

An Automatic road network extraction from satellite images using Modified SOFM approach

¹P.Karmuhil, ²Dr. Latha Parthiban

¹Assistant Professor, Research Scholar, Periyar University, GSS Jain College for Women, Chennai, India

karmuhil_2006@yahoo.com

²Assistant Professor, Research Supervisor, Periyar University, Pondicherry University Community college, Pondicherry, India

lathaparthiban@yahoo.com

Abstract

Objective:

The objective of this study is an Automatic Extraction of road networks from very high resolution satellite images. It is an important research area in remote sensing field.

Methods/Analysis:

We present fully automatic road extraction from high resolution satellite images using modified self organizing map. Firstly, it focuses a road detection using self organizing map algorithm. At the end, the T-Cluster method is used to improve the segmentation in road networks.

Findings:

Experimental results show the significant accuracy (90%) and efficiency of proposed approach.

Application/Improvement:

The modified T-SOM technique provides the resources for readily creating, maintaining and updating the road transportation databases used in vehicle tracking and traffic management.

Keywords: Road extraction; Remote sensing field; Self organizing map; T-Cluster, T-SOM.

1. Introduction

In GPS navigation system, road extraction from high resolution satellite images plays an important role in a number of geospatial applications, such as cartographic, Transportation planning and traffic direction system. However, owing to complexity of an urban view, still road network is a challenging and difficult task. Generally, Roads are appeared as dark lines in high resolution satellite images for city and sub-urban areas. Many research algorithms have been applied [1, 2, 3] automatically and semi-automatically. But no single algorithm gives an accurate result from very high resolution satellite images. The conventional algorithms are not attaining the desired effects of road detection and Extraction. When features such as high resolution of images, low image quality, obstructions, and other presence of linear but non-road features are considered as roads. It creates the task of road identification overwhelmingly complex. In low resolution images, we can easily avoid the disturbances like shadows, cars and other small objects and detect the roads owing to its linear structure [4]. In high resolution images the geometric attributes (curvature and width) accuracy is much improved [5]. The method [6] proposed an automatic road extraction based on profile matching leads to obtain accurate results with better performance. The Technique [7] explained a gradient process and the formation of skeletal rays over the roads and achieved notable performance is obtained than other traditional methods. It is implemented for all satellite images for road extraction. The experiential evaluation of the proposed algorithm proposes that the algorithm is capable of extracting majority of the road network, and it poses promising performance results. The novel approach [8] is defined to remove roads based on spectral index and classification. It extracts asphalt roads accurately. The method [9] is a width and color based geometric active deformable model for road extraction from high resolution images with minimal human interception and it is evaluated with many high resolution images with less computation time in complex images. An approach [10] is based on fuzzy inference algorithm for fully automatic road detection and here, trous algorithm for filtering and de-noises the satellite images. The result of this study obtained high degree of accuracy for non-urban areas. In urban areas this approach is not well suited. Automatic and semi automatic road network extraction techniques have significantly increased the extraction rate of road networks. Automated methods still yield some inaccurate and incomplete results and costly human intervention is still required to evaluate results and correct errors. This proposed algorithm presents fully automatic road network extraction with improved results.

2. Materials and methods

This study is focused on extracting road information from high resolution remote sensing imagery based on modified SOFM algorithm. It has the following steps:

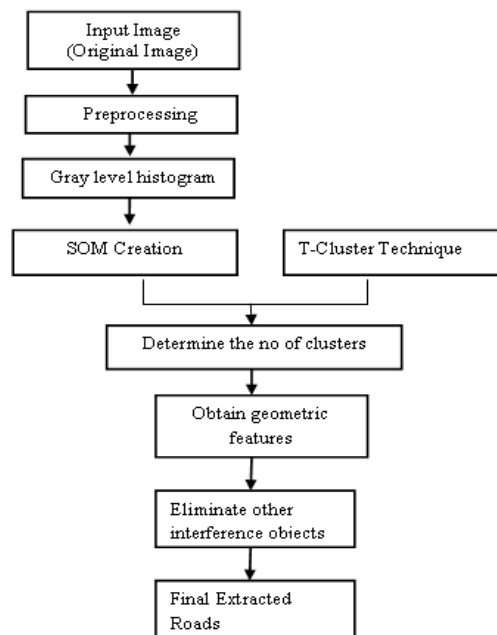
Procedure:

- a) First, Preprocess the image to gray histogram level to assign initial weights of nodes.
- b) Secondly, Creation of SOFM to train this neural network by randomly selected RGB values of image pixel (training neurons with minimum data set) and clustering the image information.
- c) Third, Threshold Cluster method is used to reduce over segmentation.
- d) Finally, obtaining exact geometric features (Roads).

2.1. System sketch

The following Figure 1. Shows the complete structure of the proposed technique.

Figure 1. System Sketch



2.2. Preprocessing(Gray histogram Technique)

The high resolution RGB image is taken as input and converts into gray image for easy segmentation which was used to initialize the weights of neurons at the Competitive layer. The following Figure 2 is an Input image, Figure 3 is RGB colors analyzed by Image analyzer and this RGB color image is converted into gray image shown in Figure 4.

Figure 2. Input image1



Figure 3. Image Analyzer with RGB colors

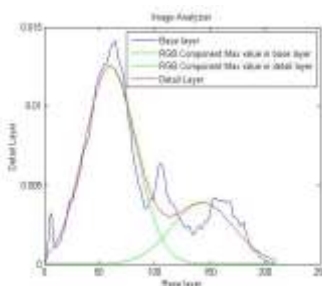


Figure 4. Gray image



2.3. Self Organizing Feature Maps for segmentation(SOFM)

Self organizing feature map is an unsupervised neural network. It converts multidimensional input pattern into two dimensional output patterns and it preserves the neighborhood relations of the input vector. SOFM consist of two layers as input and output (competition layer). The output neuron is always in two dimensional arrays. Each input vector attached with all neurons. Initially weights are small and random and supplies the final stage output with minimum data samples.

The SOM network is used to cluster automatically according to the information of the imagery point and can adjust the levels of classes and numbers according to the actual need is an autonomous and unsupervised learning model with no supervision signals. This technique improves the validity and accuracy of obtained results compared with other conventional methods [11, 12].

In this method, Self organizing neural network algorithm uses a two-level structure which includes input layer and competition layer. The number of input neurons is equal to the dimensions of the input data. Additionally, RGB images which are composed by three parameters of R, G and B are objects of this proposed method. **Image analyzer** is used to identify the RGB colors and considered as three nodes in the input layer. The RGB image has features that the composed three colors are high correlation which are not segment the image directly[13]. To achieve accurate result; these RGB colors need to normalize as:

$$\left. \begin{aligned} r &= R/(R+G+B) \\ g &= G/(R+G+B) \\ b &= B/(R+G+B) \end{aligned} \right\} \quad (1)$$

Weight initialization, node training and Iterative process:

The basic SOFM model includes an input layer and output layer. Each input neurons is mapped to each output nodes through weight nodes. The weights are automatically adjusted for every iteration. Let INPUT=[a₀,a₁,a₂,.....a_{n-1}]^K be the set of n number of input nodes in Sⁿ and which comprises every a_n dimensions. Let OUTPUT=[b₀,b₁,b₂,.....bn.₁]^T be the set of n number of output nodes which has two dimensions space vector and W denotes the set of weights W_j = [w_{0j},w_{1j},.....w_{(n-1)j}]^T and represent as reference vectors. Here the weight vector w_{ij} represents the weight from input node i to output node j iteration h.

Before iterating the neural network, we must initialize the weighted value W_j=[w_{j1},w_{j2},w_{j3}]^T of competition layer nodes and w_{j1},w_{j2},w_{j3} corresponding to the normalized results of tri-color values of RGB respectively. These weight initializations of nodes are set by generating random numbers.

Input data can be transferred to the competition layer through input nodes, weight values with competitive layer node vector .It is determined Euclidean distance, and minimum distance neurons win the competition. The weights are updated by the winning entity and finding the best matching unit is computed by the minimum Euclidian distance to the input neuron and neighborhood is nearer to the accessible input node. The Best matching unit is found by whose distance d_{ij} is in least value. An Euclidean distance is measured by d_{ij}, as follows:

$$d_{ij} = \min_j \|a_i(t) - w_{ij}(t)\|^2 \quad (2)$$

Let be a learning rate, H_{ij} (t) which is used to adjust the weight vector of winning neuron and to compute its neighbours. The weight is updated by the following rule defined as:

$$w_{ij}(t_1 + 1) = w_{ij}(t_1) + H_{ij}(t_1)[a_i - w_{ij}(t_1)] \quad (3)$$

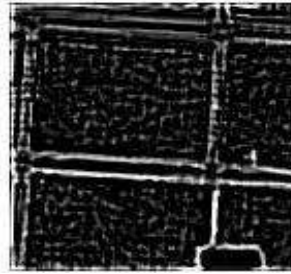
where H_{ij}(t₁) is a smoothing kernel defined over winning neuron and it is written in terms of *Gaussian* function as :

$$H_{ij}(t_1) = \alpha_i \exp\left(-\frac{d^2(l,i)}{2(\sigma(t_1))^2}\right) \quad (4)$$

H_{ij}->0 when t₁->T₀ where T₀ is the number of iterations.α₀ is the initial learning rate and is equal to 0.1 which is updated in every iteration. σ(t₁) is uncover distance at iteration t₁. d²(l,i) is the distance between winning neuron l and its neighborhood neuron i.As learning proceeds, the size of the neighborhood should be diminished until it includes only a single unit.

After meets the equilibrium state of SOFM, the original image is mapped from a high color space to a low color space. This no of color space defines the number of neurons of SOFM network. The end up weight vectors in the map is considered as the new sample space. This final data set is implemented for clustering and allows determining a set of clusters.(very small, small and large clusters) .The following Figure 5 shows the result with many clusters.

Figure 5. segmenting roads using SOFM



2.4. SOFM with Threshold based processing(TSOFM)

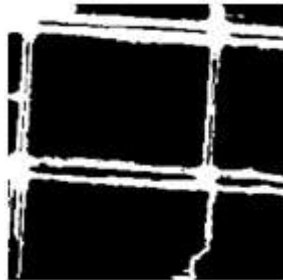
The above SOFM algorithm clusters number of small clusters leads to over segmentation. To avoid over segmentation problem, (small clusters with minimum pixels)the Threshold Cluster technique is applied. Technique which is able to be applied to image segments to clusters with spectral properties [14]. It includes the following steps:

- a)The process of clustering starts by computing the distance space between the values of the cluster centers
- (b)Determine the predefine threshold value T_h .
- (c)If the distance between two cluster centers $< T_h$,cluster centers are combined.
- (d)using that procedure, the clusters with minimum pixels is merged with bigger one.

$$d(V(P_i),V(P_j)) \leq T$$

Where t is a predefined threshold value and $V(P_i)$ is the value of the three bands of the cluster center P_i .The value represents the sum of the resultant 3 weights obtaining from running SOM each weight is multiplied by 255. $V(P_j)$ is the value of the three bands of another cluster P_j .These two cluster centers are combined together if the distance value is less than a predefined threshold value T .the value of the final cluster which has higher number of pixels. TSOFM works sequentially in order to complete the segmentation process. The figure 6 represents final segmented result after TSOFM Technique.

Figure 6.Final extracted roads using Threshold cluster technique



The Modified SOFM algorithm (SOFM with T-Cluster Technique)is combined together and iteratively process in order to end up with segmentation task.TSOFM is used to arrange the image pixels in a class label group. The Sharp histogram encompasses with Threshold cluster and to produce proper road extraction in high resolution satellite images.

3. Results and Discussions

Automatic Road network extraction from remote sensing imagery is a complex task as some inference information such as shadows of buildings & trees, Vehicles etc. It may change the original geometric feature of the Roads and it leads to obtain improper results. In order to identify the road target accurately and completely, we require combining variety of feature information of road targets, and making a complete identification. During extraction of road targets, the geometric features which are contained size, perimeter, ,the geometric center,aspect ratio, direction etc.These features are used to eliminate other inference objects in roads. The proposed method is eliminate the unnecessary inference objects in roads and achieved significant performance evaluation. The proposed system is implemented using Mat lab 7.10. In the process of extracting road information from remote sensing imagery shown in image 1, image 2 and image 3.

Figure 7.(a)Image2



Figure 8.(b) Segmented roads of image2



Figure 9.(a)Image3



Figure 10 .(b) Segmented roads of image3



We have Figure 7 and Figure 9 as input images which gives the segmented output of given images are Figure 8 and Figure 10. Some small amount of road is not extracted due to inference objects. As a result there are fewer amounts of mistakes also identified such as some pavement and buildings with roof are also segmented as road feature.

Accuracy assessment plays a vital role to determine an approach. In this research, standard quality measures are used to evaluate the results by using false alarm rate(FAR),detection rate (DR)and overall quality percentage(QP)[15] such as:

$$DR = \frac{tp}{tp + fn} \tag{5}$$

$$FAR = \frac{fp}{tp + fp} \tag{6}$$

$$QP = \frac{tp}{tp + fp + fn} * 100 \tag{7}$$

tp -true positive, no of road pixels are correctly recognized

fn-false negative, no of non- road pixels are identified

fp-false positive, no of non- road pixels are recognized as road pixels.

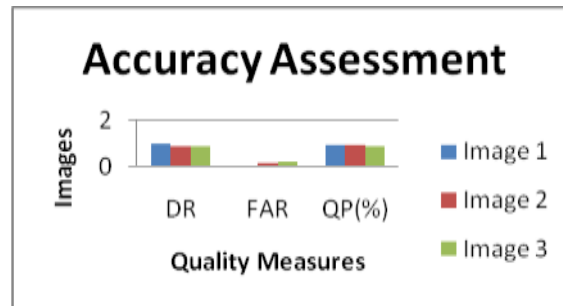
From the above quantitative analysis and comparison with the manual identified measures. It can be seen that almost all the road features are detected with acceptable accuracy and better performance. The following Table 1 is shown Accuracy Assessment of Extracted Roads in Image 1,Image 2,Image 3.

Table 1. Accuracy Assessment of Extracted Roads

Input Images	DR	FAR	QP(%)
Image 1	0.99	0.05	95.1%
Image 2	0.91	0.18	92%
Image 3	0.88	0.22	87.7%

The following figure 11 clearly shows the accuracy assessment of extracted features (Roads).

Figure 11. Accuracy assessment of Segmented Roads



3. Conclusion

In this research, the modified self organizing feature map method automatically detects the roads from high spatial resolution satellite images. It can detect the geometric feature with various size and type of remote sensing imagery. This method can deal with the segmentation size flexibly, solve the problem of over segmentation and extracts the road features correctly. The obtained results are shown the acceptable accuracy and Performance than other conventional methods [4]. The future enhancement of this work will include the post processing algorithms to diminish noise in segmented roads which improves the detection rate with noisy, low resolution and unclear images.

5. References

1. A. Grote, C.Heipke. Road Extraction for the update of road databases in sub urban areas. The International Archives of the photogrammetry, Remote Sensing and Spatial information Sciences.2008; XXXVII, Part B2b, 563-568.
2. L. Xu, T. Jun, Y. Xiang, C. Jianjie. The rapid method for road extraction from high resolution satellite images based on usm algorithm. International conference on Image analysis and signal Processing, Hangzhou, China, November, 2012.
3. D. Chaudhuri, N. Kushwaha, A. KsSamal. Semi-Automated Road detection from High resolution Satellite images by Directional Morphological Enhancement and Segmentation Techniques. IEEE Journal of selected Topics in Applied Earth observations and Remote Sensing. 2012; 5(5), 1538-1544.
4. A Lizy, M. Sasikumar. A Fuzzy based Road network Extraction from Degraded satellite images. IEEE, International Conference on Advances in computing Communications and Informatics (ICACCI). 2013; 2032-2036.
5. Z. Shu, D. Wang, C. Zhou. Road Geometric Features Extraction based on Self organizing map(SOM) Neural network. Journal of Networks. 2014; 9(1), 190-197 .
6. S. Jenitha. Hybrid Heuristic-Based Artificial Immune System for Task Scheduling. International journal of Distributed and Parallel Systems(IJDPS). 2011 November; 2(6),1-12.
7. T. Ranjani Mangala, S. G. Bhirud. A New Automatic Road Extraction Technique using gradient operation and Skeletal Ray Formation.International Journal of Computer Applications,2011 September; 29(1), 17-25.
8. K. Shahi, Z. M. Helmi, Z. M. Shafri, E. Taherzadeh, S. Mansor, R. Muniandy. A Novel spectral index to automatically extract road networks from WorldView-2 satellite imagery. Elsevier, The Egyptian Journal of Remote Sensing and Space Sciences. 2015.
9. S. Leninisha, K. Vani.Water flow based geometric active deformable model for road network. ISPRS Journal of Photogrammetry and Remote Sensing. 2015; 102,140-147.
10. T. Onur. Fully Automatic Road Network Extraction from Satellite Images. IEEE, 2007; 708-714.
11. T.Kohonen.Self-Organizing Maps. (2nd edn), Springer-verlag. 1997.
12. P.Y. Shinzato, D.F. Wolf. A Road network following approach using Artificial Neural Networks combinations.Journal of Intelligent & Robotic systems. 2011 June; 62(4), 527-546.
13. J. Deng, J. Hu, J. Wu. A study of color space transformation method using nonuniform segmentation of color space source.Journal of computers.2011; 6(2),288-296.
14. K. P. Kaliya murthie, D. Parameswari.Remote Sensing imaging for Satellite Image Segmentation.Indian Journal of Science and Technology. 2015; 8(31),1-5.
15. C. Simon, K. Peter, R. Rranz.The Automatic Extraction of Roads from Lidar data.ISPRS,Istanbul,Turkey, 2004,July, 12-23.