FROM ROAD EXTRACTION TO MAN-MADE OBJECT DISCRIMINATION IN HIGH RESOLUTION SAR DATA

Amberg Virginie[(1) (2)], *Marc Spigai*[(1)], *Martial Coulon*[(2)], *Philippe Marthon*[(2)]

(1)Alcatel Space, av. JF. Champollion, BP 1187, 31037 Toulouse Cedex 1 France
(2)ENSEEIHT/IRIT/TéSA, 2 rue Camichel 31000 Toulouse France, Email : virginie.amberg@tesa.prd.fr

ABSTRACT

This article handles with the problem of man-made structure extraction in high resolution Synthetic Aperture Radar (SAR) data. The ability of new sensors to provide fine resolution imagery of the Earth surface leads to new remote sensing applications. As a matter of fact, the extraction and recognition of smaller and smaller structures in crowded environment is now possible: in dense urban areas the detection of structures from building to car is expected. In this article, a chain of structure extraction in urban areas is proposed: the problem is split into different levels, detecting at each level smaller and smaller structures. In this framework, SAR data classification, road extraction and man-made target discrimination are considered and three algorithms inspired from the image processing community are proposed.

1. INTRODUCTION

The ability of new sensors to provide fine resolution data of the Earth surface leads to new remote sensing applications. As a matter of fact, the extraction and recognition of smaller and smaller structures in crowded environment is now possible: in dense urban areas, a new challenge lies in detecting and recognizing structures from building to car.
In this article, we focus on data from a sub metric resolution Synthetic Aperture Radar (SAR) of urban areas. Because SAR systems functioning are independent of weather and daylight conditions, the use of such data for civilian and military applications has received increasing attention during the last years. Despite these advantages of SAR, the problem of man-made structure extraction and object recognition must deal with some specific difficulties. As a matter of fact, in coherent imagery, the main difficulty lies in the speckled environment in which the different structures of the urban scene are hidden. Furthermore, new problems of non-stationarity appear when the resolution increases. More precisely, whereas coarser resolution systems assume that both the scene and the targets are usually isotropic, this assumption is mistaken with high resolution SAR. The spectral signature of targets and their environment are quite dependent of the sensor characteristics (wavelength, incidence angle, integration time…). Thus a sole method for scene interpretation can not be developed: efficient algorithms to tackle this specific problem are dependent on the structure/object to be recognized and on the sensor that generates the data (wavelength, incidence, integration time…).

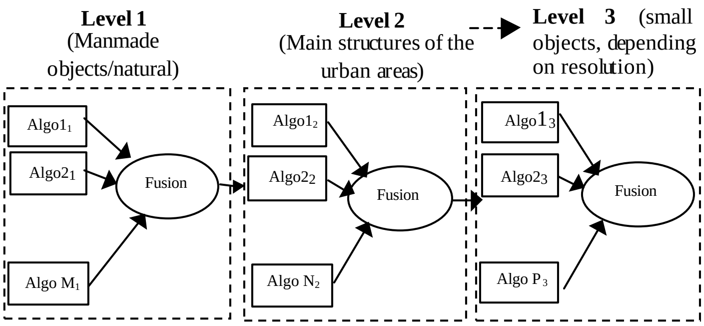


Fig.1 : A hierarchical approach for structure extraction in urban situations.

The purpose of our work is the classification of single look sub-metric SAR data of urban areas and more precisely the characterization and recognition of urban structures like roads and smaller objects like cars or road signs.
This article will be structured in four parts. Firstly, a hierarchical chain for structure extraction and interpretation of sub-metric SAR urban areas is presented. In this framework, in the second, third and fourth parts, we focus on three particular algorithms:

- A scene statistical classification algorithm,
- A road extraction method based on Hough transform and dynamic programming,
- An urban target discrimination algorithm by image-based processing.

2. PRESENTATION OF A SCENE INTERPRETATION CHAIN

This part presents a hierarchical chain for urban scene interpretation and structure extraction. The difficulty of SAR urban data interpretation is increased by the complexity and the disturbed aspect of urban scenes at such resolution: many objects and structures that interfere are now visible. Thus, it is better, before searching for a specific structure/object, to reduce successively the research space for this structure/object in order to reduce the false alarm risk and to improve the detection rate. Therefore the proposed chain, already introduced in previous works [1][2], approaches the problem at three levels detecting at each level smaller and smaller structures (see Fig. 1). A first level of the chain will consist in separating the scene in very thematic classes depending on the next objectives. For instance, we will begin by separating man-made areas from big natural ones (e.g. public gardens or rivers) on the basis of statistical properties. At a second level, the man-made areas extracted at the first level are considered and the main structures of the town (e.g. buildings, roads) are identified. Finally at a third level, the extraction and identification of objects such as non-moving cars on roads is expected.

At each level, it is better to apply different sets of complementary algorithms, each algorithm choice depending on the result of the previous level. A fusion of all algorithms is then done so as to improve results of each single algorithm.

3. STATISTICAL CLASSIFICATION

In this first part, we focus on the first level of the previous interpretation chain. As explained before, the objective of this first step is to classify the scene in thematic classes on the basis of radiometric properties.

It is important here to remain that in SAR image processing, the multiplicative noise (speckle) of this kind of data is generally considered as a random variable entirely described by statistical models [3], which features depend on the underlying scene. Thus, in the images, areas of buildings, vegetation or roads (for instance) appear generally with different probability density function. That is why classification processes of SAR data are generally based on statistics. Few researchers have already addressed the problem of statistical classification of high resolution SAR data [4], and further algorithms have been already proposed.

The objective of this section is to introduce the supervised classification method developed in the framework of the of in three steps:

- A pre processing step,
- A learning step of class distribution,
- A classification step.

The following sub-sections describe more precisely each step of the method. The first sub section is devoted to introduce the pre processing step. The second sub-section presents an accurate statistical model used to describe the particular behaviour of high resolution data. Finally the classification algorithm is briefly presented.

3.1 Pre processing

It is well known that speckle has very bad effect on classification algorithm performance of single look amplitude SAR data. Whereas some authors proposed to tackle this problem by a Markovian method [4], another solution less time computing consuming can consist in pre processing the data before classification in order to reduce the signal to noise ratio. Thus the first step of the classification consists in filtering the data with an appropriated filter. Adaptive filters as Lee or Frost ones [5] have even shown their efficiency on coarser resolution SAR data.

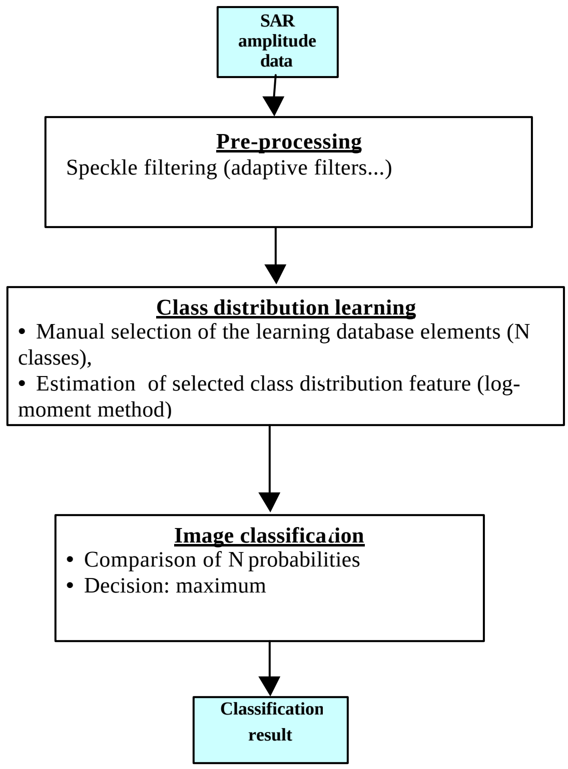


Fig. 2: Level 1; ML classification of filtered data.

3.1 Amplitude SAR data distribution

To perform a statistical classification of the data, an accurate statistical model is needed. Standard statistical models (K, Nakagami Rice or Weibull) seem to be no longer sufficient to fit the high diversity of high resolution data distributions (from heavy tail behaviour of man-made areas to non-heavy-tail behaviour of natural areas). In [4], the authors show the accuracy of Fisher distributions to well described high resolution SAR amplitude behaviour. The advantage of these distributions is their ability to fit a high diversity of urban areas surface distribution.
The estimation method of Fisher distributions is the algorithm based on second kind detailed in [4].

3.2 Classification algorithm

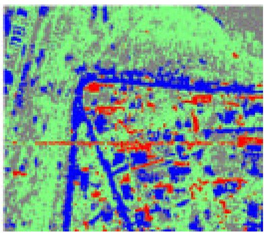
Thus, the classification algorithm of filtering data is as follows:

- Manual selection of relevant classes and learning of each class distribution on a training database.
- Maximum likelihood classification performed on pre-processed data.

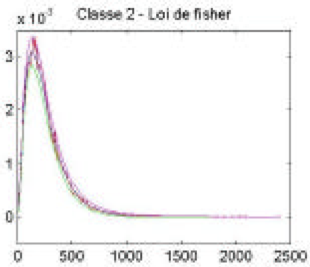
3.3 Experimental results

The previous algorithm was tested on real high resolution airborne SAR data over urban areas (copyright DGA/ONERA). These ones are X-band single look complex data. The resolution is sub-metric and selected areas are residential. The classification performance are evaluated on the basis of confusion matrix on a test database. This database also is manually selected.
Four classes have been selected: ground/shadow, soil/dark vegetation, bright vegetation, brigth man-made structure. For each class, the accuracy of the Fisher model can be verified. On fig. 3 (c) is represented in red the empirical distribution of a class and in blue the estimated fisher ones: this last one fits well the first one. The classification results are shown on figure 3 (b).

(a)



(b)



(c)

	bright vegetation	soil/dark vegetation	ground/ shadow	bright man-made structure
bright vegetation	90.19	2.4713	0	9.17
soil/dark vegetation	5.7949	93.03	11.99	0.18
ground/ shadow	0	4.49	88	0
bright man-made structure	4.0087	0	0	90.6456

(d)

Fig. 3: ML algorithm on filtered data result. (a) Amplitude data. (b) Classification result image: blue, ground/shadow class; grey, soil/dark vegetation; green, bright vegetation; red, bright man-made structure. (c) Fisher estimation of a class distribution. (d) Confusion matrix.

We can note that diagonal values are quite satisfactory for the four classes. There are some misclassification between bright vegetation and man-made structure, and between soil and road.

In conclusion, first results of the method are satisfying. It could be interesting to see if some misclassification can be avoided by introducing other information in the classification process, for instance texture or shape information. This work is in progress.

4. ROAD EXTRACTION ALGORITHM BASED ON HOUGH TRANSFORM AND DYNAMIC PROGRAMMING

Once the thematic classification done, more particular man-made structures can be considered. In this part, we focus on a road extraction problem. This process takes place in the second level of the previous chain.

Considering the result of the classification step, the proposed method works on supposed road pixels. It acts in two steps: a first step consists in extracting slightly curved streets of the scene by dynamic tracking, whereas a second step deals with the special case of strong bends. The following sections describe briefly each step of the method. (for more details on the method, referred to [2].)

4.1 Road extraction by dynamic programming

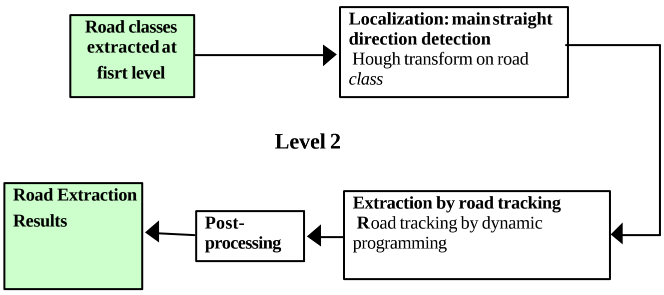


Fig. 4. The road extraction procedure

The objective here is to detect and localize slightly curved roads. The proposed method is a three-step procedure:

- First of all, the main roads of the scene are localised by detection of the main straight direction of the data. The process used is a Hough transform on the edge of the road class identifying at the pre-processing step.
- Once the main roads localised, the road network must extracted. Given the disturbing character of the scene and the difficulty to accurately visualize the road edge position, we have chosen to use a dynamic algorithm to perform this operation. Such algorithms have yet been employed for road tracking in the case of optical high resolution data and low resolution SAR data [6][7] and we have yet proposed its use in the framework of high resolution SAR data in [2].
- The last step consists in post-processing the road dynamic tracking results so as to obtain a continue layout of the road network. Thus the tracking result is smoothing by local linear approximation and little gaps in a same direction

are filled up by means of distance criterion (These gaps are generally due to building layover that involve break during the road tracking process).

4.2 Strong bends detection

The main limitation of the previous chain for road extraction by dynamic programming is that strong curved streets remain difficult to extract: the algorithm is efficient only on slightly curved roads. The case of strong bends, often present in European towns, must be treated separately.

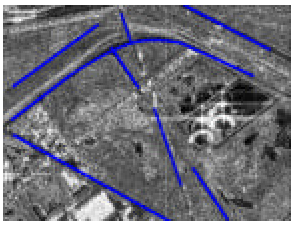
The objective of this second step of the process is to detect strong bends of the urban scene. The main idea of the method is to assume that a strong bend starts and ends usually by a straight road. Thus bend can be approximated by a hyperbola [2] and the problem of strong bend detection is amount to find the best hyperbola that could connect two linear roads. This process is still done thanks to a Hough transform. Given the non-linearity of the problem, the implemented algorithm works in two steps as shown in [2]:

i) hyperbola centre estimation;
ii) shape parameter computation.

4.3 Experimental results

The road extraction algorithm was tested on the same data than section 3. Two different areas are selected: a residential area and an industrial area. These two areas present slightly curved roads and strong bends. Some layover effects are well observed and the residential areas are quite dense. Roads extraction results are presented on Fig. 5.

(a)



(b)

Fig. 5: Road tracking results. (a) Residential areas (b) industrial areas

On these results we can see that the main roads are detected by the dynamic programming method even if some little streets are missed. A more relevant results validation is done by means of the three following indexes [8]:

- completeness,
- correctness,
- quality.

Results are summarised in the following table:

	completeness	correctness	quality
Image (a)	94%	98%	93%
Image (b)	84%	97%	82%

5. URBAN OBJECT DISCRIMINATION

This section deals with the last step of the interpretation chain. We propose in this section to detect and characterize small man-made objects of the town like non-moving cars, road signs, trees and bushes. For instance, roads previously extracted are considered and parked cars are searched and characterized.

In this section, a pattern recognition method [9] is considered to tackle this difficult problem. This approach is briefly summarized in the first following sub-section before showing first results of the method for urban object discrimination.

5.1 The pattern recognition approach

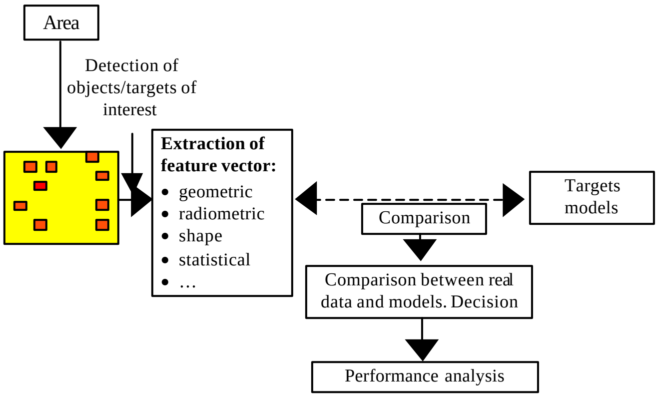


Fig. 6: Pattern recognition algorithm

As shown on fig. 6, a pattern recognition algorithm consists in comparing detected objects of the image with predefined object models. Each pattern of interest is described by a relevant feature vector. For instance, these features could describe statistical, geometric, textural, radiometric or shape properties of the patterns; and the comparison algorithm is a classification algorithm (maximum likelihood criterion or other).

The main difficulty of the problem remains in choosing the more relevant feature vector that will ensure the best classification result. In the following, some accurate features are proposed in the framework of man-made object characterization in high resolution SAR context.

5.2 Applications to man-made object characterisation

As already seen in previous work [1], objects in remote sensing data can be classified into two different kinds according to their electromagnetic behaviour:

- man-made targets,
- natural clutter.

Thus the proposed method acts in two main steps. Firstly, we start by discriminating natural objects from man-made ones on the basis of physical properties. In fact, while man-made objects are composed of some spatially well organized bright scatterers that tend to significantly change their appearance with the sensor, natural ones show a high non-organisation of their bright scatterers. Two features can differentiate these two different behaviours: the fractal dimension of the brightest potential target scatterers, and the percentage of energy in the same scatterers[1].
In a second time, we work on man-made objects and propose to use geometric features (length and width) and shape features (edge descriptors) to characterize each kind of man-made objects.

5.3 Experimental results

In this last section, the proposed method was tested on the MSTAR database in order to show the accuracy of each feature vector.

As mentioned in the previous sub-sections, the urban object discrimination process starts by discriminating natural clutter from man-made targets on their electromagnetic behaviour. The first following section will show the results of this step. The performance of the discrimination algorithm is done by means of confusion matrix.
The second section is devoted to man-made targets characterisation.

5.3.1 Man-made targets vs natural targets

A set of 50 natural and man-made targets is extracted from the MSTAR data. For each target the fractal dimension and the percentage of energy in the brightest scatterers are computing and the feature space "fractal dimension/bright scatterer energy" is drawn. Results are shown on Fig. 7.

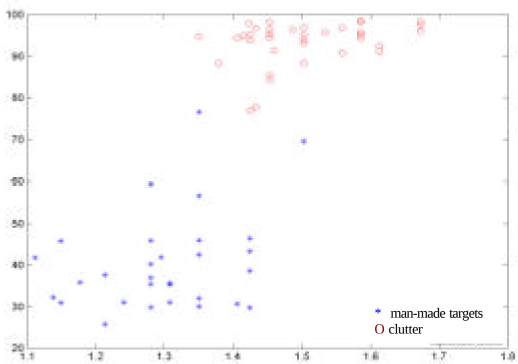


Fig 7: Fractal dimension versus energy in bright scatterers of natural clutters (circle marker) and man-made targets (asterisk marker).

On the previous results, we observe that classes are quite well separated, ensuring that the result of a classification on these features could be good.

A classification is then done by a maximum likelihood classifier. The performance classification was evaluated by means of confusion matrix. Results are quite satisfactory.

	Natural clutter	Man-made targets
Natural clutter	100%	0%
Man-made targets	7%	93%

5.3.2 Man-made targets characterization: accuracy of shape features

In this section, we work on the man-made targets extracted in the last section. The final objective of such characterization is the identification of each kind of man-made targets (for instance: cars, trucks, bus, road signs ….). The topic of this section is to prove the accuracy of shape features and image processing methods to ensure a good identification of man-made targets.

The proposed method was also tested on the MSTAR data. Three kinds of tanks, viewed from different incidence angle, were selected and the geometric features (width and length) were computed (estimation done by means of the main ellipse of targets). Results are shown on Fig. 8.

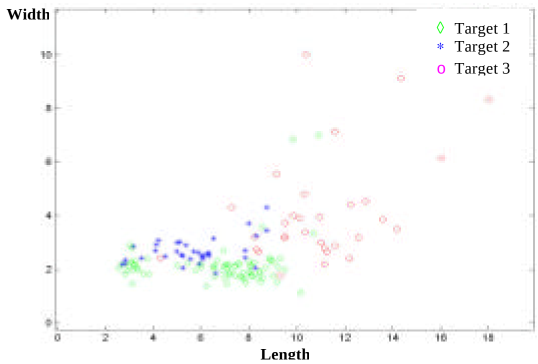


Fig. 8: Dimension features (Length vs width)

At the first sight, shape features of a same target family are very spread out. More precisely on fig 8, we can see that the feature variances for a same target is very high. This result would have been predictable given the aspect dependent behaviour of targets between the sensor. Thus it seems difficult to accurately estimated target dimension from SAR data from a single look data of the target. Furthermore to ensure a good classification on feature shape, it seems indispensable to take into account the view condition (incidence angle, wavelength,…) in the classification process.
On the other, from a second sight, it is interesting to notice that some main point groups are quite visible on each feature space. Furthermore, each group of points are generally composed of target of the same kind (see fig 8, how green or blue points are gathered together).

First studies have been started on another kind of shape features: Fourier descriptors of target edges (the twenty first coefficients: c_1, …c_{20}). At the time of this article, these features have been computed on optical data only. The main difficulty to apply such features in a SAR context is that no efficient automatic edge detector exists for the moment in the framework of small targets. Results on optical data are shown on fig. 9.

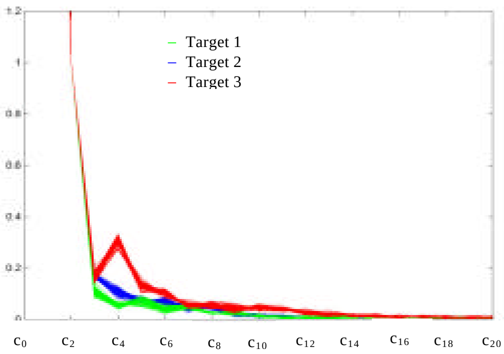


Fig. 9: Edge descriptors features on optical data.

On this figure we can see that edge descriptor features seem to bring interesting information that could be of great help in an automatic target recognition process. In fact, some Fourier coefficients seem to allow a good separation of each kind of target independently of the view conditions (especially coefficient number 4 to 6). These results on optical data are very promising and merit to be more investigated on SAR data.

As a conclusion of this part, the information brought by shape features is very promising for the future ATR (automatic target recognition) process. However, this features need now to be tested on a more relevant and greater target data base. In fact, for the moment we do not have enough target data so as to perform a complete classification process and well evaluate the contribution of shape features for target identification in SAR data.

10. CONCLUSION

This paper has introduced a chain for structure extraction in high resolution SAR data of dense urban areas. This chain proposes to handle the problem at different levels, detecting at each level smaller and smaller objects. We focused on the three main steps of this chain and three different algorithms have been presented: a thematic classification method of HR SAR data by statistical approach, a road extraction algorithm by dynamic programming and Hough transform, and discrimination of man-made objects by using image processing-based algorithms. All the algorithms studied present interesting results. Next step will consist of validating all these algorithms on a greater data base.

11. REFERENCES

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