Road Network Detection by Mathematical Morphology

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ABSTRACT

An approach to achieve automated road network detection from digital images is presented. The method is based on mathematical morphology analysis while most road extraction algorithms are based on linear analysis methods. As the image resolution increases, road networks appear to be areas with certain width rather than thin lines. The approach proposed in this paper firstly classifies the image to find road network regions, and then morphological trivial opening is adopted to avoid noise including objects that have similar spectral characteristics as road surfaces. The developed method has been tested on high resolution simulation images and aerial photos. The result shows that mathematical morphology provides an effective tool for automated road network detection.

KEYWORDS: Road Detection, Mathematical Morphology, Trivial Opening, Granulometry

1. Introduction

The extraction of roads from digital image has drawn considerable attention in recent years. The major problem is the complex structure of the images, which contain many different objects, such as roads, houses, trees, etc. with differences in shape, tone, and the texture. A large number of publications about road extraction appeared and various approaches for road extraction have been proposed. The strategies fall into two broad categories. A semi-automatic scheme requires an operator to provide interactively some information to control the extraction. In (Mckeown et al. 1988, Vosselman et al. 1995, Airault et al.1996), the extraction algorithms are based on road tracking which start from an initial point and direction, extract parallel edges by extrapolation and match road profile. With a few points of a road segment provided by an operator, (Gruen and Li, 1995, 1997a, 1997b) developed LSB-Snakes to extract road simultaneously in multiple images. This is advantageous because the path is more constrained and the result is more robust, particularly in the areas which are occluded in only some of images.

These semi-automatic approaches can be extended to fully automatic operation by means of automatic seed point detection (Zlotnick et al. 1993). The common automatic methods first extract reliable hypotheses for road segments through line and edge detections and then establish connections between road segments to form road network (Bajcsy et al. 1976, Fischler et al. 1981, Ton et al. 1989, Wang et al.1992, Trinder et al. 1997). The contextual information was taken into account to guide the extraction of roads (Ruskone, 1996). In (Baumgartner et al 1997, Mayer et al. 1997), road detection is based on the extraction of lines in an image of reduced resolution through scale space analysis of image (Steiger, 1998). Baumgartner then extracted edges in the original image, where the final result was the combination of results at two resolutions based on a set of rules, while Mayer adopted ribbon snakes to verify roads and
discriminate them from other line type objects in original image by means of consistency of width.

Knowledge-based methods involve the use of existing GIS database or map and rule based systems. (Stilla et al. 1994, Border et al. 1997) used map and cartographic database respectively as a guide for image interpretation. In (Vosselman et al. 1997) the old database is used not only to verify but also to detect new road branchings from the given data.

Several road models have been developed by researchers. For example, (Gruen and Li 1995) defined a generic model which includes photometric and geometric properties, and (Heipke et al. 1995) defined a road model at different scales which also consists of radiometry and geometry. The road appearance in the imagery depends on sensor sensitivity and its resolution. The authors’ approach will be restricted to high resolution gray scale image with 1 metre resolution. A road in high resolution images is a light continuous and homogeneous region such that the gray value of its surface usually does not change significantly, and the surface often has a good contrast with its adjacent area (Gruen and Li, 1995). This suggests that the gray values of a road range within a certain values. Roads usually have a constant width, and the width of roads will vary according to the class of the road, e.g. a main road is wider than a path. In the real world and in the imagery, roads form a network, which suggests that road detection should take knowledge of the road topology into account. The detected roads can serve as the seed points and reduce search space for automatic road extraction.

The objective of this study is to develop an algorithm for automated road network detection from 1 metre high resolution images using mathematical morphology. Firstly a road is segmented from background. Morphological trivial opening has been developed for the purposes: (1) to perform granulometry analysis of objects in image and obtain size information of road network, and (2) to extract the road network from preprocessed images and differentiate them from other features with similar properties as roads, based on the information provided by the granulometry.

2. Morphological Trivial Opening and Granulometry

Mathematical morphology is a set theory approach, developed by (Matheron 1975) and (Serra 1982). Based on a formal mathematical framework, mathematical morphology provides an approach to the processing of digital images that is based on geometrical shape. It uses set operations such as union, intersection and complementation. The reader is referred to the books of mathematical morphology for a complete background to dilation, erosion, openings, closings and the derived operations such as Hit or Miss, thinning, their properities and their use.

2.1 Morphological Trivial Opening

Trivial opening (denoted hereafter TO) is defined by (Serra and Vincent 1992). Let X be an image, \( \{X(n)|n = 1, 2, 3, ..., N\} \) is a series of connected components in the image, \( x(i) \) is a point in \( X(i) \). We define the trivial opening with a criterion T, as follows.

\[
TO = \begin{cases} 
X(i), & \text{if } X(i) \text{ satisfies the criterion } T \\
\phi, & \text{otherwise} 
\end{cases}
\]  

[1]
Therefore $TO$ is the trivial opening associated with criterion $T$. It is an morphological opening, because it is idempotent, anti-extensive and increasing. In image processing, this operation uses the criterion $T$ to filter the connected components that satisfy the criterion $T$.

Trivial opening based on criterion $T$ provides a practical means of object detection and identification. (Vincent 1993a) derived area opening from connected and trivial opening to find the connected regions in an image with a certain area. Trivial opening does not affect the shape and size of the connected regions that are preserved because it preserves the entire connected regions. Since a road in high resolution image appears as a narrow homogeneous area forming whole network, the criterion can be selected as *the long axes of minimum ellipse which encloses an object*. Trivial opening for road detection is expressed as follows.

$$\text{TO}_{-} \text{ROAD}_{-} \text{DETECTION} = \{X \mid \text{Long axis of minimum ellipse enclosing } X(i) \geq T\} \quad [2]$$

Figure 1 shows three different ellipses and their long axes.

![Fig. 1 Minimum Ellipse Enclosing Objects and their Long Axes](image)

The connected components are reached by morphological reconstruction. Suppose one pixel $Y$ in $Xi$ is searched, then the reconstruction of $Xi$ from $Y$ is obtained by iterating elementary geodesic dilation of $Y$ inside $Xi$ until stability. This is expressed as follows. Fig.2 demonstrates the reconstruction of an object by morphological reconstruction.

$$\text{Recon}_{Xi}(Y) = \bigcup_{n=0}^{\infty} \delta_{X_i}^{(n)}(Y) \quad [3]$$

where

$$\delta_{X_i}^{(n)}(Y) = \delta_{X_i}^{(1)}(Y) \cap \ldots \cap \delta_{X_i}^{(1)}(Y) \quad [4]$$

is $n$-size geodesic dilation. And

$$\delta_{X_i}^{(1)} = (Y \oplus H) \cap X_i \quad [5]$$

is elementary geodesic dilation obtained via a standard dilation of one size followed by an intersection (Vincent, 1993b).
Once the connected components are reconstructed, the attributes associated with area, length, ratio of length to width, and long axis of an ellipse can be computed. Only the connected components which satisfy the criterion $T$ are retained in the output as shown in Fig.3 (here the unit of $T$ is taken as the long axe of the minimum ellipse which encloses the smallest rectangle). From the following analysis, morphological trivial opening proves to be an effective filter to avoid noise. It can also be implemented directly from gray scale image for segmentation, based on certain criteria (Edmond et al. 1996).

2.2 Granulometry

For automatic object detection, the criterion used in trivial opening can be regarded as a threshold which should be determined from the image analysis with respect to granulometry or the pattern spectrum.

The granulometric techniques can be used to measure the size and shape of objects in image. The concept behind granulometry is to determine the size and shape distribution of objects present within image. Consider to apply Opening operation to decompose an image through a series of structure elements with a specific shape. The opened images are compared with the original image to generate measures with respect to different size of structure element but with same shape. These measures can be used as shape and size signature of the original image and can be plotted as a pattern spectrum.

Let $SE_n$  $n = 1, 2, \ldots N$ be a series of structure elements, $SE_n = nSE_0$, $n$ determine the size of structure elements. Suppose $X$ be the original image, $X_n$  $n = 1, 2, \ldots N$ is a sequence of images being opened as follows

$$X_0 = XOSE_0, \ldots, X_n = XOSE_n$$  

Since opening is anti-extensive, that is $X_j < X_i$ for $j > i$. Let $S[X_n]$ be the size or shape measure of $X_n$, the following relations are obtained.

$$S[X] > S[X_0] > S[X_1] > S[X_2] \ldots > S[X_n]$$  

Granulometry is then defined as the mapping $n \rightarrow XOSE_n$, $S[X_n]$ is known as the size distribution (Dougherty et al. 1992). The normalized size distribution is defined as below

$$SD_n = \frac{S[X] - S[X_n]}{S[X]}$$  

$S[X_n]/S[X]$ is the percentage of the filtered objects. $SD$ increases from 0 to 1 as the size of structure element increases. It is equivalent to a probability distribution. Similar to the derivative of a probability distribution yields the probability density function, the derivative of Equation [8] yields the granulometry size density function, and can be expressed in discrete form as follow

$$dSD_n = SD_{n+1} - SD_n$$  

Equation [9] is often referred to as pattern spectrum. Given a series of structure elements with same shape but different size, $S[X_n]/S[X]$, $SD$, $dSD$ can be obtained and plotted against the sizes of structure elements to provide shape-size descriptions of objects in image.

Trivial opening developed in 2.1 can also be used to perform granulometry. However, the notion of structure element size must be reconciled with that of an increasing criterion $T$. This can be achieved by ordering a criterion $T$ in a set of criteria $T(i)$, $i = 1, 2, \ldots, N$ under the following constraints: if a connected component $CC$ does not satisfy $T(i)$, it does not satisfy $T(i+1)$. Fig. 4 shows an example of size distribution in the case shown in Fig. 1 by trivial opening with a criterion of long axes of minimum ellipse which encloses objects.

![Fig. 4 S[X_n]/S[X], SD and Pattern Spectrum](image-url)
It is clear from $S[X_1]/S[X]$ and SD plot that there are three objects with their long axes of minimum ellipse that enclose them equal to 1, 3 and 12 respectively. In the pattern spectrum plot, three pulses are found. They represent three objects in image.

3. **Experiment on road detection**

An experiment was designed and conducted to detect road network from a 1m resolution simulation image in Toronto, Canada as shown in Fig.5. The image has been orthorectified and distributed by EarthWatch Inc. The roads in the image are continuous regions which form a network. Houses are very dense in the image, some roofs of which have similar spectral characteristics as roads. Dark trees along the road are located close to houses.

To detect the road network from high resolution imagery, some pre-processing is needed to separate roads from the background. As the resolution is high, the roads appear as areas with defined width rather than thin lines. This makes the line based extraction algorithms less effective but creates an opportunity for classification based methods. Gong (1996) compared different classification approaches for separating roads from airborne camera digital image. Other literature can be also found for road extraction based on classification (Benjamin et al 1990, FORD et al 1992, Lianghu 1992). Image segmentation in this study is achieved through ISODATA (Iterative Self Organizing Data Analysis Technique). The main procedures for road network detection are described in Fig. 6. In the histogram of the test image
in Fig. 5(a) road surface intensity values range approximately between 200 and 230 as shown in Fig. 5(b). Roads with other features are extracted as shown in Fig. 7. Other features include house roofs, small paths, light objects etc, due to the fact that trees stand near houses and roads, and their casting shadow on the roads make them as broken or partially invisible features.

Morphological trivial opening is then applied. In contrast to the roads extracted on the pre-processed image, houses are small regions almost separated from each other, while the roads are long features. This allows the definition of the criterion as the long axis of minimum ellipse.
that encloses an object to eliminate roads from houses. Granulometry analysis with this criterion gives the size distribution of objects in the image as shown in Fig. 8 with $S[x_x]/S[X]$ against criterion $T$.

![Fig. 8 S[x_x]/S[X] plot of Test Image](image)

It can be seen that when $T\geq 110$, the characteristics of the remaining objects do not change and until $T\geq 440$ all objects are filtered out. Since roads are much longer than other objects in the image, $T=110$ can be selected as a threshold for trivial opening. Actually any value of $T$ in the range $[110, 440]$ is suitable for road network detection.

The trivial opening with this criterion $T\geq 110$ gives the result shown in Fig. 9. It preserves the road area and filters out almost all the houses and small clusters of noise as well. There are small holes on the road surface, which is due to pixel spectral difference on road. Morphological closing is therefore applied to fill the holes. An initially extracted road network image is then obtained as shown in Fig. 10.
As seen in Fig. 10, some houses still remain connecting with road network via paths in the road network image after trivial opening. Further processing is needed to remove small paths and these houses.

Since the width of paths is less than that of the main road, an opening operation with the structure element whose size is smaller than main road but slightly larger than that of path can remove the paths. Another effect of this operation is that houses connected with the road network via paths are separated as shown in Fig.11. Again trivial opening is applied to remove isolated houses as shown in Fig.12. The reason why a house in the left center remains is due to the existence of a connected path with thicker width.

Since trees standing near roads cast shadow on them, some road parts are partially invisible. These parts are thinner in the initially extracted road network image. The side effect of opening is that it also removes these road parts. It is necessary to developed tools to reconstruct these road parts. This can be done with the following procedures. The idea is to locate endpoints from a thinned image. For every endpoint, search for other endpoints within a given range, determine a local window which includes these endpoints, then recover contents of this window from previous initially extracted road network image.
The first step is to apply closing on Fig. 12 with a structure element size equal to main road width. This has the effect of filling the small gaps caused by opening, and also smooth the road network (see Fig. 13).

Fig. 11 Result of Opening Operation to Remove Paths

Fig. 12 Result of the Second Trivial Opening

Fig. 13 Effect of Closing to Fill Small Gaps (there are still gaps as shown in square frame)
The two problem areas with gaps are shown in Fig. 13 with a square frame. The procedures below were implemented to recover these road segments from the initially extracted road network image.

Suppose that the initially extracted road network image is $X$ (see Fig. 10), and $X_{open}$ (see Fig. 13) is the Closing image, then

1. Thin $X_{open}$ to one pixel wide. The thinned image is denoted as $Y$.

2. In order to obtain a window containing the missing road segment, locate the points set $Z$ that is backward $n$ pixel from the endpoints of $Y$, where $n$ is the structure size used for the opening operation to remove the small path.

\[
\text{repeat above } n \text{ times, then } \]

\[
Z = \bigcup_{i=1}^{8} (\text{TEMP} \ominus E_i)
\]

Where $E_i$ are the structure elements to search and find endpoints (see Fig. 14(a))

3. For every points $z_{ij}$ in $Z$, search for other endpoints inside a circle with radius equal to a given certain length. If there are several endpoints found in the circle, only the points that there is no path inside the circle connecting to $z_{ij}$ are selected. If there are no endpoints found inside the circle, then $z_{ij}$ is an open endpoint, and does not connect to any road segment.

4. From these selected points, find normal lines $L$ with direction individually vertical to its tangent. These lines intersect the initial road network image. Then a window $W$ can be created.

\[
\text{initL} = \bigcup_{i=1}^{8} (\text{TEMP} \ominus E_i) \ominus E_1
\]

\[
L = \bigcup (\text{initL} \cap X)
\]

The above procedure is repeated until initL $\cap X$ equal to $\phi$.

where $E_1$ is structure element to create normal lines (see Fig. 14(b)).

Window $W$ is created with its left-down corner $(\max(i), \min(j))$, top-right $(\min(i), \max(j))$, $i$ and $j$ are the pixel location index in L from top to bottom and left to right.

5. Intersect $W$ with $X$, the shadowed road segment is obtained.

\[
\text{Shadowed \_road} = W \cap X
\]

(6) Paste this result back to image $X_{open}$, the shadowed road is reconstructed and the main road network is extracted.

\[
\text{Final} = \text{Shadowed \_road} \cup X_{open}
\]

This procedure can be illustrated in Fig. 15.
Fig. 14 Structure Elements to Create Endpoints (E) and to Create Normal Lines (E1)

Fig. 15 Reconstruction of Road Gaps

The image with the shadowed road segments was recovered as shown in Fig. 16. This image is followed by a closing operation with the structure element size equal to road width (see Fig. 17). The final operation of thinning gives the approximate road center line as shown in Fig. 18 overlaid on the original image.

Fig. 19 shows another result based on this approach, applied to another part of the same image in Toronto. Fig. 20 focuses on a portion of an aerial image from the ATOMI project. The scale of the original image is about 1:16,000. The image is scanned with 28 microns, thus the footprint is about 0.45 m. The result is satisfactory even when the road is occluded a lot by tree shadows (see the road on the left in the image).
Fig. 16 Connect Road Network

Fig. 17 Closing Operation Applied to Control Road Width

Fig. 18 Final Result of Road Network Detection with Thinned Center Line (black) Superimposed on Original Image
Fig. 19 Result of another part in Toronto

Fig. 20 Result of a portion from aerial image in Switzerland
(Courtesy of Federal Office of Topography, Bern)
4. Discussion and Conclusion

Line based methods for automatic road network extraction from high resolution images involves edge-line detection, thresholding, grouping and road linking. The difficulties arise when threshold selection and linking based on conditions such as proximity, orientation and some geometrical constraints, e.g. paralleling. With the complexity in the image due to occlusions and difference of materials on both sides of road, these conditions normally are not satisfied. This makes line based method less effective for high resolution images.

In this paper we proposed an approach to detect road network from high resolution image using a combination of mathematical morphology operations, particularly trivial opening and its application to size distribution analysis, which have not been applied to remote sensing images for feature extraction by any other researchers. The algorithm is based on the assumption that road network forms an elongated area which can be extracted as the connected components with certain criteria. Trivial opening has been developed to preserve the whole road network and filter out the noises. Granulometry analysis was performed with trivial opening to provide size information of objects in the image. The result showed that this approach can provide sufficient information from successive steps for automatic road extraction with better results than those obtained by other research methods.

The proposed approach can be used as an initial step for automated road network extraction for providing the approximated location, and hence reducing searching space.

The problems still remain for road surfaces that are completely broken caused by tree shadows, because there is no other information in the area supporting linking with the road network. Difficulty also arises where a house is connected to road network through a wide path. In this case, it is impossible to remove wider paths while keeping road network unchanged. There is an additional problem existing when a road is cut into much shorter length because of the image frame.

Like (Zlotnick et al. 1993 and Steger 1998), the developed algorithm assumes that roads are either darker or brighter than the background, but not both in the same image. This results in some roads being only partially detected and some entirely missed. However, it could be improved by using multi-band image for classification.

In conclusion, a combination of trivial opening and a new concept of granulometry was successfully demonstrated for automatically detecting a road network with the significant width on high resolution images. The integration of this approach with other technologies, such as active contour models, context, and other spectral information, such as colour or stereo image, will provide more reliable and accurate results for automatic road extraction.
5. References


