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UNPAVED-ROAD EXTRACTION FROM SATELLITE IMAGES

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ABSTRACT: *This paper presents a technique for extraction of unpaved roads from high resolution satellite images. Sandy region candidates were obtained through thresholding of relevant colour space components from HSV and YC_BC_R. Logical combination of these candidates were performed to give the sandy region. Morphological operation (Dilation) was used to refine the sandy region, while Hough transform was used to extract road section from the whole sandy region. The developed algorithm was implemented in MatLab and tested with samples of satellite images acquired from Google Earth Map. Subjective (visual quality inspection) and objective parameters (Gap Statistics) were used for performance evaluation. The result shows that the new algorithm successfully extracts unpaved roads from satellite images. Areas of application includes security and surveillance systems, such as tracking of insurgents and kidnappers in tropical regions up to semi-arid regions.*

KEYWORDS: Unpaved Roads, Colour Space Models, Dilation, Hough Transform, Geographical Information System.

INTRODUCTION

Elements from satellite images such as roads, railroads, drainages, water bodies, vegetation and other curvilinear structures have been extracted through various techniques from satellite images (Wang J. and Zhang, Q., 2000) (Bong, Lai and Joseph, 2009) (Luo, J. Sheng. Y., Shen, Z., Li, J.,, 2010) (Mangala T Rajani and S.G. Bhirud, 2010) (Duong, 2012). Availability of a high resolution satellite images has given rise to extraction of road-networks and this has received much attention (I, 1986) (Quackenbush, 2004). Many applications ranging from transportation planning, traffic management, navigation systems, location-based services, and fleet management utilize digital road information.

Satellite images comprise of features such as colour, texture, shapes, edges, shadows and temporal details (Trinder, J.C. and Wang, Y., 1998) (Suetens, P. Fua, P., and Hanson, A.J., 1992). In order to extract desired elements from satellite images, most developed techniques make use of feature models that include the information relating to a range of characteristics that corresponds to the desired elements to be extracted. Road, water bodies, vegetation, and many others features have been successfully extracted from satellite images using feature extraction models (Suetens, P. Fua, P., and Hanson, A.J., 1992) (Bong, Lai and Joseph, 2009) (Yan Li and Ronald Briggs, 2009).

Network of paved roads can be visibly seen in high resolution satellite images, which makes paved road extraction an easy task. However, little or no emphasis has been laid on the extraction of unpaved roads. Development of techniques for the extraction of unpaved roads can be very resourceful and helpful in security and surveillance,

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Every element in the satellite images has a colour that best describes it (Bong, Lai and Joseph, 2009). Hence, elements can be extracted from images based on the peculiarity of their colour. This paper proposes a technique for the extraction of unpaved road from high resolution satellite images based on the assumption that unpaved roads have the same colour features as sandy region. Colour Space models, Morphological dilation and Hough Transform are combined in order to extract unpaved roads from satellite images.

METHODOLOGY

Algorithm and Flowchart

The flowchart for the extraction of unpaved road from satellite images is as shown in Figure 1, while the algorithm is as follows:

Processing Flow / Algorithm.

1. Input image.
2. Perform Adaptive Histogram Equalisation on image
3. Convert image from RGB to HSV and YC_BC_R .
4. Set Thresholds $T_{\min H}, T_{\max H}$, $T_{\min S}, T_{\max S}$, $T_{\min L}, T_{\max L}$.

   where $T_{\min H}, T_{\max H}$, are the minimum and maximum pixel values of Hue corresponding to sandy region respectively on HSV

   $T_{\min S}, T_{\max S}$ are the minimum and maximum pixel values of Saturation corresponding to sandy region respectively on HSV

   $T_{\min L}, T_{\max L}$ are the minimum and maximum pixel values of Luminance corresponding to sandy region respectively on YC_BC_R
5. Perform Segmentation on H, S and Y by Computing

   $H_{candidate} = T_{\min H} < H < T_{\max H}$,

   $S_{candidate} = T_{\min S} < S < T_{\max S}$, and

   $Y_{candidate} = T_{\min Y} < Y < T_{\max Y}$
6. Create a mask of $(H \oplus S \oplus Y)$ (where $\oplus$ is logic 'AND' combination)
7. Perform dilation on the output of (6)
8. Apply Hough Transform to the output of (7`1)
9. Output result.

The acquired satellite images were converted from RGB colour space to HSV and YC_BC_R colour spaces. Equations 1 through 5 give the mathematical formulae that represent the conversion process. Hue, Saturation, and Luminance are the parameters used for the colour extraction.

$$\text{Hue:} \quad H = \begin{cases} \theta & B \leq G \\ 360 - \theta & otherwise \end{cases} \tag{1}$$

$$\text{where } \theta = \cos^{-1}\left\{ 0.5 \left[\frac{(R-G)+(R-B)}{\sqrt{\left((R-G)^2 + (R-B)(G-B)\right)}} \right] \right\} \tag{2}$$

$$\text{Saturation:} \quad S = 1 - \left(\frac{3}{(R+G+B)} \right) \quad [Min(R,G,B)] \tag{3}$$

$$\text{Value:} \quad V = \left(\frac{R+G+B}{3} \right) \tag{4}$$

$$\text{Luminance:} \quad Y = 65.481R + 128.553G + 24.966B + 16 \tag{5}$$

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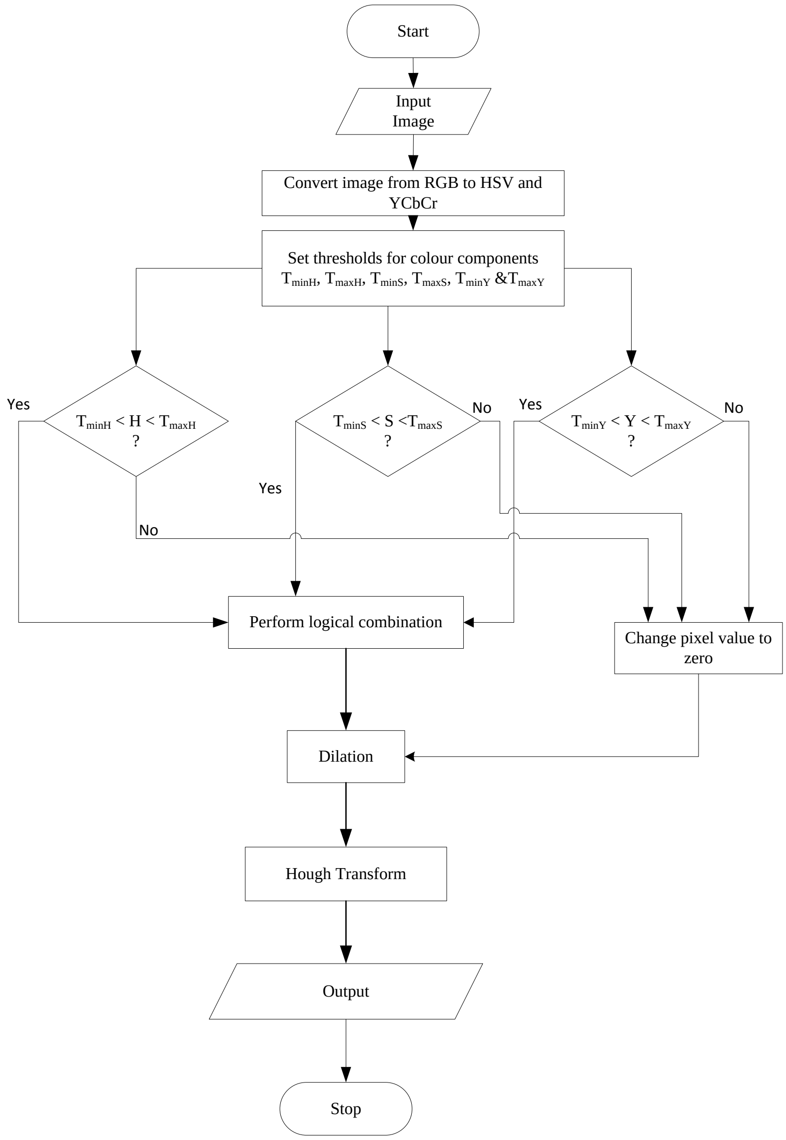

Figure 1: Flowchart of the developed Algorithm.

Extraction of sandy regions and elimination of undesired features was done by finding the minimum and maximum pixel values of the colour space parameters (hue, Value and luminance) that correspond to sandy region. These values are used as thresholds for segmentation. Pixels within this range are accepted as candidates of sandy region, while the others are discarded. This process is followed by logical combination of the outputs of the thresholding stage to give the sandy region in the image.

Dilation is used to enhance the output of the combination stage. Some areas that are not extracted based on the previous stages but that are sandy region are filled up by the process of dilation. Dilation is known to expand the foreground of an image. Hence, some breakages in the continuity of the extracted roads which may be due to different reasons such as shadows, presence of tree canopy, or abrupt change in the intensity, are being filled up by dilation. Two iterations of dilation process were used. Dilation of a binary image A by structure element B, denoted as $A \oplus B$ is given in Equation 8.

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$$A \oplus B = \{a + b \mid for\, a \in A, b \in B \tag{8}$$

Dilation can also be written as an equivalent to a union of translates of the original image with respect to the structure element as shown in Equation 9.

$$A \oplus B = \bigcup_{b \in B} A_b \tag{9}$$

However, not all sandy regions correspond to unpaved roads. Therefore, *Hough transform* was used to extract roads from the whole sandy region. Based on the hypothesis that roads are laterally bounded, part of the sandy regions that are laterally bounded by edges are extracted as roads. *Hough transform* is a transformation that maps a straight line

$$y = mx + c = \rho \cos\theta \tag{10}$$

into a point in the (x, y) plane or the (ρ, θ) plane, where m is the gradient and c is the intercept (Marques de Sa, 2001).

Gap Statistics were used to evaluate the performance of the developed algorithm. These are number of gaps per kilometre, mean gap length and completeness.

(a) Number of gaps per kilometre is the number of gaps that can be found in an extracted road, and is given as

$$No.of\ gaps\ per\ km = \frac{n}{length\, of\ the\, road\,(km)} \tag{11}$$

where n is the number of gaps in the result

(b) Mean gap length is the summation of all gaps length that are present in an extracted result divided by the number of gaps in the result, and is given as

$$Mean\ gap\, length\,[m] = \frac{\sum_{i=1}^{n}(gli)}{n} \tag{12}$$

where gli is the length of the *i-th* gap.

(c) Completeness is the degree at which the road to be extracted is present in the result after extraction.

$$Completeness = 1 - \left(No\, of\ gaps\ per\ km \times \frac{mean\ gap\ length}{1000} \right) \tag{13}$$

EXPERIMENTAL RESULTS

The developed algorithm was implemented in MATLAB® 7.4.1, while the performance of the algorithm was evaluated using gap statistics (number of gaps per kilometre and mean gap length) and completeness as evaluation parameters. Three samples of satellite images are

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shown in Figures 2 to 4. In each of the images (a) shows the original satellite images and (b) shows the result of the developed algorithm. Figure 2 contains a linear unpaved road, Figure 3 contains a two linear unpaved roads with a T-junction interception, while Figure 4 contains a network of unpaved road. For an ideal system having an efficiency of 1, the value for No. of gaps per km is 0, which implies complete absence of gaps in the result. In addition, the Mean gap length (m) of such system is 0, while completeness is 1.

Visual inspections of the result show that the developed algorithm was able to extract high proportion of unpaved roads from satellite images. In addition, the result of the objective performance evaluation is presented in Table 1. Results from the test images Figures 2, 3 and 4 show that the No of gaps per km is 0, 0 and 1.9512 respectively; mean gap length of 0, 0 and 45.83 m respectively and completeness of 1, 1, and 0.91 respectively. Comparing the average No. of gaps per km of the developed algorithm with that of an ideal system, it shows that the developed algorithm performs well. The values of completeness (1, 1, 0.91) i.e. (100%, 100% and 91%). This implies that the developed algorithm performed excellently for linear unpaved roads (100%), while it performed adequately well (91%) for an image with a network of unpaved roads.

Table 1: Performance Evaluation Results

Parameters	Figure 2	Figure 3	Figure 4
Dimensions (pixels by pixels)	350×332	350×284	350×287
Total road length (km)	0.49	0.726	1.5375
Total gap length (m)	0	0	137.50
No of gaps per km	0	0	1.9512
Mean gap length (m)	0	0	45.83
Completeness	1	1	0.91

Figure 2 (a) Linear unpaved road (b) Output of the developed technique.

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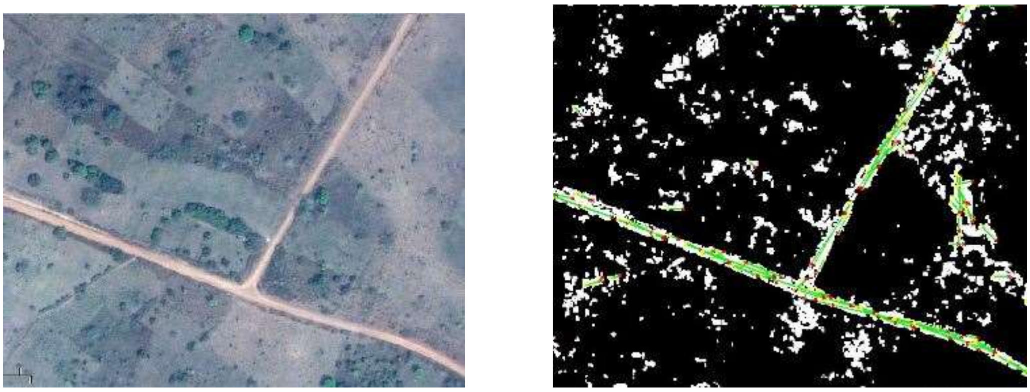

Figure 3 (a) Unpaved road at T-junction (b) Output of the developed technique.

Figure 4 (a) Complex unpaved roads network. (b) Output of the developed technique.

CONCLUSION

An algorithm for extraction of unpaved roads from high resolution satellite images has been presented in this paper. Hue, Saturation, and Luminance components of colour space models HSV and YC_BC_R were thresholded, in order to extract unpaved road from satellite images based on its colour attribute. Enhancement was performed through Morphological dilation, and Hough transform was used in highlighting the part of the results that are laterally bounded by edges. Evaluation of results showed that the algorithm gave excellent performance. The algorithm can find applications in security and surveillance systems, such as tracking of insurgents and kidnappers in tropical regions up to semi-arid regions. Future works shall focus more on the development of a filtering technique that can successfully differentiate unwanted patches from extracted unpaved road in the result.

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