TRAFFIC PARAMETER ESTIMATION USING TERRASAR-X DATA

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ABSTRACT:

Vehicle detection and traffic parameter estimation is motivated by different applications, e.g. logistics, planning of roads and transportation research. Therefore, automated traffic monitoring with air- or spaceborne data has evolved to an important research issue. SAR satellite missions, e.g. TerraSAR-X and RADARSAT-2, provide high resolution dual-channel SAR data and hence a possibility to collect traffic measurements of large areas. In this paper, a method to derive traffic parameters from such images is presented, where the different effects of moving objects are exploited. In addition to previous work, available multi-temporal satellite data is integrated to improve the detection of vehicles.

1 INTRODUCTION

1.1 Motivation

Due to increasing traffic, vehicle detection and traffic parameter estimation has become an important issue. To derive information of the traffic situation on road networks, an observation of large areas, preferably at any time, is necessary. Spaceborne SAR missions can be a solution for this aim. With the TerraSAR-X or RADARSAT-2 mission, SAR data with high resolution is available. Additionally, the Dual Receive Antenna (DRA) or Aperture Switching (AS) mode (Runge et al., 2006) enables the reception of two SAR images of the same scene within a small temporal gap, which can be utilized for interferometric detection approaches (Sikaneta and Gierull, 2005), (Gierull, 2002).

Since moving objects suffer from special effects in the SAR processing algorithm, specific methods to detect vehicles are required. In military research this problem is known as Ground Moving Target Indication (GMTI). The vehicles get blurred or displaced in the SAR images due to their motion. The presented detection approach in this paper considers simultaneously the effects in SAR images, which are caused by the vehicle's motion in across- and along-track. The scheme is derived from statistical detection theory and its principle relies on comparing an expected signal with the actual measurement. Different information are combined in this detection algorithm. The expected signal, the measured signal and their variances are included to decide wheter a vehicle is present or not.

To enhance the detection of moving vehicles, multi-temporal data is used in addition to gain more information about the acquired and evaluated scene. Persistent scatterers which may be identified wrongly as moving objects can be eliminated by using this kind of further apriori knowledge. Also the statistics for the detection process can be improved to yield better results.

In the next section a short summary is given of the different effects in SAR images caused by the vehicle's motion and about how to derive the apriori knowledge which is used in the presented detection approach. This detection scheme is explained in Sect. 3. Afterwards the performance of this detector is analysed using TerraSAR-X AS-data in Sect. 4 and conclusions are drawn in Sect. 5.

2 MOVING OBJECTS IN SAR IMAGES

In SAR images moving objects are not imaged ”correctly” since the stationay world assumption of the SAR imaging process is violated. The moving and accelerating objects suffer from a shift i.e. from a dislocation in the image, peak power reduction and from blurring (Hinz et al., 2007).

A constant motion in across-track direction of a moving target causes an additional linear phase trend in the echo signal. This linear phase component of the spectrum corresponds to a shift in the time domain. Hence, vehicles moving in across-track get displaced in azimuth direction in the image depending on their line-of-sight velocity v_{los}. This shift can be expressed in meters:

$$\Delta_{azimuth} \approx -R_0 \frac{v_{los}}{v_{sat}}, \quad (1)$$

where R_0 is the distance between point target and radar platform, and v_{sat} the velocity of the satellite.

The interferometric phase of a moving object of the acquired two antennas is dependent on the along track baseline B_{ATI}, i.e. the distance between the two phase centers in flight direction:

$$\phi = \left(\frac{4\pi B_{ATI} v_{los}}{\lambda v_{sat}}\right), \quad (2)$$

with λ the wavelength. ϕ is sensitive to across track velocities, but vanishes for objects, which are stationary or moving purely in along track.

If the vehicle is moving in along-track, the relative along-track velocity between sensor and target differs from stationary objects, which causes a change of the Frequency modulation (FM) rate of the echo signal. When focusing with a stationary world matched filter, this leads to a spread of the signal in the image. The blurring of moving objects in SAR images may also be caused by accelerations (Sharma et al., 2006).

Knowing the positions and the directions of roads from GIS data, it is possible to derive apriori knowledge for the acquired scene. Depending on the distance of a pixel to an associated road segment, which corresponds to Δ_{az}, the expected phase ϕ can be forecasted for each pixel. In Fig. 1 one can see ϕ for the acquired scene (TerraSAR-X data take DT01516) which is analysed in Sect. 4. Only the parts up to a maximum displacement (i.e. corresponding to a maximum velocity) are forecasted. The white parts are excluded from evaluation.

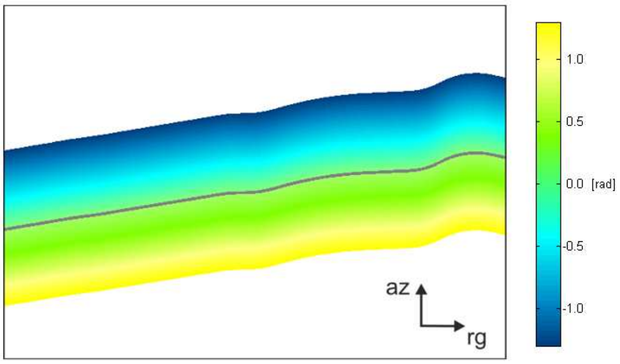


Figure 1: Expected Phase derived from GIS data

Such a mask can also be estimated for the FM rate (Eineder et al., 2006).

3 LIKELIHOOD RATIO DETECTOR

3.1 Detection Scheme

To detect a moving vehicle the different effects caused by its motion (Sec. 2) are exploited and the apriori knowledge is integrated to decide whether a vehicle is existent or not. Assuming the existence of a vehicle, an expected signal hidden in clutter is compared with the actual measurement in the SAR data.

The mathematical framework for this proposed approach is derived from statistical detection theory. Two hypotheses H_0 and H_1 are defined:

H_0: only clutter and noise are existent
H_1: signal plus clutter and noise are existent

Together with the corresponding probability density functions $f(\vec{x}|H_0)$ and $f(\vec{x}|H_1)$, these hypotheses allow setting up a likelihood ratio test given by:

$$\Lambda = \frac{f(\vec{x}|H_1)}{f(\vec{x}|H_0)} \tag{3}$$

where

$$f(\vec{x}|H_0) = \frac{1}{\pi^2 |C|} exp\left\{-\vec{X}^H C^{-1} \vec{X}\right\} \tag{4}$$

and

$$f(\vec{x}|H_1) = \frac{1}{\pi^2 |C|} exp\left\{-\left(\vec{X}-\vec{S}\right)^H C^{-1} \left(\vec{X}-\vec{S}\right)\right\} \tag{5}$$

are circular Gaussian Random Processes with $\vec{S}$ being the expected signal, $\vec{X}$ being the measured signal, C being the covariance matrix, and $(*)^H$ being the Hermitian Matrix. See e.g. (Bamler and Hartl, 1998) for their derivation.

Finally, from Eqs. 3-5 we can derive the Bayesian decision rule of log-likelihood test, which computes to:

$$\left|\vec{S}^H C^{-1} \vec{X}\right| > \alpha \tag{6}$$

which is the mathematical framework for the detection scheme.

In particular, following pieces of information are combined in this detection approach: the expected signal $\vec{S}$, the measured signal $\vec{X}$, as well as their covariances C, which are described in more detail below.

The measured signal consists of the SAR images from the two apertures:

$$\vec{X} = \begin{pmatrix} X_1 \\ X_2 \end{pmatrix} \tag{7}$$

with the indices standing for the two channels.

With the phase ϕ from Fig. 1 the expected signal $\vec{S}$ can be derived:

$$\vec{S} = \begin{pmatrix} S_1 \\ S_2 \end{pmatrix} = \begin{pmatrix} exp\left\{j\frac{\phi}{2}\right\} \\ exp\left\{-j\frac{\phi}{2}\right\} \end{pmatrix} \tag{8}$$

where also the indices can be interpreted as two channels. The covariance matrix is defined as in (Bamler and Hartl, 1998):

$$C = E\left\{XX^H\right\} = \begin{pmatrix} \bar{I}_1 & \gamma\bar{I} \\ \gamma^*\bar{I} & \bar{I}_2 \end{pmatrix} \approx \bar{I}\begin{pmatrix} 1 & \gamma \\ \gamma & 1 \end{pmatrix} \tag{9}$$

with $\bar{I} = \sqrt{\bar{I}_1 \bar{I}_2} = \sqrt{E\left[|u_1|^2\right] E\left[|u_2|^2\right]}$.

However in real scenarios with roads heading in any direction not only an interferometric phase occurs, but also a blurring of the signal over several resolution cells. Thus, neighbouring pixels are included into the mathematical framework to decide whether the considered pixel is a vehicle or not. The possible blurring effect in these adjacent pixels subject to existing along-track motion or across-track acceleration will be adjusted by variation of filters to obtain a focused object and thus an optimized peak-to-sidelobe-ratio for its signal. Therefore, a stack of resulting images processed with different FM rates is evaluated for detection. Every pixel in this stack has to be compared to the threshold, yielding in a decision for H_1 for the pixel when using the corresponding FM rate.

Therefore, the input into the detection scheme can be assumed to look like:

$$\vec{X} = \begin{pmatrix} X_{1,1} \\ \vdots \\ X_{1,n} \\ \\ X_{2,1} \\ \vdots \\ X_{2,n} \end{pmatrix}, \vec{S} = \begin{pmatrix} S_{1,1} \\ \vdots \\ S_{1,n} \\ \\ S_{2,1} \\ \vdots \\ S_{2,n} \end{pmatrix} \tag{10}$$

$$C = \begin{pmatrix} 1 & 0 & \gamma & 0 \\ & \ddots & & \ddots \\ 0 & 1 & 0 & \gamma \\ \gamma & 0 & 1 & 0 \\ & \ddots & & \ddots \\ 0 & \gamma & 0 & 1 \end{pmatrix} \quad (11)$$

The complex pulse responses, actual and forecasted, are characterized by $\vec{X}_{1,i}$ and $\vec{S}_{1,i}$ for image 1 and $\vec{X}_{2,i}$ and $\vec{S}_{2,i}$ for image 2. These signals are blurred in azimuth over the cells $i \ldots (1-n)$.

The locally varying threshold to decide if the evaluated pixel is a vehicle or not, depends on the choice of statistical parameters. The desired false alarm rate gives the cut-off value for the cumulative density function of the log-likelihood test.

3.2 Integration of Multi-temporal data

Not only apriori knowledge in terms of an expected phase for example is integrated, but also multi-temporal data. The idea behind this integration is to gain more information about the static objects of the acquired scene and enhance the detection process. As an experiment for one test site (Dresden, Germany) data takes with the same acquisition parameters are collected to set up a stack of images. By averaging over time and creating a mean or median image of the stack, noise can be reduced and permanent and stable scatterers can be identified.

Pixels that consistently have a similar signal-to-clutter-ratio (SCR) are so called persistent scatterers (Adam et al., 2004), (Adam et al., 2003) which may be excluded in order to avoid false detections. Therefore, the median image of the stack is calculated. Persistent scatterer candidates are those with a SCR greater than a certain threshold. With this information the raw vehicle detections can be verified in order to avoid that static scattering objects are included in the detection mask.

However, multi-temporal data may not only be used to exclude persistent scatteres, but also to improve the detection statistics. The probabilities for being a vehicle for one pixel over time can be taken into account to give weights to the actual probability of this pixel for being detected as a moving target or not. Also the probability density function (PDF) of an area around the evaluated pixel to determine the threshold (considering a constant false alarm rate) may be estimated over time to ensure that a possibly existing vehicle does not modify the distribution.

4 RESULTS

In prior work of our group, a modular traffic processor has already been developed which processes SAR data specifically with the objective of moving vehicle detection (Suchandt et al., 2006b), (Suchandt et al., 2006a). Different detectors (ATI and DPCA) are integrated to find vehicles and can be selected individually or can be combined. The proposed likelihood ratio detector has been included additionally into this environment. In the traffic processor an adaptive filtering method is implemented as proposed in (Eineder et al., 2006) to compensate the blurring effects of moving objects. Therefore, in the decision process of the likelihood ratio detector the component to consider adjacent pixels is postponed.

The test site near Dresden, Germany, has been used for analyses. The AS data take DT01516 was processed with the traffic processor. In our first test for the multi-temporal data, a stack of 10 images is used. For a robust statistic more images are desired, but at this moment only these data takes were available. The median image of the stack was calculated to receive an SCR-map to determine permanent scatterers. Candidates were chosen with an SCR greater than 2.0. In Fig. 2 one sees some detections as a result of the traffic processor. The detection indicated by the blue rectangle is tagged in the SCR-map as a persistent scatterer and obviously a false detection. In Fig. 3 this cutout of the blue rectangle is shown in the median image (a) and in the ps-candidates map (b).

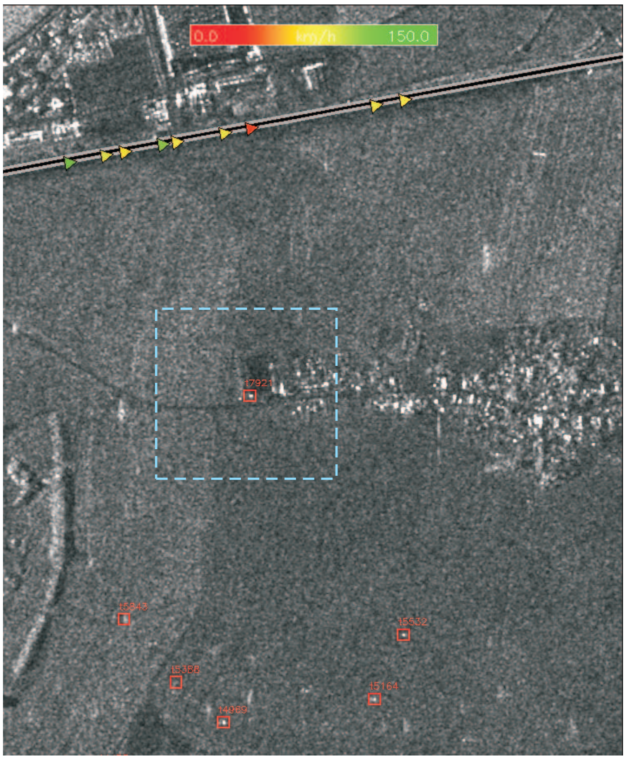
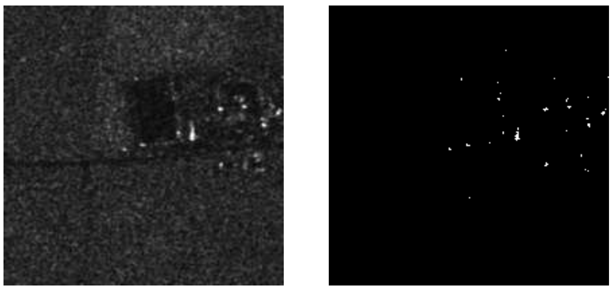


Figure 2: Detection results using the proposed likelihood ratio detector



(a) (b)

Figure 3: a) temporal median image of the stack b) ps candidates with an SCR greater than 2.0

Also the estimated velocity of this detection (38 km/h) indicates a wrong detection since all the other vehicles have an estimated velocity of more than 80 km/h. In fluent traffic such outliers with lower velocities are not very likely.

Fig. 4 shows the detection results for the test site near Dresden. It shows a 12 km long section of the motorway A4. The de-

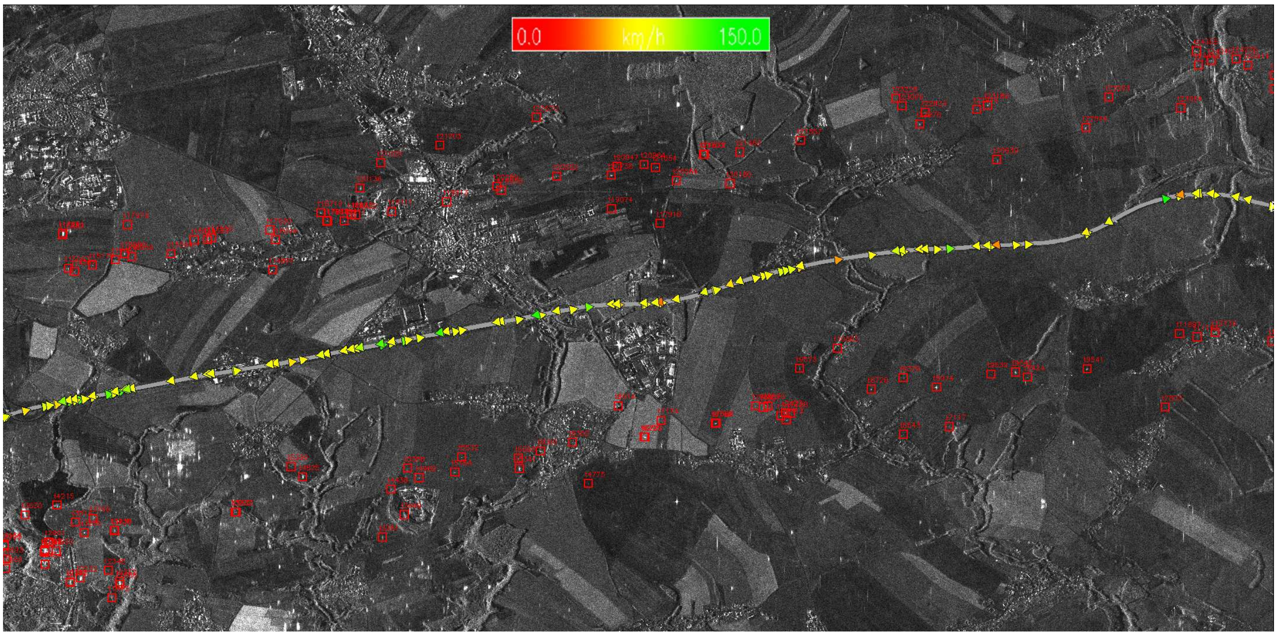


Figure 4: Traffic measurements using the proposed likelihood ratio detector for DT1516

tected vehicles at their displaced positions are marked with red rectangles. The triangels are the positions of these vehicles back-projected to the assigned road. These triangles are color-coded regarding their estimated velocity and the range is from red to green, standing for 0 to 150 km/h. Having these detections projected back onto the road axis, it is possible to derive parameters for the situation on the road and using them for example for traffic models, see e.g. (Suchandt et al., 2006b).

During the flight, video recordings of the traffic situation have been taken as reference information. The received velocities of this ground truth data represent the true traffic flow. The velocity distribution of the reference data corresponds to the one received from the detection results using DT01516 in Fig. 4. Most identified targets are trucks, hence the average of about 80 km/h is reasonable.

5 CONCLUSION

Traffic parameter estimation using TerraSAR-X data is possible with the proposed likelihood ratio detector. It considers simultaneously the effects due to the vehicle's across-track and along-track motion. The results showed the potential to deliver information from space about the traffic situation on roads for large areas. The derived traffic flow parameters from the detection in the SAR images show a good correspondance with those received from reference data. Integrating multi-temporal data helps to eliminate such wrong detections like shown and improve the reliability of the results.

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