Available online at www.elixirpublishers.com (Elixir International Journal)

Remote Sensing

Elixir Remote Sensing 56C (2013) 13374-13379

ISSN: 2229-712X

An Approach to Automatic Road Detection on High Resolution Remotely Sensed Imagery

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ARTICLE INFO

Article history:
Received: 29 January 2013;
Received in revised form:
5 March 2013;
Accepted: 6 March 2013;

Keywords
Road Detection,
High Resolution RS Images,
Panchromatic Image.

ABSTRACT

In this paper, the application of the fully automated road detection for high resolution panchromatic images is proposed. This approach includes image binarization, boundary tracing algorithm and mathematical morphology reconstruction in order to retrieve main regions which have high potential to be regarded as road. Fuzzy C-means clustering is used for image binarization. Moore-Neighbour tracing algorithm modified by Jacob's stopping criteria is applied for tracking and labelling regions then flood-fill algorithm is exerted on regions in order to fill holes. Afterwards, four main shape-factors are introduced which can effectively discriminate between road and other terrain features. The R, H, Q and C factors that are relevant to shape of road are defined in this research. K-means cluster is then utilized to separate the roads from others, based on mentioned shape-factors. The algorithm has been tested with PANchromic (PAN) image of Worldview2 sensor. The results demonstrated development in road detection based on shape-factor clustering.

Introduction

In the last two decades there has been an intensive effort to produce fully automatic method for road detection. The main advantages of automatic road detection are its ability to detect roads where human eyes cannot identify, fast performance in order to update GIS-database and its ability to uniform the approach to different images. Road data enables GIS applications to facilitate a variety of services which include satellite navigation, route planning, transportation system modelling (K.Lee and H. Ryu, 2004), health care accessibility planning (J.Sherman. et al, 2005), land cover classification (J.Rocha and M.Queluz, 2002) and even infrastructure management (B. Ayalew, et al, 2003). Even with the presence of various road detection methods, they can be separated to: road edge detection and tracking methods, morphological algorithms and image-segmentation, extraction and integration of parallel lines, dynamic programming and based-on knowledge methods. Considerable interest has been generated for new transforms that exclusively address the problem of edge detection, especially in case of road detection in high resolution Remotely Sensed (RS) images. They are based on multi-resolution analysis, time-frequency analysis, pyramid algorithms and wavelet transform (Gonzalez, R. C., 2010). P.N ANIL (P.N.Anil et al, 2010) proposed a new approach based on image-segmentation. In his research Statistical Region Merging (SRM) was used for image segmentation and road network was extracted by skeleton pruning method based on contour partitioning. Trinder J (Trinder J, 2005) worked on extraction of parallel line, where key steps were producing parallel lines from linked edges and determining whether a pair of parallel lines belonged to a road. Some researches [e.g. (A. P. Dal Poz, G. M. do Vale,2008)] focused on introducing cost function between the start point and the end point of road and utilize the dynamic programming algorithm (ANN, GA, PSO) to find the most reasonable route. Knowledge-based methods involved the use of existing GIS database or map and rule based systems. In (Bordes Ghislaine, et al, 1997) and (Stilla, U, 1995) used map and cartographic database respectively as a guide for image interpretation. In (Vosselman, G., de Gunst, M., 1997) the old database was used not only to verify but also to detect new road branching from the given data.

The aim of this paper was to improve the traditional road detection methods in high resolution PAN images based on image binarization, mathematical morphology reconstruction, boundary tracing algorithm and clustering effective shape-factors. Fuzzy C-Means (FCM) binarization method has been used to make binary image. In general all histogram thresholding techniques worked very well when the image grey-level histogram was bimodal, on the other hand, unlike the bimodal case, there was no clear separation between object and background pixel occurrences. Thus we preferred to make use of Fuzzy-C means clustering rather than histogram techniques because it could efficiently deal with multimodal cases. Afterwards tracing boundary was carried on regions by Moore algorithm then tiny objects were eliminated by adaptive thresholding before clustering and holes were filled by flood-fill method; finally, the relevant shape-factors were introduced where the correlation between roads and complex terrain features was significantly decreased.

Methodology

The method approaches basically the problem of road detection through clustering of regions that were more discernable in high resolution PANchromic (PAN) RS images. The overview of the algorithm is shown in figure 1.

Pre-processing

Image enhancement is among the simplest and the most appealing areas of digital image processing. Basically, the idea behind enhancement techniques is to bring out detail that is obscured, or simply to highlight certain features of interest in an image. In first step, a linear stretch mapping with a two percent

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clip was applied in this study. Two percent of the brightest pixels were converted to white and two percent of the darkest pixels were converted to black. Other gray values were linearly mapped between those two extremes. This step was done in order to make visions of road objects differ from background.

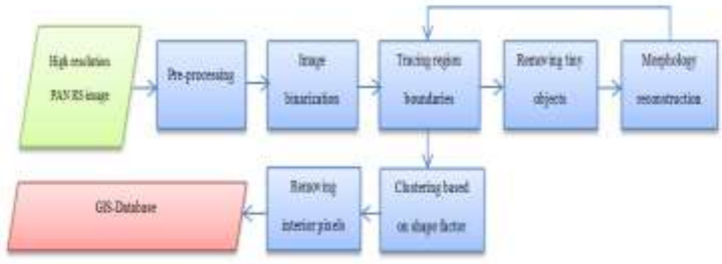


Fig 1.The flow chart of the proposed methodology

Image Binarization

The purpose of this step was to separate that objects and background into nonoverlapping sets. Image binarization based on FCM clustering was utilized in this paper. Fuzzy clustering was more natural than hard clustering. Objects on the boundaries between two classes were not forced to fully belong to one of the classes, but rather were assigned membership degrees between zero and one indicating their partial membership. FCM is a method of clustering which allows one piece of data to belong to two or more clusters. This method developed by Dunn in 1973 and improved by Bezdek in 1981. It is based on minimization of the objective function 1 (James C.Bezdek, et al, 1978) :

$$J_m=\sum_{i=1}^{N}\sum_{j=1}^{C}u_{ij}^{m}x_i-c_j{}^{2} \qquad 1\le m<\infty \qquad (1)$$

where m is any real number greater than one and in this project it was set to two, C is the number of clusters, u_{ij} is the degree of membership of x_i in the cluster j, x_i is the ith of d-dimensional measured data, c_j is the d-dimension center of the cluster, and ||*|| is any norm expressing the similarity between any measured data and the center. Fuzzy partitioning was carried out through an iterative optimization of the objective function 1, with the update of membership u_{ij} and the cluster centers c_j by (James C.Bezdek, et al, 1978):

$$u_{ij}=\frac{1}{\sum_{k=1}^{c}\left(\frac{x_i-c_j}{x_i-c_k}\right)^{\frac{2}{m-1}}}$$

$$\mathbf{c_j}=\frac{\sum_{i=1}^{N}\mathbf{u_{ij}^{m}}.\mathbf{x_i}}{\sum_{i=1}^{N}\mathbf{u_{ij}^{m}}}$$

This iteration stopped when, $\mathbf{max_{ij}}\left\{\left|\mathbf{u_{ij}^{(k+1)}}-\mathbf{u_{ij}^{(k)}}\right|\right\}<\boldsymbol{\varepsilon}$, where ε was 1e-5 in this work, whereas k are the iteration steps. This procedure converged to a local minimum or a saddle point of J_m.

In order to make image binarization, the number of clusters was set to two. For each pixel we had two values of membership belonging to two clusters. Here the higher value of membership was selected and labelled according to the corresponding cluster number. For instance, a pixel had membership value: [0.9, 0.1]. Therefore this pixel was labelled cluster one. Accordingly all pixels were labelled to represent a binary image.

Tracing region boundaries

Before taking any further action, the boundaries had to be traced. Moore neighbour contour tracing algorithm was used for this purpose. Moore Neighbourhood of a pixel is the set of eight pixels which share a vertex or an edge with that pixel. The basic idea is when the current pixel p is white; the Moore neighbourhood of p is examined in clockwise direction starting with the pixel from which p was entered and advancing pixel by pixel until a new white pixel is encountered. The algorithm terminates when the start pixel is visited for second time. The main weakness of Moore Neighbour tracing lies in the choice of stopping criteria *i.e.* visiting the start pixel for second time. If the algorithm depends on this criterion all the time it fails to trace contour of large family of patterns. So mostly it uses Jacob's stopping criterion (Gonzalez, R. C., 2010). This criterion defined as: stop after entering the start pixel a second time in the same direction you entered it initially.

Removing tiny objects

After binarization, many small regions that were irrelevant to road were identified. The main attribute of these regions related to noise, texture and tiny objects had low perimeter. A simplified approach for this solution was to assume that perimeter of all regions follows normal distribution; therefore regions that had perimeter lower than $\boldsymbol{\mu}+\boldsymbol{\sigma}$ could be omitted. Where μ and σ were mean and standard deviation of perimeters of all regions respectively.

Morphology reconstruction

Reconstruction was a very useful operator provided by mathematical morphology (J. Serra,1982 and 1988). They are two definitions for reconstruction in binary image:

Definition in terms of connected components:

Let I and J be two binary images defined on the same discrete domain D in such that $J \subseteq I$. In terms of mapping, this means that: $\forall p \in D;\ J(p)=1 \Rightarrow I(p)=1$. J is called the marker image and I is the mask. Let $I_1, I_2, \ldots, I_n$ be the connected components of I (Luc Vincent, 1993).

The reconstruction $\rho_I(J)$ of mask I from marker J is the union of the connected components of I which contain at least a pixel of J (Luc Vincent, 1993):

$$\rho_I(J)=\bigcup_{J\cap I_k\neq\emptyset} I_k$$

This definition is depicted in figure 2.

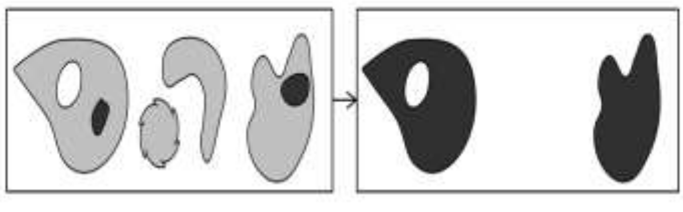


Fig 2. Binary reconstruction from markers

Definition in terms of geodesic distance

Given a set X (the mask), the geodesic distance between two pixels p and q is the length of the shortest paths joining p and q

which are included in *X*. This distance between two pixels within a mask depends on the type of connectivity (Luc Vincent, 1993). The geodesic distance was introduced in the framework of image analysis in (C. Lantuejoul and S. Beucher, 1981) and is the basis of several morphological operators (C. Lantuejoul and F. Maisonneuv, 1984). The geodesic dilations defined as:

Let $\mathbf{X} \subset \mathbf{Z}^2$ be a discrete set of Z and $\mathbf{Y} \subseteq \mathbf{X}$. The geodesic dilation of size $\mathbf{n} \geq 0$ of *Y* within *X* is the set of the pixels of *X* whose geodesic distance to *Y* is smaller or equal to *n* (Luc Vincent, 1993):

$$\delta_X^{(n)}(Y) = \{p \in X | d_X(p, Y) \leq n\}$$

Geodesic dilation of a give size *n* can be obtained by iterating n elementary geodesic dilations (Luc Vincent, 1993):

$$\delta_X^{(n)}(Y) = \underbrace{\delta_X^{(1)} o\, \delta_X^{(1)} o \ldots o\, \delta_X^{(1)}}_{n\ times}(Y)$$

When performing elementary geodesic dilations of a set *Y* inside a mask *X*, the connected components of *X* whose intersection with *Y* is non-empty are progressively flooded. Thus reconstruction can be stated as follows:

The reconstruction of *X* from $\mathbf{Y} \subseteq \mathbf{X}$ is obtained by iterating elementary geodesic dilations of *Y* inside *X* until stability. In other words:

$$\rho_X(Y) = \bigcup_{n \geq 1} \delta_X^{(n)}(Y)$$

Before performing the clustering procedure, the Flood-fill algorithm based on the mathematical morphology reconstruction principle (P. Soille, 1999) was used to fill holes in order to ensure that regions from the binary image were without holes. Afterwards tracing region boundaries was again used for labelling regions.

Clustering based on shape-factor

Until this step, many regions were retrieved that merely few of them belonged to road. Features that exclusively discriminate between road regions and others should be defined in order to extract road regions. The lesser correlation between features of roads and other terrain objects, the more precise the clustering would be; therefore the road would readily be separated. Figure 3 represents some sample shapes to introduce shape-factors more comprehensively.

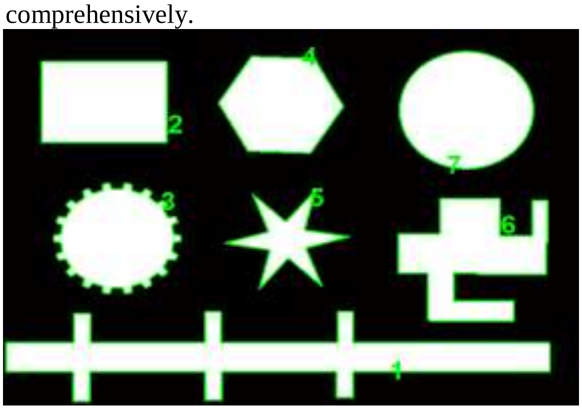


Fig 3. Sample shapes

They were four shape-factors proposed in this research:

R factor:

The first feature was *R* which was based on shapes' circularity. A shape's centroid was calculated, and all the Euclidean distances from the centroid to each boundary pixel were measured. With this set of distances, the mean (μ) and the variance (σ^2) were calculated. These statistical parameters were used on a ratio that calculates the circularity, *R*, of a shape. This circularity measure was given by:

$$R = \frac{\sigma^2}{\mu}$$

The *R* feature was evaluated for the shapes presented in table 1:

Table 1. R values for samples

Region #	1	2	3	4	5	6	7
R factor	58.41	1.99	0.2	0.16	4.99	6.35	0

H factor:

This shape feature was defined to obtain a quantitative compactness value of a shape. The discrete distance transform was used to estimate the shape factor *H* uses. This was done by defining a ratio between the addition of distances and the cube of farthest distance from border. This factor was given by:

$$H = \frac{\sum_{i=1}^{N} x_i}{[\max(x_1, x_2, \ldots, x_N)]^3}$$

Where x_i was the value generated by the discrete distance transform, and *N* was the number of region's pixels.

The *H* feature was evaluated for the shapes presented in table 2:

Table 2. H values for samples

Region #	1	2	3	4	5	6	7
H factor	24.44	2.04	1.08	1.19	2.3	3.78	1.06

Q factor:

The *Q* shape factor was another compactness value of a shape. This factor was defined by a ratio between the area of region and the square of maximum farthest distance from border, that is:

$$Q = \frac{A}{[\max(x_1, x_2, \ldots, x_N)]^2}$$

Where x_i was the value generated by the discrete distance transform, *N* was the number of region's pixels and *A* was area of the corresponding region. The *Q* feature was evaluated for the shapes presented in table 3:

Table 3. Q values for samples

Region#	1	2	3	4	5	6	7
Q factor	58.31	5.34	3.48	3.51	8.85	11.8	3.14

C factor:

The last feature was the old ratio of shape compactness which was formulated by:

$$C = \frac{P^2}{4\pi A}$$

Where *A* was area of the shape and *P* was perimeter of the shape. The *C* feature was evaluated for the shapes presented in table 4:

Table 4. C values for samples

Region #	1	2	3	4	5	6	7
C factor	8.74	1.28	2.47	1.21	6.5	3.78	1.04

K-means clustering

In this step the K-means clustering method, which is an unsupervised clustering method, was used in order to classify the regions into roads and other regions based on shape-factors mentioned above. K-means used an iterative algorithm that minimizes the sum of distances from each object to its cluster centroid over all clusters. This algorithm moved objects between clusters until the sum could not be decreased further. The result was a set of clusters that were as compact and well-separated as possible. K-means computed centroid clusters differently for the different supported distance measures. In this step squared Euclidean distance was opted. Two clusters were set for separating road from other terrain features. Like many other types of numerical minimizations, the solution that k-means reached depended on the starting points. It was possible for k-means to reach a local minimum, where reassigning any one point to a new cluster would increase the total sum of point-to-centroid distances, the clustering was repeated ten times in this study, each with a new set of initial cluster centroid positions and then it returned the solution with the lowest value for sum of distances.

Removing interior pixels

There was an advantage of having binary image to remove interior pixels rather than using edge detection approaches. This approach set a pixel to zero if all its 4-connected neighbours are one, thus leaving only the boundary pixels on.

Results And Discussion

In order to evaluate the capability of this method, the PAN image of Worldview2 sensor was used. WorldView2 provides 46 cm resolution images in panchromatic mode. In pre-processing step, the image was enhanced in order to make objects slightly differ from background (figure 4).

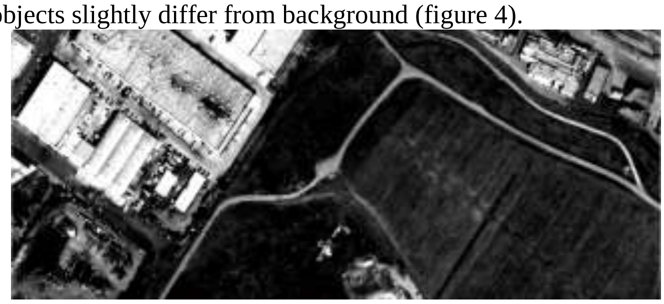


Figure 4. Enhanced image.

FCM was carried out to accomplish image binarization. The final cluster centers were 26.78 and 204.71. The histogram of the enhanced image and the cluster centers are shown in figure 5.

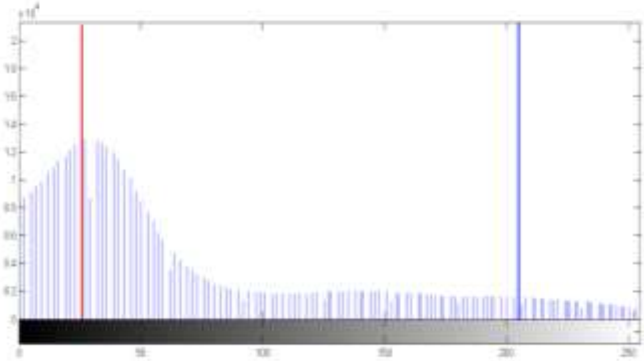


Figure 5. The image histogram of enhance image and final cluster centers.

After labelling corersponding cluster number based on the higher value of membership , the image binarization was created (Figure 6).

Figure 6. Image binarization's result.

Boundary tracing was then perfomed and tiny objects related to noise and textures were removed. Afterwards, with using Flood-fill algorithm, regions were free of holes that could hinder having errounes result of the shape-factors (Figure 7).

Figure 7. Removing tiny objects and filling holes.

Boundary tracing was again used for calculating the shape-factors in next step. The result of boundary tracing is shown in figure 8.

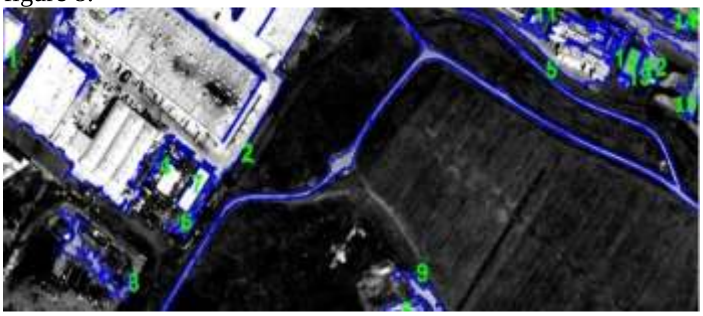
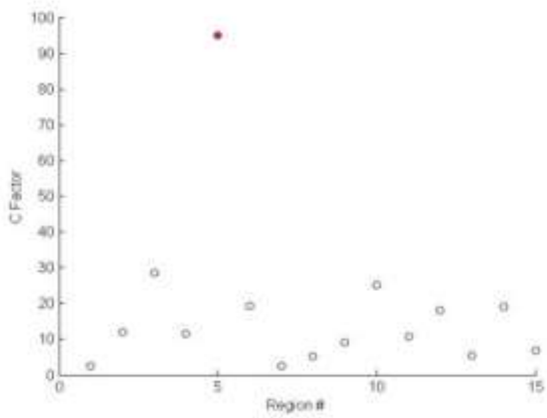


Figure 8. The result of boundary tracing

The value of shape factors for labled regions are shown in figure 9. Note that the red circle is region #5 which is reprsented road.



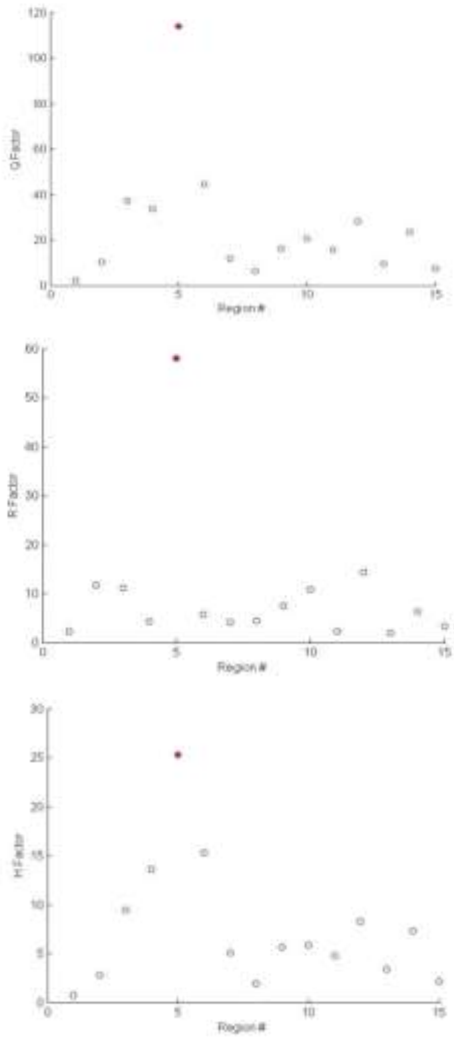


Figure 9. The value of shape-factors for the regions.

By using K-means for clustering regions into road and other, the result showed that shape-factors could even discriminate complex or elongated terrain features from the road. The interior pixels also were removed for representing the edge form of regions. The final cluster centers for four used shape-factors are listed in table 5.

Table 5. The final cluster centers.

Shape-Factor	Cluster1 (The Road)	Cluster2 (Others)
R	58.0404	6.4513
H	25.2767	6.1772
Q	114.0082	19.0970
C	94.9159	12.6011

The final result of the proposed approach is shown in figure 10.

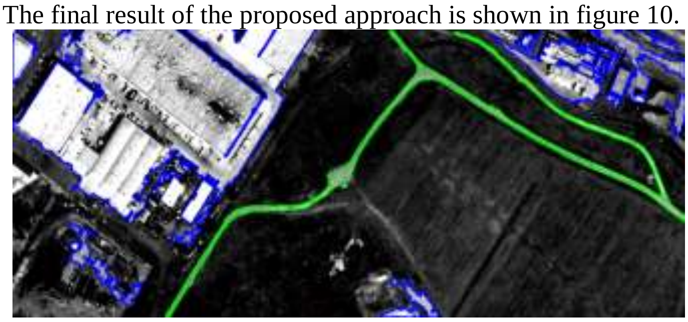


Figure 10. The final result of road detection.

Conclusion And Future Work

In this paper a new technique for road detection from high resolution imagery was proposed. This study focused on introducing new shape-factors that were important features in PAN image. The approach was evaluated using Worldview2 PAN channel. The experiments showed that the approach and shape-factors were effective and accurate in extracting road regions. However, since the image binarization reduced the information significantly, as for future work, similar methodology will be developed for urban areas by adding color image segmentation method (*e.g.* modified SRM or automatic merging regions). Our general conclusion is that the proposed method clearly exhibits appropriate performance despite that still a great deal to be done to improve this methodology for urban areas.

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