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A fusion concept for road extraction from multi-aspect SAR data

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ABSTRACT: Automatic road extraction from synthetic aperture radar (SAR) images is regarded as a complicated task. Due to the side-looking geometry of SAR, shadow- and layover-effects often occlude roads in urban- and forestry-areas. By illuminating the scene from different directions (e.g. multi-aspect images), these effects are reduced. But multi-aspect SAR images contain different information and extracted information 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, we describe an extension of an automatic road extraction procedure developed for single SAR images towards multi-aspect SAR images. A fusion concept based on the Bayesian probability theory is proposed. Before fusion, the uncertainty of each extracted line segment is assessed by means of predefined probability functions learned from training data. As prior information, global context is incorporated.

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.

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 coincides 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 Section 2. The main focus of this paper is the proposed fusion module, which is explained in Section 3. Some intermediate results of an uncertainty assessment of line segments based on a training step and global context are discussed in Section 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 2 m (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 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 the 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).

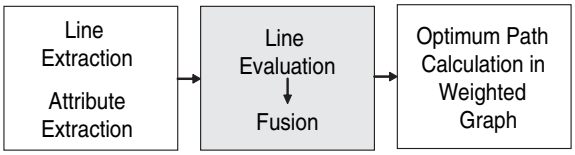

Figure 1. Automatic road extraction process.

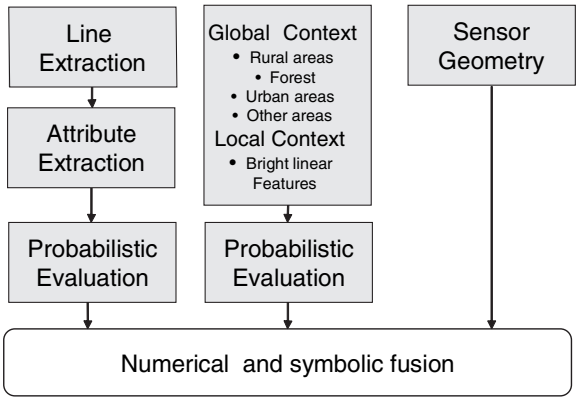

Figure 2. Fusion module and its input data.

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. The fusion process and its inputs are illustrated in Figure 2.

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,

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

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

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

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 factorised likelihoods cannot 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.

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

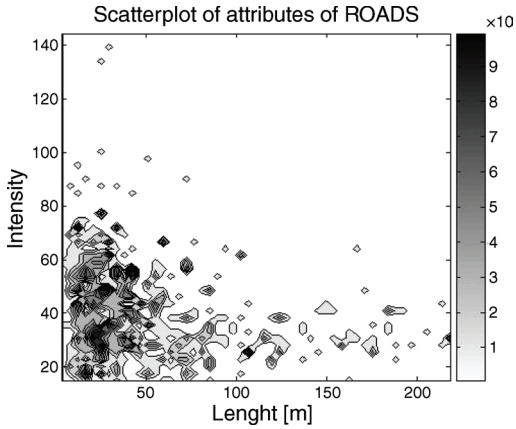

Figure 3. Scatter plot of attributes intensity and length.

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 μ and σ since it allows to introducing a-priori variances. Figures 4a–b show the histogram of the attribute *length* and its fitted lognormal distributed curve. 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,

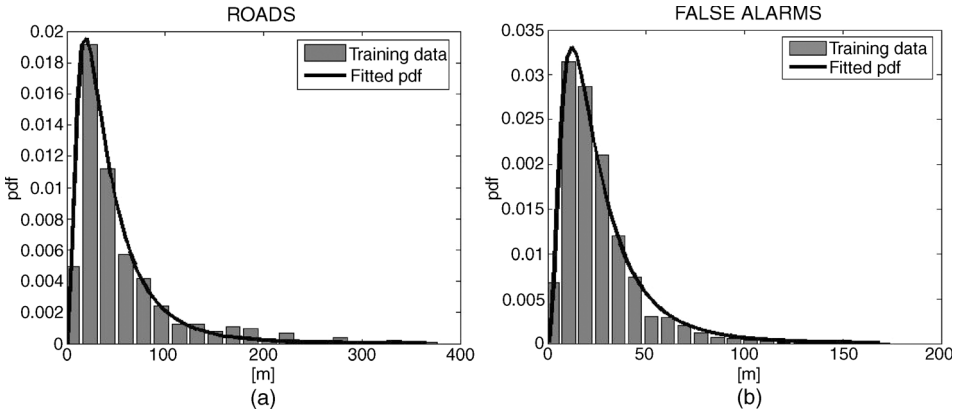

Figure 4. A lognormal distribution is fitted to a histogram of the attribute length (a) ROADS (b) FALSE_ALARMS.

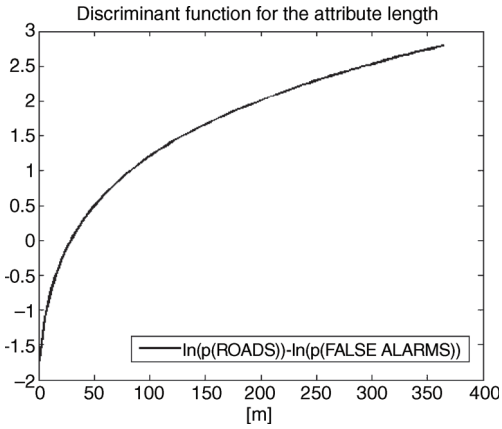

Figure 5. Discriminant function for the attribute length.

the histograms in Figures 4a–b seem to overlap. However, Figure 5 exemplifies for the attribute *length* that the discriminant function

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

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

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.

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 parallel view direction contain a road flanked by high trees on one side (see Figures 6a–b). The road is oriented along-track in both scenes. While in the first image, shadow regions of the trees occlude the road; the road is visible in the second image. The parallel appearance of features in both views (dark-shadow/bright-layover) would stand for local contest, while the whole forest 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 Figures 7b).

(a) (b)

Figure 6. Anti-parallel SAR-views of a rural scene close to Ravensburg (a) illuminated from the left, (b) illuminated from the right (MEMPHIS, 35GHz, resolution of 1m, $\theta \approx 60°$, © FGAN-FHR).

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 Table 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.

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

Table 1. Prior terms for different global context areas.

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

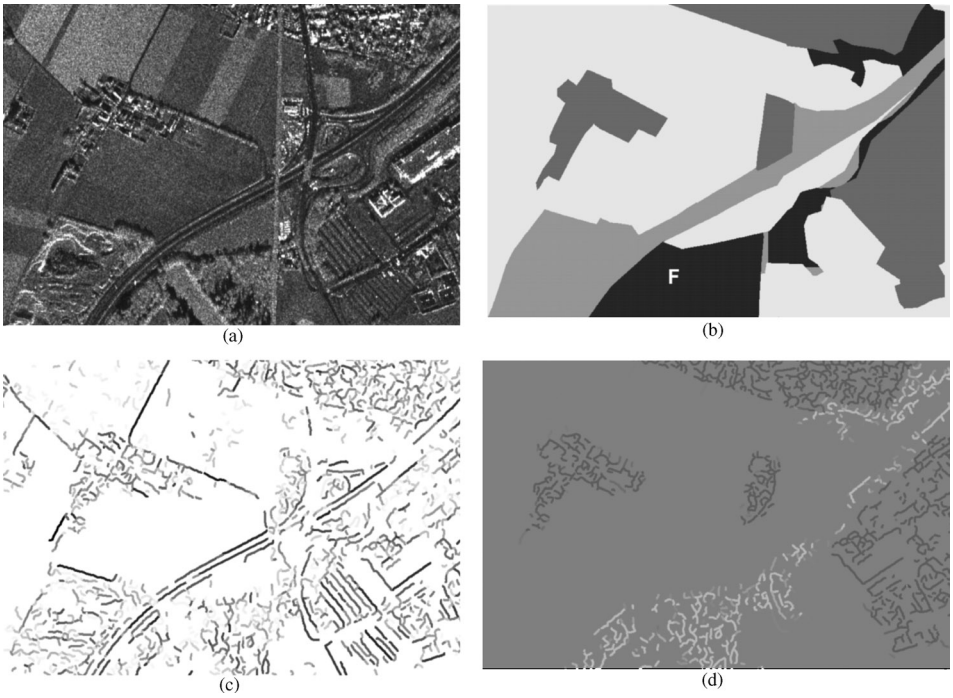

Figure 7. (a) SAR image (b) Manual extraction of global context (c) Results of discriminant function neglecting global context (d) Differences resulting from discriminant function incorporating and neglecting global context.

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 $p(\text{ROADS}) = 0.3$ and $p(\text{FALSE\_ALARMS}) = 0.7$.

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 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 Figure 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. The difference image resulting from discriminant function incorporating and neglecting global context can be seen in Figure 7d. Darker color represents positive values (i.e. discriminant function incorporating global context delivers higher values), while lighter color represents negative values. Incorporating global context reduces the number of false alarms in forest regions (marked with an ‘‘F’’ in Figure 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 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 Figures 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 further aspect of interest is the investigation if the likelihood functions are transferable to images acquired by another sensor, for example Memphis (Figure 6).

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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REFERENCES

Bacher, U. & Mayer, H. (2005). Automatic road extraction from multispectral high resolution satellite images. In: Stilla U, Rottensteiner F, Hinz S (eds) Object Extraction for 3D City Models, Road Databases, and Traffic Monitoring – Concepts, Algorithms, and Evaluation (CMRT05). International Archives of Photogrammetry and Remote Sensing. Vol 36, Part 3 W24: 29–34.

Conover, W.J. 1999. *Practical nonparametric statistics.* New York, Wiley.

Dell' Acqua, F., Gamba, P. & Lisini, G. 2003. Improvements to Urban Area Characterization Using Multitemporal and Multiangle SAR Images. *IEEE Transactions on Geoscience and Remote Sensing*, 41(9), pp. 1996–2004.

Ender, J.H.G. & Brenner, A.R. 2003. PAMIR – a wideband phased array SAR/MTI system. IEE Proceedings – Radar, Sensor, Navigation, Vol 150(3): 165–172.

Roth, A. 2003. TerraSAR-X: A new perspective for scientific use of high resolution spaceborne SAR data. *2nd GRSS/ISPRS Joint workshop on remote sensing and data fusion on urban areas, URBAN 2003*. IEEE, pp. 4–7.

Steger, C. 1998. An unbiased detector of curvilinear structures, *IEEE Trans. Pattern Anal. Machine Intell.,* 20(2), pp. 549–556.

Stilla, U., Michaelsen, E., Soergel, U., Hinz, S. & Ender, H.J. 2004. Airborne Monitoring of vehicle activity in urban areas. In: *Altan MO (ed) International Archives of Photogrammetry and Remote Sensing*, 35(B3), pp. 973–979.

Tupin, F., Houshmand, B. & Datcu, M. 2002. Road Detection in Dense Urban Areas Using SAR Imagery and the Usefulness of Multiple Views, *IEEE Transactions on Geoscience and Remote Sensing*, 40(11), pp. 2405–2414.

Wessel, B. & Wiedemann, C. 2003. Analysis of Automatic Road Extraction Results from Airborne SAR Imagery. In: *Proceedings of the ISPRS Conference "Photogrammetric Image Analysis" (PIA03), International Archieves of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Munich 2003, 34(3/W8), pp. 105–110.

Wiedemann, C. & Hinz, S. 1999. Automatic extraction and evaluation of road networks from dsatellite imagery, *International Archives of Photogrammetry and Remote Sensing*, 32(3-2W5), pp. 95–100.