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An Ant Colony Algorithm for Roads Extraction in High Resolution SAR Images

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ABSTRACT

This paper presents a method for the detection of roads in high resolution Synthetic Aperture Radar (SAR) images using an Ant Colony Algorithm (ACA). Roads in a high resolution SAR image can be modeled as continuously straight line segments of roadsides that possess width. In our method, line segments which represent the candidate positions for roadsides are first extracted from the image using a line segments extractor, and next the roadsides are accurately detected by grouping those line segments. For this purpose, we develop a method based on an ACA. We combine perceptual grouping factors with it and try to reduce its overall computational cost by a region growing method. In this process, a selected initial seed is grown into a finally grouped segment by the iterated ACA process, which considers segments only in a search region. Finally to detect roadsides as smooth curves, we introduce the photometric constraints in ant colony algorithm as external energy in a modified snake model to extract geometric roadsides model. We applied our method to some parts of TerraSAR-x images that have a resolution of about 1 m. The experimental results show that our method can accurately detect roadsides from high resolution SAR images.

Keywords

Ant Colony Algorithm (ACA); perceptual grouping; roadside detection; synthetic aperture radar (SAR); Snake.

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1. INTRODUCTION

With the development and lunch of new high resolution of SAR sensors such as TerraSAR-X, Radarsat-2, and Cosmo/Skymed, urban remote sensing based on SAR data has reached a new dimension. Thus extraction of roads from the high resolution SAR image is one of the most important applications of mapping.

Much research has been carried out on this topic since the 1970s [4]. Fischler 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 [7]. McKeown and Denlinger proposed a road-tracking algorithm for aerial images, which relied on road-texture correlation and road-edge following [12].

Gruen and Li also proposed a semi-automatic road extraction algorithm for aerial images [8]. 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.

Barzohar and Cooper presented an automated approach to locate the main roads in aerial images [5]. Tupin proposed a nearly automatic detection algorithm for linear features such as the main axes of road networks [16].

Jeon presented a technique for the detection of roads in a SAR image using a genetic algorithm [10]. Amini proposed a method for automatic road extraction in high resolution optical image (IKONOS) based on a fuzzy algorithm [3]. Auclair presented a method for automatic updating of road databases from high resolution imagery [1].

Jeon proposed an automatic road detection algorithm for satellite images [9]. They presented a map-based method based on a coarse-to-fine, two-step matching process.

As we seen, many works on road extraction have been done using the automatic or the semi-automatic methods in aerial or satellite images. Compared with other methods, the objective of the proposed algorithm in this paper is one of the most challenging methods because it attempts to detect roadsides in high resolution SAR images without any user intervention. It is well-known that detecting roads in high resolution SAR images is difficult because these images have *speckles*. In this paper, we show in spite of the speckles in SAR images, our method can detect roadsides in high resolution SAR images with high accuracy. To detect roadsides, we first extract the edges in SAR image as curve segments. Next we segment connected components above a threshold hopefully coinciding with straight or curved object contours.

The extracted curve segments seem to represent the candidate positions of roadsides; therefore, we can detect roadsides accurately by grouping these segments. For this task, we present a grouping method based on an Ant Colony Algorithm (ACA). Although there are many methods for optimization, we choose the ACA since it can find the best solution of the problem through a guided search over the solution space by constructing the pheromone information. The ACA of our method uses perceptual grouping factors, such as proximity and Continuity, and the characteristics of roadsides in SAR images, such as intensity.

From the results of the grouped segments obtained with the ACA, the roadsides are finally detected after the postprocessing step, including noisy segment removal and the modified snake model. We applied our method to some sample regions of TerraSAR-X data. Experimental results show that the proposed method is accurate and computationally efficient. Fig. 1 presents the overall flow of our algorithm.

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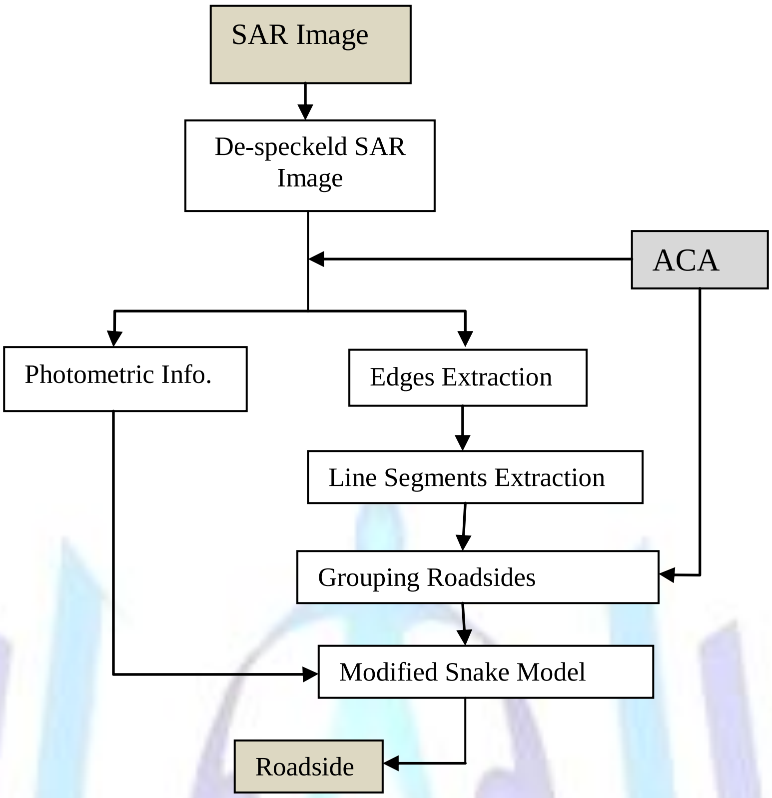

Fig 1: Overall flow of our roadsides detection algorithm

2. Preprocessing

The input images of the proposed method are some sample regions of TerraSAR-X 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 filter developed by Sumantyo and Amini because it suppresses speckles with the least amount of blurred edges and fine details, and it is computationally efficient [14].

Next, because the roadsides are curvilinear segments, these segments can be candidates for true roadsides. Based on this assumption, we first extract these segments in the preprocessed SAR images by Ant colony and Mohan's method [13].In this method, the edges of the de-speckled SAR images are first detected using ACA, then the edges are linked into curvilinear, which are then segmented into straight lines segments.

In the ant colony method, a number of ants move on the SAR image to construct a pheromone matrix which each entry represents the edge information at each pixel location of the image. Then the decision process is performed to detect the edges. The movement of each ant from the pixel (*l*,*m*) to its neighboring pixel (*i*, *j*) is based on a transition probability that is defined as Dorigo [6].

$$p^{n}_{(l,m),(i,j)} = \frac{\left(\tau^{(n-1)}_{i,j}\right)^{\alpha}\left(\eta_{i,j}\right)^{\beta}}{\sum_{(i,j)\in\sum\Omega_{(l,m)}}\left(\tau^{(n-1)}_{i,j}\right)^{\alpha}\left(\eta_{i,j}\right)^{\beta}} \tag{1}$$

where $\tau^{n-1}_{i,j}$ is the pheromone value of the node (*i*, *j*), $\Omega_{(l,m)}$ is the neighborhood nodes of the node (*l*,*m*), $\eta_{i,j}$ represents the heuristic information at the node (*i*, *j*). The constant α and β represent the influence of the pheromone matrix and the heuristic matrix, respectively.

In this paper, it is proposed to determine the heuristic information $\eta_{i,j}$ by the local statistics at the pixel position (i, j) as

$$\eta_{i,j} = (I(i,j) - I_m(i,j))^2 \tag{2}$$

where $I(i,j)$ is the intensity value of the pixel at the position (*i*, *j*) of the SAR image. $I_m(i,j)$ is the average value of intensity values of a window with size of 3×3 centered on (*i*,*j*). Fig 2 shows and SAR image and the straight line segments extracted from it.

The parameters of the ACA set as:

Ω : 8-connecting neighborhood,

L=40; Number of ant's movement stage,

N=10; Number of construction step,

K=512; Number of ants, and

$\tau_{init} = 0.1, \alpha = 1, \beta = 0.1,$

We want to detect roadsides by selecting some meaningful line segments among a collection of *base segments* with the help of a grouping scheme.

Fig 2: Extraction of straight line segments. (a) Original SAR image and (b) extracted straight line segments in the preprocessed SAR image.

3. Line segments grouping by the ant colony algorithm

3.1 Geometrical relationship of line segments

Our method is a detection method based on the line segments grouping, where line segments are 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 ACA. In both steps, to group segments we use perceptual grouping factors such as similarity, proximity and continuation as shown in Fig. 3 [13].

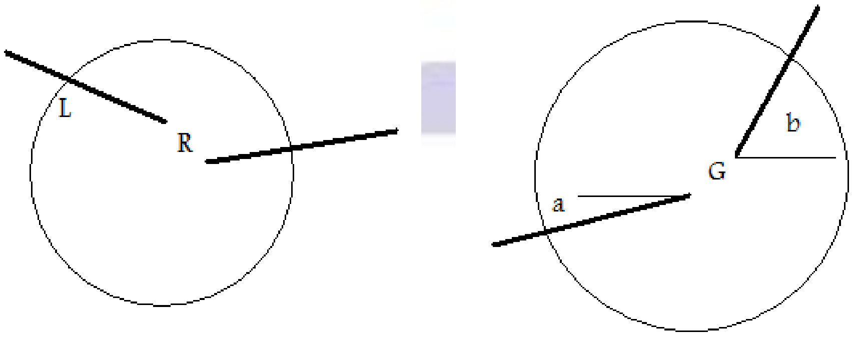

Fig 3: Perceptual grouping factors. (a) Proximity and (b) continuation

Similarity: similar line segments are grouped together

Proximity: Line segments that are close together tend to be grouped together. It is formulated as follows:

$$P = \frac{L}{2D\pi R^2} \tag{3}$$

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

Continuation: line segments that lie along a common line or smooth curve are grouped together. Roadsides are smooth and get projected as smooth curves in the image. Collations of line segments in the form of smooth curves are detected by a local, no iterative process that selects the most collinear, or least bent, joins among neighboring tokens. This formulation of continuity-based organization is influenced by the experiments by Stevens and Brooks which indicate that the grouping process can be modeled by local selection of most collinear pairings [15]. The Continuation between these two segments is calculated by:

$$C = \frac{1}{(a^2 + b^2)(\lambda + \kappa G)} \quad (4)$$

Where λ controls the departure from collinearity of the joined line segments, and κ controls the sensitivity to the length of the gap G. For the experimental, $\lambda = 1.0 \; and \; \kappa = 0.1$ are used, and a and b are tangent angles of segments at joined endpoints (see Fig. 3(b)).

3.2 Initial Grouping

As mentioned earlier, the aim of the proposed method is to detect roadsides of high resolution SAR images by grouping segments using the ACA. However, the method of considering all the base line segments in the scene at a time is not efficient. Therefore, we incorporate a concept of region growing into the ACA. This method first selects an initial seed and performs a grouping around it by using the ACA. 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 roadsides (i.e., the largest segment) by grouping base line 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 three perceptual grouping factors explained in Section III-A. Its procedure is as follows. Let each base line segment that we consider be the reference segment. Other base line 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 line segment with the largest Continuity, 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 line segments remaining.

3.3 Grouping by the Ant Colony Algorithm (ACA)

In this step, we detect line segments representing roadsides using the ACA-based grouping method. To make our algorithm efficient, we incorporate the concept of region growing into the ACA, 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 roadsides. As mentioned earlier, the reason why we use multiple seeds is that our algorithm can detect road networks, and we perform groupings by the ACA 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 times in the same manner.

Ant colony algorithm is a metaheuristic used to find good solutions to NP-hard optimization problems, such as problem of grouping line segments. In this paper, we model the grouping problem over a complete bipartite graph on the line segments.

As an ant traverses the graph, its decision on where to go next is influenced by *heuristic information* and current pheromone deposition. For line segments grouping for roadsides detection, the heuristic information will take into account both local shape descriptors and proximity. After a number of ants have traversed the graph, known as an iteration of ACA, a certain amount of pheromone is also *evaporated* from all edges. Pheromone evaporation occurs in nature and in ACA, it can help the ants escape from bad local minima. When examining the ACA, we see that, at first, ants will tend to freely explore the whole solution space, leading to many different solutions. However, over time, pheromones will accumulate only on edges that are part of those traversals favored by the objective function; this causes the ants to gradually follow only a limited number of traversals. Moreover, heuristic information and pheromones have to be combined to guide an ant. The former is necessary to bias the ants to construct good traversals at the start, when the pheromones are set to random initial values. On the other hand, the pheromones are necessary for later iterations of the algorithm, when they reinforce the traversal of the graph edges that lead to good solutions

3.4 ACA for grouping of roadside segments

This section formulates the grouping of roadsides segments and describes how the ACA metaheuristic is applied at each stage of region growing.

Fig. 4 shows line segments and corresponding graph in a region, the grouping problem can be stated as finding line segments belong the roadsides which minimizes a given objective function.

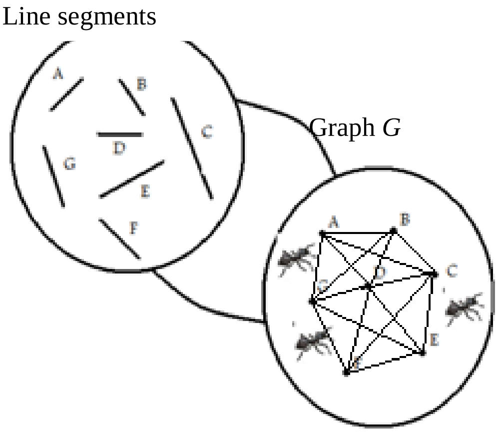

Fig 4: Line segments in a region

As in Fig. 4, we define the graph $G = \{V,E\}$ that is to be traversed by the ants as a complete, directed bipartite graph. The set of vertices of this graph is composed of the line segments in the regions. The directed edges E fully connect the segments. The path that is determined by the traversal of an ant on G corresponds to a possible solution to the grouping problem. When an ant traverses a directed edge that connects a vertex in i to a vertex j, an assignment from i to j is determined.

When traversing from a vertex i to a vertex j, the probability P_{ij}^{k} of an ant k choosing the edge that connects to vertex j is given by

$$p_{ij}^{k} = \frac{(\tau_{ij})^{\alpha}(\eta_{ij})^{(1-\alpha)}}{\sum_{l \in \Sigma_{N_i}} (\tau_{il})^{\alpha}(\eta_{il})^{(1-\alpha)}} \tag{5}$$

where τ_{ij} quantifies the pheromones accumulated on edge (i, j), η_{ij} indicates the probability of traversing (i, j) based on heuristic information (defined in the following), and $Ni = \{l :(i, l) \in E\}$ is the immediate neighborhood of vertex i. The parameter $0 \le \alpha \le 1$ regulates the influence of pheromones over the heuristic information.

We can see that the choice of the traversed edge is stochastic, where the sum of probabilities

$\sum_{j \in N_i} p_{ij}^{k} = 1$. Moreover, when traversing back from j to i, an edge pointing to any vertex that has not been visited yet can be chosen. Each edge from j to i has the same probability of being selected, and no pheromones or heuristic information are considered.

After $m \ge 1$ ants have traversed the graph, completing one ACA iteration, the solutions are evaluated and the pheromones are accordingly updated. The cost of each solution is given by objective function.

Pheromones are updated at the end of one ACA iteration. First, pheromones are evaporated at a constant *pheromone evaporation rate* ρ $(0 \le \rho \le 1)$ as:

$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij} \tag{6}$$

for all edges (i, j). Next, new pheromone is updated only on *edges that were traversed by the ants*, as:

$$\tau_{ij} \leftarrow \tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \tag{7}$$

where $\Delta\tau_{ij}^{k}$ is the amount of pheromone that ant k has deposited on edge (i, j)**.** What remains to be determined now is how to compute the probability based on the heuristic information η_{ij} in (5). Naturally, our proposed heuristic is a combination of the perceptual grouping factors, in a manner similar to the objective function.

we designed the objective 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 edges that were traversed by the ants, its objective function is determined by four factors: *proximity, Continuity*, *homogeneity,* and *length,* which are represented by

$$P = \sum_{i=1}^{N} p_i / N$$

$$C = \sum_{i=1}^{N} c_i / N$$

(8)

$H = \sum_{i=1}^{N} h_i / N$

$L = \sum_{i=1}^{N} l_i / N$

Where p_i, c_i, h_i, and l_i are proximity, Continuity, homogeneity, and length of the *i*th segment of the traversed path. The continuity of the *i*th segment c_i is determined as the maximum value out of continuity between the *i*th segment and the other segments in the path, and its proximity is set equal to the proximity between the *i*th segment and the one that gives the maximum continuity value. The factor of homogeneity 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 *i*th segment is in the predefined range, the value of this pixel is set to one. The value represents the number of pixels with 1's in the *i*th segment divided by the total number of pixels in that segment. Using all of these factors, the heuristic information η_{ij} is defined as:

$$\eta = \alpha P + \beta C + \gamma H + \delta L \qquad (9)$$

where α, β, γ, and δ are the four weighting factors for the fitness, and in the experiments, they are set to 0.6, 1.0, 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.

3.5 Modified snake model

After the line segments are grouped by our method based on region growing. These segments are only parts of the roadsides and do not completely describing the roadsides we want to detect. Therefore, to completely detect roadsides from grouped segments, we use *a modified Snake model* introduced by Kass but redefine the external energy of the snake by using the ant colony algorithm to find the photometric constrains as external energy [11]. This energy is constructed from extracted roadsides segments. The snake is applied to gap regions between grouped segments. The points on the roadsides are detected by an energy-minimizing process, where initial control points of the snake are automatically chosen by interpolating grouped segments. Hence, the final roadsides consist of points from the segments grouped by the ACA and points detected by the snake.

At last we wish to fit smooth curve to the points v^i to extract geometric roadsides model (see Fig. 5). We pass a set of cubic splines $r^i(s)$ through the points, using a new cubic in each interval, to extract geometric roadsides model [2].

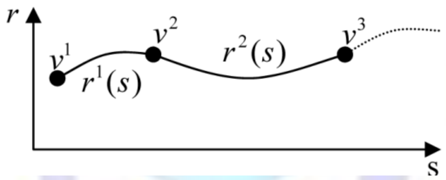

Fig 5: Interpolation of the points in roadsides with the modified Snake model.

4. Experimental results

We applied our algorithm to some sample regions of Iran TerraSAR-x images in spotlight acquisition mode. The resolution of the data used in our experiments is about 1m in HH polarization. The experimental results are shown in Fig. 6.

Fig 6: Experimental results. (a) Extracted stright lines grouped by ACA, and (b) detected roadsides overlaid on the filtered image of Fig. 2(a).

To detect roadsides as shown in Fig. 6(b) overlaid the original image, we apply the ACA sequentially using multiple seeds. For each seed, we detect roadside using the same ACA and use postprocessing methods as those used for the roadsides. We finally obtain the geometric roadsides model by combining step-by-step all of the detected roads.

In Table I, performance analysis results of the algorithm proposed in this paper are given. We detected a total of 567 road points in the five test images, where a road point means a point sampled from the grouped segment of the ACA 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 roadsides in the SAR images, with the average error determined as the total errors in pixels divided by the total number of road points. As seen in Table 1, the proposed algorithm detects roadsides in the high resolution SAR images with an accuracy of 93.8% (correct detections of 532 points), and, with an average error about 0.5 pixel, which corresponds to 0.5m. The falsely detected points have errors of only one or two pixels.

As we seen, the proposed method focuses on the high resolution SAR images, which have roads with lower intensities than those of their neighborhoods. Under this condition, our method can detect roadsides regardless of landscape and texture because it utilizes information on the road structures in the scene.

One of the limitation of our method is that it is 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 roadsides 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.

Table 1. Performance of the AC algorithm

Total number of detection	567
Number of correct detection	532
Average error of falase detection (pixels)	1-2
Detection rate (%)	93.8
Average error (pixels)	0.5

5. Conclusions

In this paper, we proposed a method for roadside detection from high resolution SAR images. Our method regarded roadsides in SAR images as straight line segments and detected them. Finally, we detected roadsides by grouping these segments using the ACA. Applying the ACA to our problem, we devised an efficient algorithm based on a concept of region growing, which considered only a portion of the total number of segments at a time. Experimental results showed that the proposed method can accurately and efficiently detect roadsides. In the applications of remote sensing, our method can be utilized to update maps.

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Authors' biography

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