Automatic Extraction of Roads Using Local Directional Pattern

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Abstract—**This paper proposes a method for Road Network Extraction from High Resolution Satellite using LDP (Local Directional Pattern). The main problem in extracting roads from other objects is spectral reflectance. LDP feature is obtained by computing the edge response values in all eight directions at each pixel position and generating a code from the relative strength magnitude. This paper utilizes the transformed image obtained from local direction pattern descriptor. The Hough Transformation provides improved results on straight lines extraction. Finally, the post processing is required to detect the roads by combining the LDP values and the hough lines with highest accuracy.**

Keywords—Local Directional Pattern; Hough transformation;Hough lines

I. INTRODUCTION

In the last few decades, road extraction plays a very important role in vehicle navigation system, urban planning, disaster management system and traffic management system. To date, numerous methods have been reported for the extraction of road features from space imagery. In the early method of satellite image analysis, the classification was mainly based on spectrum information. But now, information like texture and shape are being used to classify and extract the object more accurately from HRS image [1]. Moreover, how to extract the roads accurately has always been a challenging and complex topic [2]. The road network extraction using a probabilistic framework, consists of three phases: probabilistic road centre detection, road shape extraction, and graph-theory based road network formation [3]. Road networks detection and extraction, based on the combination of perceptual grouping theory (Gabor filtering, tensor voting) and optimized segmentation [4]. A stereoscopic aerial images is using in object space to extract roads in rural areas, particle filtering and extended Kalman Roads' patterns are complex in high resolution images. Normally, road's geometry feature, radiation feature, topology feature, contextual feature are used for road extraction [5].

Airborne LIDAR (Light Detection And Ranging) is a relatively new data acquisition system complementary to traditional remote sensing technologies. LIDAR data contains plenty of scene information, from which most ground features such as roads and buildings are discernible. Roads have homogeneous reflectivity in LIDAR intensity and the same height as bare surface in elevation. LIDAR range data is able to improve the analysis of optical images for detecting roads in urban areas [6].

In cases when shadows or buildings occluded road segments, their shape can be well detected due to the height information. LIDAR intensity data has good separability if the wavelength of the laser is suitable[7].

The methods discussed above are quite difficult and the processing time is too high. This paper presents a new system of road extraction from high resolution image in urban areas. This system is based on the application of the Hough transformation method and Local Directional Pattern descriptor to detect the road located on the image.

II. METHODOLOGY

The whole work is divided into four steps. Initially, the edges are detected from the High Resolution Satellite Image using canny edge detection method. Next, the hough transform is applied to detect straight lines on the image. In the third step, the LDP and hough transformation are combined and filtering is done to remove the unwanted lines and to detect the roads in the HR image.

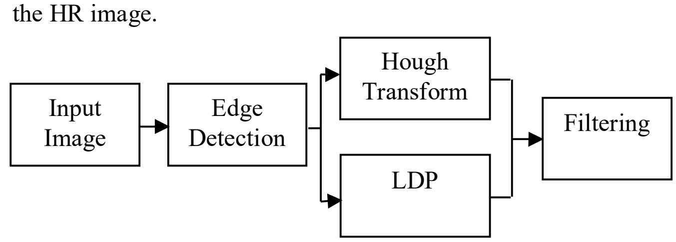


Fig.1. Methodology of the proposed system

A. Edge Detection

Canny's edge detection algorithm is well known as the optimal edge detection method, based on three main principles [8]:

a) Low error rate: Good detection with only existent edges.
b) Good localization: The distance between detected edge pixels and real edge pixels have to be minimized.

Canny's edge detection algorithm has been used in this phase to delineate objects in the image. It detects the contours from the derivate method based on the gradient. Due to the resolution of high spatial resolution satellite imagery, edge detectors may not work properly to detect road edges. They can also detect very small noisy terms in the image. These redundant edges may give rise to false alarms and increase the complexity of the problem. To address this problem, a thinning algorithm based on contours is applied to reduce the contour points.

B. Hough Transformation

The Hough Transform (HT) is a robust method developed by Paul Hough [8], to find straight lines, circles or ellipses. HT is employed, when gathering the extracted edges into a structure (straight line) is not possible, due to the image criteria or the edge detection performance. It considers a collection of parameterized structure candidates. It then groups the image edges (extracted by canny edge detector) into an appropriate structure candidate through a voting procedure. Each line is defined by the slope parameter α and the y-intercept parameter b, $y = \alpha x + b$. Hessen normal form of the line is suggested in [9] as the following,

$$\rho = x \cos(\theta) + y \sin(\theta) \qquad (1)$$

where ρ is the distance of the line from origin, and θ is the angle between the x-axis and the line's normal vector which passes through origin ($\theta \in [-2\pi, 2\pi]$). Using this equation, any point in the x-y space is equal to a sinusoidal curve in ρ-θ space. To detect the existing straight lines, Hough transform look at the two parameters (ρ and θ), and for each parameter considers a bin in a histogram. Then for every pixel, it tries to find evidences of a straight line and assign it to one of the histogram bins. After that, the bins with higher values are selected as the parameters of the existing straight lines. Finally, depending on the line lengths, the lines are localized in the image.

C. Local Directional Pattern

The LDP descriptor is an eight bit binary code assigned to each pixel of an input image that can be calculated by comparing the relative edge response value of a pixel in different directions. So that eight directional edge response values $\{m_i\}$, i=0,1,2,….7 of a particular pixel are computed using Kirsch masks in eight different orientations M_i centered on its own position. These Kirsch masks are shown in the Figure 1, and Figure 2 shows eight directional edge response positions and LDP binary bit positions. Because different importance of the response values, the k most prominent directions are considered to generate the LDP. So the top k values $\{m_j\}$ are set to 1, and the other positions are set to 0.

$$\begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix} \quad \begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}$$

East M_o North East M_1 North M_2 North West M_3

$$\begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix} \quad \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix} \quad \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix}$$

West M_4 South West M_5 South M_6 South East M_7

Fig.2.Krisch edge response masks in eight directions

To compute LDP, we calculate the principal directional numbers of the neighborhood using the Kirsch compass masks [18] in eight different directions. We define our directional number as

$$D^1_{dir} = \arg\max[\, I_i \mid 0 \le i \le 7\,] \qquad (2)$$

where D^1_{dir} is the principal directional number. I_i is the absolute response of the convolution of the image I, with the i[th] kirsch compass mask, M_i defined by

$$I_i = |I * M_i| \qquad (3)$$

Thus, we compute the absolute value of the eight kirsch mask's responses [M_0……M_7], applied to a particular pixel. More precisely, we take the two greatest responses, D^1_{dir} and D^2_{dir} .Therefore, the second directional number, D^2_{dir} is computed in the same way, with the difference that we take the maximum response in Eq.(1) instead. These directions signal the principal axis of the local texture. In each directions we compute the intensity difference of the opposed pixels in the neighborhood. That is

$$d_n^{(x,y)} = I(AD^n_{dir} + BD^n_{dir}) - I(AD^n_{dir} - BD^n_{dir}) \quad (4)$$

Where d_n is the n[th] difference for the pixel(x,y) in the n[th] principal direction, I($AD^n_{dir+} BD^n_{dir+}$) corresponds to the intensity value of the pixel I(AD^n_{dir+}, BD^n_{dir+}), which is the next pixel in the given principal direction and I(AD^n_{dir-}, BD^n_{dir-}) is the intensity value of the pixel (AD^n_{dir-}, BD^n_{dir-}), which is the previous pixel in the given principal direction. Figure 2 shows an example of LDP code with k=3.

85	32	26
53	50	10
60	38	45

313	97	503
537	X	399
161	97	303

Fig. 3. Example of an LDP code

D. LDP Pattern

After encoding an image with the LDP operator we get an encoded image I_L. We use k=3 which generates 56 distinct values in our encoded image. So histogram H of this LDP labeled image $I_L(x, y)$ is a 56 bin histogram and can be defined

$$H_i = \sum_{x,y} P(I_L(x,y) = C_i), C_i = i^{th}\ LDPpattern \quad (0 \le i < 56)$$

where $p(A)= \begin{cases} 1, ifA\ isTrue \\ 0, ifAisfalse \end{cases}$ (5)

E. Combination of LDP and Hough Transformation

After the application of Hough Transformation and Local Direction Pattern on the High Resolution satellite images separately, the obtained results are still not significant. We have to determine hypothesis to operate and enhance these results. Based on the assumption that the road is uniform, means all the pixels which belong to the same road have approximately the same value of the LDP (texture), and these values are different starting from the edges of the road to inner surface of the road. We take the lines obtained by Hough transformation which have similar values of LDP (According to our hypothesis these lines corresponds to roads), we combine and compare the resultant image of LDP descriptor and the resultant image of Hough Transformation.

In the beginning of our simulation, we take two points randomly from the straight line P (x, y, Vp), and Q (x, y ,Vq). Where Vp and Vq represent the value of LDP descriptor. Around each of these two selected points, we choose a window of 5*5. Our assumption of uniformity specifies that descriptor should be the same for all the straight line points. To verify and validate the effectiveness of our approach, we tested the values of LDP descriptor for each points belonging to the window of the two selected points. If the LDP values are uniform (almost the same values of LDP) in at least one perpendicular direction to the detected straight line P (x, y, Vp) = Q (x, y, Vq). So the points are belonging to a road. If the uniformity of the selected points is not on the right, or left of the selected points, P (x, y, Vp) ≠ Q (x, y ,Vq) then the straight line not represent a road, it is another similar object, which will be eliminated by a filter.

III. Experimental Results and discussions

In this study, the test data 1 is taken from the google images with high resolution. The test data 2 is a panchromatic image taken from IRS satellite of 2.5 m resolution which shows the small portion in the Madurai city. Test Data 3 is a multispectral image taken from CARTOSAT satellite of 0.5 m resolution in Madurai city.

The figure (a) shows different test area taken for our experiment. Figure (b) shows the lines extracted using Hough Transform. Figure (c) shows the texture feature extracted using LDP. Figure (d) shows the final extracted roads from the combination of LDP and Hough Transformation

The table below presents the result of our approach, applied on the High resolution satellite image. We have taken 50, 10 and 30 roads in test area 1, test area2 and test area3. After the application of Hough transformation 86 straight lines are obtained, which are higher values due to the number of similar objects on the resultant image in test area 1. However, after applying our approach we found 40 roads in test area 1, which is an efficient result compared to the number of roads on the original image. We got a very important value of road detection rate on the high resolution satellite image, which reached 80%.

In test area 2, we have found 10 roads. After the application of hough transform nearly 25 lines are found. So, in order to extract the roads correctly, the LBP and Hough transformation are applied and combined. After the filtering process 8 roads are extracted. Similarly in test area 3, 30 roads are found. Out of 30 roads 27 roads are extracted. According to the relevant result, our approach is able to extract almost all roads found in the image. The proposed approach has been tested on several images.

TABLE 1 COMPARISON TABLE FOR TEST DATA 1

Methods	Total number of roads	No of roads classified correctly	No of roads misclassified	Accuracy
LBP	50	30	20	60%
LDP	50	40	10	80%

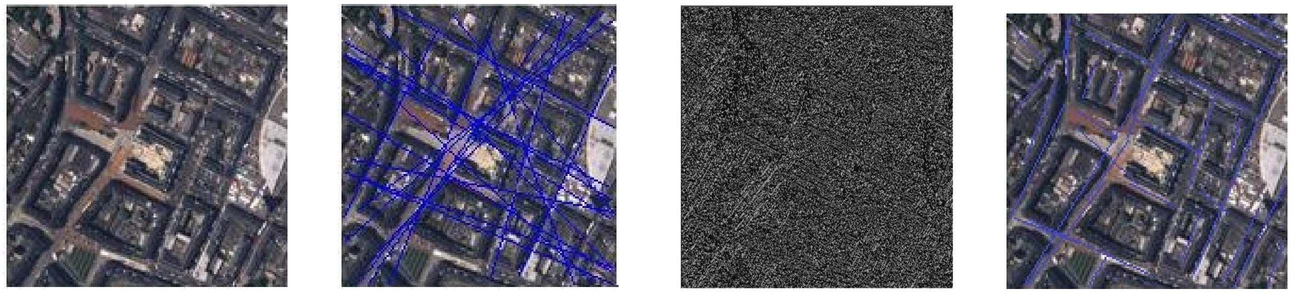
TABLE 2 COMPARISON TABLE FOR TEST DATA 2

Methods	Total number of roads	No of roads classified correctly	No of roads misclassified	Accuracy
LBP	10	5	5	50%
LDP	10	8	2	90%

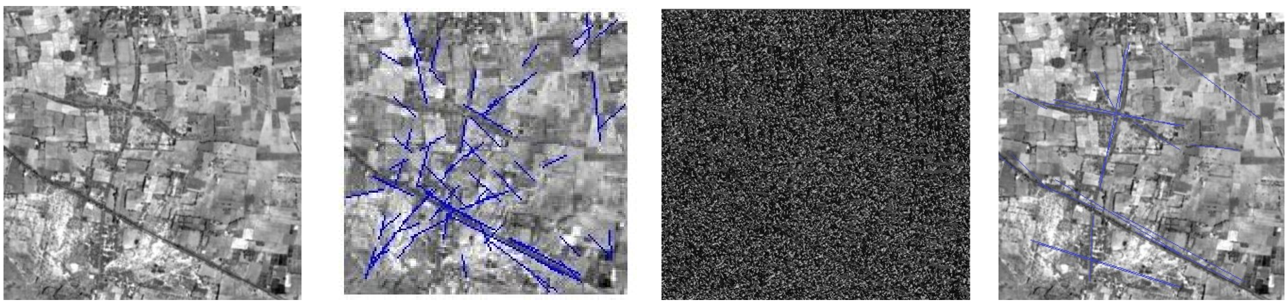
TABLE 3 COMPARISON TABLE FOR TEST DATA 3

Methods	Total number of roads	No of roads classified correctly	No of roads misclassified	Accuracy
LBP	30	18	12	60%
LDP	30	27	3	90%

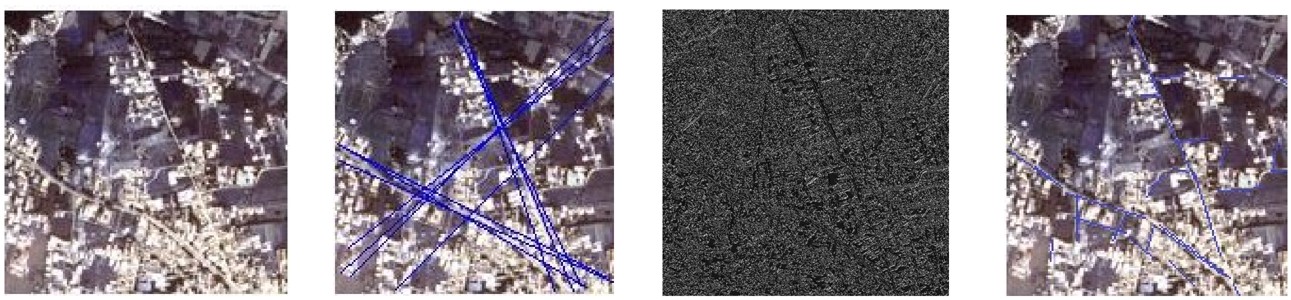
It's clear that it is able to correctly extract all the relevant roads in the image. The results also show the efficiency and the performance of our new approach based on the combination of LBP descriptor and Hough Transformation.



(a) Test area 1 (b) Hough Transformation (c) LDP (d) Extracted Roads



(a) Test area 2 (b) Hough Transformation (c) LDP (d) Extracted Roads



(a) Test area 3 (b) Hough Transformation (c) LDP (d) Extracted Roads

Fig 4. Extraction of roads with different test areas

IV. Conclusion

Our approach is developed to extracting roads from high resolution satellite images. Three stages are used to implement road extraction: edge detection, Hough Transformation, and LDP descriptor. Simulation results confirm the effectiveness of our work. The combination of Hough Transformation and the LDP operator has given efficient results reached 90% as rate detection. It has a great ability to extract the texture and better recognition accuracy. Our approach implementation is fast, robust and easy to understand. The Hough transformation is effective for detecting contours, which makes a major challenge to optimize the calculation time. As a future work, we intend to apply our approach to detect non-linear roads and to measure its performance.

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