Local Detection of Road Using Mathematical Morphology On Airborne SAR Image

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Abstract: This paper is concerned with a local detection of road on an airborne SAR image. The roads can be characterized by their geometry and radiometry. Roads are assumed as linear, thin, and elongated objects that are darker than their surroundings on an airborne SAR image. With these assumptions, a series of morphological filters are applied and tested successively. This approach is simple and almost non parametric and has been successfully applied to an airborne SAR image.

Key words: Road detection, Airborne SAR, Mathematical morphology

1. Introduction

The detection of roads by means of digital image analysis is a generic task in the field of remote sensing. Their detection can be used in several applications such as image coregistration, cartographic applications, geomorphologic studies and updating of the road network for Geographic Information Systems (GIS).

Most of the existing methods are composed of two separate steps (Fig. 1). The first step consists of the local detection of road segments in the image, whereas the second one, a global detection approach, tries to fill in the gaps existing between the detected road segments in order to fully reconstruct the road network.

Several approaches have already been proposed to solve this type of detection problems. Merlet and Aerubia[7] used dynamic programming to find roads on the SPOT image and Barzohar and Cooper[6] tried to detect roads on an aerial image using a geometrical stochastic model.

But, automatic road detection on SAR images is a difficult task due to multiplicative noise, called the speckle. Therefore, above methods are seldom very suitable for SAR images. Tupin[2] proposed a method well suited for SAR image based on the fusion of two edges detectors. This method gives encouraging results and good statistical properties. But, there are several arbitrary thresholds which have to be set.

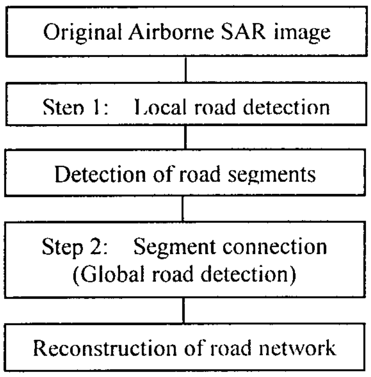


Fig. 1. A typical road detection process

Chanussot and Lambert[4] proposed a simple and fast unsupervised method, based on a series of morphological filters that do not require any threshold. The only parameters that have to be set are related to the model dimensions of the feature that has to be extracted.

In this study, Chanussot's method was employed in addition to soft morphological filters to achieve the first step of road detection process (local detection). The global detection, the second step, is beyond scope for this paper at this time.

The roads we search for can be characterized by their geometry and radiometric characteristics. The road model is based on three assumptions[4]: 1) The roads appear on an airborne SAR image as thin, elongated shape with a maximum width W_{max}, 2) they are locally rectilinear with minimum length l_0, 3) Roads usually appear as dark structures in SAR image with respect to its surroundings. With these information, a series of morphological filters with a square flat structuring element are used to retain elongated roads with a specific width.

2. Mathematical Morphology

Mathematical morphology is a mathematical theory for the analysis of shape and form of objects, using set theory, integral geometry and lattice algebra[9]. A morphological operator is given by the relation of the image (denoted by f) with another small point set B called a *structuring element* (SE). The main morphological operators that are used in our work to detect roads are briefly summarized below.

2.1 Erosion and dilation

The erosion of an image f by an SE B is denoted by $\varepsilon_B(f)$ and is defined as the minimum (infimum) of the translations of f by a vector $-b$ of B:

$$\varepsilon_B(f) = \wedge_{b \in B} f_{-b}. \quad (1)$$

Erosion of an image removes all structures that cannot contain the SE and shrinks all the others. The dual operation to erosion is dilation.

2.2 Opening and closing

A secondary operation of great importance in mathematical morphology is the opening operation. The opening of an image f by an SE B is denoted by $\gamma_B(f)$ and is defined as the erosion of f by B followed by dilation with the transposed SE $\check{B}$:

$$\gamma_B(f) = \delta_{\check{B}}[\varepsilon_B(f)]. \quad (2)$$

Opening generally smoothes the contour of an image region, breaks narrow isthmuses, and eliminates thin protrusions[9].

The other important secondary operation is closing. The closing of an image f by an SE B is denoted by

$$\phi_B(f) = \varepsilon_{\check{B}}[\delta_B(f)]. \quad (3)$$

Closing connects objects that are close to each other, fills up small holes, and smoothes the object outline by filling up narrow gulfs.

2.3 Top-hat

The top-hat operator extracts objects that follow a size and shape criterion, and isolates structures that have not been eliminated by the opening or by the closing. There are two kinds of top-hat operators.

Top-hat by opening(white top-hat) :

$$WTH_B(f) = f - \gamma_B(f). \quad (4)$$

Top-hat by closing(black top-hat) :

$$BTH_B(f) = \phi_B(f) - f. \quad (5)$$

2.4 Morphological reconstruction

2.4.1 Reconstruction by dilation/erosion

The reconstruction by dilation, denoted by $R_{g,B}(f)$, of a mask image g from a marker image f is defined as the geodesic dilations of f with respect to g until stability is reached (i.e. until the propagation of the marker image is totally impeded by the mask image) :

$$R_{g,B}(f) = \delta_{g,B}^{(n)}(f) \quad (6)$$

Where n is such that $\delta_{g,B}^{(n)}(f) = \delta_{g,B}^{(n+1)}(f)$. The reconstruction by erosion is equivalent to the complement of the reconstruction by dilation of g^c from f^c.

2.4.2 Opening/closing by reconstruction

The opening by reconstruction of size n of an image f is defined as the reconstruction of f from the erosion of size n of f :

$$\gamma_{R,B}^{(n)}(f) = R_{f,B}(\varepsilon_B^{(n)}(f)). \quad (7)$$

Contrary to the morphological opening, The opening by reconstruction preserves the shape of the components that are not removed by the erosion. The closing by reconstruction is the dual transformation of the opening by reconstruction.

2.5 Soft mathematical morphology

In soft mathematical morphology the SE is divided into two parts which are the *hard center*(B_1) and the *soft boundary* (B_2). The basic concept is that the minimum/maximum operators that are used in typical mathematical morphology are substituted by other order statistics. The results related to the soft boundary and the hard center (repeated k-th times) are ordered in a increasing/decreasing sequence. The k-th element of this sequence is the result of the soft erosion/dilation. The soft dilation of a gray level image f, using a soft SE[α, β, k] is [3] :

$$f \oplus [\alpha,\beta,k](x) = max^{(k)}(\{k\Diamond(f(x-y)+\alpha(y))\} \cup \{f(x-z)+\beta(z)\}), \quad where\ (x-y),(x-z) \in F,\ y \in B_1, z \in B_2. \quad (8)$$

The soft erosion of f, using a soft SE[α, β, k] is:

$$f \ominus [\alpha,\beta,k](x) = min^{(k)}(\{k\Diamond(f(x+y)-\alpha(y))\} \cup \{f(x+z)-\beta(z)\}), \quad where\ y \in B_1, z \in B_2. \quad (9)$$

The notations used in equation (8) and (9) are the following. The number k is *order index*. $min^{(k)}$ and $max^{(k)}$ is the k-th maximum and the k-th minimum element, respectively. $x,y \in Z^2$ is the spatial coordinates. The mathematical expression $k \Diamond (\ldots)$ denotes a repetition of the operation $(\ldots)$ k times.

3. Local Detection of Road Network

According to the road model, we are looking for elongated and narrow structures in the image. We utilized the classical topographic analogy for the representation of images, then, the image can be considered as a topographic relief. The numerical value of each pixel determines the corresponding point elevation. The bright structures and the linear dark structures are considered as "peaks" and "valleys", respectively. Three different types of noisy structures have to be removed using a series of mathematical morphology filters. We will firstly remove bright structures corresponding to peaks, since we are only interested in dark structures. And then, we will remove non-linear dark structures corresponding to valleys. Finally, we will remove the remaining linear valleys that are too wide. Before applying these filters, we perform a directional median filter to remove speckle noise.

3.1 Directional median filtering using local anisotropy

To remove speckle noise and preserve structured small-sized details, for instance, thin lines, we implement a directional median filter to the original image using local anisotropy measures[8]. We firstly compute local anisotropy at every pixel. Let A_i, i=1,2,3,4, be the average gray value of the pixels of the processing window U marked with the digit i in Fig.2. Their extreme values are:

$$A_M = \max_{i=1..4}\{A_i\} \quad \text{and} \quad A_m = \min_{i=1..4}\{A_i\}. \quad (10)$$

Then, the anisotropy measure can be defined as

$$\alpha = \frac{A_M - A_m}{A_M + \varepsilon} \quad (11)$$

where $\varepsilon \ll 1$ is introduced for avoiding divisions by zero.

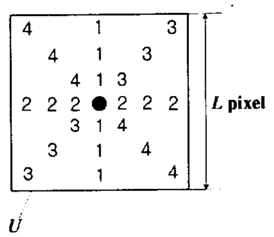


Fig. 2. Processing window U of L×L pixels. The digit i=1…4 indicate the elements of the one-pixel stripes in the four main directions[8].

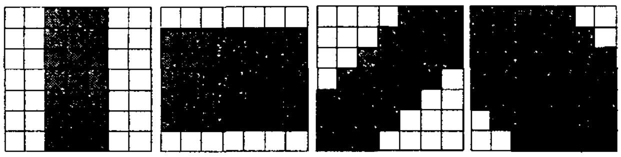
After computing the local anisotropy values of each pixel, the directional median filter is applied on the original image using a rectangular window of $L \times L_1$ pixels($L_1 \le L$) instead of the square window. The parameter L_1 is controlled by the local anisotropy:

$$L_1 = 2Z_1 + 1$$

$$\text{with} \quad Z_1 = \textit{nearest integer of}\,[(1\text{-}\alpha)(M\text{-}1)] \qquad (12)$$

$$\text{and} \quad M = (L+1)/2.$$

The window is oriented in the direction i ($1 \leq i \leq 4$), for which the gray value variance, determined over the one-pixel stripes of Fig.3., is a minimum. The result of the directional median filter is shown in Fig.5(b).



(a) (b) (c) (d)

Fig. 3. Examples of anisotropy-controlled $7 \times L_l$ window shapes for each of the four main directions and for different widths Z_l. (a, c) Z_l=1, L_l=3: (b, d) Z_l=2, L_l=5.

3.2 Removing non-flat peaks

We firstly performed the morphological opening by reconstruction to remove non-flat peaks using a square flat SE of size 5[5]. Fig. 4(a) shows a zoom of the small image taken in the original image (white square in Fig. 5(a).) and its corresponding relief. Fig. 4(b) presents result of the morphological opening by reconstruction and its relief.

3.3 Removing non-linear dark valleys and remaining peaks

According to [4], the elimination of non-linear valleys can be obtained by using a directional closing in a specified number of successive directions. Unfortunately, the operation of the typical morphological closing is very sensitive to additive noise and small variations in the shape of the objects[3]. To overcome this problem, we applied a soft directional closing[1] with an order index equal to 5 and a linear non-flat SE of size l_0 which is successively oriented in 36 different directions. The SE is composed of a hard center with a value equal to $l_0/2+1$ and a soft boundary with linearly decreasing values, starting from the center, towards both ends. The resulting value at each pixel should be infimum of all these directional closings. The soft directional closing makes dark valleys shorter than minimum length l_0 be removed, and fills the small basins of a topographic relief.

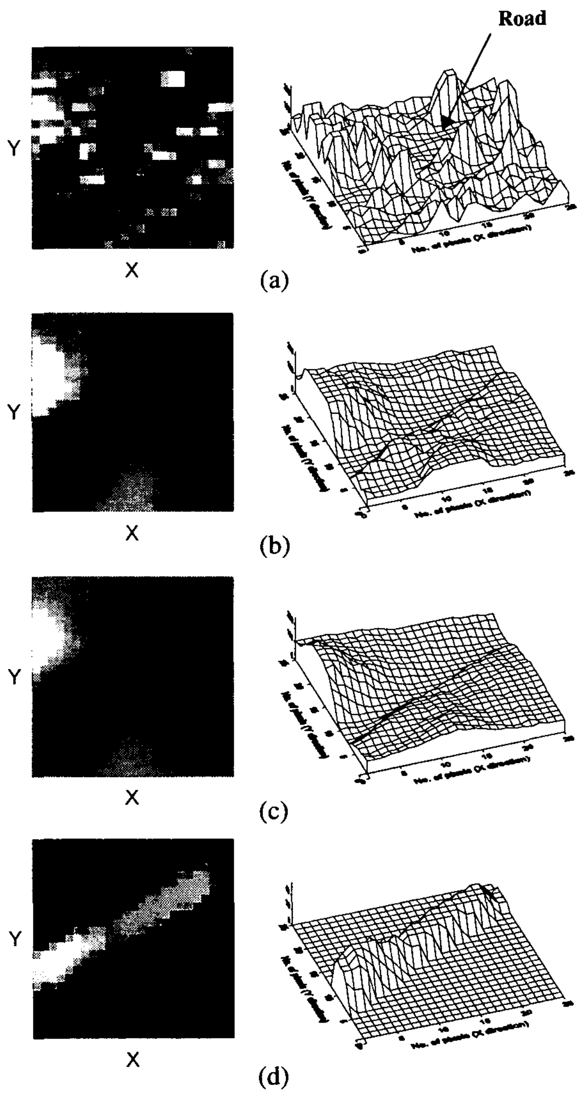


Fig.4. A series of morphological filtering process: (a) The small part of the original image (Fig. 5(a)) and the corresponding relief(right), (b) an opening by reconstruction, (c) a soft directional closing, and (d) a closing Top-hat operation.

In this work, we have chosen the minimum length l_0 equal to 40 pixels. Fig.5(d) represents the result of the soft directional closing. After applying the soft directional closing, we perform a simple opening using a flat square SE of size 5 to remove isolated peaks that could lead to false detection in the next step.

3.4 Removing wide valleys and extraction step

As the last processing, a closing Top-hat operator with a flat square SE of size W_{max} is used to remove wide valleys. After this operator, The only remaining structures are the dark structures that are up to W_{max} wide. Any other pixel that belongs either to a plateau or to a valley that is more than Wmax wide is put to zero.

Fig. 5(e) shows result of this operator. We can see that many small structures are detected. To remove them and to clean up the result image, an area opening is applied. This morphological filter removes all the connected components whose surface is smaller than a given number n_0 of pixels. It can be seen as the supremum of all the different possible openings computed with all the different connected SE that have the given area n_0:

$$area\_\gamma_{B_c,n_0}(f) = \bigvee_{B \in B_{B_c,n_0}} \gamma_B(f)$$
$$B_{B_c,n_0} = \{ x \subset F : x \text{ is } B_c\text{-connected}, Area(x) \geq n_0 \}. \quad (13)$$

In this work, the parameter W_{max} is set to W_{max}=7.

Fig.5(f) represents the cleaned result superimposed on the original image after applying the area opening of size 90.

4. Results and Conclusions

The L-band(80MHz) NASA/JPL airborne SAR (AIRSAR) image which is acquired on September 30 in 2000 during PACRIM-II Korea Campaign is used to test for this approach. The spatial resolution is approximately 2.5 meters. Therefore, the minimum road length l_0 is corresponding to approximately 100 meters ground length for AIRSAR image. A rural area adjacent to Kyungju is selected for the test area(Fig.5(a)). After removing speckle noise with a directional median filter that is controlled by the local anisotropy, different kinds of morphological filters with a different size of SE are implemented to extract roads which satisfy the three road models: linear, thin elongated and darker structures. The sequence of morphological filtering consists of: (1) an opening by reconstruction for removing the non-flat peaks, (2) a soft directional closing in 36 successive directions for the purpose of removing non-linear valleys. (3) an opening for removing remaining peaks, (4) a closing Top-hat operator in order to remove wide valleys, (5) an area opening to clean the result image. The size of SE used in each filtering step is 5, 40, 5, 7, 90, respectively. As the result of above processing, the two main roads are almost perfectly detected. But, some roads are only partially detected and there are also some false detections, for instance, some dark fields are considered as potential roads(Fig. 5(f)). In spite of these defects, this method has some good properties that it is very simple and almost non-parametric process.

5. Further Research

In this paper, we describe only local detection step of roads and extract some road segments. Therefore, the first interest is concerned with the reconstruction of disconnected road segments, called global detection or grouping step. Tupin[2] proposed a grouping method utilizing the Markov Random Field model defined on a set of segments. The additional use of *a priori* knowledge should improve the local detection result. The second is to investigate the effectiveness of the detection performance in heavily textured environments such as urban areas.

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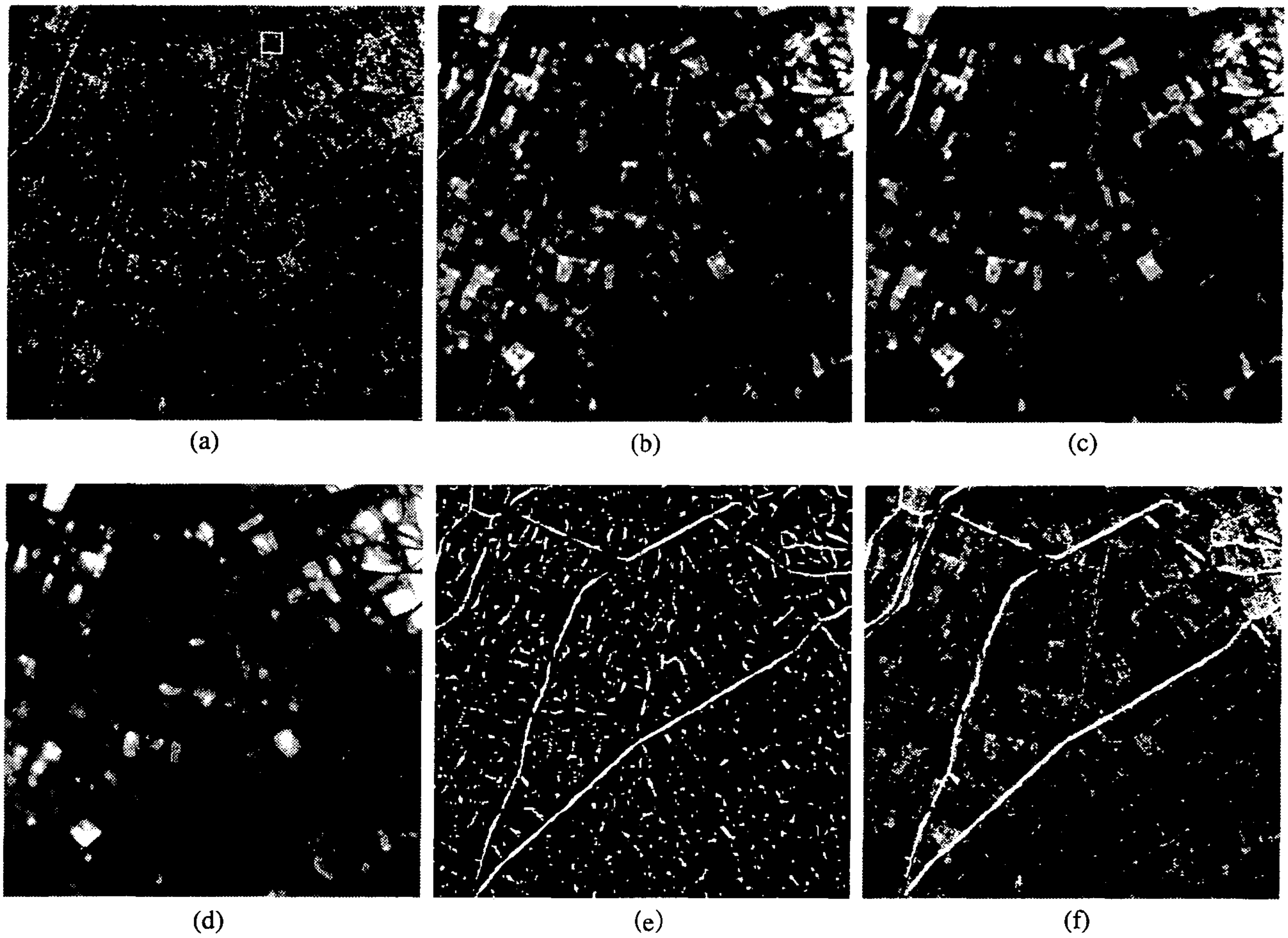

Fig. 5. (a) Original AIRSAR L-band, HH-polarization image, (b) directional median filtered image, (c) the result of opening by reconstruction, (d) soft directional closing image in 36 successive directions, (e) closing Top-hat operation and (f) cleaned road segments superimposed on original image.