A PROBABILISTIC FUSION STRATEGY APPLIED TO ROAD EXTRACTION FROM MULTI-ASPECT SAR DATA

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ABSTRACT:

In this paper, we describe an extension of an automatic road extraction procedure developed for single SAR images towards multi-aspect SAR images. Extracted information from multi-aspect SAR images is not only redundant and complementary, in some cases even contradictory. Hence, multi-aspect SAR images require a careful selection within the fusion step. In this work, a fusion step based on probability theory is proposed. Before fusion, the uncertainty of each extracted line segment is assessed by means of Bayesian probability theory. The assessment is performed on attribute-level and is based on predefined probability density functions learned from training data. The prior probability varies with global context. In the first part the fusion concept is introduced in a theoretical way. The importance of local context information and the benefit of incorporating sensor geometry are discussed. The second part concentrates on the analysis of the uncertainty assessment of the line segments. Finally, some intermediate results regarding the uncertainty assessment of the line segments using real SAR images are presented.

1. INTRODUCTION

Synthetic aperture radar (SAR) holds some advantages against optical image acquisition. SAR is an active system, which can operate during day and night. It is also nearly weather-independent and, moreover, during bad weather conditions, SAR is the only operational system available today. Road extraction from SAR images therefore offers a suitable complement or alternative to road extraction from optical images [Bacher & Mayer, 2005]. The recent development of new high resolution SAR systems offers new potential for automatic road extraction. Satellite SAR images up to 1 m resolution will soon be available by the launch of the German satellite TerraSAR-X [Roth, 2003]. Airborne images already provide resolution up to 1 decimetre [Ender & Brenner, 2003]. However, the improved resolution does not automatically make automatic road extraction easier, yet it faces new challenges. Especially in urban areas, the complexity arises through dominant scattering caused by building structures, traffic signs and metallic objects in cities. These bright features hinder important road information. In order to fully exploit the information of the SAR scene, bright features and their contextual relationships can be incorporated into the road extraction procedure. Detected vehicles and rows of building layover as well as metallic scattering caused by road signs are indicators of roads [Wessel & Hinz, 2004], [Amberg, et al. 2005].

The inevitable consequences of the side-looking geometry of SAR, occlusions caused by shadow- and layover effects, is present in forestry areas as well as in built-up areas. In urban areas, the best results for the visibility of roads are obtained, when the illumination direction coincide with the main road orientations [Stilla et al., 2004]. Preliminary work has shown that the usage of SAR images illuminated from different directions (i.e. multi-aspect images) improves the road extraction results. This has been tested both for real and simulated SAR scenes [Tupin et al. 2002], [Dell'Acqua et al., 2003]. Multi-aspect SAR images contain different information, which is both redundant and complementary. A correct fusion step has the ability to combine information from different sensors, which in the end is more accurate and better than the information acquired from one sensor alone.

In this article we present a fusion concept based on a Bayesian statistical approach, which incorporates both global context and sensor geometry. A short overview of the road extraction procedure will be given in Sect. 2. The main focus of this paper is the proposed fusion module, which is explained in Sect. 3. Some intermediate results of an uncertainty assessment of line segments based on a training step and global context are discussed in Sect 4.

2. ROAD EXTRACTION SYSTEM

The extraction of roads from SAR images is based on an already existing road extraction approach [Wessel & Wiedemann, 2003], which was originally designed for optical images with a ground pixel size of about 2m [Wiedemann & Hinz, 1999]. The first step consists of line extraction using Steger's differential geometry approach [Steger, 1998], which is followed by a smoothening and splitting step. By applying explicit knowledge about roads, the line segments are evaluated according to their attributes such as width, length, curvature, etc. The evaluation is performed within the fuzzy theory. A

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weighted graph of the evaluated road segments is constructed. For the extraction of the roads from the graph, supplementary road segments are introduced and seed points are defined. Best-valued road segments serve as seed points, which are connected by an optimal path search through the graph. The approach is illustrated in Fig. 1.

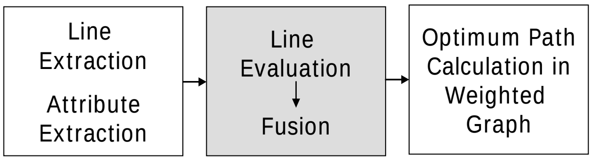

Figure 1. Automatic road extraction process

The novelty presented in this paper refers on one hand to the adoption of the fusion module to multi-aspect SAR images and on the other hand to a probabilistic formulation of the fusion problem instead of using fuzzy-functions (marked in gray in Fig. 1).

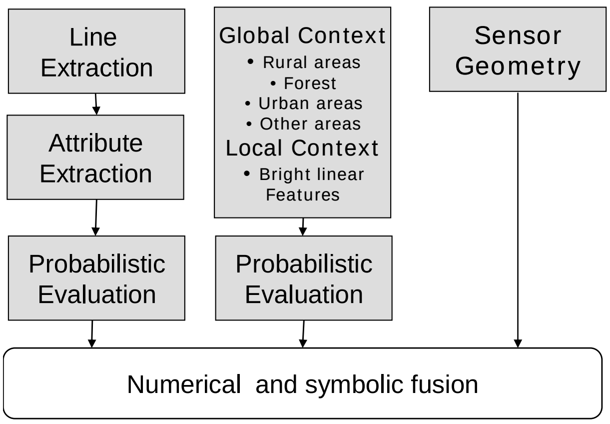

Figure 2. Fusion module and its input data

3. PROBABILISTIC FUSION CONCEPT

Line extraction from SAR images often delivers partly fragmented and erroneous results. Especially in forestry and in urban areas over-segmentation occurs frequently. Attributes describing geometrical and radiometric properties of the line segments can be helpful in the selection and especially for sorting out the most probable false alarms. However, these attributes may be ambiguous and are not considered to be reliable enough when used alone. Furthermore occlusions due to surrounding objects may cause gaps, which are hard to compensate. One step to a solution is the use of multi-aspect SAR images. If line extraction fails to detect a road in one SAR view, it might succeed in another view illuminated from a more favourable direction. Therefore multi-aspect images supply the interpreter with both complementary and redundant information. But due to the over-segmented line extraction, the information is often contradicting as well. To be able to solve possible conflicts, the uncertainty of the incoming information must be considered.

Many methods, both numerical and symbolic, can be applied for the fusion process. Some frameworks worth to mention, are evidence theory, fuzzy-set theory, and the probability theory. The last one is, regarding its theoretical foundations, the best understood framework to deal with uncertainties. In this chapter we will discuss a fusion process accommodating for these aspects.

3.1 Features, Attributes and Evaluation

Man-made objects in general tend to have regular geometrical shapes with distinct boundaries. The main feature involved in the road extraction process is the line segment, which can either belong to the class ROADS or to the class FALSE_ALARMS. The selection of attributes of the line segments is based on the knowledge about roads. Roads in SAR images appear as dark lines since the smooth surface of a road acts like a mirror. Therefore radiometric attributes such as *mean* and *constant intensity,* and *contrast* of a line as well as geometrical attributes like *length* and *straightness* should be representative attributes for roads.

Other features of interest are linked to global and local context. Bright linear features (BRIGHT_LINES) represent the local context in this work. The global region features applied in this work are URBAN, FOREST, FIELDS and OTHER_AREAS. These regions are of interest, since road attributes may have varying importance depending on the global context region. For example, length becomes more significant for roads in rural areas, but may be of less importance in urban areas.

By means of an attribute vector $\boldsymbol{x}$, the probability that a line segment belongs to the class ω_i (i.e. ROADS or FALSE_ALARMS) is estimated by the well-known Bayesian formula,

$$p(\omega_i|\mathbf{x}) = \frac{p(\mathbf{x}|\omega_i)\; p(\omega_i)}{\sum_{j=1}^{M} p(\mathbf{x}|\omega_j)\; p(\omega_j)}. \qquad (1)$$

If there is no correlation between the attributes, the likelihood $p(\mathbf{x}|\omega_i)$ can be assumed equal to the product of the separate likelihoods for each attribute

$$\begin{aligned} p(\mathbf{x}|\omega_i) &= p(x_1, x_2,..x_n|w_i) \\ &= p(x_1|w_i)\; p(x_2|w_i)\; \ldots\; p(x_n|w_i) \end{aligned}. \qquad (2)$$

It is important to show that this simplification is valid for the data used. Furthermore, it should be noted that this is not a definite classification; instead each line segment obtains an assessment, which is necessary for the subsequent fusion of multi-aspect SAR images.

3.2 Definition and Validation of Probability Density Functions

Each separate likelihood $p(x_j|\omega_i)$ is approximated by a probability density function learned from training data. Learning from training data means that the extracted line segments are sorted manually into two groups, ROADS and FALSE_ALARMS. The global context (URBAN, FOREST, FIELDS and OTHER_AREAS) is specified for each line segment as well. A global context term will be helpful by the latter estimation of the prior term $p(\omega_i)$. The training data used is X-band, multi-looked, ground range SAR data with a resolution of about 0.75 m. The small test area is located near the airport of DLR in Oberpfaffenhofen, southern Germany.

The independence condition has been empirically proved by a correlation test using the training data. Only two attributes, *mean intensity* and *constant intensity,* showed any correlation, which in fact can be expected due to the speckle characteristics of SAR data. As a conclusion, the factorized likelihoods can not be applied for these two attributes. The rest of the attributes did not indicate any dependence. Figure 3 exemplifies this for the two attributes length and intensity.

A careful visual inspection indicated that the histograms might follow a lognormal distribution, i.e.

$$p(\omega_i|x) = \frac{1}{S\sqrt{2\pi}\ x} e^{-\frac{(\ln x - M)^2}{2S^2}} \quad . \qquad (3)$$

A reasonable way to test the match of histograms and parameterized distributions is to apply the Lilliefors test [Conover, 1999]. This test evaluates the hypothesis that x has a normal distribution with unspecified mean and variance against the alternative hypothesis that x does not have a normal distribution. However, the Lilliefors test tends to deliver negative results, when applied to histograms of manually selected training data, since the number of samples is naturally limited. To accommodate for this fact, the probability density functions have been fitted to the histograms by a least square adjustment of S and M since it allows to introducing a-priori variances. Figs. 4 and 5 show the histogram of the attribute *length* and its fitted lognormal distributed curve. A fitting carried out in a histogram with one dimension is relatively uncomplicated, but as soon as the dimensions increase, the task of fitting becomes more complicated. Since mean intensity and constant intensity tend to be correlated, fitting of a bivariate lognormal distribution shall be carried out. This is under development and until than, only the one-dimensional fitting of *mean intensity* is applied.

Please note that the estimated probability density functions should represent a degree of belief rather than a frequency of the behaviour of the training data. The obtained probability assessment shall correspond to our knowledge about roads. At a first glance, the histograms in Figs. 4 and 5 seem to overlap. However, Fig. 6 exemplifies for the attribute *length* that the discriminant function

$$g(x) = \ln\big(p(x|ROADS)\big) - \ln\big(p(x|FALSE\_ALARMS)\big) \quad (4)$$

increases as the length of the line segment increases. The behaviour of the discriminant function corresponds to the belief of a human interpreter. The behaviour of the discriminant function was tested for all attributes. All are illustrated in Fig 6a-d.

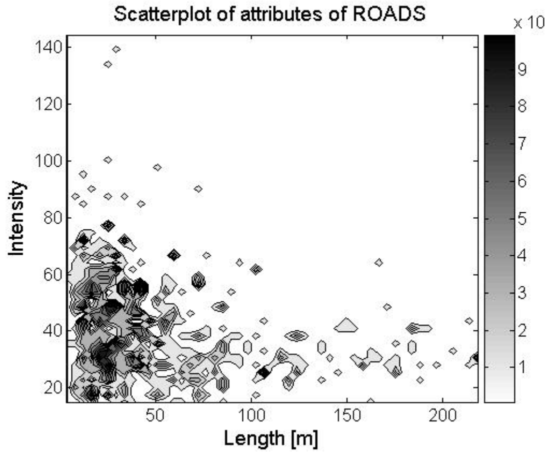

Figure 3. Scatter plot of attributes intensity and length

It should be kept in mind that statistical attributes addressing deviation and mean are not reliable for short line segments of only a few pixels length. Since these line segments are considered unreliable with respect to their short length, they can simply be sorted out. It should also be pointed out that more attributes does not necessarily mean better results, instead rather the opposite occur. A selection including a few, but significant attributes is recommended.

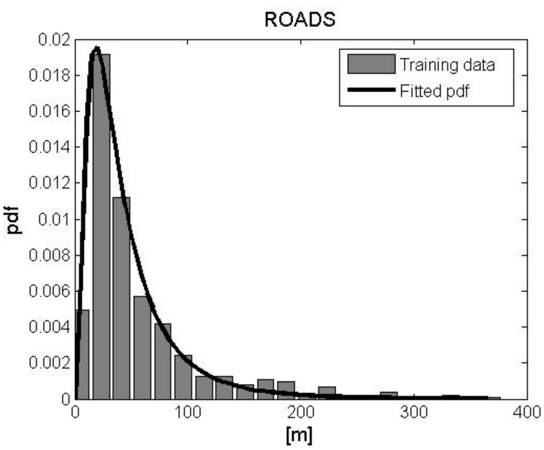

Figure 4. A lognormal distribution is fitted to a histogram of the attribute length (ROADS).

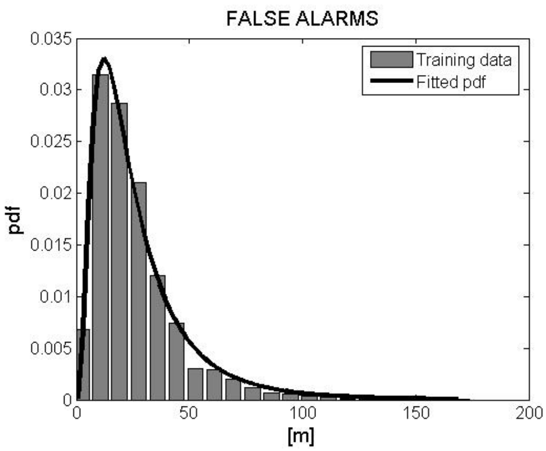

Figure 5. A lognormal distribution is fitted to a histogram of the attribute length (FALSE_ALARMS).

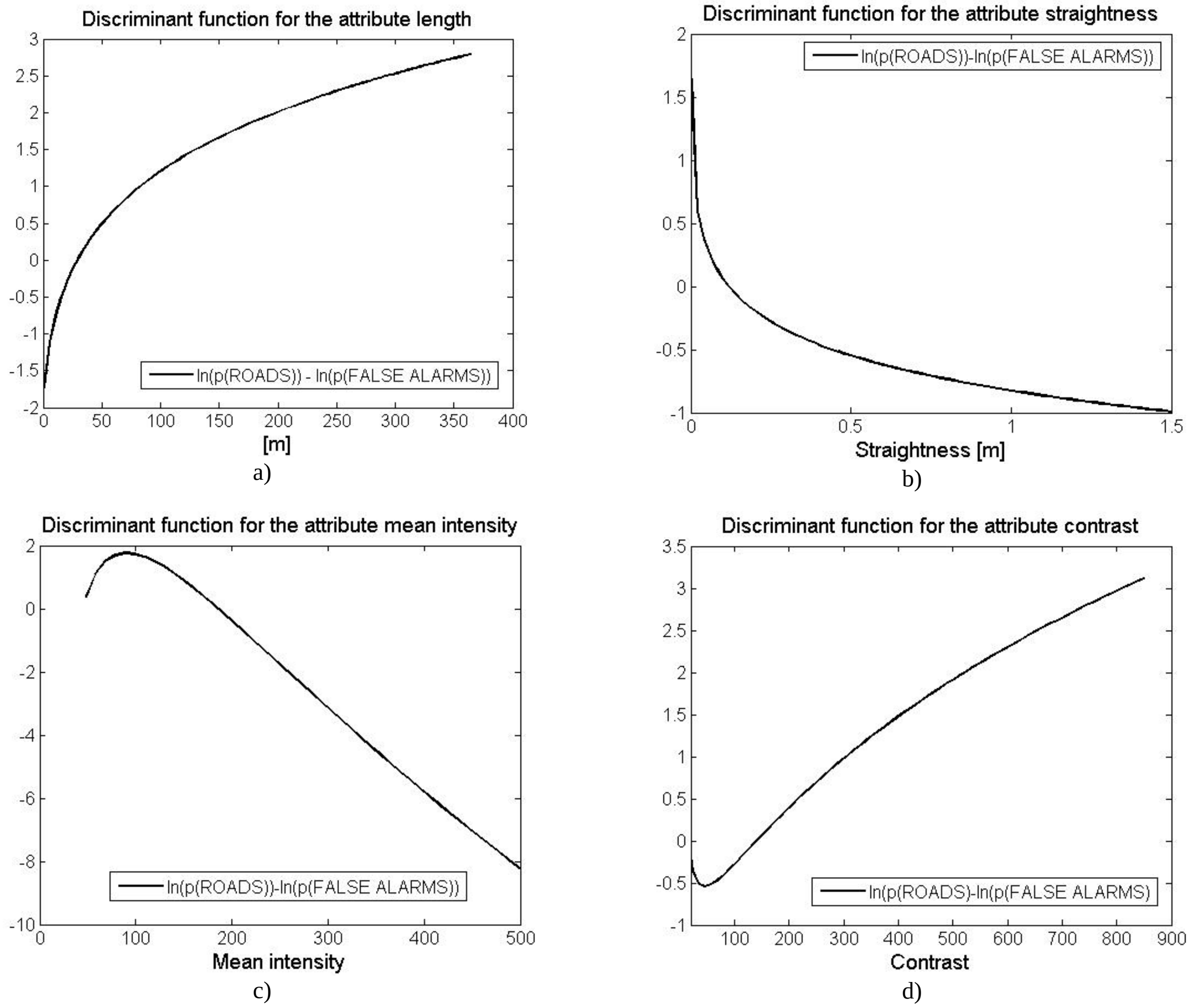

Figure 6 a-d. Discriminant function for the attributes a) Length, b) Straightness, c) Inner intensity and d) Contrast.

3.3 Global and Local Context

Since even a very sophisticated feature extractor delivers generally results with ambiguous semantics, additional information of global and local context is helpful to support or reject certain hypotheses during fusion. Assume, for instance that two SAR images with perpendicular view direction contain a road flanked by high buildings. The road is oriented across-track in one scene and along-track in the other scene. While in the first image, the true road surface is visible, in the second image, merely the elongated shadow of the fore-buildings and the bright, elongated layover area of the buildings across the road are detectable. The parallel appearance of bi-polar linear features (dark/light) would stand for local context, while the whole urban area would represent the global context region. Hence, a correct fusion of both views must involve a reasoning step, which is based on the sensor geometry and its influence on the relations between the extracted features. Relations between features, which appear due to local context, usually need to be detected during the extraction process. Consequently also the features involved in local context relations should be attached with confidence values.

Global context regions are derived from maps or GIS before road extraction, or can be segmented automatically by a texture analysis. As a start, global context (URBAN, FOREST, FIELDS and OTHER_AREAS) is extracted manually (see Fig. 7b). Global context plays an important role for the reasoning step within the fusion module as well as for the definition of the priori term. The frequency of roads is proportionately low in some context areas, for instance in forestry regions. The a-priori probability must be different in these areas. In this work the user specifies the priors (see Tab. 1). Therefore the priors represent the belief of the user to a certain degree. In future work, these values will be compared with values learned from training data.

Global context	*p(*ROADS*)*	*p(*FALSE_ALARMS*)*
FIELDS	0.4	0.6
URBAN AREAS	0.5	0.5
FOREST	0.1	0.9
OTHER AREAS	0.3	0.7

Table 1. Prior terms for different global context areas

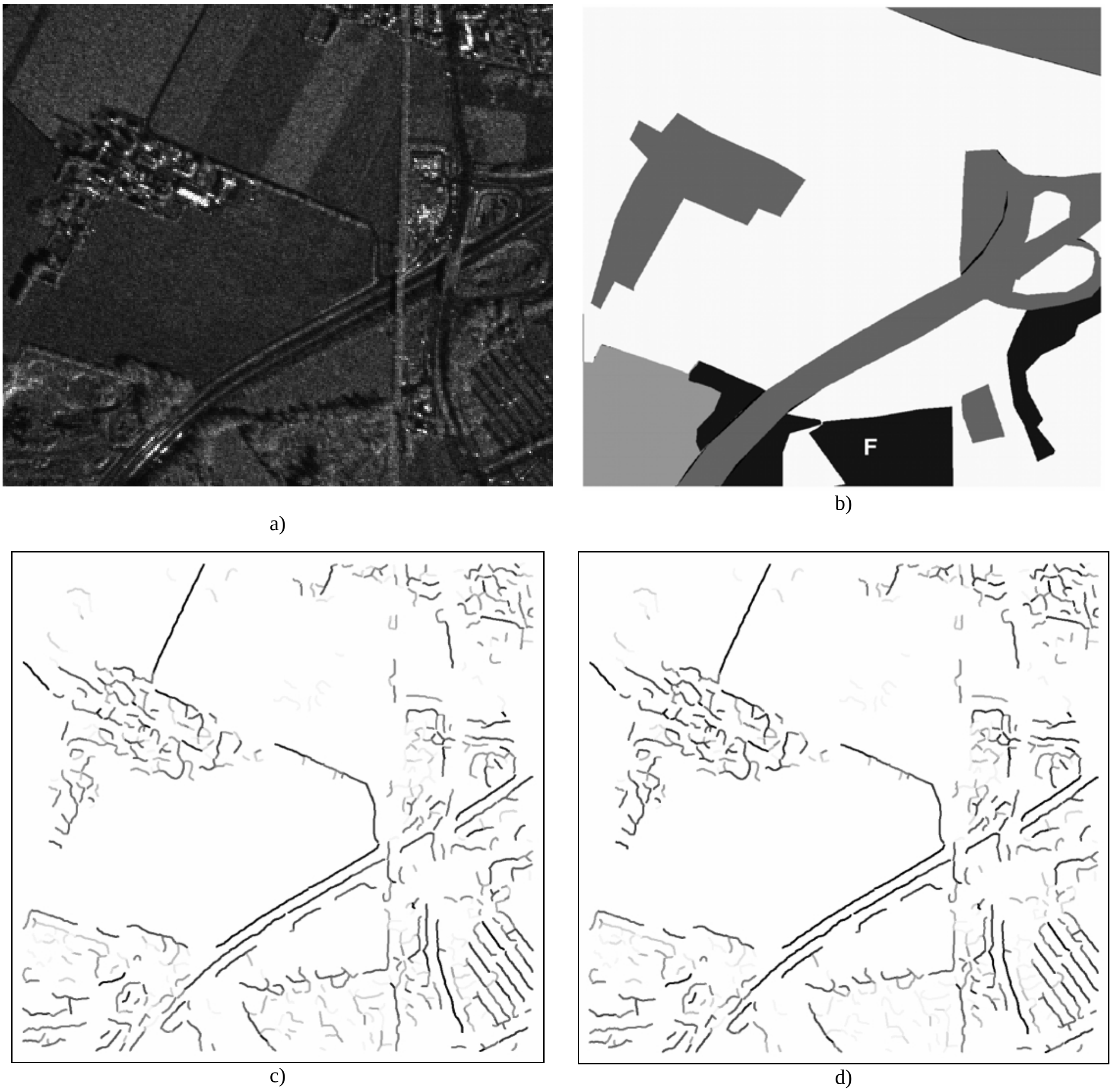

Figure 7. a) SAR image analysed in this work b) Manual extraction of global context from previous SAR scene c) Results of discriminant function neglecting global context d) Results of discriminant function incorporating global context

4. RESULTS AND DISCUSSION

A cross-validation was carried out in order to examine if the assessment of a sample of the training data (1220 line segments) delivers a correct result. 83.5% of the line segments belonging to the class ROADS were correctly classified and 76.0% of the FALSE_ALARMS were correctly classified. An assessment ignoring global context did not change the number of correctly classified road segments, but deteriorated the classification of FALSE_ALARMS. As much as 54.3% of the FALSE_ALARMS are falsely classified as road segments. The prior terms of each classes were assumed to be *p(*ROADS*)=0.3* and *p(*FALSE_ALARMS*)=0.7.*

The assessment was also tested on a line extraction carried out in a scene taken by the same sensor as the training data but now performed with different parameter settings. In order to test the derived likelihood functions in terms of sensitivity and ability to discern roads from false alarms, we allowed a significant over-segmentation. Results of this test are illustrated in Fig. 7c). The derived discriminant value $g(x)$ of each line segment is coded in gray, i.e. the darker the line the better the evaluation. Two assessments are carried out, one incorporating global context and one containing the same priori terms for all context areas.

A fact that comes clear from the comparison of Figs..7c) and d) is the importance of using global context for the evaluation, in particular for determining the Bayesian priors. Incorporating global context reduces the number of false alarms in forest regions (marked black in Fig. 7b). Still many line segments are falsely classified in urban regions, which indicates the need of additional local context information and a different assessment in these regions. The attribute *length*, for instance, should have less influence on the final evaluation since short line segments may also correspond to roads.

As can also be seen from Fig. 7, most line segments that correspond to roads still got a good evaluation. On the other hand, many of the false alarms in the urban and forest area are rated worse, even though also some correct segments got a bad rating. However, keeping in mind that this evaluation is only an intermediate step before fusion and network-based grouping (see flow charts in Figs. 1 and 2) the learned likelihood functions seem indeed being robust enough to be applied to different parameter settings as well as different images – of course under the condition that the image characteristics do not differ too heavily.

The results achieved so far are promising in terms that the evaluation of the lines is on one hand statistically sound and, on the other hand, it closely matches the assumptions on the significance of different attributes with respect to their distinctiveness. However, the fusion of evaluated lines from different views and thereby taking into account local context needs still to be done and analysed in depth.

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