TEXTURE-BASED LIDAR GRAY IMAGE SEGMENTATION USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT:

Using artificial neural network，a synthetical image derived from light and ranging data was segmented based on the height texture and intensity texture measure. Focusing on a coastal area near ZhuHai city, south of china, land covers have been identified and segmented in a gray image. The approach used LiDAR points to generate a DEM and DSM, returns intensity was transform to gray image, and ground roughness index was calculated to indicate land cover character. Five texture feature including mean, entropy, various, second moment and homogeneity texture have been measured, and then sequentially been used to segmented land cover into five class: cropland, bare land, water body, man-made constructions and sparse tree land. Comparing with the result from spectral image, there have over average 87% pixels coincide with LiDAR image classification result.

1. INTRODUCTION

LiDAR (Light Detection And Ranging) is an active optical remote sensing system that generally uses near-infrared laser light to measure the range from the sensor to a target. LiDAR can be used to fast identify the elevation of the ground as well as earth surface. LiDAR data have been recently used in several applications such as DEM generation，3D urban regain modeling，objects automatic detection.

Texture of LiDAR gray image is qualitatively and quantitatively defined by height, variation of height in local windows and measures. When a small-area patch has a wide variation of gray level primitives, the dominant property is texture. Maas (1999) has used height texture for segmentation of LiDAR data. Filin (2002) has proposed a surface clustering technique for identifying regions in LiDAR data that exhibit homogeneity in a certain feature space consisting of position, tangent plane and relative height difference attributes for every point. Most of the previous work on classification of aerial LiDAR data has concentrated on unsupervised clustering on a smaller number of classes often resulting in coarse classification while a few have attempted parametric classification with or without segmentation. In recent years，a site of new texture characters were presented in order to adapt the LiDAR height image and special land cover survey. And a site of intelligent algorithms has been used to interpretation the LiDAR image such machine learn, decide tree and Artificial Neural network. Dimitrios C (2007）presents an advanced multi-scale and textural features algorithm for object identification. Poonam S.（2008）Use machine learn(ML) classification measured LiDAR Height Texture, and objects like buildings, single trees, and roads were recognized. Machine Learn(ML) classification was used to process High-Posting-Density LiDAR Data and identify the ground object land cover classification（Jungho I, 2008）. Previous researches demonstrate the advantage of LiDAR height texture in LiDAR data interpretation. And LiDAR height texture could be used effectively in LiDAR gray Image segmentation, land cover identification, target identification and other applications. In these researches, grey images were derived from LiDAR points cloud as surface or band such as digital elevation model (DEM), digital surface model (DSM). Texture measures were carried out in every single surface and subsequently were used to object identify or land cover classification. Because height texture is hypsography map based, the result of classification come from height texture was hardly compared with the classification result from spectral or optics image. Therefore, this model was usually used to special ground object identification such as buildings, road, and trees. There were difficulties in extending this model to globe segmentation or complex classification.

The study presented is focus on the segmentation of LiDAR gray image using height texture measures. 5 height texture measures and intension texture measures of LiDAR reflection were discussed and used to define the segmentation rule. Height texture measures used in this paper include mean texture, various texture, second moment texture, entropy texture, homogeneity texture. These texture measures are used as bands. An artificial neural network was trained by ground samples. Training data was collected from these texture measures image. And then, the LiDAR height gray image was segmented by trained neural network. 5 different land cover could be identified, including water body, man-made construction area, high trees, bare land and meadow. Finally, future work and extensions of the proposed technique were discussed.

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2. METHODOLOGY

2.1 Study area

In this study, we focusing on a 3.5km2 coastal site closed ZhuHai city, south of china. Study area is local in a fame belt with in general less 2 degree terrain variance. A small village is in northwest corner of study area. There have 5 land cover classes in study area including: cropland which with dwarf shrubbery or crops, bare land or bare cropland, water body which are several ponds and a creek, man-made constructions and sparse tree land.

2.2 Data process

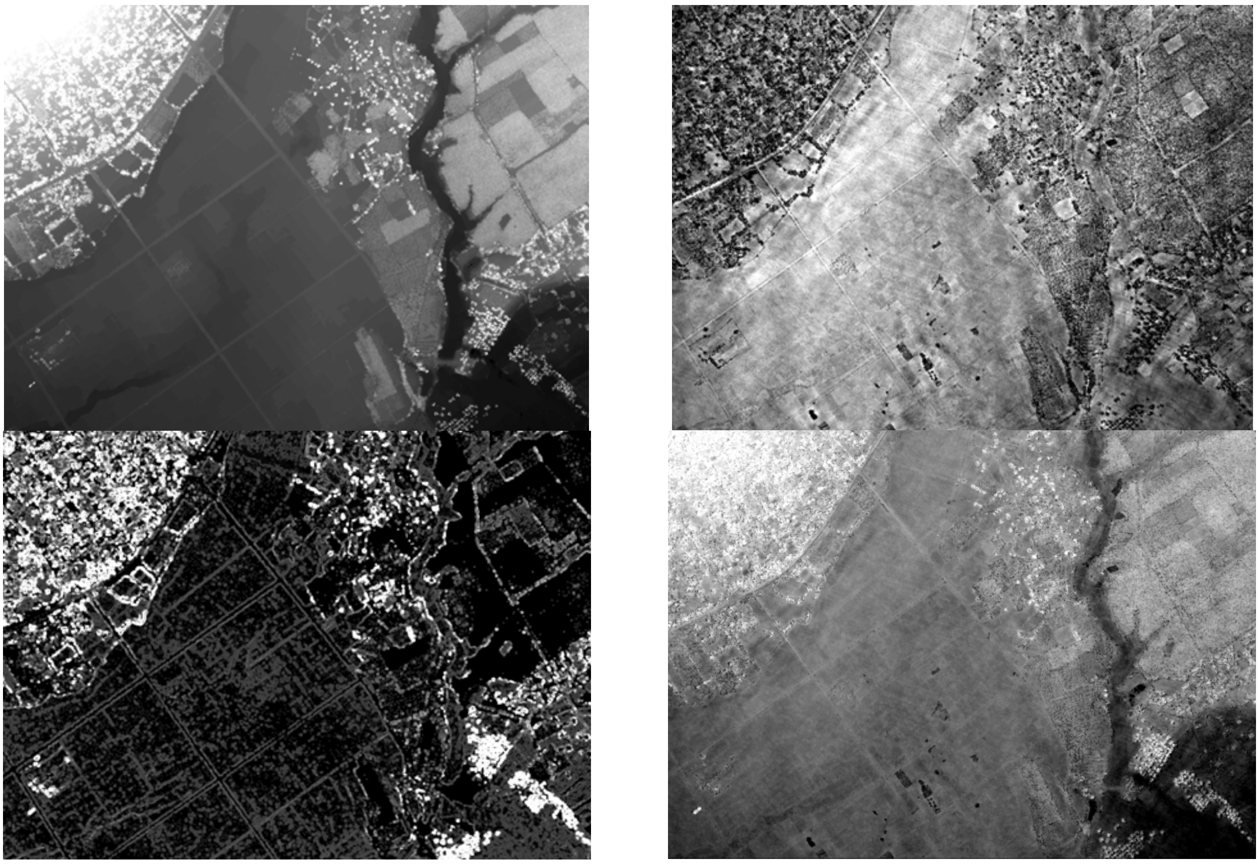
LiDAR data were collected on November 14, 2006 using Leica Airborne Laser Scanner 50 sensor. The LiDAR operated within the near-infrared spectrum and average distance sampling among footprint was approximately 23 cm. Data were acquired flying in an east–west direction at a nominal altitude of 1200m. The collected points cloud have approximately 700,000 points with first return recode. Coordinates were provided with an absolute accuracy of < 0.8 m in the x and y directions and < 0.15 m in the z direction. Intensity of return was recorded as 10 grades also. Using TerraSolide's TerraScan software, LiDAR points were split into two parts: ground points and other class points by slope threshold at 2 degree iteration angle. DEM surface and DSM surface were generated from ground points and whole the points with 0.8m grid. In order to indicate the relative roughness of land cover, the index of high roughness (C_p) was calculated as follow by the area ratio of the two surfaces:

$$C_p = \frac{\sum_n S_{idsm}}{\sum_n S_{idem}} \qquad (1)$$

Where, S_{idsm}, S_{idem} = surface area of cell i .
n = the number of cell i's neighbor.

Using TerraSolide's TerraScan software, 3 grey image were derived from LiDAR points with 0.8m*0.8m resolution: intensity grey image, roughness index image and elevation gray image (Hodgson, 2005). Subsequently, they were stretched to full gray scale and demonstrated as figure 1.

Showing as figure 1(a,b,c), same land cover could have different character in these image. And it could be a cue of classification. Layer stack operation was executed on the three images and then merged into one gray image with different weight (Hodgson,1999). Figure.1(d) is the merged image with weight of 0.5, -0.5and 1.0 on height surface, roughness index image and intensity image.



a. elevation b. returns intensity
b. roughness index d. merged image

Figure 1. Grey images derived from LiDAR points

2.3 Work flow

Figure 2 show the flow diagram of the methodology used in the study. A total of three surfaces were merged into an synthesize image and being used to measure the texture. Five texture images were extracted for ANN land cover segmentation. Details are described in the following sections.

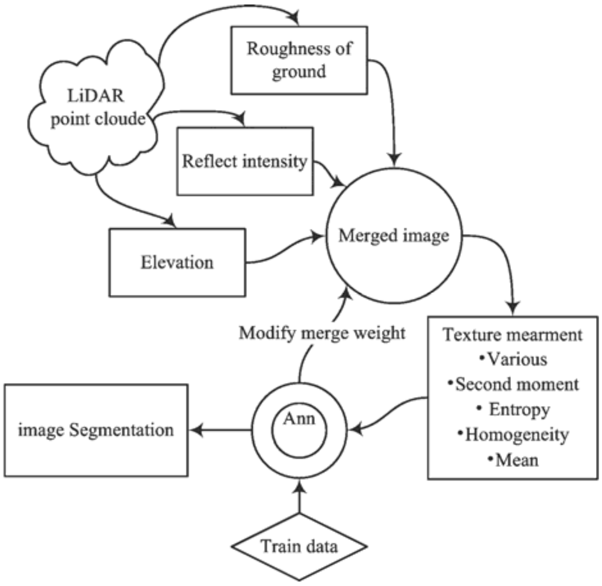


Figure 2. Work flow of study

2.4 Texture measure

Texture measure

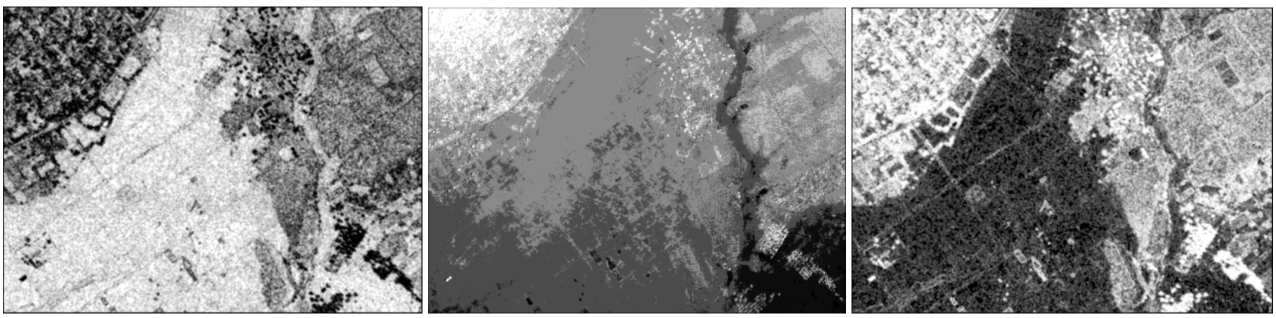
Texture used in this study is based on brightness value spatial-dependency grey-level co-occurrence matrices (GLCM). GLCM is a probability matrices of pixel grey levels occur in a scene. The GLCM texture transformations have been widely used in image segmentation, object identification. The four GLCM textures (homogeneity, height, entropy, and second moment) and mean texture were measured as material of ANN classification.

Texture measure methodologies used in the study are arranged in the tab.1.

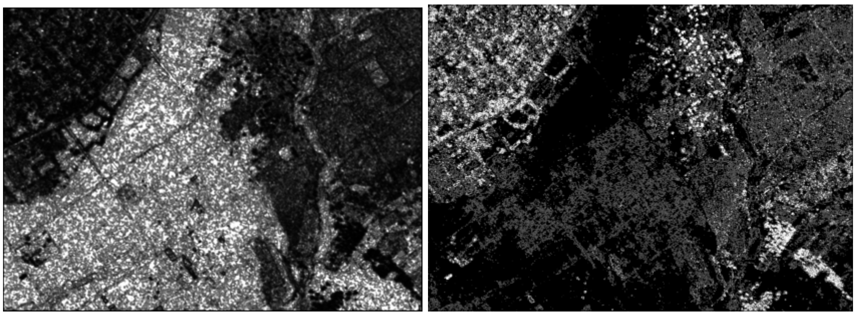
Where *p(n)* = the DN value of pixel,
n = the number of neighbour pixels:

Metric	Equation	Description
Various	$V=\frac{\sum(p(n)-M)^2}{n-1}$	*M* = mean DN value of moving window
Second moment	$ASM=\sum_n[p(n)]^2$	------
Entropy	$E=-\sum_n p(n)\lg p(n)$	------
Mean	$E=\frac{\sum_n p(n)}{n}$	The mean DN value of detect window
Homogeneity	$H=\sum_n\left(\left(\frac{1}{1+(i-j)^2}\right)\frac{p(n)}{\sum_n p(n)}\right)$	*i,j* = the number of rows or columns.

Table.1 Texture measure methodologies



a. Entropy b. Mean c. Homogeneity



d. Second moment e. Variance

Figure 3. Texture measure

2.5 ANN training and classification

Artificial neural networks (ANNs) are a functional abstraction of the biologic neural structures of the central nervous system. Artificial Neural networks（ANNs）are trainable architecture and are operated as black-box, model-free, and adaptive tools for learning knowledge form the sample-training. They are powerful pattern recognizers and classifiers. Using neural network, the detection rule of objective can be derived from high-dimensional Feature Space. During the past decade, ANNs have been wildly used in remote sensing applications, especially focusing on image classification (Minh, 2005).

A three-layer ANNS was constructed with 5 input nerve cells coincide with 5 texture feature, 5 output nerve cells for 5 land cover classes and 3 hidden nerve cells. Back Propagation Algorithm was used to search optimize classification parameter. 800 pixels were sampled from known ground class regions, 500 pixels of them input into ANN as training data, another 300 pixels were used as test data. After 1200 training iterations, ANN reached convergence conditions and the classification accuracy of after training for test data is 94%.

Figure 4 shows the classification result of ANN for whole study area. 5 land cover class can be identified obviously. However, there still have classification errors found by visual inspection, most of the errors were along the boundaries between land cover classes, such as the boundary between a building and trees. Besides that, because the height of road has similar high value and return intensity with crop land or bare land (shown as fig.1 a, c), most of road are not segmented into man-made constructions. Trees and buildings are well segmented by texture measure though they have similar height in most of study area. Sparse grasses distribute alone the creek, and the land cover there was recognized as bare cropland. Streamlet with shallow and slight shape water cannot be identified entirely because this kind of patch is slight and cannot fill in the texture measure windows and cannot be detected. (Raber, 2007)

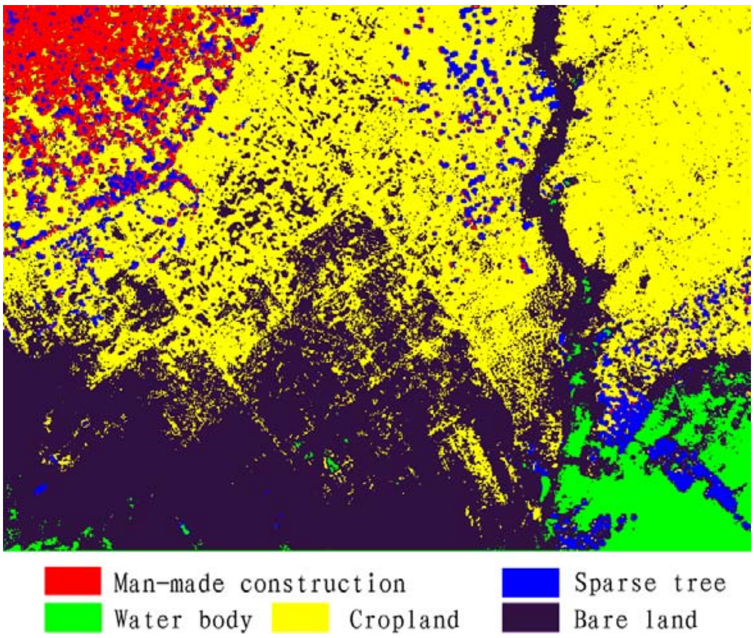


Figure 4. Result of segmentation

3. RESULTS AND DISCUSSION

3.1 Results

Experiment above shows that the gray image integrated intensity, height and ground roughness information can be used effectively to classify land cover. And the approach of using ANN to recognize texture measures of the merged image is helpful in image segmentation.

We also executed land cover identification and segmented image on the same region spectral image collected by ALOS AVN IR2 and PR IS M_PAN sensor, almost a month later than data of LiDAR points collected. ALOS images have different spatial resolutions and different dynamic ranges of pixel values with LiDAR image. ALOS merged image was re-sampled to 0.8m resolution using an averaging algorithm. NDVI was calculated and was used to classify the land cover. 500 same pixels were sampled from LiDAR and ALOS images randomly. Because multi- spectral image hardly recognize the height of vegetation, the classes of bare land (with sparse grasses), tree and cropland were combined as vegetation. Comparing with the result from spectral image, there have over average 87% pixels coincide with LiDAR image classification result. Error matrixes of classification were demonstrated in table 2.

spectrum imag / LiDAR image	Man-made construction	Vegetation	Water body	Total Errors （%）
Man-made construction	105	8	0	7.76
Vegetation	45	287	16	17.58
Water body	0	3	46	6.12

Table 2． Error matrix of classification

3.2 Discussion

Height gray image combining with intensity information derived form LiDAR points cloud have capacity to recognize the land cover type. Height texture is the statistics of elevation feature, and ANN is one of effective approaches to identify the type of land objects or covers from height textures which depend on objects relative height difference. The bigger difference of relative height between surfaces, the easier identification the land objects are, such as the buildings, single tree and ditch or bank. The approach presented in this paper can be used not only in single LiDAR data source but also in combining texture data such as height texture together with optical texture. Future research will include finding suitable texture model of LiDAR height image and applications of the method to more complex ground environments.

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