EVALUATION OF A STATISTICAL FUSION OF LINEAR FEATURES IN SAR DATA

A. Karin Hedman, B. Stefan Hinz, C. Uwe Stilla

A. Astronomical and Physical Geodesy, B. Remote Sensing Technology, C. Photogrammetry and Remote Sensing
Technische Universitaet Muenchen, Arcisstrasse 21, 80333 Munich, Germany

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. During fusion each extracted line primitive is assessed by means of Bayesian probability theory. The assessment is based on the attributes of the line primitive (i.e. length, straightness, etc), global context and sensor geometry. The fusion and its integration into the road extraction system are tested in a sub-urban SAR scene.

Index Terms— SAR data, fusion, road extraction

1. INTRODUCTION

By the development of new, sophisticated SAR-systems, automatic road extraction has reached a new dimension. Satellite high resolution SAR data are already provided by the German satellite TerraSAR-X and the Italian satellite system COSMO-SkyMed. Airborne images already provide resolution up to 1 decimeter [1].

When working with road extraction from SAR images, one should also keep in mind the inevitable consequences of the side-looking geometry of the SAR sensor; occlusions caused by shadow- and layover. In case of adjacent high buildings and narrow streets, the roads might not even be visible on the SAR image. Strong scattering caused by metallic objects or by adjacent vegetation occur frequently and hinder important information about the roads. Furthermore it is hard, even for an experienced SAR user to distinguish between real roads and linear shadow regions.

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 [2][3].

In this paper we will discuss the results of a fusion approach developed for multi-aspect SAR data and its implementation into an automatic road extraction system.

2. ROAD EXTRACTION SYSTEM

The extraction of roads from SAR images is based on an already existing road extraction approach [4][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. By applying explicit knowledge about roads, the line primitives 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 primitives is constructed. For the extraction of the roads from the graph, supplementary road segments are introduced and seed points are defined. Best-valued road candidates serve as seed points, which are connected by an optimal path search through the graph. The road extraction approach is illustrated in Fig. 1.

The fusion module presented in this paper is adopted towards multi-aspect SAR images. Instead of using fuzzy-functions (marked in gray in Fig. 1), a probabilistic formulation is introduced.
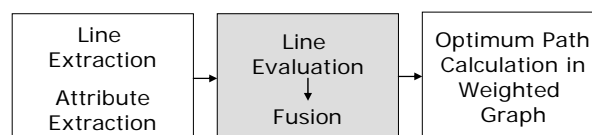

Fig. 1. Automatic Road Extraction Process

3. FUSION MODULE

A line extraction from SAR images often delivers partly fragmented and erroneous results. Especially in forest and in urban areas over-segmentation occurs frequently. Even an experienced SAR user might have problems to differentiate between true roads and linear shaped shadows. Attributes describing geometrical and radiometric properties of the line primitives can be helpful in the selection. However, these attributes may be ambiguous and are not considered to be reliable enough when used alone. Furthermore, occlusions due to surrounding objects cause gaps in the line extraction, which are hard to compensate.

The concept of the fusion module presented here is that the fusion shall make use of both sensor geometry information as well as context information.

3.1. Fusion based on Bayesian probability theory

The underlying theory of the approach originates from Bayesian probability theory

$$p(Y|X,I) = \frac{p(X|Y,I) \cdot p(Y|I)}{p(X|I)} \qquad (1)$$

Bayes' theorem follows directly from the product rule:

$$p(Y,X|I) = p(Y|X,I) \cdot p(X|I). \qquad (2)$$

The strength of Bayes' theorem is that it relates the probability that the hypothesis Y is true given the data X to the probability that we have observed the measured data X if the hypothesis Y is true. The latter term is much easier to estimate. All probabilities are conditional on I, which is made to denote the relevant background information at hand.

The main feature involved in the road extraction process is the line primitive, which can either be identified as ROADS (Y_1), or as something else (i.e. FALSE ALARMS, SHADOWS, RIVERS etc..). In this work we have chosen to incorporate the two classes FALSE ALARMS (Y_2), and SHADOWS (Y_3). The class FALSE ALARMS represent the relatively bright line extractions mainly occurring in forest areas, caused by volume scattering.

In our case the measured data X corresponds to geometric and radiometric attributes of the line primitive - an attribute vector. The selection of attributes of the line primitives is based on the knowledge about roads. The attributes used in this work are mean intensity, length, and straightness. More attributes do not necessarily mean better results, instead rather the opposite occur. A selection including a few, but significant attributes is recommended. If there is no correlation between the attributes, the likelihood $p(X|Y_i)$ can be assumed equal to the product of the separate likelihoods for each attribute.

$$p(X|Y_j) = p(x_1,x_2,..x_n|Y_j) = p(x_1|Y_j)\, p(x_2|Y_j) \cdots p(x_n|Y_j) \qquad (4)$$

Each separate likelihood can $p(x_i|Y_j)$ be approximated by a probability density function learned from training data as discussed in [8]. Please note that the estimated probability density functions should represent a degree of belief rather than a frequency of the behavior of the training data. The obtained probability assessment shall correspond to our knowledge about roads.

Since we work with multi-aspect SAR data extracted information shall be combined from two or more SAR scenes. Then the hypotheses above will be extended to the assumptions whether a ROAD truly exist in the scene or not. We need to add a third term to our measured data X; the fact that a line has been extracted (L) or not extracted ($\bar{L}$) from one or more images.

Additional information of global and local context is helpful to support or reject certain hypotheses during fusion. Global context play here an important role and can be incorporated in the posterior as well as the prior probabilities. Roads are more likely to appear in urban areas. Shadows occur frequently in forest areas, which are likely to be mistaken as roads. Furthermore one can assume that it is much more likely to successfully detect a road surrounded by fields than a road in the middle of the forest.

Exploiting sensor geometry information relates to the observation that road primitives in range direction are less affected by shadows or layover of neighboring elevated objects and should therefore be better evaluated than road primitives in azimuth direction.

By incorporating the detection of the line, L, the global context C as well as the sensor geometry as input information, and in the end, we have the following expression;

$$p(Y_j|X_1,..,X_n,L_1,..,L_n,C_1,..,C_nI) \propto$$
$$p(X_1,...,X_n,L_1,..,L_n,C_1,..,C_n|Y_j,I) \cdot p(Y_j|I) \qquad (5)$$

By means of this statement and by means of the product rule, the expression above can be written as;

$$p(Y_j|X_1,X_2,...,X_n,C_1,C_2,...C_n,L_1,L_2,...L_n,I) \propto$$
$$p(X_1|L_1,C_1,Y_j,I),..,p(X_n|L_n,C_n,Y_j,I)\,p(L_1|C_1,Y_jI), \qquad (6)$$
$$..,p(L_n|Y_j,C_j,I)\,p(C_1|Y_j),...,p(C_n|Y_j)\,p(Y_j|I)$$

where
$p(X|C_nL_n,Y_1,I)$ = the posterior probability that the data X is measured if a ROAD exist AND surrounded by the context C_n AND a line has been extracted. Most probably the attributes of the line depends on the surrounding context. Roads tend to be relatively shorter in urban areas than in other global context areas. Since the probability density functions of the attributes are defined by training data in all context areas, we apply the theorem of marginalization.

$$p(X|L,Y,I) = \int_{-\infty}^{+\infty} p(X|C,L,Y,I)\,dC \qquad (7)$$

$p(L_n|C_n,Y_1,I)$ = the posterior probability that a line primitive is extracted, if a ROAD truly exist. This term is varied due to both context area and the relationship between

the road's direction and the SAR sensor geometry. By assuming a simple geometric model (see Fig. 2), the posterior probability $p(L_n|C_n,Y_1,I)$ is varied depending on incidence angle of the SAR sensor, θ, and the difference between the look angle of the SAR sensor and the direction of the road, β. This term is especially useful by supporting or rejecting hypotheses regarding SHADOWS and ROAD.

$p(C_n|Y_1,I)$ = the posterior probability that the context C_n occur if a ROAD exist. This term might be hard to define, but can be of significance in urban areas, if the main directions of the road are known in advance. In this work, this probability is set equal to all occasions.

$p(Y_1,I)$ = the prior or subjective probability that a road exist in the image. Here one can take advantage of global context. Global context regions can be derived from maps or GIS before road extraction, or can be segmented automatically by a texture analysis. As a start, global context (BUILT-UP AREAS, FIELDS, FOREST and OTHER) is extracted manually.
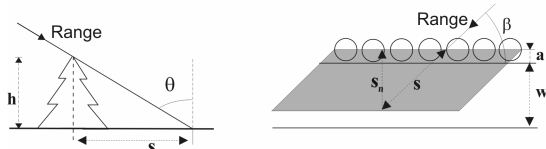
Fig. 2. A tree with the height h stands nearby a road with the width w and causes a shadow, S_n. θ is the incidence angle of the SAR sensor, β is the difference between the sensor's look angle and the direction of the road.

3.2. Fusion of line primitives

First of all, the line primitives are sorted according to its discriminant value

$$g(x) = \ln\left(p(x|L,Y_1,I)\right) - \ln\left(p(x|L,Y_2,I)\right) \quad (8)$$

The line primitive with the highest discriminant value is chosen first. Then, all neighbouring primitives are searched for. Those parts of the neighbouring primitives, which satisfy overlap and collinearity criteria (i.e. buffer width and direction difference) are assumed to be redundant extractions and are removed. If only a part of the neighbouring line primitive is fused, the line primitive is clipped and the non-fused part remains in the search. Also, lines with an all too deviant direction according to the best-evaluated line remain. The best-evaluated primitive obtains a probability based on (6) depending on integrating context information or not.

Then, the primitive yielding the second highest maximum likelihood of being ROAD is chosen and processed with the same algorithm. The whole fusion process ends after all primitives have been processed.

4. RESULTS AND DISCUSSION

Three tests were carried out; single SAR scene (1), two multi-aspect SAR scenes (one illuminated from the top and one from the upper right corner, - with 45° difference) without (2) and with (3) context information (Figs. 3-8). The subjective posterior and prior probabilities used in this work can be seen in Tab. 1 and 2.

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 results also exemplify the complexity of road extraction from multi-aspect SAR images. On one hand a more complete results is achieved, but on the other hand, the correctness is rather poor in comparison to results extracted from one single image (Tab. 1). The reason for this is the over-segmentation in combination with the severe behavior of the Bayesian fusion. Incorporating global context and sensor geometry improves the correctness, but not significantly. In the future this part can be modeled rather as a reasoning step than assessed by means of probabilities. Still the fusion has to be tested on larger scenes with different complexities as well as be analyzed further in detail.

Global context, C_G	P(Y,I)		
	Y=ROAD	Y=SHADOW	Y=F A
FIELD	0.3	0.3	0.4
URBAN	0.4	0.3	0.3
FOREST	0.1	0.3	0.6

Table 1. Prior probabilities used in test 3.

Sensor geometry	P(L|FIELD,Y,I)			
	Y=ROAD		Y=SHADOW	
	C_R	$\overline{C}_R$	C_S	$\overline{C}_S$
L	0.9	0.73*)	0.7	0.3
$\overline{L}$	0.1	0.27	0.3	0.7

Table 2. Posterior probabilities used in test 3. The criteria are defined based on the model in Fig. 3, assuming h=15m and w= 10 m. C_R: Roads within a β, which gives a possible shadow less than a 1/3 of its width w. C_S: Width of shadows caused by trees/buildings equal to the width parameter of the line extraction. *) Estimated from training data.

	One single image	Fusion of two images - no context C	Fusion of two images incorporating context C
Completeness	55 %	75 %	74 %
Correctness	90 %	58 %	69 %

Table 1. Completeness and correctness as defined in [6]

Fig. 3. The ground truth and one of the SAR images analyzed in this work
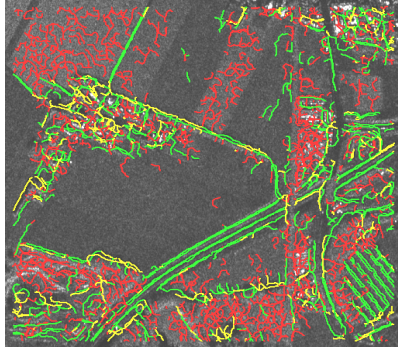

Fig. 4. Line primitives extracted from the two SAR scenes and classified into three classes; ROAD (green), SHADOW (yellow), FALSE ALARMS (red)
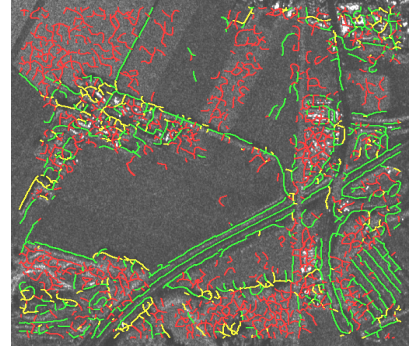

Fig. 5. Classification of the line primitives after fusion; ROAD (green), SHADOW (yellow), FALSE ALARMS (red)

Fig. 6. Extracted roads from one single SAR scene

Fig. 7. Extracted roads from two multi-aspect SAR scenes

Fig. 8. Extracted roads from two multi-aspect SAR scenes. Global context and the sensor geometry are incorporated during the fusion process.

REFERENCES

[1] J.H.G. Ender, A.R. Brenner, "PAMIR - a wideband phased array SAR/MTI system," IEEE Proceedings - Radar, Sensor, Navigation, 2003, vol 150(3): pp. 165-172.

[2] F. Tupin, B. Houshmand, M. Datcu, "Road Detection in Dense Urban Areas Using SAR Imagery and the Usefulness of Multiple Views", IEEE Transactions on Geoscience and Remote Sensing. Vol. 40, No 11, pp. 2405-2414, Nov. 2002.

[3] F. Dell'Acqua, P. Gamba, G. Lisini, "Improvements to Urban Area Characterization Using Multitemporal and Multiangle SAR Images", IEEE Transactions on Geoscience and Remote Sensing. Vol. 4, No. 9, pp. 1996-2004, Sep. 2003.

[4] B. Wessel, C. Wiedermann, "Analysis of Automatic Road Extraction Results from Airborne SAR Imagery", In: Proceedings of the ISPRS Conference "PIA'03", International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, Munich 2003, 32(3-2W5), pp. 105-110

[5] U. Stilla, S. Hinz, K. Hedman, B. Wessel, "Road extraction from SAR imagery", In: Weng Q (ed) Remote Sensing of Impervious surfaces. Boca Raton, FL: Tayor & Francis, 2007

[6] C. Wiedemann, S. Hinz, "Automatic extraction and evaluation of road networks from satellite imagery", International Archives of Photogrammetry and Remote Sensing. 32(3-2W5), Sep. 1999, pp. 95-100.

[7] C. Steger, "An unbiased detector of curvilinear structures", IEEE Trans. Pattern Anal. Machine Intell., 20(2), pp. 549-556, 1998.

[8] K. Hedman, S. Hinz, U. Stilla, "Road Extraction from SAR Multi-Aspect Data Supported by a Statistical Context-Based Fusion", Proceedings of IEEE-ISPRS Workshop URBAN 2007, Paris, France, on CD.