ADAPTIVE DIRECTIONAL ORDER FILTERS AND MATHEMATICAL MORPHOLOGY FOR ROAD NETWORK EXTRACTION ON SAR IMAGES.

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ABSTRACT

In this paper, a method for automatic detection of linear features in SAR images, with application to road network extraction is proposed. A pre-filtering step is firstly performed using an adaptive directional weighted order filter. It aims to smooth the noise, enhance edges and preserve thin anisotropic structures. Then, the detection operator is applied : it is based on a geometrical model of the roads and uses morphological directional operators with appropriate structuring elements. Results are presented on real SAR ERS-1 satellite data.

Key words: SAR images - directional filters - road detection - mathematical morphology - non linear filtering - weighted order filters.

1. INTRODUCTION

This paper focuses on the problem of automatic line detection, with application to road network extraction in Synthetic Aperture Radar (SAR) images. This is of great importance, for instance for the registration of SAR images to existing maps.
A lot of methods have already been proposed to solve this problem, in particular in the visible domain, for instance on SPOT [Merlet-96] or aerial [Barzohar-96] images. But these methods are seldom very suitable to SAR images because these particular data are usually highly corrupted by a multiplicative noise, called the speckle.
To deal with this noisy structure, the proposed method is made of 2 different steps : a pre-filtering step followed by an automatic extraction step. Section 2 presents the filter that is used in the first stage to jointly smooth the image and enhance the significative edges and anisotropic structures. The extraction step that is performed on the filtered image is presented in section 3. Section 4 shows the results obtained on real SAR ERS-1 data. Finally, conclusions and future prospects are given.

2. PRE-FILTERING STEP

The adaptive weighted dα filter presented in [Issa-96] is used to preserve thin structures, enhance edges and smooth the noise at the same time. It belongs to the M-filters class. It is adaptive regarding the noise amplitude distribution, the orientation of structures and the anisotropy measures. For a given set $\{x_j\}$ of M pixels, the filter outpout y is defined by :

$$y = \underset{y}{\mathrm{Argmin}}\left(\sum_{j=1}^{M} c_j \left|y - x_j\right|^{\alpha}\right)$$

For each filtering window, parameter α is adaptively set according to the local noise impulsiveness, as proposed in [Issa-95]. Heavy tailed-like distributions (exponential) give small values of α, and shallow-like ones (uniform) give large values.
The filter coefficients c_j are chosen according to structure orientation and anisotropy measures by the expression :

$$c_j = (1 - \lambda)^{\Delta}$$

where :
• λ is an anisotropy parameter derived from the coefficient proposed by [Zamperoni-92]. It ranges from 0 (isotropic region) to 1 (highly anisotropic region),
• Once the most homogeneus segment that goes through the center of the filtering window has been found, Δ denotes the distance of the concerned pixel x_j to this segment (figure 1). If such a segment actually exists ($\lambda \approx 1$), pixels located on it are emphazised for

the filtering with greater coefficients and the structure is preserved ; if it does not ($\lambda \approx 0$), all the pixels have the same coefficient, and the smoothing effect is higher.

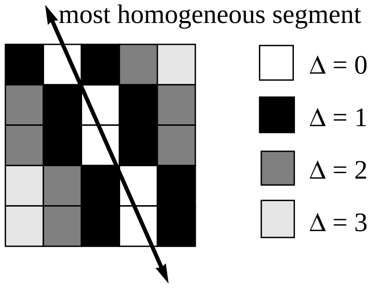

Figure 1 : orientation criterion

As a consequence, this filter takes into account both statistical and geometrical information that are locally estimated. The first leads to a better noise reduction and the second allows the enhancement of linear features.

3. DETECTION STEP

For the extraction step, the model shape and size of the features we are looking for have to be fixed. We thus decided to characterize the roads in the image as features that are :

- **locally rectilinear** : each road pixel belongs to a segment that is longer than a minimum required length l_0 . We fixed this minimum length l_0 to 21 pixels (corresponding to approximately 280 meters ground lengths for ERS-1 PRI images, which is a realistic minimum straight line length for typical countryside roads),
- **thin** : detected features must not be too wide. We decided to seek roads that are up to 3 pixels wide (which is a typical response width in SAR images for common roads),
- **contrasted** : we only considered features that are darker than their surroundings (the method can be extended to the detection of clear objects in a very straightforward way by using the dual operators).

Since the features we are looking for are intrinsically characterized by their shape, it seemed natural to us to use morphological operators [Serra-94]. The proposed method is simple, fast, un-supervised and almost non parametric [Chanussot-98]. It can be used over a wide range of images, applications and sensors, and it does not require any threshold.

In the following, we will use the classical topographic analogy for the representation of gray-scale images (Figure 2). In this representation, the image is considered as a topographic relief, the numerical value of each pixel determining the corresponding point elevation. With this analogy, we are looking for elongated and narrow valleys in a topographic relief. Three different types of structures have then to be removed, each one violating one of the basic constraints of the model definition :

- We firstly remove the **clear structures** (corresponding to "**peaks**"), since we only are interested in dark features. This is done using a morphological opening by reconstruction with a flat square structuring element of size 5 [Crespo-95]. This operator truncates the non flat peaks of the image. Furthermore, this is a connected operator. It therefore does not introduce any new discontinuity in the image : the edge information is either totally removed or exactly preserved, which is important for the next operation. Calling I_0 the original filtered image and using classical notations, we obtain the image I_1 :

$$I_1 = \bar{\gamma}_5 (I_0)$$

- We then remove **non-linear (or too short) valleys**. To preserve the valleys in which 21 pixels can be lined up in at least one direction, and to remove the others, we use the closing obtained by taking the infimum (denoted "$\wedge$") of all the possible directional closings. It can be computed using 21 pixels long linear structuring elements successively oriented in every possible direction (the infimum of different closing operators still remains a morphological closing). In a discrete 8-connectivity square grid of size 2n+1, 4n symmetrical segments with different directions d_i are usually defined. We therefore used 40 different 21 pixels long linear structuring elements, defining 40 different directional closings. We obtain the image I_2 defined by :

$$I_2 = \wedge_{di} \{ \varphi_{di} (I_1) \} \text{ , with } i \in \{1,...,40\}$$

- Since we firstly used an opening by reconstruction with an 8-connectivity grid, some "isolated" peaks remain that could lead to false detection in the next step. As a consequence, to prepare properly the following extraction operation, we now remove these remaining peaks with a simple opening using a flat square structuring element of size 5 (without any reconstruction). Behind this operation appears a new constraint : we assume that 2 different roads will be separated by at least 5 pixels, which is a realistic assumption (5 pixels approximately correspond to 60 meters on the ground). We then obtain the image I_3 :

$$I_3 = \gamma_5 (I_2)$$

- We finally remove the remaining linear valleys, that are actually at least 21 pixels long, but that are **too wide** (more than 3 pixels), and extract the desired structures. The residue between the current image and its closing by a flat square structuring element of size 3 is calculated (Top-hat operator). The only remaining structures are the dark features that are up to 3 pixels wide. Any other pixel, belonging either to a plateau or to a valley that is more than 3 pixels wide, is put to zero. We obtain the image I_4 defined as follows :

$$I_4 = \varphi_3 (I_3) - I_3$$

The final decision is taken by thresholding I_4 at zero. We consider it as important not to use any other threshold value since this would introduce a parameter to be set. Furthermore, if I_4 was thresholded at a value p>0, only the roads that are originally at least p+1 gray level darker than their surroundings would be extracted. We do not want to make this kind of assumption on the model ; in particular, we do not want to determine *how* dark the roads have to be, or, equivalently, how deep the valleys have to be, because this widely differs from an image to another, or even in one single image.

Next section presents the results of the adaptive non linear filtering and the morphological road detector on real data.

4. RESULTS & CONCLUSIONS

The method has been tested on ERS-1 PRI data (PRecision Image, with a 12,5 m resolution).
Figure 3-a- shows part of the original image. It represents a flat, agricultural region near Amsterdam.
Figure 3-b- shows the same image after the adaptive directional order filter : there is a strong noise reduction. A lot of structures are drastically smoothed (see the fields), but the linear features are perfectly preserved, and even enhanced. This allows better results for the detection.
Figure 3-c- presents the final detection superposed on the original image (note that an area opening, that removes the connected components that have less than 30 pixels, has been applied to «clean up» the result).
Figure 2 shows the topographic representation of the region defined by the 20*20 white square on the original image :
- originally (-a-) : a skilled human observer can notice that a road is crossing this image from the top left corner to the bottom right one.
- after the smoothing/enhancing filter (-b-) : the noise has been greatly reduced, the road has been preserved, and even enhanced.
- and after the top-hat operator (-c-) : the final decision is taken by thresholding this image at zero.

The results obtained are very promising : all major roads, and even some roads of the secondary network, have been correctly detected. Of course the detection is not perfect : some roads are not, or only partially, detected ; there are also some spurious detections (false alarms caused by different structures that fit the road geometrical model, such as elongated narrow dark fields). These results are nevertheless qualitatively and quantitatively comparable with those found in the literature. But we must emphasize that the extraction method we proposed is independant of the average radiometries (as the edge detector proposed in [Touzi-88] and the road detector proposed by [Tupin-97]), but it is also independant of the intensity contrast : roads just have to be darker : even one single gray level difference is enough for the detection.

5. FUTURE PROSPECTS

Usually, in order to fully reconstruct the road network, the detection step is followed by a grouping step that reconnects the detected segments . For this post-processing stage, that is not adressed by our approach, global methods, based for instance on a markovian approach [Tupin-97], could greatly improve the quality of the final result. In this case high level information and prior knowledge on the data statistics are used.
Another way to improve the results is to use multi-temporal data (the images are acquired at different dates), if they are available. The detection is performed on each image separately and the results are aggregated afterwards. Such a data fusion can take into account the information redundancy (the roads do not appear, disappear or move during the observation period) and the non-redundancy of the noise (the speckle is assumed to be decorrelated from an image to an other). The detection can thus be greatly improved, and the false alarm rate can be reduced at the same time.

Finally, let us remind that the proposed extraction method is completely generic : it has been used for a wide range of applications, such as the detection of the river network, or of the crest lines of mountainous areas in SAR images. It has also been used with other sensors, for instance for the detection of geological faults in SPOT data. In every case, the sought features fit the same model : linear structures that have a contrast with their neighbourhood.

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Figure 2 : topographic representations

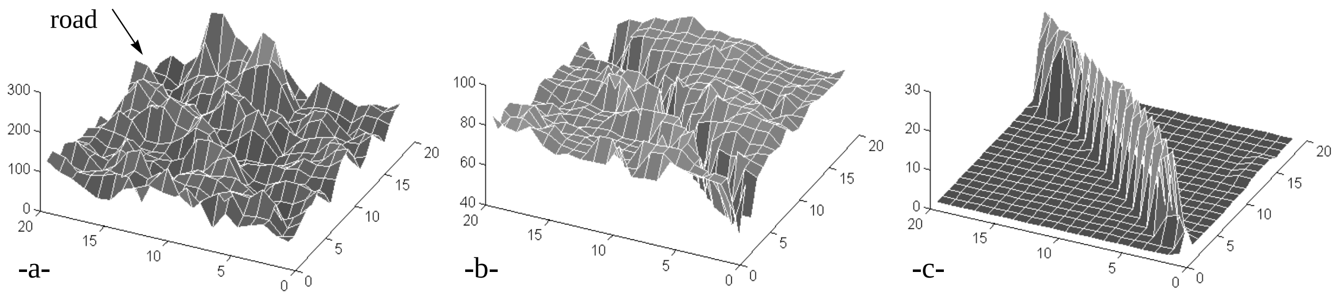

Figure 3 : original ERS-1 PRI Image (-a-), filtered image (-b) and detected roads (-c-)