A NOVEL METHOD FOR ROAD DETECTION USING HIGH RESOLUTION SATELLITE IMAGES AND LIDAR DATA BASED ON ONE CLASS SVM AND LBP FEATURES

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Abstract
Now a days, fast extraction of road network is a challenging task especially in urban areas where roads are covered by height objects like trees, buildings, parking lots, vehicles etc. Imagery, especially high resolution image is main source for road detection as it contains rich texture and spectral information. This paper proposes a method based on merging of features of high resolution satellite images and their corresponding lidar data. The intensity of Lidar point cloud data can be used as an additional feature for road extraction as road surfaces have similar reflectance. Lidar data which has LAS 1.1 format has been taken corresponding to the high resolution satellite image. Local binary pattern is the feature extraction method used to extract features of the data. The merged features of these two undergo a one class SVM classification to increase the accuracy. The overall accuracy and kappa coefficient of the proposed method were 95.05% and 0.88 respectively. The results confirmed that this method has potential for detecting roads in urban areas using high resolution images and lidar data.
Index terms: Lidar data, one class SVM, HRSI, LAS format.

I. INTRODUCTION

Satellite images with high spatial resolution such as those obtained using IKONOS-2, GEO EYE-1 and WORLDVIEW-2 enable superior detection of objects. Roads are one of the most important classes of topographic features and are attracted much research into their automatic detection to make database updated. In particular, the building class typically found in land cover classes produces several problems for high spatial resolution images. The road network is much useful in updating of maps in geospatial information systems(GIS), transportation and urban planning. During the last three decades, much prominent research has been done which led to many algorithms. Methods based on neural networks, texture analysis, fuzzy clustering and genetic algorithms (M.Mokhtarzade, M.J.valadan zoej, H.ebadi 2008), method based on level set and mean shift method (M.Rajeshwari, K.S.Gurumurthy 2011), method based on artificial neural network (Kirthika.A, Mookanbiga.A 2011), method to improve accuracy based on the output level fusion of high resolution satellite image and airborne lidar data in urban area (Yongmin kim and Yongil kim 2013) and also methods based on removal of non-linear noise segments using median filters (V Parthasarathi et al.). methods based on road network extraction from high resolution satellite images based on object oriented techniques (M. Kumar, R.K.singh 2014). Study of areal features which include shore line mapping, boundary delineation and change detection by O.Sharma et al 2010).The classification process by using a local binary pattern to determine the spatial characteristics of an image is done. However, additional information of point cloud data is also used in classification. Recently, an alternative solution has been introduced by fusing images and lidar data. Fusing different types of data prove effective when one data type provides an advantage during process and extraction of buildings in lidar data provide high level of accuracy than extraction from images. The height information is obtained from lidar data which was occupied as an additional band to improve detection and classification accuracy. A feature is an detail layer generated from an operation that merges spectral and spatial characteristics of the actual image, such as normalized difference vegetation index(NDVI), principal components and textural attributes. Feature-level fusion has been employed to enhance the seperability between vegetation and nonvegetation, buildings, and roads and among different tree species by integrating features derived from optical images and airborne LiDAR data when analysing spectrally similar objects. This study aimed to improve the classification accuracy of satellite images with high spatial resolution by minimizing the misclassification of building classes. Our method is based on a simple output-level fusion of satellite images with LiDAR data derived from urban environments. The methodology and experimental site used in our study are described and Finally, we apply our algorithm to a HRSI image and LiDAR data prior to assessing our results using a confusion matrix.

II. Methodology

The proposed method involves many steps in which the lidar data in the form of LAS 1.1 format has been taken for the corresponding satellite image of resolution 1m. Digital surface model DSM has been undergone with the lidar data in order to estimate the height information and can be extracted from the high resolution satellite image. Features that are extracted from local binary pattern for both lidar data and satellite image are merged together to undergo classification method. One class SVM also called binary class support vector machine in which two classes as features are taken and confusion matrix has been obtained to calculate the accuracy. The two features in one class SVM are taken as test data and training data. The road detection feature has been done by making roads as +1 in the satellite image and -1 for the remaining obstacles present in the original image. Many methods have been used for detection of roads but this paper contains lidar data features and textural features which provide a great accuracy for detecting and classification.

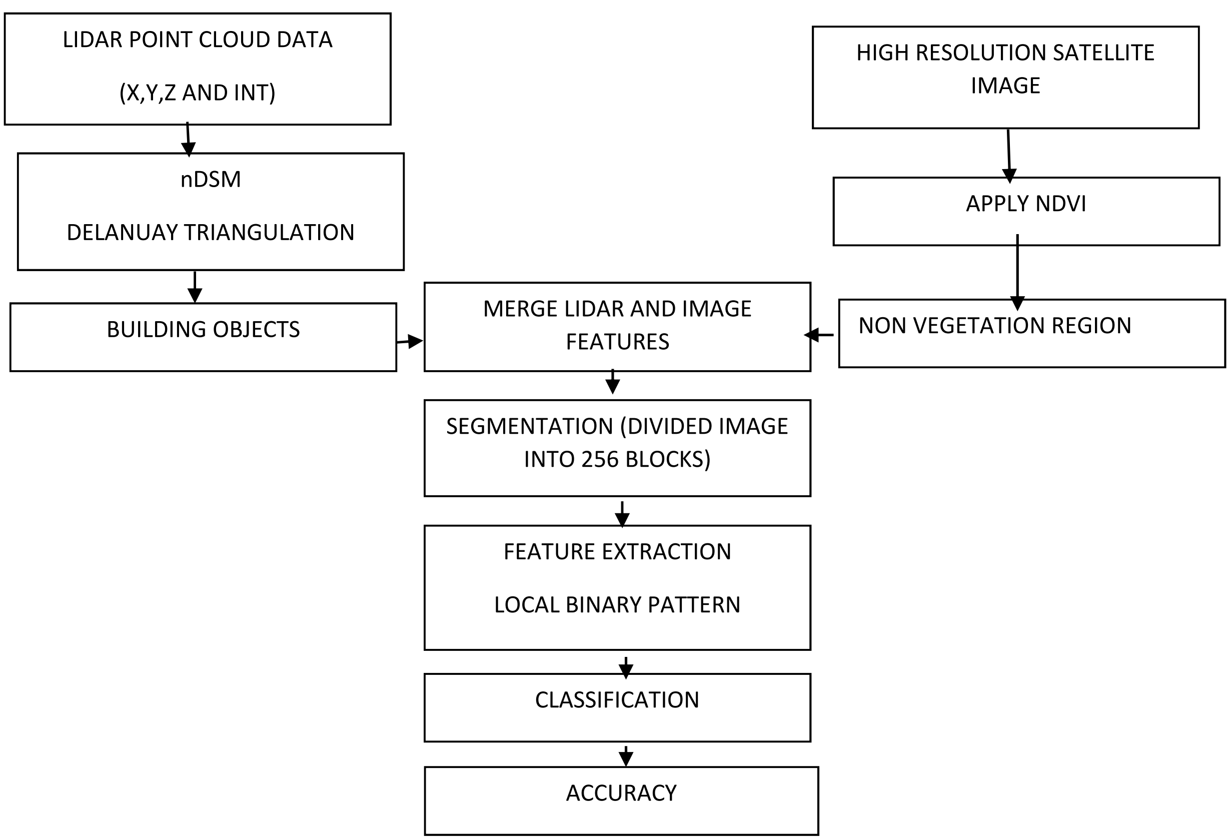


Fig. 1: Flow chart for improvement of classification accuracy

Figure 1 illustrates the workflow of the integrated processing for road feature extraction from urban environment. Our methodology is comprised of 3 main components. First, building objects are detected from lidar data using digital elevation model. Second, NDVI applied to High resolution satellite image in order to detect vegetation in the area. Third, an image of roads is taken which can be done by using ERDAS imagine 9.2 to make roads=1 and non roads= -1. Now, segmentation process is done using local binary pattern in which feature extraction is done and the last step is a supervised classification is conducted through this integrated method using a one class SVM classification.

A. Building object detection using lidar data:

The 3 D point cloud data (x, y, z) which has been read by LAS 1.1 format undergoes a delanuay triangulation. Point cloud data contains x, y and z values along with the return number, Delaunay triangulation is used to determine the density or intensity of points.

Number of points recorded: 8502

Number of points by return 1: 8308

Number of points by return 2: 188

Number of points by return 3: 6

Number of points by return 4: 0

x	y	z
Scale factor	Scale factor	Scale factor
0.001	0.001	0.001

B. Vegetation detection from HRSI:

The normalized difference vegetation index (**NDVI**) is a graphical indicator which is used to analyze remote sensing measurements, typically but not necessarily from a space platform, and assess whether the target that is going to be observed contains live green vegetation or not.

NDVI= (NIR-Red) / (NIR + Red)

For vegetation to be removed from HRSI image subtract the NDVI from the original image.

C. IMAGE SEGMENTATION:

The division of an image into regions or categories, which correspond to different objects or parts of objects is called as the image segmentation. Each pixel in an image is assigned to one of the number of these categories. A good segmentation is the one which gives similar grey scale multivariate values to form a connected region and other pixels which are in different categories have dissimilar values. Image segmentation is done in order to calculate the features of an image.

D. FEATURE EXTRACTION

Local Binary Pattern (LBP) is a simple and a very efficient texture operator which labels the pixels of an image by thresholding the neighbourhood of each pixel and considers the result as a binary number. Divide the examined window into cells. For each pixel in a cell, compare the pixel to each of its 8 neighbours. Where the center pixel's value is greater than the neighbor's value, write "0". Otherwise, write "1". This gives an 8-digit binary number. Compute the histogram, over the cell, of the frequency of each "number" occurring. This histogram can be seen as a 256- dimensional feature vector. Optionally normalize the histogram. Concatenate (normalized) histograms of all cells. This gives a feature vector for the entire window. Histogram of local binary pattern:

$$Hi = \sum I\{f(x,y) = i\} i = 0, \dots\dots, n-1 \quad (1)$$

Normalization of histograms:

$$Ni = Hi / \sum_{j=0}^{n-1} Hj \quad (2)$$

E. Merging of lidar data and HRSI

The features of the lidar data and also the features of the HRSI image after detection of buildings and vegetation provide the data without buildings and vegetation region. So, that the detection of roads will be little simple.

F. CLASSIFICATION

One class SVM: Many classification problems try to solve the two or multi-class situation. The target of the machine learning application is to recognize test data between a number of classes, using training data that basically separates all the data points from the origin and maximizes the distance from this hyperplane to the origin. The result is the binary function which apprehends regions in the input space where the probability density of the data lives. Thus the function returns +1 in a small region (capturing the training data points) and −1 elsewhere.

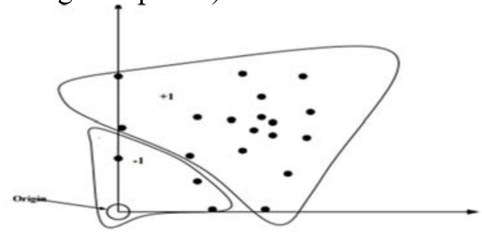


Fig:1 One-Class SVM Classifier. The origin is the only original member of the second class.

Minimization function:

$$\min_{\omega,\xi,p} \frac{1}{2}\left|\left|\omega\right|\right| + \frac{1}{vn}\sum_{i=1}^{n} \xi - p \qquad (3)$$

Here it is the parameter ν that characterizes the solution;

1. It sets an upper bound on the fraction of outliers (training examples regarded out-of-class) and,
2. It is a lower bound on the number of training examples used as Support Vector.

Again by using Lagrange techniques and using a kernel function for the dot-product calculations, the decision function becomes:

$$f(x) = sgn\left(\left(\omega.\phi(xi)\right) - p\right.$$
$$= sgn\left(\sum_{i=1}^{n} \alpha i\, K(x, xi) - p\right. \quad (4)$$

Kernel function: Kernel methods are a class of algorithms which are used for pattern analysis, whose best known member is the support vector machine (SVM). This approximation is called the "kernel trick". Kernel functions have been found for sequence data, graphs, text, images, as well as vectors.

$$K(x, \acute{x}) = \exp\left(-\frac{||x-\acute{x}||2}{2\sigma 2}\right. \qquad (5)$$

III. RESULTS

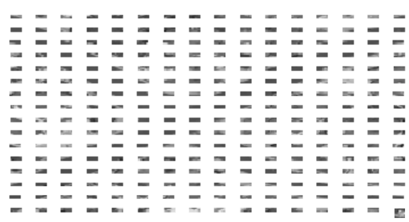
INPUT IMAGE: Dataset Name: 2005 San Diego Urban Region Lidar.

Dataset Short Name: SAN2005

DOI: 10.5069/G9XW4GQ0

Grayscale image:

Divided into 256 blocks:



LIDAR DATA :

Visualization:

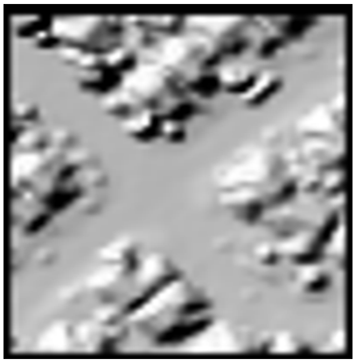
Images & Google Earth KML: Yes

Altitude of Light: 45

Azimuth of Light: 315

Resolution: 1m

Max Triangle Size: 50



Final confusion matrix:

Finalconfmat =

494	18
20	236

Thresholding output:

Image overlaying:

IV. CONCLUSION

In this paper, an approach to detect road and a method for improving classification accuracy based on the merging of high-resolution satellite images and LiDAR data. The proposed method consists of output level fusion which minimizes the misclassification of buildings and road objects. The proposed method gives an accuracy of 95.05% and a kappa value of 0.88 by one class SVM classification. In future studies, we can focus on reducing the misclassification of other objects such as shadow and water. Misclassification problems may be partially resolved through the use of 3-D characterisics of bulding segments.

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