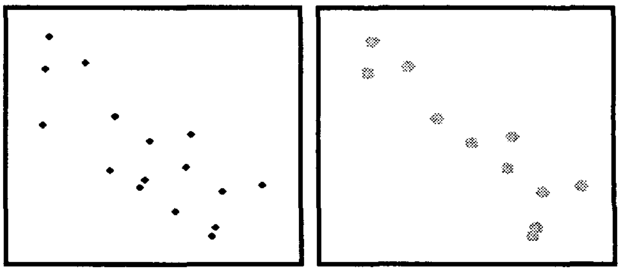

Fig 3. Vehicles' error point (L : not considering time value, R : considering time value

3) Extracting the parameters of vehicles

Vehicles' rotation transformation

As can be seen in the Fig 2, the distribution of vehicle points are unsuitably floated on the X-Y axes when we extracted the attributes of vehicles. Thus, we approximately determined the 1st least square curve from the extracted vehicle points, which were inversely rotated as the gradient of 1st curve.

Extracting the calculated parameters of vehicles

In order to classify the vehicle types, we had to extract the characteristic parameters of vehicles and used a five-parameter representation that includes the size of the vehicle footprint. Here vehicle width(W) was not considered as characteristic parameter and thus excluded the "W" parameter. Then, we used two parameter cases, four parameters h1, h2, h3, and L and only three vertical parameters h1, h2 and h3. The vertical average height values were computed over the three equally sized region whereas the vertical average height value was calculated by the points in the 95% confidential interval as shown in Fig 4. The result table is shown below

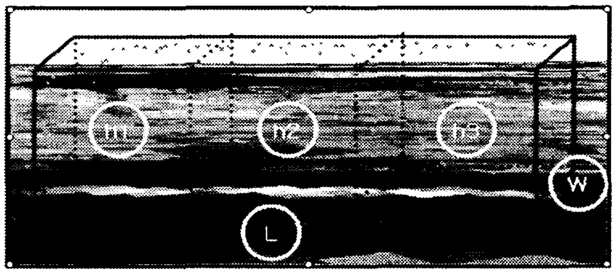

Fig 4. Parameterization of the LiDAR point representing the vehicle

Table 2. Parameters for representing the vehicles (unit : m)

Vehicle Number	h1	h2	h3	L
1	1.1567	1.8367	1.89	3.9871
2	0.905	1.3733	1.015	3.4747
3	1.175	1.67	1.2875	4.0538
Λ	Λ			
61	1.1775	1.48	1.2167	4.0948

4. Classification of the vehicle types

In this paper, we have classified the vehicle types in two ways. The first is applying MDC classifier using the raw extracted parameters (3 and 4 parameters) data set. The second is applying MDC classifier using the data distribution in the new feature space from the PCA analysis. The ultimate goal is to classify the vehicles into the seven types as identified below.

Table 3. Vehicle types

Class	Color	Vehicle Category
1	Red	Truck (small size:unloaded)
2	Cyan	Truck (small size:half loaded)
3	Magenta	SUV
4	Green	Passenser Car
5	Blue	Truck (Large size)
6	Black	Bus
7	Yellow	Bongo&Truck (small size:full loaded)

The MDC classifier is based on a class description involving the class centers which are calculated by averaging feature components of each class. An unknown pattern is classified by computing the distance between the pattern and all class centers and the smallest distance determines in which class the pattern will be classified. The distance calculation based on the Euclidean measure (1) in the computed parameters

$$D_j = \sqrt{(x - \bar{x}_j)^2 + (y - \bar{y}_j)^2} \qquad (1)$$

Where, the class center of class j is denoted by $\bar{x}_j$ and $\bar{y}_j$

In case of using the four parameters, the result will not be good as the vehicles' length parameter is a not characteristic value that represent a vehicle type. Thus, in this paper, we have omitted this case and have considered only the three parameter case.

1) Classification the raw parameter of vehicle data

We have applied the MDC classifier using the raw extracted parameters data set. The result is in the Fig.5.

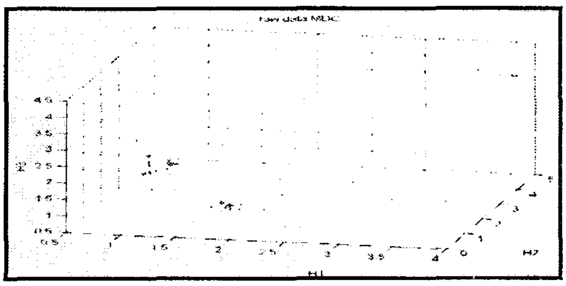

Fig 5. Vehicle distribution in the raw extracted parameters data set, three parameter data

2) Classification the new feature space's data using the PCA analysis

We have applied the MDC classifier using the data distribution in the new feature space obtained from the PCA analysis, which is an effective tool for handling classification problems where there is a significant correlation among the parameters describing the data from various classes.

The correlation can be determined and a reduced parameter can be defined, both of which represent the information in a more compact way and which can support and efficient classification in the reduced feature domain. An obvious merit of this method is that it does not require any physical modeling of the data.

During the test, we computed the PCA . In both cases, all 61 vehicles were used in the computation. Table 4 shows the correlation matrix for the three parameters

The eigenvalues and the information contents are listed in Table 5

Table 4. Correlation matrix of the three vertical parameters

1	0.66236	0.71399
0.66236	1	0.97016
0.71399	0.97016	1

Table 5. Eigenvalues and information contents

Eigenvalues	2.5726	0.40027	0.027095
Information contents(%)	84.254	99.097	100

In analyzing the results, we can say that more than 99% percent of the original information content is preserved among only the two eigenvalue components that were used for data representation. To see the MDC classification performance, the 61 vehicles were converted into two-dimensional space as plotted in Fig. 6

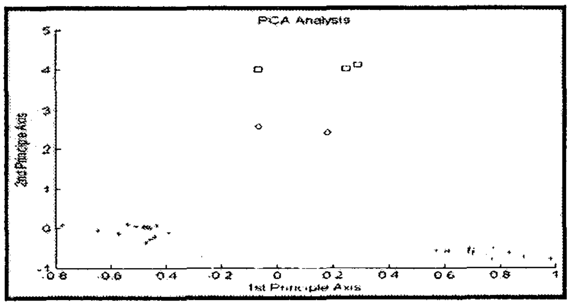

Fig 6. Vehicle distribution in the two dimensional feature space, three-parameter data

5. Results

The air-photo was contemporarily obtained with the LiDAR DATA. So, we used the air-photo as the reference data set. In the air-photo, 14 vehicles in the upper lane were recognized, and we could determine the vehicle groups. The used air-photo is as below :

Fig 7. Reference Image

As you see in Table 6, both of the two cases showed good results, and height information was enough to classify the vehicle types. According the PCA analysis results, we could see that the height information had a certain pattern representing the vehicles. But we found a flaw in the results. In the reference data set, Vehicle No. 15 was a bongo and No. 17 was a truck (small size : full loaded), but they were recognized as falling under the same group due to their similar height information. And the result of classification is variable depending on the determined the types of vehicles by user

Table 6. Result of Classification

Vehicle Number	Ref group	Raw-3p	PCA-3p
1	3	3	3
3	4	4	4
4	1	1	1
6	1	1	1
9	5	5	5
10	1	1	1
11	3	3	3
13	1	1	1
14	1	1	1
15	7	7	7
17	7	7	7
18	1	1	1
19	4	4	4
21	4	4	4

6. Conclusion and Future Work

From this study, we were able to make the following conclusions. First, we proved that is possible to classifiy the vehicles that is one of the factors for determining LOS in traffic flow using the LiDAR DATA. In the state of the density of point figure (5.17 point/㎡), the length and width information are not proper variables for classifying the types of vehicles and only the height information can be used. We would be able to expect better classification performance if the point of density figure was much higher.. Second, because the result of classification is a variable dependent on several types and conditions of vehicles, many of the user's experience are needed for determining the vehicle types.

In the future, we plan to conduct a study on the extracting of the various factors required for obtaining vehicle count per lane and vehicles' velocity for determining the LOS in traffic flow. And research is demended for the appropriate density of point will be performed when utilizing five parameter for representing and classifying vehicles.

Acknowledgement

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