IJCSI International Journal of Computer Science Issues, Vol. 8, Issue 3, No. 2, May 2011
ISSN (Online): 1694-0814
www.IJCSI.org

Automatic Road Extraction based on Level Set,Normalized Cuts and Mean Shift Methods

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Abstract

The Urban population is growing so fast in India that planning officials are racing to keep up with urban development .Use of geographic information like satellite imagery helps urban planners manage the ever-changing urban environment accurately and efficiently. Roads are one of the most important features to be extracted from Satellite imagery for urban planning. Manual extraction of roads is operator dependent and time-consuming task. Hence Automatic extraction of roads from high resolution satellite images has grown in importance in the last decade. An approach for automatic road extraction from high resolution based on Level set, Normalized Cuts and Mean Shift algorithms is developed. Initially the image is preprocessed to improve the tolerance by reducing the noises (buildings etc.,) then roads are extracted based on the three methods. Finally the comparison of accuracy of automatic road extraction of three methods is quantitatively assessed with manually extracted reference data.

Keywords*- Road extraction; Level Set; Mean Shift method; Normalized cuts; Performance evaluation;*

1. Introduction

Today satellite remote sensing systems provide large volumes of data that are invaluable in monitoring Earth resources and the effects of human activities. Road feature extraction from remotely sensed images has been a long-term topic of research and because of its complexity is still a challenging topic. Urban road mapping from high spatial resolution images are an asset because they allow the discrimination of urban features, but they also bring new problems because, a lot of the urban features can be considered as noise. For example, cars, shadows, trees, etc hinder the discrimination of roads.

Much effort is devoted to search for solutions to these problems. In the Literature there are papers based on Level Set [1], Normalized Cuts [2] and Mean Shift [3] algorithms.

Level set method is a search algorithm that determines evolving curve's boundary pixels the level set propagates as long as the speed function is greater than zero. For the road extraction problem speed function has to be greater than zero at the edges of the true road boundary. Therefore Level set is an efficient technique for extracting road. In the literature on level set algorithm Trish et al., [4] provide an initial seed point on the road of interest, then evolving the region using level set method. Fast marching level set method machine learning for parameter tuning and information fusion for refinement of object delineation has been used by Cai et al., [5]. Ravanbaksh et al., [6] provide junction outline to focus the attention on a specific area later constraints are introduced to distinguish road junctions level set method. Bibo et al., [7] have applied Level set for the segmentation of the image. Then second order moment is calculated and the road networks are extracted using prior information about geometric shape. Rajeswari et al., [8] and Senthilnath et al., [9] have used pre-processing for removing noise in the image and then Level Set Evolution without Re-initialization (LSER) with the initial seed point provided by the user.

Normalized Cuts is a graph-based method taking both local and global characteristics of the image. The combination of local and global aspects ignores noise, small surface changes and weak edges and producing extraction with most segments covering only a road area. This makes normalized cuts suitable for automatic road extraction. Normalized cuts is used for initial segmentation step by Qihui Zhu; Mordohai, P. [10] also requires priori information like depth and intensity measurements from the range sensor for LIDAR data and then extracts roads using hypothesis testing. A.Groth et al. [11, 12] have applied Normalized Cuts algorithm for dividing image into Segments with color and edge criteria. Then, the initial segments are grouped to form larger segments and are then evaluated using shape criteria to extract road parts.

Mean Shift method is a clustering technique used to classify data into different categories and does not require information about specific object and extracts road information exactly by object-oriented method .Zhanfeng et al., [13] extracted segments from the image based on different scales, and are analyzed using transcendental knowledge. In Sun [14], the user inputs a set of nodes of the road and then the partitioning of the image is done using Mean Shift Method and roads are extracted between the nodes using Fast Marching Method. Yao-Yi [15] and Simler [16] applied mean shift as a filter to reduce the number of colors in the input image. Guo [17] applied mean shift to determine average saturation to classify the object. Saturation image is noisy and the road boundary is not recognizable. Hence post processing is used to extract roads.

We propose an approach for road network extraction in urban areas without the priori information about road or DSM. Main goal of the paper is to show the effectiveness of the approach for Road extraction. Initially image is preprocessed to remove small linear structures appearing as noise then the Level set, Normalized cuts and Mean shift methods are used to extract the roads & are fully automatic. The quality measures evaluated show that this approach is more accurate compared to the earlier works based on these methods.

In Section 2 description of the road network extraction process is presented. Section 3 Experimental results and analysis of qualitative measures are described. Performance measures are described in Section 4.concluding remarks are given in Section 5

2. Methodology

The proposed road extraction methodology has been broadly divided into three steps: the pre-processing which extracts the elongated road regions, the road extraction using three methods and the image overlaying.

2.1 Pre-processing

A series of pre-processing steps are applied to improve the image quality and to generate the elongated road network for further processing.

2.1.1 Classification

The image used is a Quickbird's panchromatic 0.61m resolution satellite image of Commercial Street area of Bangalore city in Karnataka, India. It has dimensions of 550x 550 pixels. By setting the threshold value 0.95, the high resolution image was grouped into 20 clusters in an unsupervised classification, five of which correspond to road networks. A level one classification was carried out by dividing the image into two classes: Roads and non-roads.

2.1.2Filtering

Median filtering technique is applied to remove the clutter (Buildings etc). In Median filtering the value of an output pixel is determined by the median of the neighborhood pixels, rather than the mean. The median is much less sensitive than the mean to extreme values (called outliers). Median filtering is therefore better able to remove these outliers without reducing the sharpness of the image.

2.2 Road Extraction

2.2.1Level Set Method

The level set method (LSM) tracks the evolution of a boundary front which is moving with a speed function that is normal to the boundary curve. The road extraction problem is considered as a boundary evolution problem within the level set framework. The level set will propagate as long as the speed function is greater than zero. For the road extraction problem, speed function must be greater than zero, at the edges of the true road boundary. For this an external energy is defined that moves the zero level curve toward the object boundaries [15].
The edge indicator function g is defined by

$$g = \frac{1}{1 + |\nabla G_\sigma * I|^2} \quad (1)$$

where I is an image, G_σ is the Gaussian kernel with standard deviation σ.

Then the external energy for a function ϕ (x, y) is

$$\varepsilon_{g,\lambda,\nu}(\phi) = \lambda L_g(\phi) + \nu A_g(\phi) \quad (2)$$

where λ > 0 and ν are constants, and the terms $L_g(\varphi)$ and $A_g(\varphi)$ are defined by

$$L_g(\phi) = \int_\Omega g\partial(\phi)\,|\nabla\phi|\,dxdy \quad (3)$$

and

$$A_g(\phi) = \int_\Omega gH(-\phi)\,dxdy \quad (4)$$

respectively, where δ is the univariate Dirac function, and H is the Heaviside function. The total energy functional is

$$\varepsilon(\phi) = \mu P(\phi) + \varepsilon_{g,\lambda,\nu}(\phi) \quad (5)$$

The external energy Eg,λ,ν drives the zero level set toward the object boundaries, while the internal energy μP(ϕ) penalizes the deviation of ϕ from a signed distance function during its evolution.

By calculus of variations, the Gateaux derivative (first variation) of the functional Equation (5) can be written as

$$\frac{\partial\varepsilon}{\partial\phi} = -\mu[\Delta\phi - \mathrm{div}(\frac{\nabla\phi}{|\nabla\phi|})] - \lambda\partial(\phi)\mathrm{div}(g\frac{\nabla\phi}{|\nabla\phi|}) - \nu g\partial(\phi) \quad (6)$$

where Δ is the Laplacian operator. Therefore, the function ϕ that minimizes this function satisfies the Euler-Lagrange equation ∂E/ ∂ ϕ = 0. The steepest descent process for minimization of the functional E is the following gradient flow:

$$\frac{\partial\phi}{\partial t} = \mu[\Delta\phi - \mathrm{div}(\frac{\nabla\phi}{|\nabla\phi|})] + \lambda\partial(\phi)\mathrm{div}(g\frac{\nabla\phi}{|\nabla\phi|}) + \nu g\partial(\phi) \quad (7)$$

This gradient flow is the evolution equation of the level set function The second and the third term in the right hand side of (7) correspond to the gradient flows of the energy functional $\lambda L_g(\phi)$ and $\nu A_g(\phi)$, respectively, and drive the zero level curve towards the object boundaries.

2.2.2 Normalized cuts

In Normalized cut method for extracting road segments, each individual edge weight is a measure for the similarity between two connected pixels. If the road segments that are to be extracted have distinctly different intensities then intensity should be used as similarity measure. Often, several similarity measures are combined, because the differentiation cannot be realized using only one criterion. The weight, which is the combination of all similarity measures, has a value between 0 and 1. The graph representing the image is then cut into segments aiming at a large dissimilarity between different segments and at the same time a large similarity within the segments

Consider an undirected graph G = (V, E), where V is the set of nodes and E is the set of edges. A pair of nodes p and q is connected by an edge and is weighted by w (p,q). Let X and Y be a partition of the graph where X ⋃ Y = V and X ⋂ Y = ϕ . Therefore cost of cut is defined as the similarity between the groups X and Y and it is formulated as:

$$\mathrm{Cut}(X, Y) = \sum_{p\in X, q\in Y} w(p, q) \quad (8)$$

Minimum cut is the cut of minimum weight, where weight of cut (X,Y) is given in (8). The limitation of using minimum cut is described in [16, 17]. However, the minimum cut criterion favors grouping small sets of isolated nodes in the graph because it cuts with lesser weight than the ideal cut [17]. In other words, the minimum cut usually yields over clustered results when it is recursively applied. This induces several modified graph partition criteria. One of them is the Normalized similarity criterion used to evaluate a partition and is known as normalized cut [16].

$$\mathrm{Ncut}(X,Y) = \frac{\mathrm{cut}(X,Y)}{\mathrm{volume}(X)} + \frac{\mathrm{cut}(X,Y)}{\mathrm{volume}(Y)} \quad (9)$$

where volume(X) is the sum of cost of all edges that touch X and volume(Y) is the sum of cost of all edges that touch Y i.e.

$$\mathrm{volume}(X) = \mathrm{assoc}(X, V) = \sum_{p\in X, q\in V} w(p,q)$$

$$\mathrm{volume}(Y) = \mathrm{assoc}(Y, V) = \sum_{p\in Y, q\in V} w(p,q)$$

where assoc(X, V) is the total connection from nodes in X to all the nodes in the graph and assoc(Y, V) is the total connection from nodes in Y to all the nodes in the graph.

The main advantage of using the normalized cut is that minimizing Ncut(X, Y) maximizes a measure of similarity within the sets X and Y and this results in optimal partition.

Let W be the cost matrix, i.e. W (i, j) = ci,j; is the weight between the nodes i and j in the graph and D be the diagonal matrix such that D(i,i) = $\sum_j W(i, j)$ is the sum of costs from node i and D(i,j) =0. Based on this input, Shi and Malik showed that the optimal partition can be found by computing:

$$\min N_{cut}(X,Y) = \min_y \frac{y^T(D-W)y}{y^T D y} \tag{10}$$

such that $y(i) \in \{1,-b\},\ 0 < b \leq 1, \text{ and } y^T D 1 = 0$

If y is allowed to take real values then the minimization of equation (10) can be done by solving the generalized eigenvalue system.

$$(D-W)y = \lambda D y \tag{11}$$

Therefore, the approximation to the optimal partition can be computed efficiently.
To compute the cut, graph is divided into two clusters. To get a good segmentation, the weight on the edges should represent pixels affinity for being in the same group. The weights for the pixel pairs are inserted in a symmetric similarity matrix (W-matrix) whose row and column dimensions equal the number of pixels. The weight between regions i and j is defined as

$W = N \times N$ *symmetric matrix, where*

$$W(i,j) = \begin{cases} e^{-\|F_i - F_j\|/\sigma_F^2} \times e^{-\|X_i - X_j\|/\sigma_X^2} & \text{if } j \in N(i) \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

where $\|F_i - F_j\| = \text{Image feature similarity}$
$\|X_i - X_j\| = \text{Spatial Proximity}$

$D = N \times N$ *diagonal matrix, where*

$$D(i,i) = \sum_j W(i,j) \tag{13}$$

Here, high weight edges for pixels that have similar intensity are close to each other. The minimum can be found by calculating the eigenvectors of a matrix derived from the W-matrix using equation (12). The "generalized" eigen system in (11) can be transformed into a "standard" eigen value problem as given below

$$D^{-\frac{1}{2}}(D-W)D^{-\frac{1}{2}}Z = \lambda Z \tag{14}$$

$$\text{where } Z = D^{\frac{1}{2}} y$$

2.2.3 Mean Shift Method

Given n data points xi, i=1,…,n in the d-dimensional space Rd, the kernel density estimation at the location x can be calculated by

$$\hat{f}_K(x) = \frac{1}{n}\sum_{i=1}^{n} \frac{1}{h_i^d} k\left(\left\|\frac{x - x_i}{h_i}\right\|^2\right) \tag{15}$$

with bandwidth parameter hi > 0. The kernel K is a spherically symmetric kernel with bounded support satisfying [20],

$$K(x) = c_{k,d}\, k\left(\|x\|^2\right) > 0 \qquad \|x\| \leq 1 \tag{16}$$

where the normalization constant $c_{k,d}$ assures that K(x) integrates to one. The function k(x) is called the profile of the kernel. Assuming derivative of the kernel profile k(x) exists, using g(x) = -k'(x) as the profile, the kernel G(x) is defined as $G(x) = c_{g,d}\, g(\|x\|^2)$. The following property can be proven by taking the gradient of Equation 8 as follows,

$$m_G(x) = C\frac{\hat{\nabla} f_K(x)}{\hat{f}_G(x)} \tag{17}$$

where $m_G(x)$ is called Mean Shift vector. C is a positive constant and, it shows that, at location x, the Mean Shift vector computed with kernel G is proportional to the normalized density gradient estimate obtained with kernel K. The Mean Shift vector is defined as follows

$$m_{h,G}(x) = \frac{\sum_{i=1}^{n} x_i\, g\left(\left\|\frac{x - x_i}{h}\right\|^2\right)}{\sum_{i=1}^{n} g\left(\left\|\frac{x - x_i}{h}\right\|^2\right)} - x \tag{18}$$

The Mean Shift vector thus points toward the direction of maximum increase in the density. The Mean Shift procedure is obtained by successive computation of the Mean Shift vector and translation of the kernel G(x) by the Mean Shift vector. it converges at a nearby point where the estimate has zero gradient [19]. The Iterative equation is given by

$$y_{j+1} = \frac{\sum_{i=1}^{n} \frac{x_i}{h_i^{d+2}}\, g\left(\left\|\frac{y_j - x_i}{h}\right\|^2\right)}{\sum_{i=1}^{n} \frac{1}{h_i^{d+2}}\, g\left(\left\|\frac{y_j - x_i}{h}\right\|^2\right)} \quad j = 1,2,\ldots \tag{19}$$

The initial position of the kernel (starting point to calculate y_1) can be chosen as one of the data point x_i. The modes (local maxima) of the density are the convergence points of the iterative procedure.

2.3 Image Overlaying

In order to illustrate the accuracy, the extracted road region using is converted into binary image format. This binary image is overlaid on the original panchromatic image leads to display the road topology by avoiding the complex noise element. In the overlaid image the thin lines indicate the road topology.

3. Performance Analysis

The automatically extracted roads are compared with manually traced reference roads to perform accuracy assessment. Since roads have linear features, it is possible to use all the data rather than just sample points to conduct the accuracy assessment. In [22] several quality measures to evaluate the quality of extracted roads is proposed. The measures for accuracy assessment of road extraction are:

$$\text{Completeness} = \frac{TP}{TP + TN} \qquad (20)$$

$$\text{Correctness} = \frac{TP}{TP + FN} \qquad (21)$$

$$\text{Quality} = \frac{TP}{TP + FP + FN} \qquad (22)$$

$$\text{Redundancy} = \frac{TP - [1 - FP + FN]}{TP} \qquad (23)$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i-1}^{N} d(der_i - ref)^2}{N}} \qquad (24)$$

N=number of pieces of unmatched extraction

$$\text{Number of Gaps/km} = \frac{n}{\text{Length of reference[km]}} \qquad (25)$$

n=number of gaps

$$\text{Mean gap length[m]} = \frac{\sum_{i-1}^{n} g(l_i)}{n} \qquad (26)$$

l_i = length of the i th gap(m)

Completeness represents the percentage of reference data being correctly extracted. Correctness indicates the percentage of correctly extracted roads. Therefore, completeness is producer's accuracy and Correctness is users' accuracy. The quality represents the overall accuracy Redundancy gives the percentage of correctly extracted roads which overlap as they correspond to the same ideal road RMSE (Root Mean Square error) expresses the geometrical accuracy of extracted roads, the number of gaps per unit length and the mean gap length, where a gap corresponds to a part of the ideal road that is not found. To calculate these quality measures, buffer zones are generated around the extracted roads and the reference roads. The chosen buffer width is approximately half of the actual road width. The direction difference is derived directly from the vector representations of both networks. A true positive (TP) is where the derived result coincides with the reference result. A false positive (FP) is where there is a road pixel in the derived result that is not in the reference data. A false negative (FN) is where there is a road pixel in the reference data that is not present in the derived result.

4. Results and discussion

The input is a QuickBird's panchromatic satellite image from Commercial Street area of Bangalore city in Karnataka, India. Image with 0.61m ground resolution covering area of a 550 x 550 pixels is considered. The images were executed on a system with 1.83 GHz and 2GB RAM using Matlab 7.4.Figure 1 is a 0.61 meter resolution panchromatic IKONOS image (550 x 550 pixels).. Figure 2 3 and 4 are extracted road images using level set normalized cut and mean shift methods after overlaying the original and extracted image. Figure 5 and Figure 6 show the comparison of road extraction results of two methods. The pre processed image is given as input to level set algorithm. Earlier road extractions using level set required road seed points and is eliminated in this paper by setting the radius of pixels circle and signed distance to the pixel circle for the road extraction. The result obtained by the level set method is shown in Figure 2 .It is seen that level set method extracts road boundaries accurately in the presence of other objects on the road, surface properties of the road but the extraction is not fully complete. The normalized cuts algorithm is applied for the pre processed image to extract the road segments. Earlier road extractions used normalized cut for initial segmentation leading to over segmentation and additional steps are used to remove non road segments. Figure 3 shows that the extraction is successful as most segments cover only a road area and also contains a non road segment in the bottom right side of the image. The mean shift algorithm is applied for the pre processed image to extract the road segments. Earlier road extractions have used mean shift for initial filtering and additional steps are used to remove non road segments. The result obtained by mean shift method is shown in Figure 4.Smaller roads are also extracted by mean shift along with that few non road segments are also extracted.

Figure 1. Original Image

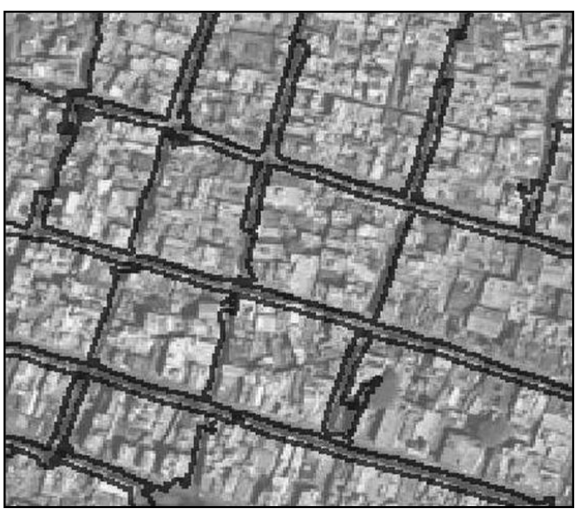

Figure 2. Extracted road network using Level Set Method

Figure 3. Extracted road network using Normalized cuts Method

Figure 4. Extracted road network using Mean Shift Method

To show the effectiveness of the approaches used more clearly the quantitative analysis of the automatically extracted road network is done by comparing them with the manually extracted road regions. The completeness, correctness, quality, redundancy, RMS and gap statistics of the road parts are computed according to Weidemann et al., [19] the results are shown in figure 5 and figure 6. They are determined on a per-pixel level and thus refer to the extracted areas. Figure 5 gives the completeness and correctness values for the three methods. Completeness of 93.81% and 86.45% were obtained using mean shift and normalized cut respectively compared to 77.35% using level set method which is still better than that obtained in [8]. The correctness is 92.99 %for level set and 93.1%, 98.25% for mean shift and Normalized cuts. The accuracy of mean shift is 87.72%, normalized cut is 85.14% compared to 73.09% in level set. Figure 6 shows that the overall number of gaps is smaller in mean shift and the mean gap length is more in normalized cuts. RMSE is least in Normalized cuts. Overall Mean shift has produced better results compared to other two methods in extracting road network

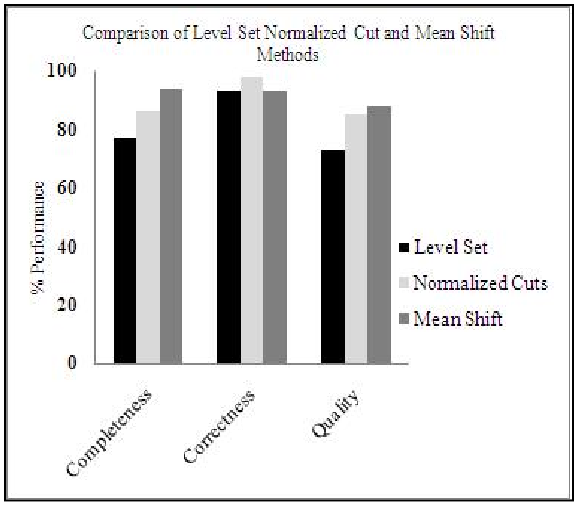

Figure 5. Comparison of Completeness, Correctness and Quality measures

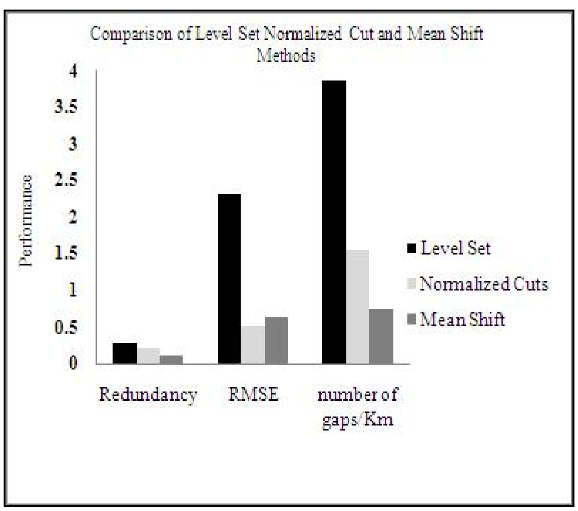

Figure 6. Comparison of Redundancy,RMS (m) and No of Gaps/km measures

5. Conclusion

Road Extraction is of fundamental importance for the urban planners to manage the ever-changing urban environment. An integrated approach for automatic road extraction from high resolution satellite imagery is developed based on Level set, Normalized cuts and Mean Shift Method. When compared with the literature using these methods all three algorithms have performed well in our approach. The main contribution of this paper is using these methods on the preprocessed data to produce greater accuracy and is fully automatic. Level set method has to be refined to extract the unidentified road regions. Normalized cut need improvement to extract smaller roads and improve the accuracy of road delineation. Of the three techniques tested mean shift is most robust all. The limitation of mean shift is fixed kernel bandwidth. The change in the road width requires an adjustment of the kernel bandwidth to consistently track the road. Future work includes addressing these issues to obtain complete accuracy in road extraction.

Acknowledgment

This work is supported by the Space Technology Cell, Indian Institute of Science and Indian Space Research Organization grant.

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