



Road Extraction using High Resolution Satellite Images based on Threshold Based Methods



K. Pavani¹ | Ch. Tejaswini²

¹PG Scholar, Department of ECE, V.R.Siddhartha Engineering College, Vijayawada, AP, India.

²Assistant Professor, Department of ECE, V.R.Siddhartha Engineering College, Vijayawada, AP, India.

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

Copyright © 2016 International Journal for Modern Trends in Science and Technology
All rights reserved

I. INTRODUCTION

Today satellite remote sensing systems [1]-[7] 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[6]. The ability of the next generation sensors to provide fine spatial resolution data has motivated the urgency for automated road extraction research.

Accurate and up-to-date road network information is essential for urban planning, automated road navigation, and emergency response applications [3]. Automated methods have the potential to improve the speed and utility for road mapping and are therefore highly desirable. Roads are only extracted in the regions around database roads. Road extraction is difficult in the presence of context objects such as buildings or trees close to the road, disrupting the appearance of the road or occluding it.

Many approaches for road extraction have been developed. However, only few approaches work in urban scenes which complicates the task of automatic road extraction [1]. The comparison of the two methods i.e. normalized cuts method and mean shift method is done in this literature. A normalized cut is a graph based method taking both local and global characteristic of the image [3]. The combination of the local and global aspects ignores noise, small surface changes and weak edges and producing extraction with most segments covering only a road area [8]. In this approach, only the boundaries are considered. The advantage of this method is that hard constraints are not needed to gain information about roads. This makes this method more conducive for automatic road extraction.

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. In this method, data is segmented and these segments are analyzed to detect road – like and non- road segments.

II. ROAD FEATURES AND MODELS

The difficulties of road extraction from RS images lie in that the image characteristics of road features can be affected by the sensor type, spectral and spatial resolution, weather, light variation, and ground characteristic, etc. In practice, a road network is too complex to be modeled using a general structural model. Hence, the analysis of road features and road models is very important. In the following part, these two aspects will be described.

2.1. Road features

In general, we have to make an image enhancement so as to extract useful information from a RS image. A road in a RS image appears as elongated geometric features with slowly changed gray values. As described by Vosselman and Knecht (1995), the road features in an image are summarized from four different aspects. Based on their description, the road features in an image can be concluded as follows:

(1) Geometric features

A road has a stripe feature its width does not suddenly vary much and its length is not as short as its width. The ratio between length and width is very large. The road junctions usually can be presented as the signs of “T”, “Y”, or “+”.

(2) Photometric features

Photometric features are also known as radiation features. It means there are two obvious road edge lines, and the edge gradient is larger. Meanwhile, the gray values or colors of roads are relatively consistent and change slowly, but they are very different from those of the neighboring non-road areas such as trees and buildings, etc.

(3) Topological features

Generally, a road has intersections. The road network is not suddenly interrupted.

(4) Functional features

A road has specific functions in the real world. In order to realize those functions, it must have some constraint conditions.

(5) Texture features

Textures in an image have the regional characteristics, which are a kind of visual features to reflect the homogeneity phenomenon in the image. It has nothing to do with the color and intensity information. The essence of texture features is to find the spatial distribution of pixel gray levels in the neighborhood (Wang et al., 2014).

In practice, many road extraction methods use multiple road features rather than only one feature. However, due to the influence of illumination, shadow and occlusion, a road in an image does not have all the features mentioned above, which makes it difficult to extract road from a RS image.

2.2. Road model

The road model establishment can help us extract road more effectively. Baumgartner et al. (1999) proposed a classical road model according to the form of road in a RS image, which is

shown in Fig. 1. In practice, the RS image quality can be affected by different factors such as the sensor type, spectral and spatial resolution, weather, light variation, and ground characteristic,

etc. Hence, the following interference factors must be considered (Herumuti et al., 2013; Shi et al., 2014; Zhang, 2007):

(1) The observed appearance of a road from a RS image has large variations (spectral reflectance, objects shadow, occlusion, and contrast), which makes the image segmentation more difficult.

(2) In the bad weather, the vague gray value difference between road and background makes the road edge fuzzy, which leads to a bad segmentation result.

(3) The road width is designed at different levels to meet different requirements. All roads with different widths and lengths intersect together.

(4) Discontinuous phenomenon is easy to appear because of the influence of object shadow, occlusion, especially the influence of tunnel and underground.

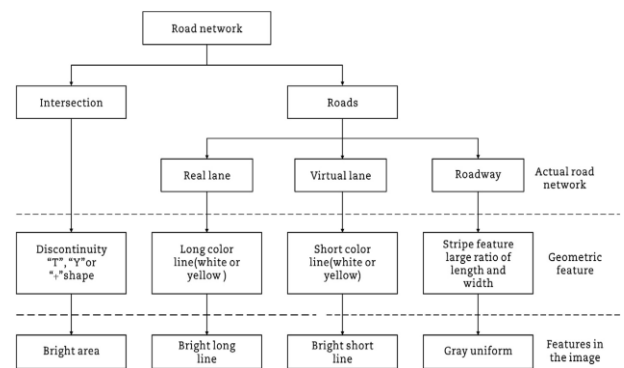


Fig. 1 Classical road model.

(5) A RS image includes a large amount of information. Furthermore the speed, accuracy, completeness and correctness of the road extraction algorithm should be taken into account.

Fig. 2 shows the RS images including a main road, a large area of water, several tree blocks, grass blocks, and other areas. In light of different areas (city, suburb or rural), different images (aerial or RS images), and different types of roads (highways, rural roads or streets), many scholars put forward different road extraction methods. In the next section, the recent research achievements of these

different methods will be discussed and classified.

III. ROAD EXTRACTION METHODS

Although many researchers have classified the road extraction methods, it is still difficult to classify them in detail due to various applications. In a qualitative survey, it can be found that most of the methods suggested in literature for road extraction consist of one or more types of algorithms: classification based, knowledge-based, mathematical morphology, active contour model, and dynamic programming, etc. In the following section, the research results of various methods are briefly summarized.

3.1. Classification-based methods

Classification-based methods usually use the geometric features, photometric features and texture features of a road. The classification accuracy is far from satisfactory because of the misclassification between road and other spectrally similar objects such as building blocks, field blocks, water areas and parking lots, etc. According to the use of labeled training samples, the classification-based methods can be divided into supervised and unsupervised.

3.1.1. Supervised classification methods

Supervised classification methods are to train the labeled samples. To a large extent, the accuracy of supervised classification methods relies on the selected features and labeled samples.

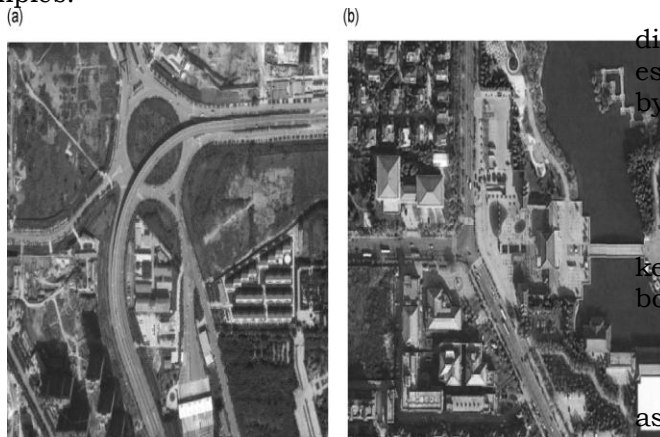


Fig. 2 Examples of two RS images. (a) Road mainly with grass. (b) Road mainly with water and buildings.

3.1.2. Unsupervised classification methods

Unsupervised classification methods do not need training samples, which have many advantages in solving classification problems. However, the accuracy of the methods is lower than that of the supervised classification methods in general. Instead, the unsupervised classification methods are often used in knowledge discovery, parameter determination, characteristic analysis and other preprocessing

steps. The most common algorithms are various clustering algorithms, which include K-means, spectral clustering, mean shift and graph theory, etc. However, this paper only focuses on the mean shift method and the graph cut method.

Proposed Mean shift

The mean shift algorithm is a non-parameter iterative algorithm based on kernel density estimation (Yang et al., 2003). It has many advantages, such as it does not need to assume the type and the number of data distribution, and it does not depend on the selection of starting point of data. So it has been widely used in the field of pattern recognition, image smoothing and image segmentation, etc. Miao et al. (2014) suggested a semi-automatic method to detect road networks from high resolution satellite images. Firstly, the geodesic method was used to extract the initial road segments to link the road seed points prescribed in advance by users. Secondly, the road and non-road classes were separated by a further direct threshold operation. Finally, the geodesic method was used once again to link the foregoing road seed points to generate a kernel density estimation map. However, the seed points needed to be manually selected. The mean shift algorithm does not require any prior knowledge and has high efficiency and stability, especially suitable for the object detection from RS images. However, the current research work in this area is relatively limited.

Given n data points $x_i, i=1, \dots, n$ in the d -dimensional space R^d , the kernel density estimation at the location x can be calculated by

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

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

$$K(x) = c_{k,d} k\left(\frac{\|x\|}{h_i}\right) > 0 \quad \|x\| \leq 1 \quad (2)$$

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,

$$m_G(x) = C \frac{\nabla \hat{f}_K(x)}{\hat{f}_G(x)} \quad (3)$$

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

$$m_{k,p}(x) = \frac{\sum_{i=1}^n x_i \mathcal{G}\left(\left\|\frac{x-x_i}{h}\right\|^2\right)}{\sum_{i=1}^n \mathcal{G}\left(\left\|\frac{x-x_i}{h}\right\|^2\right)} - x \tag{4}$$

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

$$y_{j+1} = \frac{\sum_{i=1}^n \frac{x_i}{h_j^{d+2}} \mathcal{G}\left(\left\|\frac{y_j-x_i}{h}\right\|^2\right)}{\sum_{i=1}^n \frac{1}{h_j^{d+2}} \mathcal{G}\left(\left\|\frac{y_j-x_i}{h}\right\|^2\right)} \quad j=1,2,\dots \tag{5}$$

The initial position of the kernel (starting point to calculate y1) can be chosen as one of the data point xi. The modes (local maxima) of the density are the convergence points of the iterative procedure.

3.4. Active contour model

Active contour models include parameter active contour model and geometric active contour model, and they are respectively represented by snake and level set. The principle of the models is to use a continuous curve for expressing the object profile, and to define an energy function in order to make the process of image segmentation turn into the minimum value of the energy function. The value can be achieved by solving the Euler's equation. Once the energy reaches to the minimum, the object profile can be achieved.

Proposed Level set

Level set was firstly proposed by Osher and Sethian (1988).It is a numerical analysis method using partial differential equations to solve the problem of curve evolution, and it is applicable to any dimension space. Applying the level set method to a road image segmentation from a RS image, Hinz and Baumgartner (2003) combined the multi-spectral characteristics with road geometry to construct a new speed function; He mainly used the prior knowledge in order to realize the road feature extraction. Niu (2006) studied a method that integrated the boundary gradient with the area information to construct a model. The level set method is used to get the road network.According to the road characteristics, Ma et al. (2006) established an appropriate level set model, and used a fast marching method to combine the image intensity gradient threshold to obtain the initial contour curve of

the road, then adopted the curvilinear motion to achieve road image segmentation. Abraham and Sasikumar (2013) provided an efficient algorithm based on fuzzy inference system for road network extraction from degraded satellite images. Firstly,a wavelet filter was used to smooth the image because roads, buildings, vehicles and shadows cause rapid changes for the image intensity. Secondly, the watershed segmentation algorithm was used to compute the extended minima transform of the gradient image and impose the regional minima on the gradient image. Thirdly, an image was reconstructed by performing the inverse wavelet transform with the help of reconstruction filters. Finally, the mean and the standard deviations were chosen as two linguistic variables for the fuzzy system, and then the Hough transform was chosen as the third variable. Using the level set method combining with other types of road extraction methods (such as morphology and clustering) is also a main trend to make good image segmentation results on RS images.

The edge indicator function g is defined by

$$g = \frac{1}{1+|\nabla G_\sigma * I|^2} \tag{6}$$

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

$$E_{g,\lambda,v}(\phi) = \lambda L_g(\phi) + v A_g(\phi) \tag{7}$$

where λ > 0 and v are constants, and the terms Lg(φ) and Ag(φ) are defined by

$$L_g(\phi) = \int_{\Omega} g \delta(\phi) |\nabla \phi| \, dx \, dy \tag{8}$$

$$A_g(\phi) = \int_{\Omega} g H(-\phi) \, dx \, dy \tag{9}$$

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

$$E(\phi) = \mu P(\phi) + E_{g,\lambda,v}(\phi) \tag{10}$$

The external energy E_{g,λ,v} 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 (10) can be written as

$$\frac{\partial E}{\partial \phi} = -\mu[\Delta \phi - \text{div}\left(\frac{\nabla \phi}{|\nabla \phi|}\right)] - \lambda \delta(\phi) \text{div}\left(g \frac{\nabla \phi}{|\nabla \phi|}\right) - v g \delta(\phi) \tag{11}$$

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

$$\frac{\partial \phi}{\partial t} = \mu [\Delta \phi - \text{div}(\frac{\nabla \phi}{|\nabla \phi|})] + \lambda \alpha(\phi) \text{div}(\frac{\nabla \phi}{|\nabla \phi|}) + \nu g \alpha(\phi) \quad (12)$$

This gradient flow is the evolution equation of the level set function. The second and the third term in the right hand side of (12) correspond to the gradient flows of the energy functional $Lg(\square)$ and $\nu Ag(\square)$, respectively, and drive the zero level curve towards the object boundaries.

IV. 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:

$$\text{Completeness} = \frac{TP}{TP + TN} \quad (13)$$

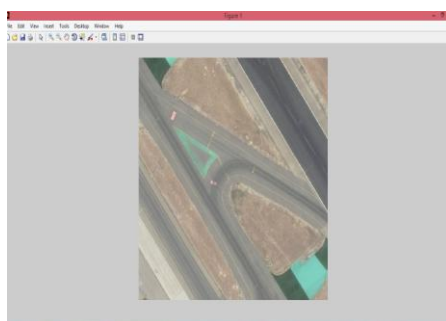
$$\text{Correctness} = \frac{TP}{TP + FN} \quad (14)$$

$$\text{Quality} = \frac{TP}{TP + FP + FN} \quad (15)$$

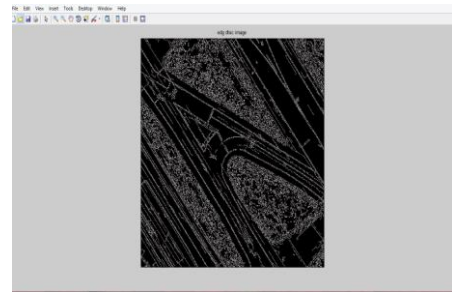
$$\text{Redundancy} = \frac{TP - [1 - FP + FN]}{TP} \quad (16)$$

V. RESULTS AND DISCUSSION

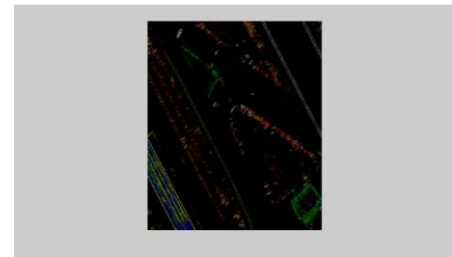
Level Set Simulation Results:



(a) Input Image



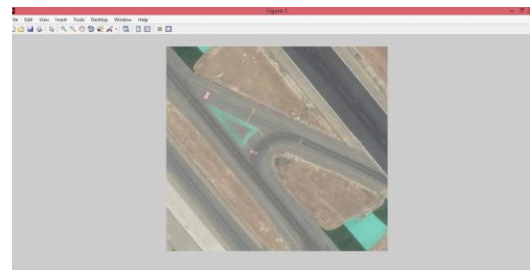
(b) Threshold Image



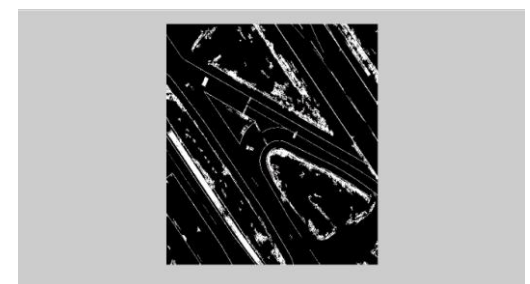
(c) Level set image

Fig 3: Level set of a Satellite image

Mean Shift Simulation Results



(a) Input Image



(b) Threshold Image



(c) Mean Shift image

Fig 4 : Mean Shift of a Satellite image

Five test images are used to measure the performance of our proposed system. The test images are shown in fig:



(a)



(b)



(c)



(d)



(e)

Table 1 shows the comparison between Level set and Mean shift

parameters	Level set method	Mean shift method
Completeness	80%	100%
Correctness	80%	100%
Quality	66.66%	96%
Accuracy	90%	90%
True positive rate	80%	90%
False positive rate	20%	0

VI. 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.

REFERENCES

- [1] Chunming Li , Chenyang Xu , Changfeng Gui , and Martin D. Fox (2005), Level Set Evolution Without Reinitialization: A New Variational Formulation Proceedings of the 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05) 2005
- [2] Shi, J. and Malik, J. (2000) Normalized cuts and image segmentation. IEEE Transactions on Pattern Analysis and Machine Intelligence 22(8): 2000 888-905.
- [3] COMANICIU D., MEER P.: Mean shift: A robust approach toward feature space analysis. IEEE Trans. Pattern Anal. Mach. Intell. 24, 5 (2002), 603-619.
- [4] Trish Keaton and Jeffrey Brokish(2002). A level set method for the extraction of roads from Multispectral Imagery, Proceedings of the 31st Applied Imagery Pattern Recognition Workshop (AIPR.02) 0-7695-1863-X/02 \$17.00 © 2002 IEEE
- [5] X. Cai, A. Sowmya and J. Trinder (2006), A Machine Learning Approach for Automatic Road

- Extraction, Proceedings of the ASPRS 2006 Annual Conference, Reno, Nevada, USA, May 1-5, 2006.
- [6] M. Ravanbakhsh, C. Heipke, K. Pakzad, Extraction of Road Junction Islands from High Resolution Aerial Imagery Using Level Sets, The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. Vol. XXXVII. Part B3a. Beijing 2008
- [7] Bibo Lu, Yongxia Ku, Hui Wang, "Automatic Road Extraction Method Based on Level Set and Shape Analysis," *icicta*, vol. 3, pp.511-514, 2009 Second International Conference on Intelligent Computation Technology and Automation, 2009
- [8] M. Rajeswari S. N. Omkar and Senthilnath J, "Semi Automatic Road Extraction using high resolution satellite imagery in urban areas", Indian Engineering Congress 2007, Uadipur, Rajasthan, , 14-15 December, 2007
- [9] Senthilnath, J.; Rajeshwari, M.; Omkar, S. N. "Automatic Road Extraction Using High-Resolution Satellite Images Based on Level Set Evolution Without Reinitialization XXVIII INCA International Congress, Gandhinagar, Gujarat, India. November 4-6, 2008,
- [10] Qihui Zhu; Mordohai, P.; , "A minimum cover approach for extracting the road network from airborne LIDAR data," Computer Vision Workshops (ICCV Workshops), 2009 IEEE 12th International Conference on , vol., no., pp.1582-1589, Sept. 27 2009-Oct. 4 2009