

Roads Extraction and Mapping from Aerial and Satellite Images

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Abstract: Automatic man-made objects detection from aerial and satellite images be a very important research field to understand the changes in our environment and gives an important source of information to be used in many fields as an infrastructure, mapping generation, planning traffics and cartographic. This study describes and evaluates an automated method for roads extraction and mapping. For roads extraction we follow these steps: The first step is pre-processing of images to reduce noises and increase the contrast between contours and to improve the quality of the initial image by using the bilateral filtering, the second step deals with Statistical Region Merging to segment the image into homogenous regions, in the third step roads are detected based on modified active contour with adaptive initial contour to localize the region of road followed by edge detection and linking. For road centerlines extraction and mapping, skeleton centerlines of roads were calculated by using the fast-marching distance transform. The proposed method is tested on several images with high resolution and experiments results show that can extract and map roads with a better accuracy of 93.36%.

Keywords - Roads extraction, statistical region merging, active contour, bilateral filtering, fast marching distance transform, aerial and satellite images.

1. Introduction

Satellite images and remote sensing systems provide a large of information that can used in many domains and useful for analyses of changes in land, the extracting information are used in an infrastructure, mapping generation, planning traffics and cartographic, The issue that interests us in this paper is the problem of road detection from aerial and satellite images that is becoming an important problem in computer vision and remote sensing, road detection has been a long term and challenging topic of research and is difficult in the presence of a lot of objects: buildings, trees, grass etc. that occluding the appearance of the roads. Large collections of satellite images are becoming available to the public, from satellite images to aerial photos.

Many searches have been conducted in road detection from satellite and aerial images. Mokhtarzade et al. [15] implemented the road detection from high resolution satellite images by using artificial neural networks algorithms [26], the authors Asif M. et al. [1,2] proposed a simple approach for road tracking by using firstly the B-spline function for road model to define the initial contour of the image, secondly extracting feature points by processing image. Finally, active shape model concept is used for contour deformation integrated with recursive curve fitting method for pose and orientation

measurement their methods Lin. Y. and Saripalli S. [11] introduced a road detection method based on three steps: firstly, a possible road regions are detected using a histogram based thresholding method, secondly local line segment extracted using a probabilistic Hough transform and finally implement point clustering for detecting the final region. Jin H. et al. [10] proposed an integrated approach for road feature extraction from rural and urban areas in very high resolution aerial images based on homogeneity histogram thresholding and Gabor filters. Firstly, they used the homogeneity histogram image segmentation to extract the color information and the spatial features.

Unsalan C. and Sirmacek B [20] focused on detecting road very on high resolution satellite and aerial image sets by using a novel method that based on probabilistic road center detection, road shape extraction, and graph-theory-based road network formation. In the first step, they extract edge pixels as primitives. Then, they use these to detect road centers by probabilistic method. In the second step, they extract the road shape by a binary balloon algorithm. In the third and final step, graph theory is used to represent the extracted road segments in a graph formation. Shi W. et al. [18] introduced two-step method for urban main road extraction by applying spectral-spatial classification and shape features. Firstly initial road map is created by information fusion

of morphological profiles (MPs) for spectral-spatial classification using mathematical morphology based on paths openings and closings and secondly the road class is filtered by shape features to remove misclassified roads.

MauryaR. et al. [12] have developed a method based on the K-Means clustering based segmentation to find the road cluster, and morphological operations are used to filter the area which has similar features as the road. Miao Z. et al. [13] used shape features and spectral information to extract road segments from a binary map after a preprocessing, and road centerlines are extracted from road segments by using the multivariate adaptive regression splines, and then, final road maps are created after road segments connecting. Miao Z. et al. [14] presented a semi-automated method for road centerline extraction from VHR Images by using geodesic method to link seed points prescribed in advance by users in order to extract the initial road segments, thresholding operation is applied to separates the image into road and no road classes, and a kernel density estimation map is generated, Movaghati S. et al.[16] presented a new algorithm for road extraction from satellite images by combining Extended Kalman Filter (EKF) with a special Particle Filter (PF). Roads are road traced using EKF until a stopping criterion, and then, the PF algorithm is applied to fin and identify all possible road branches. Valero S. et al. [21] integrated approach introduces the use of Path Openings and Path Closings in order to extract structural to extract the linear geometrical pixel information which allow to classify each pixel as road or non-road. DallaMura M. et al. [6] extracted road features on very high resolution by using morphological attribute profiles, and then the features extracted were used for the classification in order to extract road, building, shadow and vegetation.

Methods proposed by several researchers to detect road in satellite and aerals images are briefly summarized in Table 2.

The rest of the paper is organized as follows. Next describes road characteristics, materials for this paper and the proposed method are presented in detail in Section 3, experimental results and discussions are reported in Section 4, while the paper is ended by conclusion and perspectives.

2. Road features

To detect roads from satellite or aerals images it does necessary first understand their physicals properties as follows:

- The surface of the road is firm and smooth; this characteristic is spectral;
- The geometric with between boundaries of road is almost constant;
- Roads have a local curvature its maximal curvature is lower for high way than for a rural road, and road are straight locally but not globally;
- Roads have a higher density and connections in urban areas than rural ones, this links and networking are topological properties.

3. Materials and method

The input data consist of images differ in term of resolution, the resolution of the images has a strong influence on the representation of both roads and other objects. To evaluate the proposed method, we have tested it in two types of images: the first type are QuickBird images downloaded from VPLab [23] with a spatial resolution of 0.6 m/pixel, the study area had a spatial size of 512×512 pixels and the second type of images are aerial images captured from an airplane by a Canon Eos 1Ds Mark III camera at a height of 1000 meters above ground, the ground sampling distance is approximately 13cm used in the paper (K. Liu and G. Mattyu, 2015), in those images the roads appear as regions and a lot of noise can decrease the quality of the image.

The proposed method consists of five steps, namely: contrast enhancement, region merging, contour active application, edge detection, and skeleton extraction, Figure 1 shows the main steps of the proposed methods.

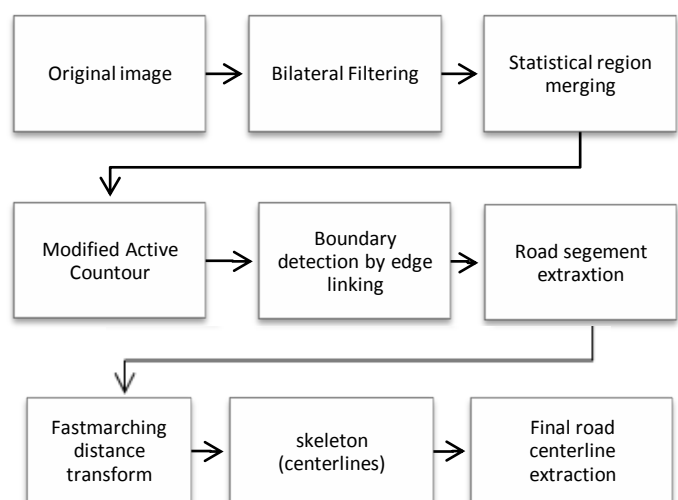


Figure 1. Overview of the proposed method.

3.1. Image preprocessing and contrast enhancement

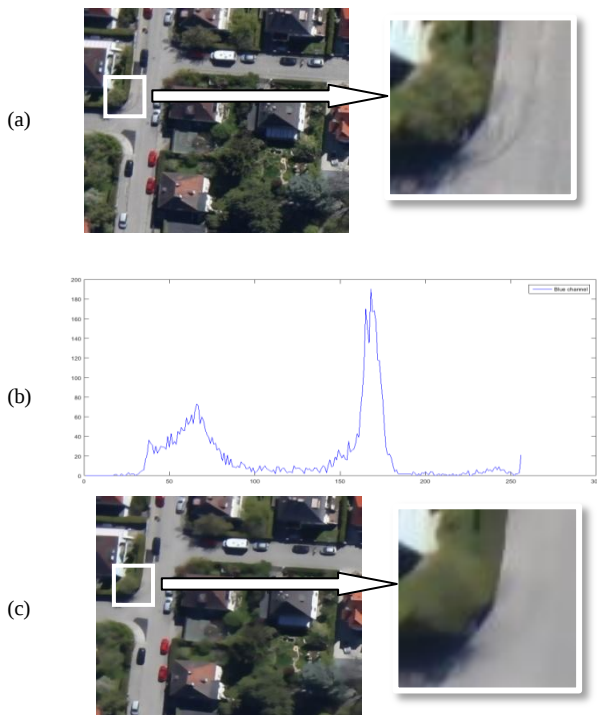
After the acquisition of the image, in this subsection we are interested to reduce noise and illuminate small disturbances in order to improve the quality of the image. The input image is enhanced using the Bilateral Filtering [19] in a color space.

Table 1. Summary of previous related works on road detection.

Authors	Method used	Input data	Resolution
Asif M et al. [1,2]	- B-spline function and active shape model	Visual Guidance Systems Images	-
Mokhtarzade M et al. [15]	- Artificial neural networks (ANNs)	Satellite images Ikonos and Quick-Bird images	High resolution
Movaghati S. et al. [16]	- Combination of Extended Kalman filter with a special particle filter	IRS satellite image IKONOS images	5.8-m SR 0.8-m SR
Valero S. et al. [21]	- Path opening and closing and pixel classification	Remote sensing images	Very high resolution
Dalla Mura M. et al. [6]	- Multi-attribute approach based on morphological attribute filters.	Panchromatic images	Very high resolution
Maurya R. et al. [12]	- K-Means clustering fellow by morphological operations	-	-
Lin, Y. et al. [11]	- Thresholding, Hough transform, Point clustering	Aerial images obtained using UAV	Low altitude
Jin H. et al. [10]	- Homogeneity histogram thresholding and Gabor filters based SVM image classification	Aerial images	Very high resolution
Unsalan C. et al. [20]	- Probabilistic and Graph Theoretical Methods	Satellite (Geoeeye, Ikonos, and QuickBird) and aerial images	Very high resolution
Miao Z. et al. [13]	- Shape Features and Multivariate Adaptive Regression Splines	Remotely sensed imagery	High resolution
Shi W. et al. [18]	- Spectral-Spatial Classification and Shape Features	Remotely sensed imagery	High resolution
Miao Z. et al. [14]	- Geodesic method, thresholding operation and kernel density estimation	Satellite images	Very high resolution

- Bilateral Filtering

The bilateral filter is a non-linear technique that filters an image while respecting strong edges. It is defined as a weighted average of nearby pixels in a manner very similar to Gaussian convolution. The difference is that the bilateral filter takes into account the difference in value with the neighbors to preserve edges while



(d)

Figure 2. (a and b) The Input image and the histogram of its blue channel, (c and d) the filtered image and its histogram after bilateral filter application.

smoothing. In fact, a bilateral filter allows combining the three color bands appropriately, and measuring photometric distance between pixels in the combined

space. Moreover, this combined distance can be made to correspond closely to perceived dissimilarity by using Euclidean distance [7] in the CIE-Lab color space. To show the benefit of the bilateral filter, it is applied with 5×5 mask size, Figure 2a shows the original image and a zoomed part in it, and the Figure 2c illustrate the enhanced image that preserves large sharp edges without blurring as clearly shows in the zoomed window.

After the input image was filtered the edges are kept without blurring, that helped us to segment the image into homogeneous objects based on the spectral and spatial information in the next step.

3.2. Image segmentation by region growing and merging

The region grouping presented the transformation of the collection of pixels of an image into a visually meaningful partition of regions and objects. This method iteratively grouping the connected set of pixels until get the maximum regions by homogeneity criterion. It is a local recursive method which has a principle of growing a region before moving to the next. The image is segmented into regions. Similar adjacent pixels in a certain homogeneity criteria are grouped into distinct regions.

The growing and the fusion-division are common techniques in this category unlike the extraction of contours which is interested to edges of the regions, the segmentation into homogeneous regions is to segment the image based on the intrinsic properties the regions.

- Statistical region merging

In region merging, regions are sets of pixels with homogeneous properties and they are iteratively grown by combining smaller regions or pixels, The Statistical region merging SRM proposed in [17] is a region-grow-based segmentation algorithm, partitioning an image into non-overlapping regions called objects. As long as the SRM is greedy, two essential aspects participate in defining a statistical region merging algorithm:

Merging predicate: specify how to merge to undetermined region. To develop the predicate authors of [17] prove the following: For any fixed couple (R, R') of regions of I and any fixed $0 < \delta \leq 1$, the probability is no more than δ that:

$$|(\bar{R} - \bar{R}') - E(\bar{R} - \bar{R}')| \geq g \sqrt{\frac{1}{2Q} \left(\frac{1}{|R|} + \frac{1}{|R'|} \right) \ln \frac{2}{\delta}} \quad (1)$$

Where g is the number of image intensity level, Q can be seen as a measure of statistical complexity of the image I^* . Higher values of Q result in a finer segmentation. $\bar{R}$ indicates the average intensity across the region R and $E(R)$ is the expectation over all corresponding statistical pixels of I^* of their sum of expectations of their Q random variables for their intensity values. $|\cdot|$ indicates

cardinality. The merging predicate can be induced as following, equation (2):

$$P(R, R') = \begin{cases} true & \text{if } \forall a \in \{R, G, B\}, \\ & |\bar{R}'_a - \bar{R}_a| \leq \sqrt{b^2(R) + b^2(R')} \\ false & \text{otherwise} \end{cases} \quad (2)$$

where, R' and Rare adjacent regions, $\bar{R}_a$ stands for the observed average for component a in region R , and

$$b(R) = g \sqrt{\frac{1}{2Q|R|} \left(\ln \frac{|S_{|R|}|}{\delta} \right)} \quad (3)$$

where, $|S_{|R|}|$ indicates the set of regions with $|R|$ pixels, and if the $P(R, R')$ returns true, the R and R' can merge to be a bigger region.

Order in merging: define an order to be followed to check the merging predicate that:

Each pixel with its 4-connexity neighbors form pixel couples C is weighted by the difference of adjacent pixels, called Dissimilarity, equation (3).

$$d(p, p') = \max_{a \in \{R, G, B\}} |p'_a - p_a| \quad (4)$$

where p'_a and p_a are 4-connexity neighbors in channel a . after sorting the couples in ascending order according to their Dissimilarity by using radix sorting algorithm, the SRM traverses the couples. The principal of the method is follow: Let p and p' are the pixels of the couple C_i , and belong to the regions $R(p)$ and $R(p')$ respectively.

If the $P(R(p), R(p'))$ respectively returns true, merges $R(p)$ and $R(p')$. Else, go to next couple.

3.3. Road segment extraction using Active Contour Model

The most difficult is in finding a desired object and separating it from the other objects, there are a lot of method for image segmentation, here we interested by Active Contours Models (ACM), also called Snakes were designed for the extraction of contours in images. The CV model proposed by Chan and Vese [5] has the global segmentation property to segment all objects in an image, the geodesic active contour model (GAC) [4] can only extract the object when the initial contour surrounds its boundary, and it possesses local

segmentation property, which can only segment the desired object with a proper initial contour.

The active contours are based on the Signed Pressure Force (SPF) function defined in [25]. SPF has values in the range $[-1,1]$. It modulates the signs of the pressure forces inside and outside the region of interest so that the contour shrinks when outside the object and expands when inside the object.

In this paper, the method used active contours that based on [27] and share the advantages of the CV model and GAC model.

$$SPF(M(x,y)) = M(x,y) - (c1 + c2)/2 \quad (5)$$

$$SPF(M(x,y)) = -SPF(M(x,y)) / \max(|SPF(M(x,y))|) \quad (6)$$

$$c1(\varphi) = \frac{\int_{\Omega} M(x,y) \cdot H(\varphi) dx dy}{\int_{\Omega} M(x,y) \cdot H(\varphi) dx dy} \quad (7)$$

$$c2(\varphi) = \frac{\int_{\Omega} M(i,j) \cdot (1 - H(\varphi)) dx}{\int_{\Omega} M(i,j) \cdot (1 - H(\varphi)) dx} \quad (8)$$

where Ω is a bounded open subset of R^2 , φ is the initial level set, H is the standard Heaviside function. The result of $c1$ and $c2$ is tow constants which are the average intensities inside and outside the contour, respectively and obviously, the signs of the SPF function in Equations (5,6) are identical to what Figure 3 shows. For more detail see [27].

At the last step of the level set and after each iteration the Gaussian filter is used to regularize the selective binary level set function $u(x,y)$ that can be described as follow:

$$u(x,y) = G(x,y) \otimes u(x,y) \quad (9)$$

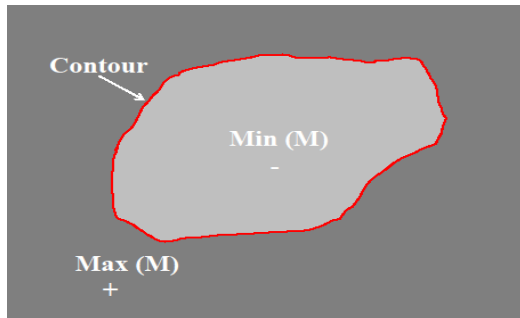


Figure 3. The signs of the SPF function inside and outside the object are opposite.

where $G(x,y)$ is the Gaussian function and $\otimes$ marks convolution operator. Smoothed Gaussian filters are used in two directions, horizontal and vertical ones as shown below in Equations 10 and 11.

$$G_x(x,y) = \frac{-x}{2\pi} \exp\left(-\frac{x^2 + y^2}{2}\right) \quad (10)$$

$$G_y(x,y) = \frac{-y}{2\pi} \exp\left(-\frac{x^2 + y^2}{2}\right) \quad (11)$$

After input image merging, to make the approach fully automatic we should know which segment is the road cluster and then segment it by using the active contour model.

To identify the road cluster we used the concept that road in the input data after the regions merging usually have the same color in all test images and appear as elongate regions cluster as shows in the Figure 4.

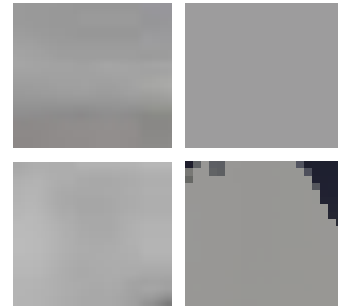


Figure 4. Learning Images used as reference for SSIM Index.

Although the proposed active contour model is used with an adaptive initial contour, this initial contour automatically localizes the object and expands to extract the road region; the stages of this step are as follows:

- For training, we select images of 20x20 pixels contains only one texture that represents the roads from the results obtained in the previous step as illustrated in Figure 4.
- A sliding window of 20x20 pixels is implemented and at each time we calculate the Structural Similarity (SSIM) Index with the training image based on the computation of three terms, namely the luminance term, the contrast term and the structural term. The overall index is a multiplicative combination of the three terms [24].
- The first area that is detected and has the high SSIM Index as the training image will chose as the initial contour as shown in Figure 5 (c,d).

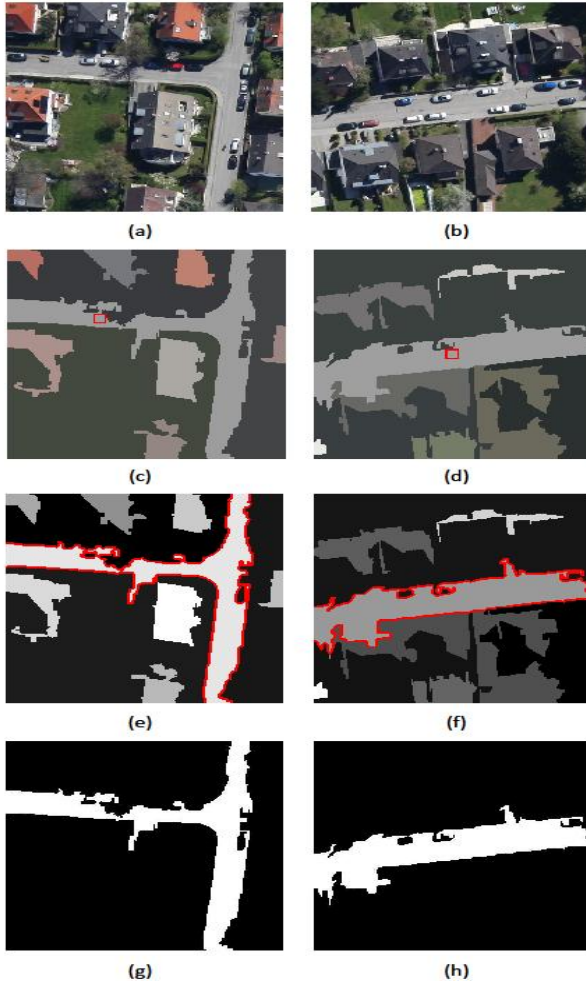


Figure 5. Results of road extraction: (a,b) original images, (c,d) Region merging and initial contour localization, (e,f) Road segmentation based on active contour model, (g,h) Final road segments.

3.4. Road network extraction

Up until present the segmented result and the binary images for road objects by using SRM and ACM are generated as showing in the Figure 5 (last row), but the problem is that the probability of misclassification is still high and many small holes enclose the main road that must be removed and the boundaries of road must be straight to correctly extract the road centerline. In this section, a novel road extraction approach is developed to accurately extract road networks from a segmented road image. This extraction process includes two main steps:

- Edge detection and linking;
- Morphological operation.

- Edge detection and linking

Candidate edges detection of roads plays an important role in tracing the boundary of roads and

makes them straighter. The following steps are followed for edge detection of roads.

After road extraction and generating of the binary image, the edge maps was produced by the detector of canny [3] in order to make edges of the road more straight and eliminate the holes. The operation of the edge detector from is best illustrated by the example in Figure 6(c,d).

The edge function calculates the gradient using the derivative of a Gaussian filter, which is a common first step in edge detection. The Gaussian function has important properties which are verified with respect to its integral as expressed as follows:

$$g(x,y) = \frac{1}{2 \times \pi \times \sigma^3} e^{-(x^2+y^2/2\sigma^2)} \quad (12)$$

where g is the Gaussian operator and σ is the standard deviations of Gaussian function, that controls the degree of smoothing. In our study we used a high value to $\sigma = 27$. Last step; the boundary of road is extracted by linking the edge components using a computational approach for edge linking [8].

The algorithm investigates the edge pixels situated at the side indicated by the endpoint direction, for each edge pixel situated in the endpoint neighborhood a linking factor is computed using a simple cost function. The linking coefficient returned by the cost function increases rapidly.

- Morphological operation

Mathematical morphology provides a wide range of image processing operators, all based around a few simple mathematical concepts of set theory. Dilation and Erosion are among the tools of Mathematical morphology.

Dilation is to expand or to increase something. Gradually enlarge the boundaries of regions of foreground pixels on a binary image by using structuring element.

Erosion is one of the basic operators in the area of mathematical morphology its main is to delete or to reduce something. Pixels matching a given pattern are deleted from the image the basic effect of erosion is to Erode away the boundaries of regions of foreground pixels.

After edge linking and extraction of the boundaries of roads in the previous phase, the result is matched with the binary image obtained in the step of segmentation as shown in Figure 6, and then closing

operator of Mathematical Morphology was used for filling the holes.

Closing is defined simply as dilation followed by erosion using the same structuring element for both operations. The closing operator therefore requires two inputs: an image to be closed and a structuring element.

$$C(A, S) = A \bullet S = E(D(A, -B), -B) \quad (13)$$

where A represents the binary image being operated on, and S is another set of pixels, a shape that operates on the pixels of A to produce the result, the set S is called the structuring element and its composition defines the nature of specific dilation. In our case in order to fill all holes we used a 15x15 disk structuring element.

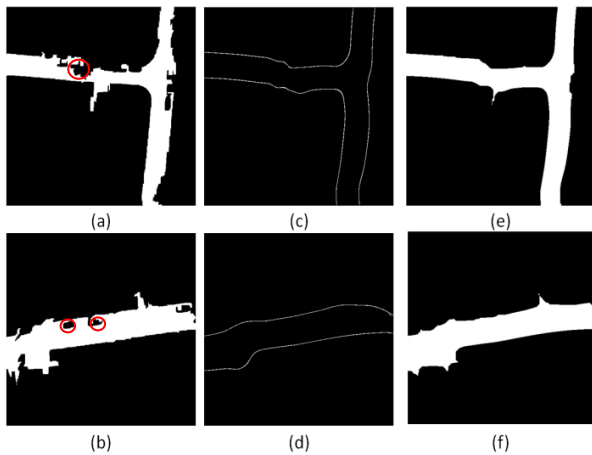


Figure 6. Results of edge linking and morphological application: (a,b) Extraction Binary images of road segments, (c,d) Road Edge detection and linking, (e,f) final road extraction.

3.5. Roads mapping and centerlines finding

In the field of image skeletonizing, there are a number of methods to choose from: Distance transformation, Voronoi diagram and Thinning algorithm. The method that we use in this paper to compute the distance is the fast-marching distance transform proposed by [22]. The Fast Marching algorithm is a numerical algorithm that uses the Eikonal equation.

Roads were mapped, skeleton and centerlines were calculated by using the distance transform. The distance transform is an operator applied to the binary image, the result of the transform is similar to the input image, except that the graylevel intensities of points inside foreground regions are changed to show the distance to the closest boundary from each point. In our case to determine the shortest distance from a list of points to

all other pixels is calculated using the Multistencil Fast Marching Method, for more detail see [9].

4. Performance measures

For performance evaluation it is necessary to construct a database containing ground truth. We collect a group of images, labeled the ground truth manually by using the polygon drawing tool in ArcGis.

In performance evaluation mode, we have used two different types of criterion:

1. Visual criterion: This criterion allows you to plot the results of the selected algorithms on the image to compare them with the reference you have selected.

2. Similarity criterion: Four similarity criteria can be computed between the result of the algorithm and the reference, (see Figure. 7 and table 2):

- Dice criterion:

$$\text{Dice} = \frac{2(R \cup A)}{R + A} \quad (14)$$

Where R and A are the reference mask and the result mask segmented by the proposed method;

- Specificity criterion:

Specificity is the measure of probability by which the method can detect a non-road pixel correctly among non-road pixels and it can be expressed as:

$$\text{Specificity} = \frac{T_N}{(T_N + F_P)} \quad (15)$$

where T_N represents the number of non-road pixels correctly detected as non-road pixels and F_P represents the number of non-road pixels which are falsely detected as road pixels.

- Sensitivity criterion:

Sensitivity is the measure of probability by which the method can detect a road pixel correctly among road pixels.

Mathematically it can be expressed as:

$$\text{Sensitivity} = \frac{T_P}{(T_P + F_N)} \quad (16)$$

where T_P represents the number of road pixels correctly detected as road pixels and F_N represents the number of road pixels which are falsely detected as non-road pixels.

- Accuracy criterion:

Accuracy of a method is the proportion of correctly detected road and non-road pixels among

total examined pixels. Mathematically, it can be expressed as:

$$\text{Accuracy} = \frac{(T_N + T_P)}{(T_N + T_P + F_N + F_P)} \quad (17)$$

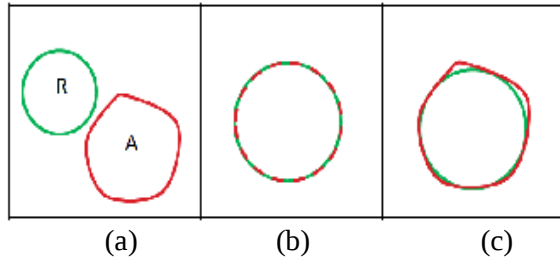


Figure 7. Different situations when computing the similarity criterion: (a) $A \cap R = \{\emptyset\}$, (b) $A = R$, (c) $A \approx R$

Table 2. Value of the similarity criteria for different situations.

Similarity criterion	$A = R$	$A \approx R$	$A \cap R = \{\emptyset\}$
Dice, Specificity, Sensitivity, Accuracy	1	≥ 0.9	0

5. Results and Discussion

This section presents the experimental results; the proposed method is implemented in MATLAB R2015b on a PC with Intel core i3 processor. The proposed approach is applied on aerial and satellite images as mentioned earlier with 512 by 512 pixels. The results of different steps of the proposed method for test images are given in Figures 5 and 6.

In Figure 5, the road regions are segmented using the Statistical Region Merging followed by active contour with adaptive initial contour. The resultant image has holes due to objects on roads as cars or tree shadows which is shown in red circle on Figure 6(a,b). Morphological operators are used for further processing to fill and close those unwanted portions followed by edge linking algorithm in order to align the boundaries of road, its final segmented result is given in Figure 6(e,f).

Table 3. Evaluation of the proposed approach by performance measures with ground truth reference.

Image	Dice	Accuracy	Sensitivity	Specificity
1	0.753	0.9490	0.8242	0.9842
2	0.593	0.9466	0.8134	0.9720
3	0.309	0.9488	0.9204	0.9555
4	0.690	0.8950	0.7985	0.9744
5	0.795	0.9286	0.7416	0.9630

From the experimental results shown in Fig. 6(e,f) as can be seen the proposed method has the best detection performance visually and almost all of the

road connected component is reliably successfully detected.

The performance of proposed method is calculated by using the statistical measures with ground truth road references which is a manually drawn. The proposed results are compared with these reference roads, and this comparison is given in Table 3. The performance measures such as Dice, Specificity, Sensitivity and Accuracy are evaluated on various test images. For this comparison, those measures are calculated base on equations (14, 15, 16 and 17 respectively) as mentioned earlier, the numerical results in Table 3 summarizes these effects.

From Table 3, it can be seen that the proposed approach indicates a good performance in the extraction of road from the test images, it clearly illustrates that the average road detection Dice, accuracy, sensitivity and specificity are 62.80%, 93.36%, 81.96% and 96.98%, respectively. These values show clearly the performance and the great potential of the proposed method for detection of roads from aerial and satellite images.

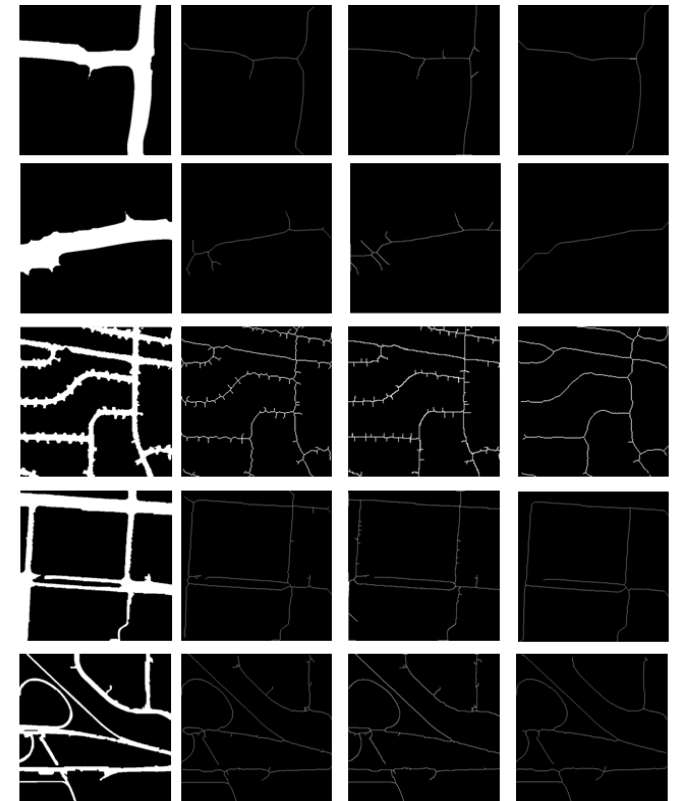


Figure 8. Results of proposed algorithm compared with other methods for various satellite images

For road skeleton extraction and mapping, the experiments visually illustrate in Figure 8. The first column shows the segmented images, second column

shows the application of morphological Thinning, third column indicates the Stentiford method and the last column is the application of fast marching distance for skeleton calculating.

From the experimental results as can be seen the fast marching distance method has the best detection performance visually and how much the Skelton is going smoothly into original road without extracting the unwanted and small branches. The fast marching distance tends to produce lines that follow the center of curves very well, resulting skeletons that accurately reflect the original image without keeping the unwanted branches. The Morphological Thinning and the Stentiford method tends to be better at extracting straight lines, but when thinning is complete, there are still pixels and unwanted branches that should be removed.

6. Conclusion

In this article a new automatic method has been proposed to extract and detect roads in aerial and satellite images. The proposed method is divided into three steps: Firstly, the SRM algorithm was used to segment the image into regions. Secondly: The extraction of roads is made by using a modified contour active based on an adaptive initial contour to locate regions of interest by calculating the similarity SSIM Index. Finally; for the part concerning road mapping, fast marching method is applied to detect the centerline of road segments by using the shortest distance to calculate the skeleton. The proposed method is implemented on the images cited above, and results are given. These results prove that the proposed method is good, but it will need some amelioration to be applied in images with different resolution and complexity problems.

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