IMPROVING ROAD NETWORK EXTRACTION IN HIGH RESOLUTION SAR IMAGES BY DATA FUSION

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ABSTRACT

In this paper, the problem of the detection of road networks in high resolution Synthetic Aperture Radar (SAR) images is addressed. Our method, which is an improvement of previous work based on line extraction and connection with Markov random field, is dedicated to dense urban areas. The major modifications are, first, the introduction of a classification in order to improve both the level of confidence and the number of extracted roads and, secondly, a multi-scale process in order to take into account all the possible widths of roads. Two examples on real data prove the improvement brought by this two adding and the accuracy of the road detection.

1. INTRODUCTION

Automatic or semiautomatic map updating using remote sensing images is an important area of research. A growing amount of remote sensing image is available today from different kind of sensors and a certain level of automation can speed-up the map updating process considerably. The paper presents one solution for one of the most relevant applications of high resolution SAR data: road network detection in dense urban areas. In the past 20 years, many approaches have been developed to deal with the detection of linear features on optic or radar images. Most of them start from SAR complex or real data and exploit two criteria: a local criterion evaluating the radiometry on some small neighborhood surrounding a target pixel to discriminate lines from background and a global criterion introducing some large-scale knowledge about the structures to be detected [1,2]. On the other hand, post-classification grouping is proposed in works like [3,4], where the authors try to discriminate the roads by grouping pixels classified as "roads" in SAR images of urban environments. In particular, their approach, based on fuzzy unsupervised clustering, starts from classification maps to extract a more precise road network.

In the present work we try an intermediate methodology between these two approaches. In particular, we aim at improving the road network extraction task in SAR images by exploiting both a line detector's and a classifier's outputs [5,9]. The method is therefore based on the joint analysis of line segments detected by means of SAR image filtering and classification maps obtained by SAR data clustering.

2 THE PROPOSED PROCEDURE

The conceptual workflow of the proposed procedure is described in fig. 1. The street extraction is made in three steps : the line detection, the network reconstruction (these two steps are processed at each scale) and the fusion of the results at different scales. The core of our proposal is the joint exploitation of a pre-computed classification [5] and the algorithms proposed in [6,9].

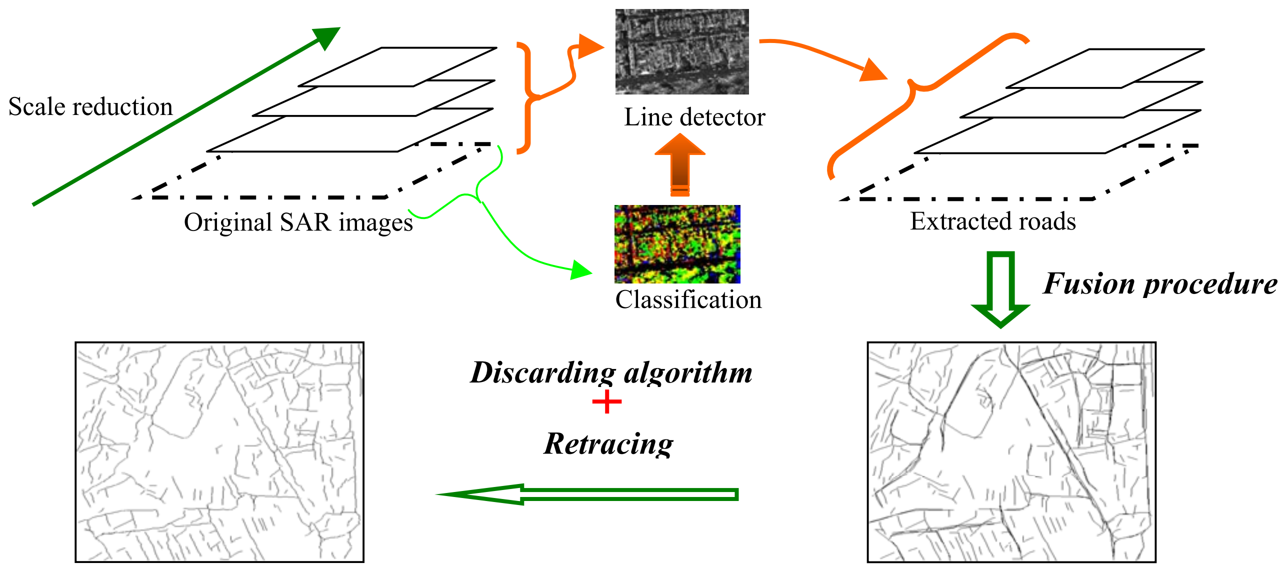


Figure 1: *Conceptual workflow of the proposed procedure*

2.1 LINE DETECTION

The line detector is based on the statistical properties of Gamma-distributed amplitude image (assumption of fully developed speckle) [7]. It results from the fusion of ratio-based detector D_1 and a correlation-based detector D_2 (see [9] for more details). For each direction θ and each width w, the two detectors are computed and merged with an associative symmetrical sum $\sigma(D_1,D_2)$ [8]. In the same time, the classification is introduced to compute a third criterion D_3, which is the percentage of pixels classified as road along the linear structure of width w and with orientation θ. Then, it is merged with $\sigma(D_1,D_2)$ in order to get a final response $\sigma(D_1,D_2, D_3)$ *(w,θ)*. The fusion is again done with an associative symmetrical sum :

$$\sigma(D_1,D_2,D_3)(w,\theta)=\frac{\sigma(D_1,D_2)D_3}{1-\sigma(D_1,D_2)-D_3-2\sigma(D_1,D_2)D_3}$$

Finally for each dimension and orientation of possible road a coefficient $\sigma(D_1,D_2, D_3)$ *(w,θ)* is obtained. In each pixel, the highest response is selected with the associated width and orientation.

The output of the line detection step is thresholded to obtain a binary image. A squeletization and linearization are applied to define a set of segments. Each segment is eventually characterized by a coefficient comprised between 0 and 1, as a function of the reliability of the extracted road. This coefficient is defined as previously by fusion of a classification measure D_3 and the merging of D_1 and D_2 . But this time all the measures are defined using the orientation of the segment. The closer to 1 it is, the higher is the probability of having a road.

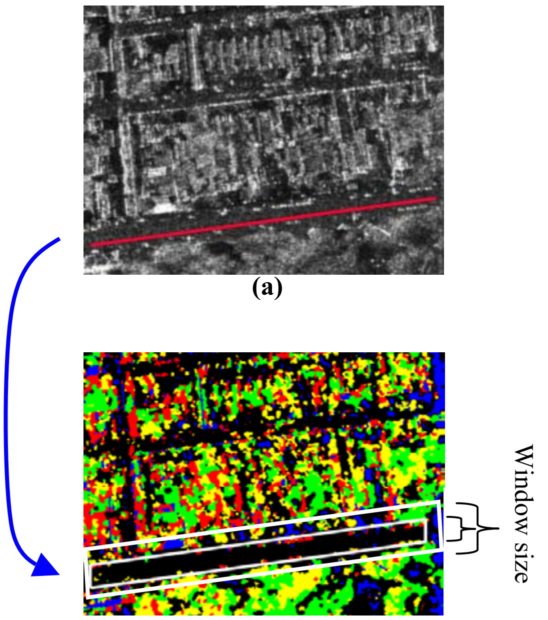


Figure 2*: (a) original SAR data with superimposed a road extracted by means of the line detection procedure, (b) the corresponding classification map, with (in white) the regions checked for the percentage of pixels in the "road" class.*

2.2 NETWORK RECONSTRUCTION

Unfortunately some extracted segments are not connected along the entire path of the roads and some others are too small to be related to a road (Figure 5-a). Therefore the previous detection is introduced in a Markovian approach defined on a graph of segment [6]. The energy function was originally defined by the probability density function of amplitude SAR image and prior knowledge about the road shape (probability of crossings and curvature limitation). To take into account the classification, the likelihood term has been modified. Indeed, the observation field which was defined as the line detector response $\sigma(D_1,D_2)$ along the graph segment, is now defined as $\sigma(D_1,D_2, D_3)$ thus taking into account the percentage of road classified pixels along the segment. The regularization term (prior probability) on the segment clique is not modified compared to [6].

2.3 MULTI-SCALE FUSION

On remote sensing image, roads appear with varied widths, depending on the effective road size and the image resolution. In the previous step, only widths (*w* parameter) from 1 to 5 pixels are tested whereas widths can vary from 1 to 30 pixels. Instead of detecting all the segment candidates and building a large graph for the connection step (and thus mixing all the networks), we prefer extracting the roads at different scales and then merging the networks with different widths. This method has the advantage of preserving the coherence of each network and produces less noisy results. The multi-scale analysis is, therefore, made in the following way:

- creation of an image pyramid; the resolution is degraded by averaging the amplitudes of *n x n* pixel blocks; only three levels with n=4, n=8 and n=16 are considered here,
- extraction of the road network at each level by the previously described method,
- merging of the different network by superimposition
- cleaning step aimed to delete redundant segments.

In order to delete as much as possible the redundant segments present in the post fusion image (fig. 5-d), we operate a pruning procedure able to discard segments that correspond to the same part of a road preserving the longest one [10]. Furthermore, using perceptual grouping concepts, we exploit collinearity by joining segments very close one to the other, or even partially overlapping, and with (almost) the same direction.

Finally, the last step of the procedure is based on dynamic programming [12] constrained by the amplitude image. The path of each road is questioned by taking into account only its beginning and end As a matter of fact, the road network extracted by the previous steps not always provides information about the exact centre line of each road. This step enables us to position the lines in the center of the roads (figure 3) .

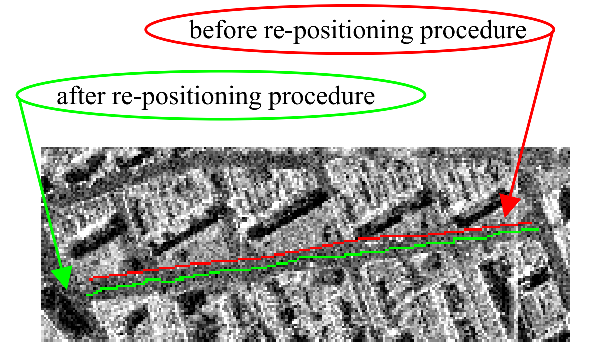
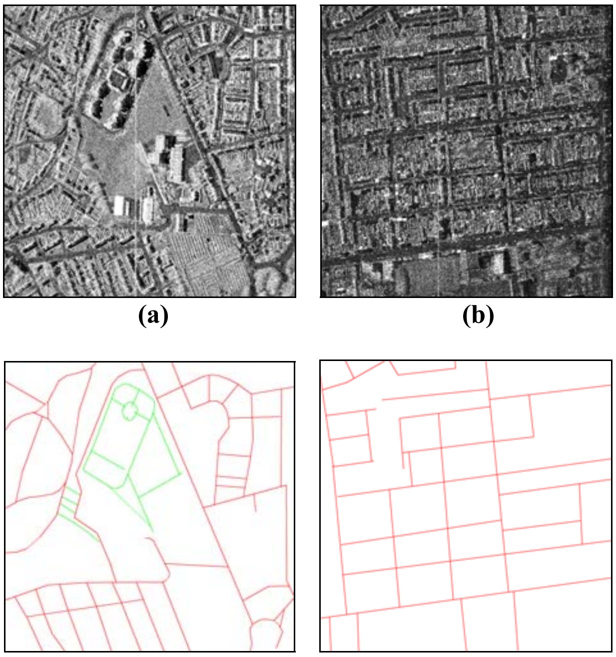


Figure 3. *Input (red) and output (green) of the repositioning procedure*

3 EXPERIMENTAL RESULTS

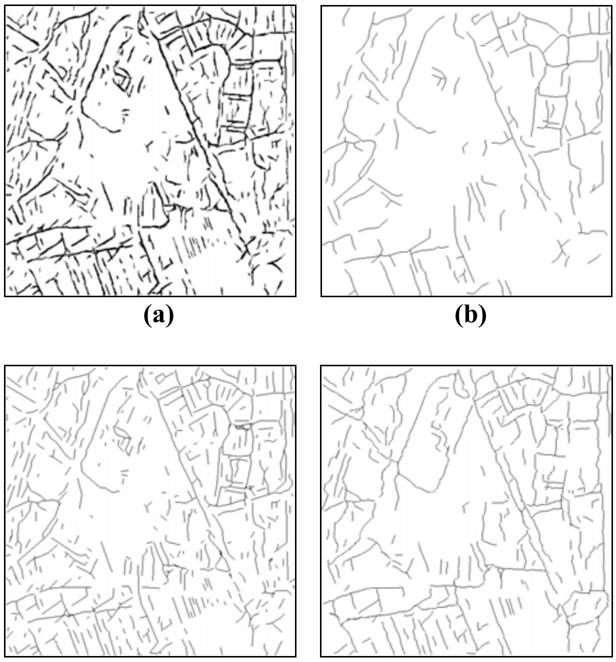
We illustrate the proposed method on two real radar images represented in fig. 4 with the corresponding ground-truth manually obtained from the amplitude image and helped by optical image. Note that only the main axis of the network roads visible in SAR images is plotted. The SAR images have been acquired by the Ramsès sensor over Dunkerque (North of France) and represent two different urban environments. The overall extraction routine provides the results in fig. 5(c) and 6(c) for the two test areas, to be compared with the output of the original procedure in fig. 5(b) and fig. 6(a). An intermediate step is also provided in fig. 5(c) and fig. 6(b), where the proposed methodology is applied without the multi-scale analysis.



(c) **(d)**

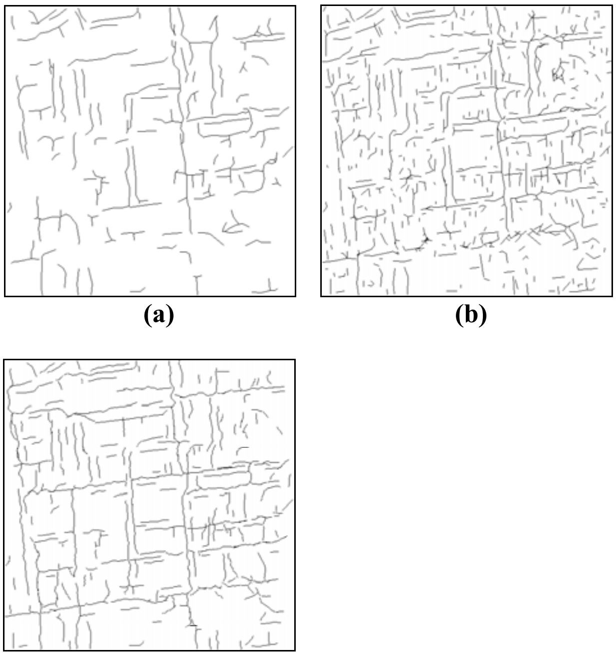
Figure 4: *(a, b) original images; (c, d) manual ground truth*

First of all, the number of the recognized roads increases from left to right. This strengthens our guess that the proposed procedure improves the original results. Furthermore, fig. 5(d) and fig. 6(c) do not present as many small segments as fig. 5(c) and fig. 6(b). The roads appear “cleaner” and more continuous, and a lot of little spurious segments has been deleted.



(c) **(d)**

Figure 5: *Extraction results for the SAR image in fig. 4(a): (a) segments extracted, (b) after MRF procedure; (c) fusing line detection and classification maps; (d) using the proposed multi-scale fusion procedure.*



(c)

Figure 6: *Extraction results for the SAR image in fig. 4(b): (a) using the original line detection + MRF procedure; (b) fusing line detection and classification maps; (c) using the proposed multi-scale fusion procedure*

A similarly interesting analysis may be done looking at the corresponding quantitative evaluation of the roads,

shown in Table I. We offer a comparison of the correctness and completeness indexes [11] for the networks in fig. 5 and 6.
The completeness index represent the fraction of ground truth length extracted while the *correctness* index, is the fraction of segments' length belonging to actual roads.
We should keep in mind, however, that the ground truth is not extremely precise, so the values in Table I has a *relative* more than an *absolute* meaning. We observe that the correctness increases from left to right, as we could expect. Completeness instead is bigger for the networks extracted with the original algorithm. However, this is mainly due to the fact that less small, spurious roads are present in such images and consequently a lower number of false detections are present.

	fig. 5(b)	fig. 5(c)	fig. 5(d)
Correctness	0.5353	0.6967	0.6967
Completeness	0.5440	0.4508	0.4955

	fig. 6(a)	fig. 6(b)	fig. 6(c)
Correctness	0.5143	0.7585	0.7836
Completeness	0.4751	0.4025	0.4610

Table 1: *quantitative evaluation and comparison of the results in fig. 5 and 6.*

4 CONCLUSIONS

This paper has presented a road detection method that includes in a multi-scale framework a data fusion procedure. It takes into account both a line detection methodology and a classification approach to improve the road extraction. The clique potentials have been modified to take into account more adapted knowledge. In a second part, the use of a fusion's procedure has shown some advantages in term of the number of the identified roads.
In particular, the multi-scale fusion approach not only recognizes roads at very different scales but increases also the percentage of real roads while reducing missing ones. Another advantage is that fusing more extractions for the same road, gaps due to missed parts are also reduced. This is visible in fig. 4(c) where the number of these gaps is clearly lower than the fig. 4(b).

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