Road Detection in Spaceborne SAR Images Using a Genetic Algorithm

Byoung-Ki Jeon, Jeong-Hun Jang, and Ki-Sang Hong

***Abstract*—This paper presents a technique for the detection of roads in a spaceborne synthetic aperture radar (SAR) image using a genetic algorithm (GA). Roads in a spaceborne SAR image can be modeled as curvilinear structures that possess width. Curve segments, which represent the candidate positions for roads, are extracted from the image using a curvilinear structure detector, and the roads are accurately detected by grouping those curve segments. For this purpose, we designed a grouping method based on a GA, which is a global optimization method. We combined perceptual grouping factors with it and tried to reduce its overall computational cost by introducing a concept of region growing. In this process, a selected initial seed is grown into a finally grouped segment by the iterated GA process, which considers segments only in a search region. To detect roads more accurately, postprocessing, including noisy curve segment removal, is performed after grouping. We applied our method to ERS-1 SAR and SIR-C/X-SAR images that have a resolution of about 30 m. The experimental results show that our method can accurately detect road networks as well as single-track roads and is much faster than a globally applied GA approach.**

***Index Terms*—Genetic algorithm (GA), perceptual grouping, road detection, synthetic aperture radar (SAR).**

I. Introduction

EXTRACTING linear features, including roads, railroads, and rivers, from satellite or aerial imagery has many applications, especially in the area of photogrammetry and remote sensing tasks. Much research has been carried out on this topic since the 1970s [1]. Fischler *et al.* [2] used two types of detectors: type I, which is a detector without false alarms, and type II, which is a detector without misdetections, and combined their responses using dynamic programming. McKeown and Denlinger [3] proposed a road-tracking algorithm for aerial images, which relied on road-texture correlation and road-edge following. This algorithm is semi-automatic. That is, an operator needs to select the initial point and the direction for tracking. Gruen and Li [4] also proposed a semi-automatic road extraction algorithm for aerial images. They used the least squares B-spline snakes (LSB-Snakes) algorithm in multi-image mode, which provided a robust and mathematically sound 3-D approach.

Geometric-probabilistic models were first built for road-image generation, and roads were found from it using MAP estimation. Barzohar and Cooper [5] presented an automated approach to locate the main roads in aerial images. Tupin *et al.* [6] proposed a nearly automatic detection algorithm for linear features such as the main axes of road networks. They presented two local line detectors as well as a method for fusing information from these detectors to obtain segments. The real roads were identified among the segment candidates by defining a Markov random field for the set of segments. Jeon *et al.* [7] proposed an automatic road detection algorithm for satellite images. They presented a map-based method based on a coarse-to-fine, two-step matching process. The roads were finally detected by applying snakes to the potential field, which was constructed by considering the characteristics and the structures of roads.

As was seen previously, much work on extracting linear features (such as roads) has been done using the automatic or the semi-automatic method in aerial or satellite images. Compared with other methods, the proposed algorithm in this paper is one of the most challenging methods because it attempts to detect roads without any user intervention; that is, automatically in *spaceborne SAR images*. It is well-known that detecting roads in satellite images is difficult because these images have *speckles*, and their resolutions are low. In spite of the difficulties mentioned earlier, our method can detect roads in spaceborne SAR images with high accuracy and low computational cost. To detect roads, we first model the roads in spaceborne SAR images as curvilinear structures, which are often simply called curve segments with certain width. Next, we locally extract ridges or ravines from these structures using Steger's method [8]. The extracted curve segments seem to represent the candidate positions of roads; therefore, we can detect roads accurately by grouping these segments. For this task, we adopt a grouping method based on a genetic algorithm (GA). Although there are many methods for optimization, we choose the GA since it can give a globally optimized solution to a problem such as ours, which cannot be solved analytically and has a vast searching space for the solution. The GA of our method uses perceptual grouping factors, such as proximity and cocurvilinearity, and the characteristics of roads in SAR images, such as intensity. Also, we improve the GA so that our algorithm will be computationally efficient by incorporating the concept of *region growing*. If the number of segments to be considered is large, the computation time of the GA rapidly increases. To reduce the computational cost, we perform two processing steps: the first is simple thresholding of image intensity to remove unnecessary segments (the preprocessing step), and the second is the method of extending the search region step-by-step by considering only a portion of the total segments at each step, instead of considering all the seg-

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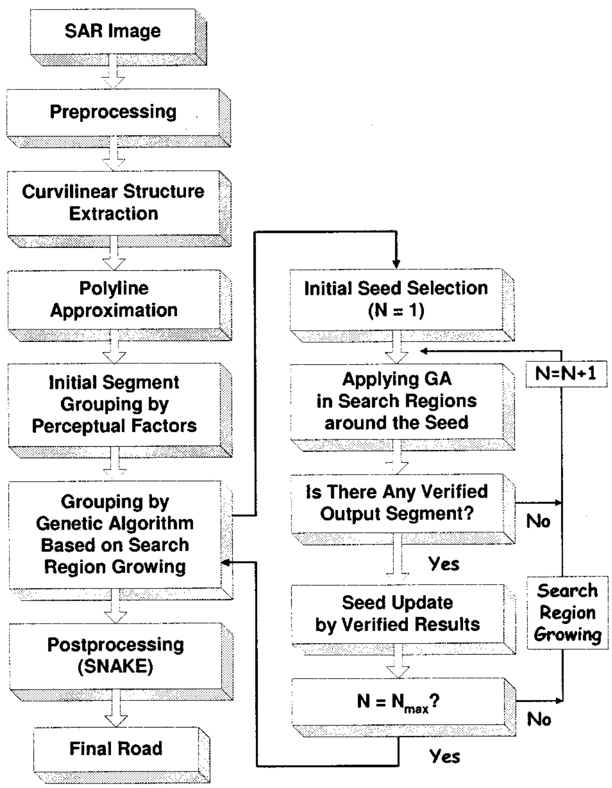

Fig. 1. Overall flow of our road detection algorithm.

ments at one time. From the results of the grouped segments obtained with the GA, the roads are finally detected after the post-processing step, including noisy segment removal and the snake operation. We applied our method to some sample regions of ERS-1 SAR and SIR-C/X-SAR data. Experimental results show that the proposed method is very accurate and more computationally efficient than a globally applied GA approach. Fig. 1 presents the overall flow of our algorithm.

II. Preprocessing

The input images of the proposed method are ERS-1 SAR and SIR-C/X-SAR images. Since the speckles appearing in SAR images can degrade the performance of road detection, we first need to reduce them. For this procedure, we use a sigma filter developed by Lee [9] because it suppresses speckles with the least amount of blurred edges and fine details, and it is computationally efficient.

As mentioned earlier, if the number of segments to be considered is large, the computation time of the GA increases. In the preprocessing step, we reduce the number of input segments of the GA by using the characteristics of roads in SAR images. Because roads appear dark in SAR images, we apply simple thresholding to the speckle-reduced SAR images to exclude regions of no interest before the extraction of curvilinear structures.

III. Curvilinear Structures and Initial Grouping

A. Extraction of Curvilinear Structures

In this paper, roads are regarded as curvilinear structures like ridges or ravines (since roads are darker than their neighborhoods in SAR images, they can be modeled as ravines). These structures can be candidates for true roads. Based on this assumption, we first extract these structures in the preprocessed SAR images by Steger's method [8]. In this method, an input image is first convolved with a Gaussian kernel, and then each pixel is assumed to be at the center position of a curvilinear structure. The width of the curvilinear structure to be found depends on the size of the kernel. To test whether the assumption is correct for the pixel under consideration, the direction in which the curvature of the cross-section of the image at the pixel is the largest is obtained from the Hessian matrix computed at that pixel. Along this direction, the first and second directional derivatives are computed. If the first derivative is zero, and the second derivative is high at that pixel, the pixel is selected as the center of a curvilinear structure. Fig. 2 shows an SAR image and the curvilinear structures extracted from it. We want to detect roads by selecting some meaningful segments among a collection of *base segments* with the help of a grouping scheme. These base segments are obtained by approximating the extracted curvilinear structures to piecewise linear segments by the iterative endpoint fit-and-split algorithm [10].

B. Perceptual Grouping Factors

Our method is a detection method based on segment grouping, where segments are curvilinear structures extracted in the previous step. The grouping method in this paper is divided into two steps: one is an initial grouping, and the other is a main grouping by the GA. In both steps, to group segments we use perceptual grouping factors such as proximity and cocurvilinearity [11], [12], as shown in Fig. 3.

1) Proximity: If two points are close together in the scene, they will project to points that are close together in the image from all viewpoints. However, it is also possible that points widely separated in the scene will project accidentally to points arbitrarily close together in the image. For each instance of proximity between two endpoints, we must calculate the probability that it could have arisen from unrelated lines through an accidental viewpoint. This calculation will be based on the assumption of a background of line segments that is uniformly distributed in the image with respect to orientation, position, and scale. In this paper, the proximity of the endpoints of two base segments reflects the perceptual significance that they project close together. It is formulated by (1). According to this equation, the value of proximity, P, between two base segments in the image, varies inversely with the probability of the relation arising accidentally and is given by

$$P = \frac{L^2}{2D\pi R^2} \tag{1}$$

where L is the minimum length of two base segments, D is the scale-independent density of the base segments ($D = 1$), and R is the minimum distance between two base segments at their endpoints [see Fig. 3(a)].

2) Cocurvilinearity: Cocurvilinearity is the structural relationship by which image tokens are grouped into smooth curves. Cocurvilinear tokens in a scene are mapped to cocurvilinear tokens in the image, and this relation is invariant to viewpoint transformations. Fig. 3(b) shows two base segments, which can

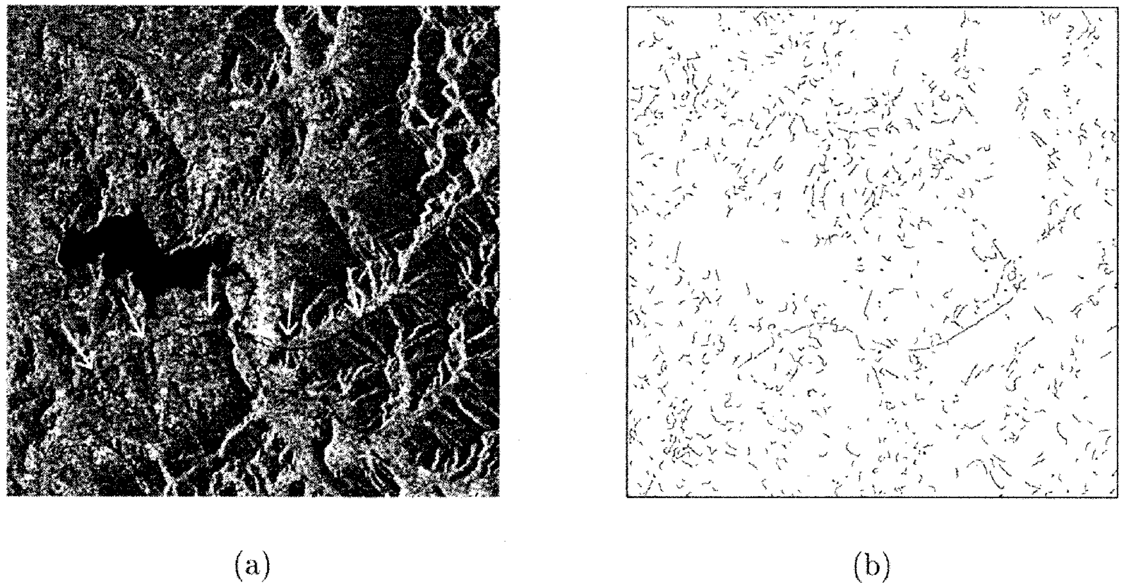

Fig. 2. Extraction of curvilinear structures. (a) Original SAR image (this is an image around Nonsan in Korea, and white arrows indicate the road to be detected) and (b) extracted curvilinear structures in the preprocessed SAR image.

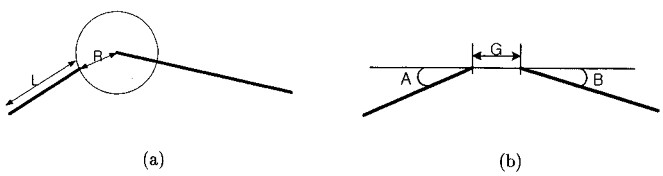

Fig. 3. Perceptual grouping factors. (a) Proximity and (b) cocurvilinearity.

be regarded as linear approximations of curve segments. The cocurvilinearity C between these two segments is calculated by

$$C = \frac{1}{(A^2 + B^2)(\alpha + \beta G)} \tag{2}$$

where α controls the departure from collinearity of the joined segments, and β controls the sensitivity to the length of the gap G. For test images, $\alpha = 10.0$ and $\beta = 0.1$ were used, and A and B are tangent angles of segments at joined endpoints.

C. Initial Grouping

As mentioned earlier, the aim of the proposed method is to detect roads by grouping segments using the GA. However, the method of considering all the base segments in the scene at a time is not efficient. Therefore, we incorporate a concept of region growing into the GA. This method first selects an initial seed and performs a grouping around it by using the GA. Next, the seed is updated by using the grouped segments, and this procedure is iterated. In the initial grouping step, we choose an initial seed, which is the most likely to be found on the road (i.e., the largest segment) by grouping base segments in a very strict sense. Multiple seeds that are longer than the threshold can also be chosen so that our algorithm can detect road networks. For the initial grouping, we use the two perceptual grouping factors explained in Section III-B. Its procedure is as follows. Let each base segment that we consider be the reference segment. Other base segments are located in search regions nearby; specifically, they are located around the two endpoints of the reference segment and have larger proximities than the threshold. Among these, a base segment with the largest cocurvilinearity, which is larger than the threshold, is determined. Next, the determined segment and the reference segment are grouped into a new segment, and this process is iterated until there are no base segments remaining.

IV. Grouping by the Genetic Algorithm

In this step, we detect segments representing roads using the GA-based grouping method. To make our algorithm efficient, we incorporate the concept of region growing into the GA, where the proposed method considers segments only within search regions around the endpoints of a seed instead of considering all of the segments in the image at one time. For the initial seeds, we choose the segments, which are longer than the threshold and are obtained by the initial grouping, since these can be regarded as the most probable segments to be found on roads. As mentioned earlier, the reason why we use multiple seeds is that our algorithm can detect road networks, and we perform groupings by the GA using each seed sequentially. For each seed, the grouping is done independently around the two endpoints of the seed with segments in each of the two search regions. The grouped segments of the current stage are used as the new seed of the next stage, and this procedure of region-growing is iterated $N_{\max}$ times in the same manner.

A. Genetic Algorithm (GA)

The GA is a method of searching a solution for an engineering theme by imitating evolutionary rules of life [13]. The procedure used at each stage of region growing is presented in Fig. 4.

1) Definition of a Chromosome: As shown in Fig. 5, we design the chromosome of an individual whose length is the same as the total number of segments in the search region. Each bit of the chromosome corresponds to each segment in the image

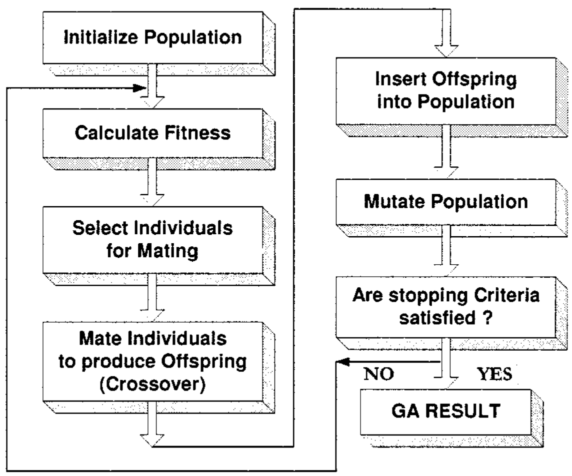

Fig. 4. Procedure of the GA.

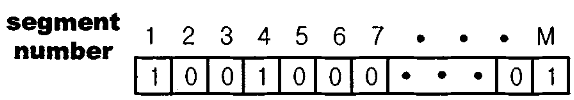

Fig. 5. A chromosome.

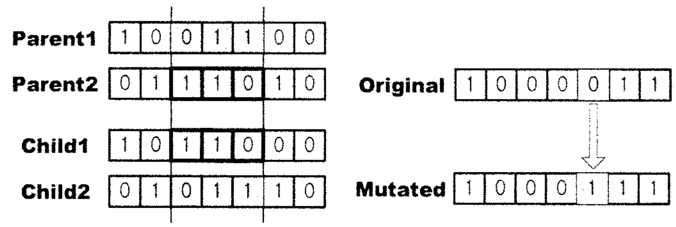

Fig. 6. Two-point crossover and mutation.

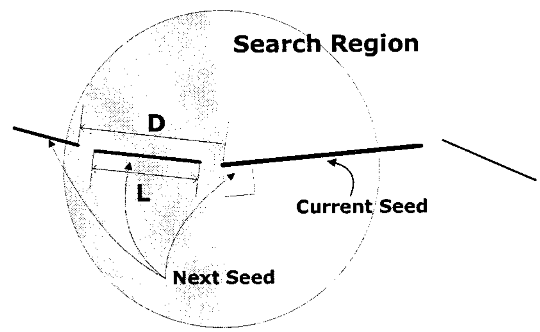

Fig. 7. Region enlarged from the current seed.

and is initialized by a randomly selected 0 or 1. The probability that 1s are allocated to bits is adaptively changed according to the number of segments in the search region. That is, if there are many segments in that region the probability is set low and, if there are few, the probability is set high. When we calculate the fitness of the chromosome during the evolutionary process, the segments with 1s are only considered, and the population size N_p, which is the number of individuals, is set to 100 in our experiment.

2) Design of a Fitness Function: In each stage of region growing, the output results of the GA are segments which correspond to bits with value of 1 in the chromosome with maximum fitness in the population. For accurate results, we designed the fitness function based on the characteristics of the roads in the SAR images, as well as on the perceptual grouping factors used in the initial grouping step. If N is the number of bits with 1s in each chromosome, its fitness is determined by four factors—*proximity* (P), *cocurvilinearity* (C), *homogeneity* (H), and *length* (L), which are represented by

$$P = \sum_{i=1}^{N} p_i/N, \quad C = \sum_{i=1}^{N} c_i/N,$$
$$H = \sum_{i=1}^{N} h_i/N, \quad L = \sum_{i=1}^{N} l_i/N \tag{3}$$

where p_i, c_i, h_i, and l_i are proximity, cocurvilinearity, homogeneity, and length of the ith segment with a bit of 1 in the chromosome. The cocurvilinearity of the ith segment c_i is determined as the maximum value out of cocurvilinearities between the ith segment and the other segments with bits of 1's, and its proximity p_i is set equal to the proximity between the ith segment and the one that gives the maximum cocurvilinearity value. The factor of homogeneity h_i reflects the characteristics of roads in SAR images in that they are homogeneous and have low gray-level values. If the gray-level value of a particular pixel on the ith segment is in the predefined range, the value of this pixel is set to one. The value h_i represents the number of pixels with 1's in the ith segment divided by the total number of pixels in that segment. Using all of these factors, the fitness $F(n)$ of the individual n is defined as

$$F(n) = \alpha P(n) + \beta C(n) + \gamma H(n) + \delta L(n) \tag{4}$$

where α, β, γ, and δ are the four weighting factors for the fitness, and in the experiments, they are set to 0.5, 10.0, 1.0, and 0.03, respectively. The values of these factors are determined so that they almost equally contribute to the fitness. Also, we can perform grouping that reflects the characteristics of the roads to be detected by adjusting these weightings.

3) Evolutionary Process: The GA evolves by the processes of *crossover* and *mutation*, which are shown in Fig. 6. In each generation, half of those individuals with higher fitness values survive, and the others are extinguished. Two parents are selected from the survived individuals, and children are generated by a *two-point crossover*. In a two-point crossover, the chromosomes of parent1 and parent2 are separated and connected at two random positions, and the individual child with the new chromosome is generated. Here, the number of generated children is the same as that of extinguished individuals; therefore, the total population is kept constant in all generations. To keep the algorithm from falling into local minima, bits are selected at random at the rate of M% (we set M to 0.1) from all the chromosomes in the population. They are reversed by a process called mutation. In this paper, the evolution of the GA stops if the maximum fitness of the population remains constant in 15 generations or if it evolves $N_{\max,\,gen}$ times (we set $N_{\max,\,gen}$ to 200). When the algorithm stops, the individual with the maximum fitness presents the optimized solution. The final result is a group of segments of bits with values equal to 1 produced by the GA.

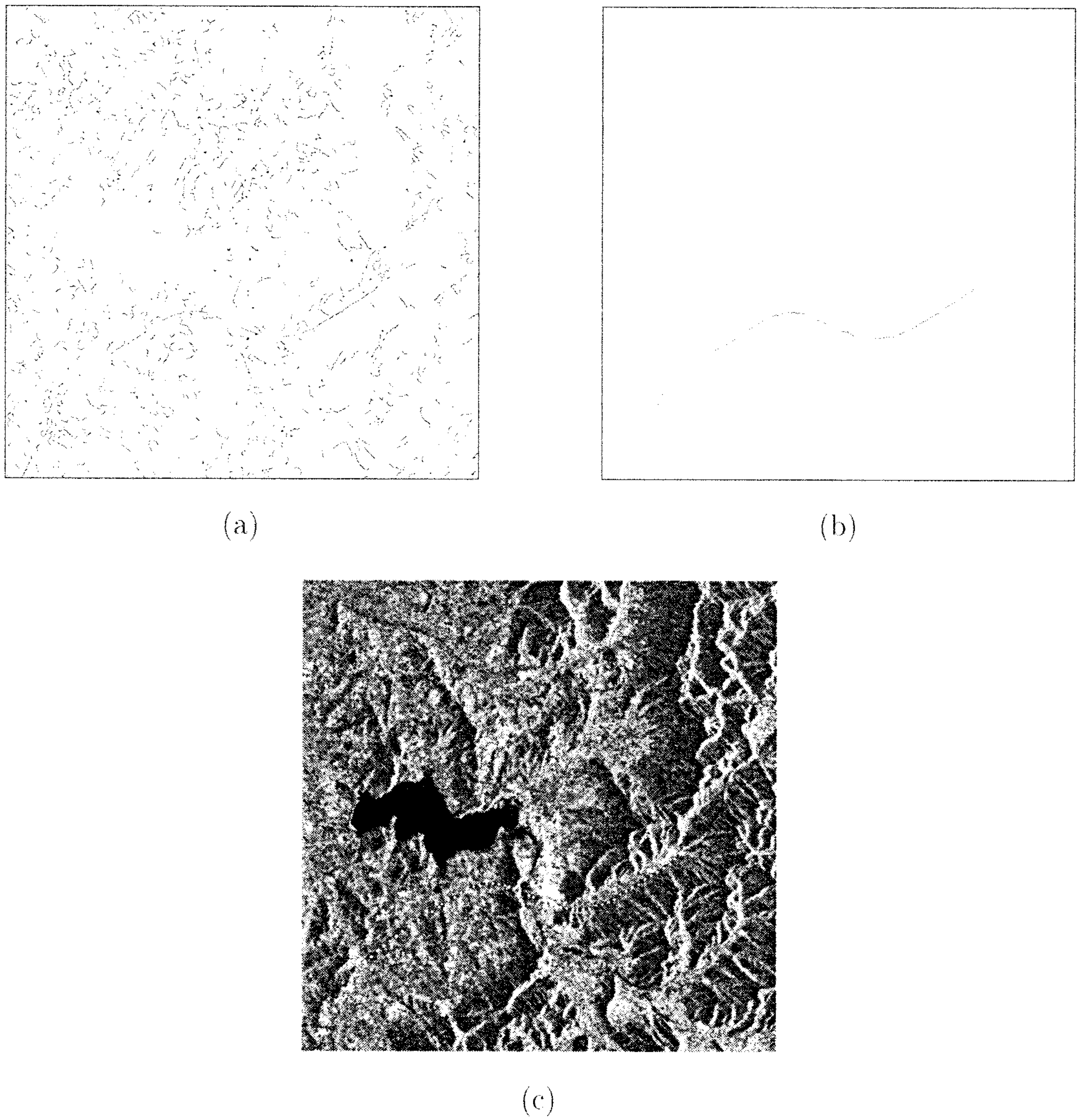

Fig. 8. Experimental results. (a) Extracted curvilinear structures (see Fig. 2), (b) grouped segments by region-growing-based GA, and (c) detected road overlaid on the sigma-filtered image of Fig. 2(a).]

B. Efficient Algorithm by Region Growing

When we optimize our problem, we can achieve efficiency by using only a portion of the segments in the image as the input of the GA. As mentioned earlier, this method selects an initial seed, performs a grouping by the GA in each region around the two endpoints of the seed, grows that seed using grouped segments, and defines the new search regions. This procedure is iterated $N_{\max}$ times in the same manner. We call this *region growing*, and the output segments of the GA at each stage are verified by checking their cocurvilinearities with other output segments. The segments with cocurvilinearities that are higher than a threshold are grouped with the current seed into a new single segment. This is regarded as the seed of the next stage. Around the new seed, search regions are newly defined (i.e., *region growing*), and grouping operations are performed in these regions. On the other hand, for the region with no segment approved by the verification, the GA is applied again to the current region without region growing.

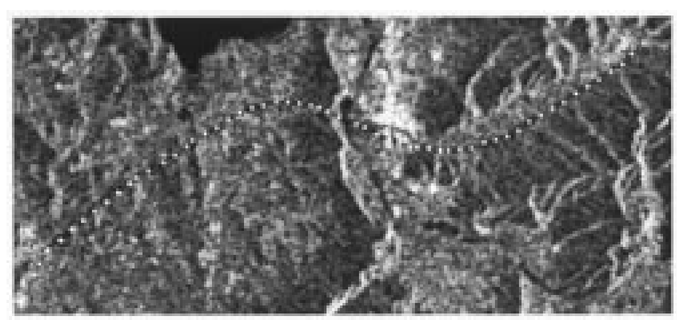

Fig. 9. Enlarged result of Fig. 8(c).

Fig. 7 shows segments detected by the GA in the search region of one side of the current seed segment, where the region is defined as a half-circle perpendicular to the current seed and rep-

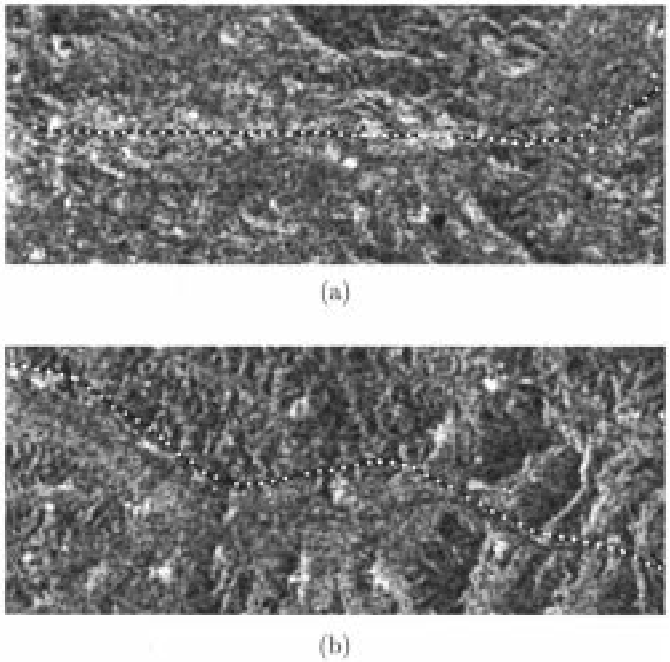

Fig. 10. Other results on single-track roads. (a) A region of Seunghwan, Korea and (b) a region of Chonan, Korea.

resented as the shaded part in the figure. Among these, only the segments, which are accepted by the verification, are grouped into a new seed of the next stage, and its endpoint is selected as follows: At the current stage, the accepted segments are sorted according to their distances from the seed in descending order. Among all the segments detected by the GA in the search region, the endpoint of the seed of the next stage should be the farthest segment from the current seed. The near distance of this segment from the current seed should be sufficiently small, or at least, the large part of the gap between this segment and the seed should be filled. These requirements are checked under the criteria of

$$\begin{aligned} &\text{Criterion } C_1: \quad D < T_1 \\ &\text{Criterion } C_2: \quad \frac{L}{D} < T_2 \end{aligned} \tag{5}$$

where D is the near distance of the considered segment from the current seed, L is the length of the segment filling the gap between the current seed and the considered segment, and T_1 and T_2 are user-specified thresholds. Criterion C_2 is applied only in cases where the segment does not satisfy C_1. After locating the segment that first satisfies C_1 or C_2, the far endpoint of that segment is determined as the endpoint of the seed of the next stage.

V. POSTPROCESSING

We can obtain grouped segments by the efficient GA based on region growing. However, these segments are only parts of the roads and do not completely describe the roads we want to detect. Therefore, to completely detect roads from grouped segments, we use the *active contour model (snake)*. We adopt Lai's snake model [14] but redefine the external energy of the snake by using the potential field [7]. This field is constructed from extracted curvilinear structures. It has characteristics that emphasize the positions of these structures and is less affected by the speckles. The snake is applied to gap regions between grouped segments. The points on the roads are detected by an energy-minimizing process, where initial control points of the snake are automatically chosen by interpolating grouped segments. Hence, the final roads consist of points from the segments grouped by the GA and points detected by the snake.

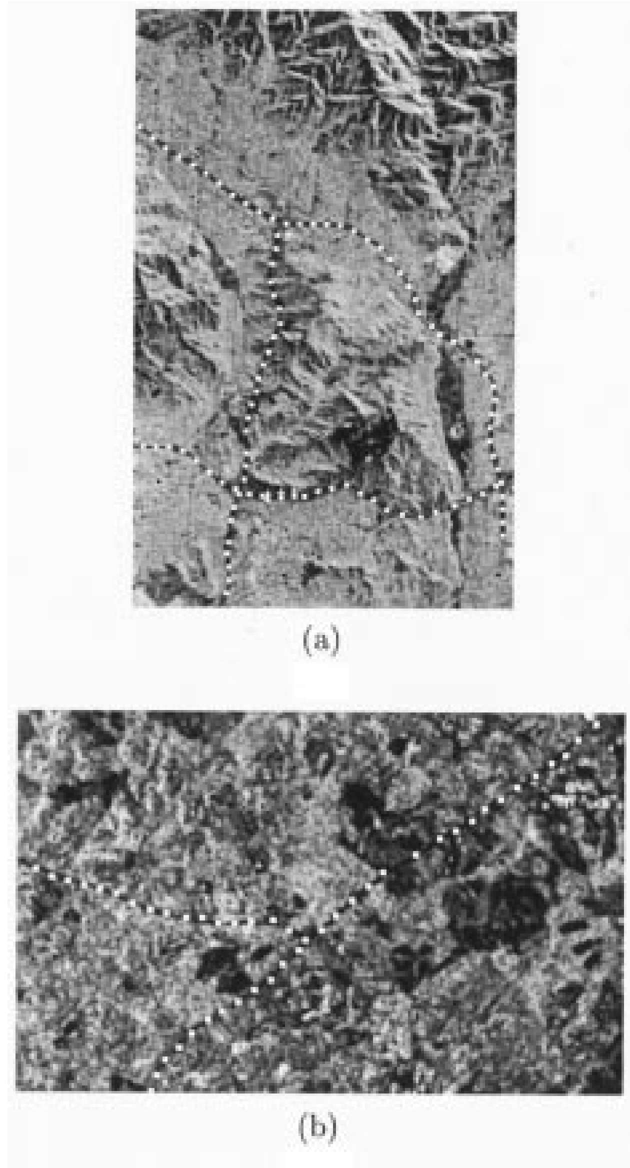

Fig. 11. Experimental results on road networks. (a) A region of California and (b) a region of Washington.

VI. EXPERIMENTAL RESULTS

We applied our algorithm to some sample regions of Korea in ERS-1 images and those of the USA in SIR-C/X-SAR images. The resolution of the data used in our experiments is about 30 m, and the pixel spacing is 16 m. The experimental results are shown in Figs. 8–11, which include road networks as well as single-track roads in mountainous and plain areas around cities. To detect road networks as shown in Fig. 11, we apply the GA

TABLE I
PERFORMANCE OF ROAD DETECTION

Total Number of Detections	332
Number of Correct Detections	306
Average Error of False Detections (*pixels*)	1.62
Detection Rate (%)	92.2
Average Error (*pixels*)	0.13 (2.08 m)

sequentially using multiple seeds. For each seed, we detect a road using the same GA and use postprocessing methods as those used for the single-track road. We finally obtain road networks by combining step-by-step all of the detected roads.

In Table I, performance analysis results of the road detection algorithm proposed in this paper are given. We detected a total of 332 road points in the five test images, where a road point means a point sampled from the grouped segment of the GA or a control point of the snake after minimization. The errors are defined as the minimum Euclidean distances in pixels between detected road points and true points manually determined on the road in the SAR images, with the average error determined as the total errors in pixels divided by the total number of road points. As visible in the table, the proposed algorithm detects roads in the spaceborne SAR images with an accuracy of 92.2% (correct detections of 306 points), and, with an average error of only 0.13 pixels, which corresponds to 2.08 m. The falsely detected points have errors of only one or two pixels (the average error of false detections is 1.62 pixels). Therefore, the proposed method is very accurate.

The proposed method focuses on spaceborne SAR images, which have roads with lower intensities than those of their neighborhoods. Under this condition, our method can detect roads regardless of landscape and texture because it utilizes information on the road structures in the scene. Although the number of the presented experimental results is not large, they represent most of the cases of a general scene by using data from different sensors and by dealing with road networks as well as single-track roads. However, our method may fail to detect roads if initial road candidates or seeds are not well extracted. In SAR data, some parts of the roads can be indistinct or occluded by neighboring topographic surfaces. In such cases, the extracted road candidates are composed of many short segments which are disconnected by large gaps. In this case, the proposed method cannot detect long and continuous roads. However, this failure seems to stem from poor conditions of input data rather than poor performance of our method. Hence, if the input SAR data is good enough to stably extract road candidates, the proposed method can reliably detect roads in spaceborne SAR images.

In addition, our region-growing-based GA can obtain a result like Fig. 8(b) within 4 min on a Ultra-SPARC processor in spite of the condition shown in Fig. 8(a), where there are more than 2000 segments. However, when we apply the simple GA, which directly uses all the segments at a time, it takes more than 24 h to obtain grouped results. Therefore, based on this performance analysis, we can assert that our algorithm can reliably detect roads in spaceborne SAR images with high accuracy as well as with low computational cost.

VII. Conclusions

In this paper, we propose an automatic road detection method for spaceborne SAR images. Our method regards roads in SAR images as curvilinear structures and detects them. Finally, we detect roads by grouping these segments using the GA. Applying the GA to our problem, we devise an efficient algorithm based on a concept of region growing, which considers only a portion of the total number of segments at a time. Experimental results show that the proposed method can accurately and efficiently detect road networks as well as single-track roads.

In a practical application, our road detection method can be utilized to update map information. In this paper, since the resolution of the data is very low, most of the detected roads are highways and smaller roads cannot be seen; therefore, cannot be detected. However, if we have high resolution data, roads smaller than highways can also be detected using the same algorithm. Then, by combining the information of all the detected roads, we can update a map more accurately. For this purpose, we geocoded the SAR data to the specified map, which has a pixel spacing of 16 m and a scale of 1 : 100 000.

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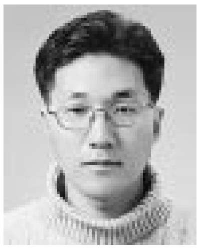
His research interests include feature extraction, segmentation and change detection in SAR images, and Bayesian statistical image analysis.



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