A Probabilistic Fusion Concept for Road Extraction from Multiple SAR Views

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Abstract

In this article, a probabilistic fusion concept for road extraction from multi-aspect SAR images, which incorporates sensor geometry and context information, is proposed. Before fusion, the uncertainty of each extracted line segment is assessed by means of Bayesian probability theory. This assessment is performed on attribute-level and is based on predefined probability density functions learned from training data. In the first part the importance of global and local context information and the benefit of incorporating sensor geometry within the fusion module are discussed. The second part concentrates on the analysis of the uncertainty assessment of the line segments. Finally, some results regarding the uncertainty assessment of the line segments using real SAR images are presented.

1 Introduction

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 [1]. Airborne images already provide resolution up to 1 decimetre [2]. 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. The inevitable consequences of the side-looking geometry of SAR, occlusions caused by shadow- and layover effects, is still present in forestry areas as well as in built-up areas.

SAR images illuminated from different directions (i.e. multi-aspect images) reduce these negative imaging effects. Preliminary work has shown that the usage of multi-aspect SAR images improves the road extraction results, which has been tested both for real and simulated SAR scenes [3],[4]. 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 Bayesian statistical approach, which incorporates both 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 are discussed in Sect. 4.

2 Road Extraction System

The extraction of roads from SAR images is based on the TUM road extraction approach [5], which was originally designed for optical images with a ground pixel size of about 2m [6]. The first step consists of line extraction using Steger's differential geometry approach [7], which is followed by a smoothening and splitting step. Afterwards a fuzzy evaluation of suitable attributes, such as length, contrast, intensity, etc., is carried out. A 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 Figure 1.

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 grey in Figure 1).

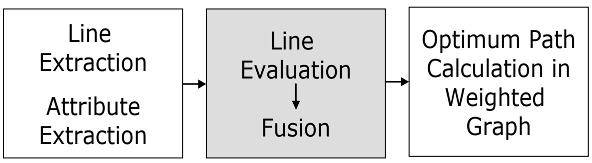

Figure 1 Automatic road extraction process

3 Probabilistic Fusion Concept

A 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.

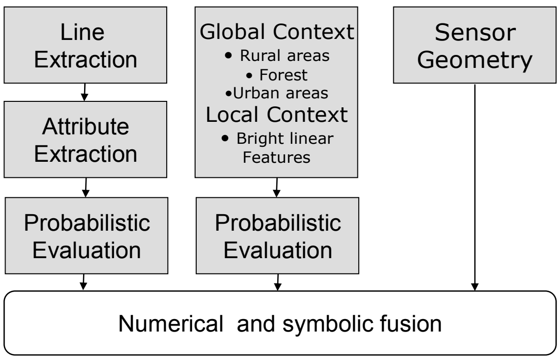

Figure 2. Fusion module and its input data

3.1 Local and Global Context

First of all, one has to define what kind of information will suit as input to the fusion process. In our case, the line segments and its probabilistic assessment are the most important input. Of course, roads are always connected to each other and therefore our goal is to find a connection between the line segments. But when line extraction fails, also additional information might be helpful.

By incorporating global and local context during fusion certain hypotheses can be supported or rejected. 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.

Global context regions are derived from maps or GIS before road extraction, or can be segmented automatically by a texture analysis. On the other hand, 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.

3.2 Features, Attributes, 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 and FIELDS. These regions are of interest, since road attributes may have varying importance depending on its 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,

$$p(\omega_i|\mathbf{x}) = \frac{p(\mathbf{x}|\omega_i)\ p(\omega_i)}{\sum_i p(\mathbf{x}|\omega_i)\ p(\omega_i)}. \quad (1)$$

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

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

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.

3.3 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 and FIELDS) 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.

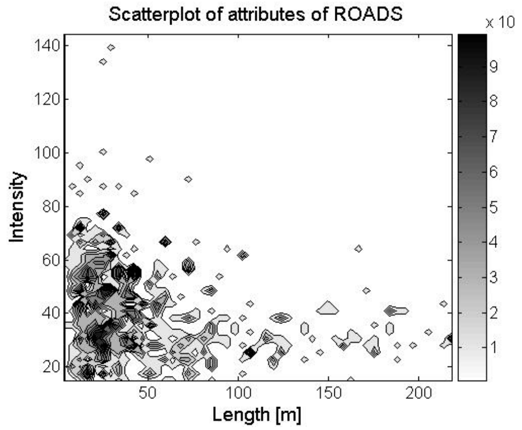

Figure 3 Scatter plot of attributes *intensity* and *length*

The independence condition is proved by a correlation test. 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,

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

A reasonable way to test the match of histograms and parameterized distributions is to apply the Lilliefors test [8]. 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 μ and σ since it allows to introduce a-priori variances. Figure 4 and 5 show the histogram of the attribute *length* and its fitted lognormal distributed curve.

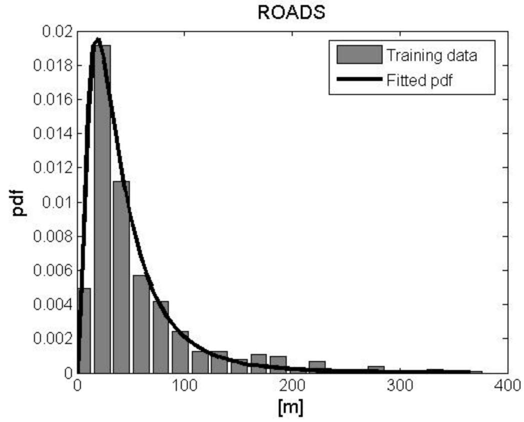

Figure 4 A lognormal distribution is fitted to a histogram of the attribute length (ROADS).

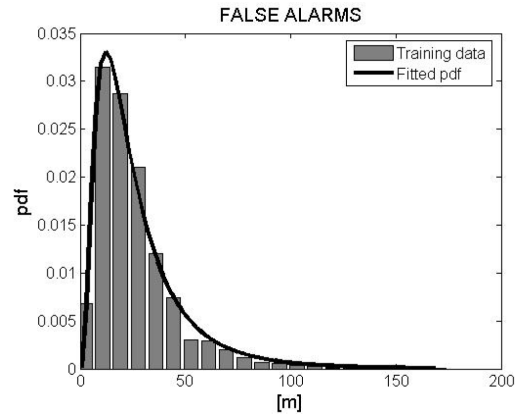

Figure 5 A lognormal distribution is fitted to a histogram of the attribute length (FALSE_ALARMS).

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 Figure 4 and 5 seem to overlap. However, Figure 6 exemplifies for the attribute *length* that the discriminant function

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

increases as the length of the line segment increases. The behaviour of the discriminant function corresponds to the belief of a human interpreter.

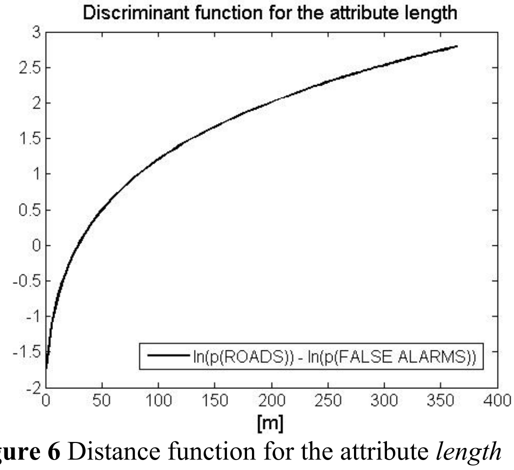

Figure 6 Distance function for the attribute *length*

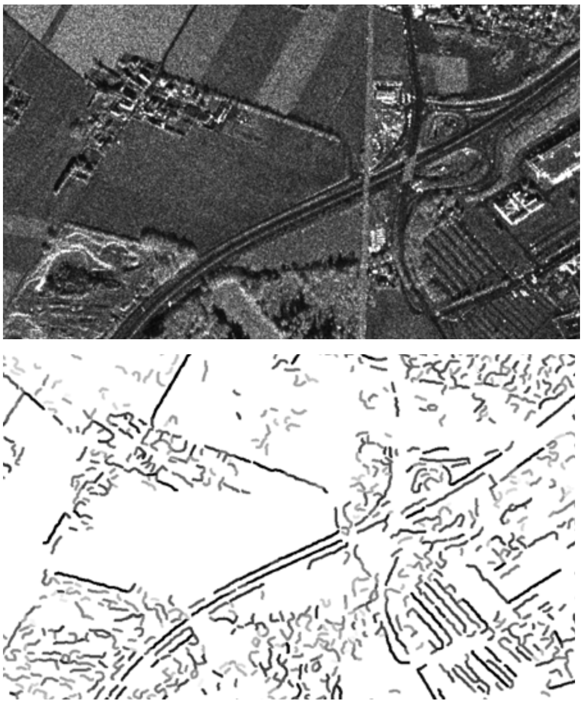

Figure 7 Assessment of a line extraction (below) from a sub-urban SAR scene (above)

4 Validation 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. The prior terms of each classes were assumed to be $p(\text{ROADS})=0.3$ and $p(\text{FALSE\_ALARMS})=0.7$. 82.3% of the line segments belonging to the class ROADS were correctly classified and 60% of the FALSE_ALARMS were correctly classified.

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 with different parameter settings In order to test 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 Figure 7. The derived discriminant value $g(x)$ of each line segment is coded in gray, i.e. the darker the line the better the evaluation. Short line segments, which are only a few pixels long, obtain high values in case of attributes such as straightness and constant intensity. As a conclusion, the assessment of these segments is considered to be unreliable and very short line segments are sorted out. As can be seen from Figure 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.

Another fact that comes clear from Figure 7 is the importance of using global context for the evaluation, in particular for determining the Bayesian priors. The number of false alarms is much higher in urban and forest area which indicating that the a-priori probability must be different in these regions. Furthermore, the attribute *length*, for instance, should have less influence on the final evaluation since short line segments may also correspond to roads.

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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