

Automatic detection of flooded areas on ENVISAT/ASAR images using an object-oriented classification technique and an active contour algorithm

R. Heremans¹, A. Willekens², D. Borghys¹, B. Verbeeck², J. Valckenborgh², M. Acheroy¹, C. Perneel¹

¹ Royal Military Academy – Signal and Image center,

Renaissancelaan 30, B-1000 Brussels, Belgium – (Roel.Heremans, Dirk.Borghys, Marc.Acheroy, Christiaan.Perneel)
@elec.rma.ac.be

² Vlaamse Landmaatschappij, OC GIS-Vlaanderen,

Guldenvlieslaan 72, B-1060 Brussels, Belgium – (Jo.VanValckenborgh@vlm.be)

Abstract – Two techniques for extracting flooded areas out of RADAR-imagery in a time-efficient way are presented in this paper. The results of the object-oriented classification technique, based on the commercial eCognition software, and the active contour technique, are both obtained on 2 ENVISAT ASAR images; one recorded during a flood period in Flanders on January the 2nd of 2003 and one during a non-flooded region on June the 26th of the same year. In both techniques the net flooded result is based on the subtraction of the existing water bodies (i.e. lakes, rivers, canals,...) obtained from the non-flooded reference image, from the image recorded during the flooded period.

Keywords: Automatic flood detection, ASAR, Active contour.

1. INTRODUCTION

Floods in Flanders are a regularly recurring event. Floods can often cause tremendous economic damage. To reduce the damage from floods, people need to be well informed.

For its flood management policy, the Flemish water administration (*Afdeling Waterbouwkundig Laboratorium en Hydrologisch Onderzoek (WLH)* and *Afdeling Water*) has already developed computer models of the most important streams under its authority. With these models the Flemish water administration tries to imitate the floods and to predict their geographical extent. For a good validation of these models, it is essential that a correct delineation of the flooded areas is available.

The Flemish water administration (*Afdeling Water*) has also developed an inundation database of the natural flooding areas and the recently flooded areas (NOG/ROG data base) in Flanders from 1988 to 2000. This database is an important instrument for the policy of regional planning and the operational water system management. This database has been built up with information from local authorities, Flemish administrations and consultancy agencies. Now, the problem arises to keep this inundation database up to date.

To ensure the production of validation material for existing flood models and to ensure the actualisation of the inundation database, the present project aims to develop an operational processing chain to extract flooded areas from RADAR-imagery. The methods were tested on ENVISAT/ASAR images (C-band, VV-polarized, spatial resolution of 30 m and a pixel spacing of 12.5 m).

Once the flooded areas are extracted, the delineations of the flooded areas are put on the geo-portal website 'Geo-Vlaanderen' on the internet so that local water managers can manually add some additional information to the inundation database.

In this paper we start by briefly introducing the pre-processing steps performed on the original ASAR images. Afterwards the

principles used to georeference both images are reviewed, followed by the main part, which explains the object-oriented and active contour techniques. In the last section the geoportal website is presented, which contains the extracted flooded results.

2. PRE-PROCESSING CHAIN

Since all SAR images, or more generally all images produced by a coherent image system like laser, sonar, ultrasound, contain a noise-like component called speckle, a first step to reduce this image degrading effect is undertaken. The actual denoiseSAR program [1-2] used here was developed at the Ghent university. The method is based on a context-based locally adaptive wavelet shrinkage. The idea is to estimate the statistical distributions of the wavelet coefficients representing mainly noise and representing useful edges. In particular, it was noted that in SAR intensity images, the magnitudes of the wavelet coefficients representing mainly noise follow an exponential distribution while the magnitudes of the wavelet coefficients representing mainly useful signal follow a Gamma distribution. This information is used to find a threshold that allows to distinguish the useful signal from the noise. Prior knowledge about possible edge configurations is introduced using a Markov Random Field. Fig. 1 shows the ASAR-image of January 2nd before (a) and after (b).

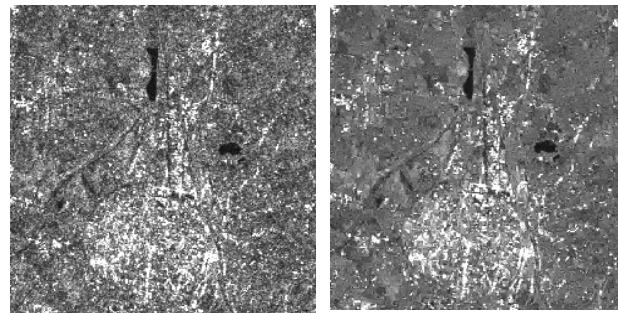


Figure 1: The original ASAR image from January shown at the region of Leuven before (left) and after (right) the speckle reduction

3. REGISTRATION

The SAR images were already converted to ground coordinates and roughly geocoded by the image provider. Since the terrain is relatively flat, we tried to apply an affine transformation for the registration. The ASAR image and 4 topographical maps from NGI were used to pinpoint the 8 GCP's, which were chosen to obtain the affine transformation parameters. The GCP's were

chosen such that the mappings on both the topological map as well as on the radar image were clearly visible.

To show the quality of the georeferencing, one of the georeferenced ASAR images is shown in Fig. 2 with the street-net superposed.

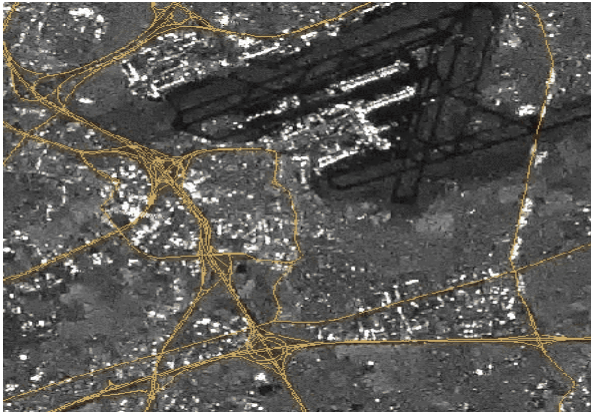


Figure 2: Quality of the georeferencing result. The street-net is superposed on the ASAR image

4. FLOOD EXTRACTION

While in many projects the detection and mapping of flooded zones are produced by manual photo-interpretation it is expected that the distinction between flooded zones and non-flooded zones is less time consuming and more objective, when automatic extraction techniques or algorithms are used on radar-imagery.

To identify flooded areas on radar-imagery, two main techniques can be distinguished, i.e. pixel-based classification techniques and object-oriented classification techniques. In the following two analyses, i.e. the object-oriented algorithm and the active contour algorithm, a combination of both techniques is used on the ENVISAT ASAR images. Both algorithms are essentially based on the fact that flooded regions in a SAR images appear as black areas, since water surfaces, or more general any flat surface, behaves as a specular surface for microwave radiation that is emitted sideways by the sensor.

The results obtained by both algorithms will be compared and evaluated at the end.

4.1. Object-Oriented Algorithm

While a vast majority of remote sensing applications still rely on 'traditional' pixel based classification methods the demand for context-based algorithms and object-oriented image processing techniques is increasing. The commercial eCognition software promotes this new perspective.

In contrast to traditional pixel-based image processing methods, the basic processing units of object oriented image analysis are image objects or segments, and not single pixels. Even the classification acts on image objects. The methodical principles of object-oriented image processing in eCognition consist of two basic domains: the segmentation and the classification.

Thus, eCognition first performs a segmentation of the imagery. Image segmentation is a bottom up region-merging technique starting with one-pixel objects. In numerous subsequent steps, smaller image objects are merged into bigger ones. This results in an extraction of image object primitives at different resolutions.

The segmentation algorithm does not only rely on the pixel values, but also on the spatial continuity of the resulting objects.

In present study the flood image and reference image were segmented with a scale parameter value of 50, a color criterion value of 0.7, a shape criterion value of 0.3, a smoothness field value of 0.9 and a compactness field value of 0.1.

The second key domain of eCognition's engine is its knowledge base classification system, which makes it possible to include many other attributes additional to the spectral information that is provided within the image. Examples are shape information, texture information, relations to neighbouring objects and a good deal more. The cornerstone of eCognition's knowledge base classification of image objects is the so-called class-hierarchy. This class-hierarchy contains the classification rules to which the image will be classified. Each class is defined by a class-descriptor and class descriptions are defined using a nearest neighbour or fuzzy membership function. When using the fuzzy nearest neighbour classifier, individual image objects are marked as typical representatives of a class, and then the rest of the scene is classified. Membership functions are a simple method to translate an arbitrary feature value into a membership degree between 0 and 1, indicating the membership of a class. Membership functions are especially suited to introducing existing knowledge or concepts into the classification.

In present study, the homogeneous image object primitives as obtained in the segmentation process were classified into flooded and non-flooded areas using two successive classifications. In a first classification, the class 'dark tone objects' was introduced in order to extract all image objects from the flood image having a mean value of less than 210. The class 'dark tone objects' will contain not only flooded areas but also other areas having a low backscattering surface (e.g. existing water bodies, airports, rivers, ...). The classification has been executed by a membership function.

In a second classification, a sub-class 'flooded area' has been introduced to separate the flooded areas from the other dark toned objects. For flooded areas a significantly decrease in pixel values is expected between the reference image and the flood image, whereas the pixel values of the other dark toned areas remain more or less the same. Therefore, a second membership function has been introduced to classify all objects, classified as 'dark toned objects' in the first classification and having a decrease in mean value bigger than 70 between the reference image and the flood image, as being flooded areas. The result of the object oriented classification technique using eCognition is shown in Fig.3.

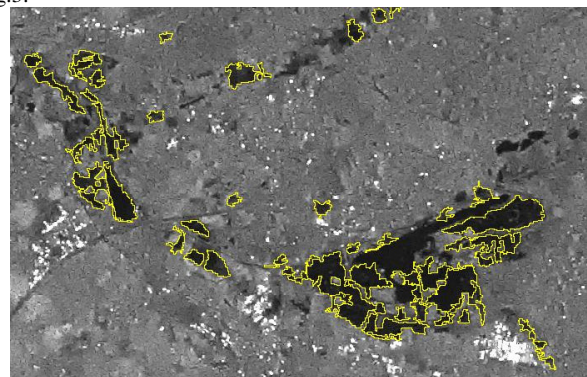


Fig. 3: Net flood result shown by the polygons on the ASAR image (Jan 2003) at the Schulens lake in Flanders using the Object-Oriented Algorithm (eCognition).

4.2. Active Contour Algorithm

A region-based algorithm, recently developed by Chesnaud et al. [3], will be introduced to delineate flooded regions in Flanders. While in this active contour algorithm an operator was needed to draw the initial polygon roughly on top of the object of interest, we will present here a way how these initial polygons can be found automatically using mathematical morphology tools. Once the initial polygons are given to the algorithm, an iterative minimization procedure will be capable of computing polygonal approximations of the object boundaries.

Initial Polygons- Mathematical Morphology: To obtain the initial polygons, which are the seeds for the main active contour algorithm, the following chain of pixel based operations are performed:

- Binary image on basis of threshold
- Mathematical Morphology Erosion (square 5x5)
- Mathematical Morphology Dilatation (square 3x3)
- Region2Object
- ObjApproximation

The speckle-reduced image is transformed into a binary image based on a threshold value of 140. All pixels with a value lower than 140 (i.e. 18 in terms of an unsigned char threshold) are replaced to one, all pixels with a value greater or equal to 140 are replaced to zero. In the second step an erosion of the flooded areas (value one in the binary image) is performed on the binary image with a square structuring element of 5x5 pixels large. This erosion is followed by a dilatation with a square structuring element of 3x3 pixels large. The size of the structuring element of the dilatation is chosen smaller than for the erosion, such that the result of the two operations deliver objects that are completely contained inside the flooded regions of interest. Afterwards, those objects are vectorized into approximated polygons, such that the number of nodes in each individual polygon is decreased decently. The only reason for this approximation step is to speed up the convergence in the iterative active contour algorithm, which is based on the replacement of a randomly chosen node of the polygon.

Active Contour Methodology: Assume that the observed scene $\vec{s} = \{s(x, y) \mid (x, y) \in [1, N_x] \times [1, N_y]\}$ is composed of two regions; the flooded region or target region $\Omega_t = \{(x, y) \mid w(x, y) = 1\}$ and the background region $\Omega_b = \{(x, y) \mid w(x, y) = 0\}$, where w denotes a binary window function that defines the shape of the target object to be found. This means that $w(x, y)$ is equal to one for a pixel (x, y) within the target and zero elsewhere. The purpose of the segmentation is now to estimate the most likely shape of W corresponding with the target in the scene. A polygonal shape W is chosen such that the log-likelihood function is maximized where t and b are the parameters of the characterized probability density function for respectively the target and background regions. Under the assumption that the probability density functions for the target and the background region are Gaussian distributed with $\vec{\mu}_t = (\mu_t, \sigma_t^2)$ and $\vec{\mu}_b = (\mu_b, \sigma_b^2)$, representing the mean and variance from respectively the target

and background region. The maximization of the log-likelihood function can be represented by:

$$J(\vec{w}, \vec{s}) = N_t(\vec{w}) \log(\hat{\sigma}_t(\vec{w})) - N_b(\vec{w}) \log(\hat{\sigma}_b(\vec{w}))$$

where only the relevant window dependent terms are mentioned.

Regularization of the contour: In the formalism described above the minimization of $J(w, s)$ corresponds with one specific inundation defined as the interior of a polygon. This polygon is characterized by a finite number of nodes. Remark that this resulting polygon can have sharp and very discontinuous boundaries. Since this is not favourable for inundated regions the following regularization term U_{in} , based on the elastic energy used in the classical snake models, is added to the previous equation:

$$J'(\vec{w}, \vec{s}, \lambda) = (1 - \lambda)J(\vec{w}, \vec{s}) + \lambda U_{in}$$

Here λ (defined between 0 and 1) represents a parameter, which allows one to balance between the internal and external energy. The internal energy U_{in} is defined as:

$$U_{in} = \sum_{i=1}^N d_i^2$$

where d_i represents the distance between node number i and the center of the segment defined by node $i-1$ and node $i+1$. N defines the number of nodes of the polygon. By putting $\lambda=0$, no regularization is taken into account.

Iterative Minimization Procedure: The minimization of $J'(\vec{w}, \vec{s}, \lambda)$ is performed using a stochastic iterative algorithm which has been described in [4] and consists of iterating the following steps:

- 1 Calculate the energy $J'(\vec{w}, \vec{s}, \lambda)$ on the basis of the initial/present polygon.
 - 1.1 Choose randomly one node of the polygon and replace it randomly over a pixel distance Δ_{L1x} and Δ_{L1y} . Here Δ_{L1x} and Δ_{L1y} are integers randomly chosen between $[-\Delta_{L1}, \Delta_{L1}]$, with $\Delta_{L1} \in \mathbb{N}^0$ a fixed parameter.
 - 1.2 Accept the replacement if it has lowered the energy $J'(\vec{w}, \vec{s}, \lambda)$, replace it back otherwise.
 - 1.3 Test if the convergence criteria are reached. This convergence criteria depends on another fixed parameter N_{L1} representing the threshold number of unsuccessful node replacement tries. This means that the iterative procedure is stopped if the number of consecutive unsuccessful tries to replace a node reaches N_{L1} .
- 2 Add a node to the present polygon each time the distance between two consecutive nodes is bigger than $d_{Lj}^{\max} (j-1)$ with $j \in \{1, 2\}$ and restart at 1.

The final polygon is found after repeating the cycle mentioned above three times. Remark that the free parameters Δ_{L1} , N_{L1} , and λ_{L1} with $i \in \{1, 2, 3\}$ can vary from one Level i to another. The reason why nodes are added to the segmentation result of a certain level is simply to refine the final result. It is clear that a complex shape will never be described by a polygon with for instance only 4 nodes. Another important point in the algorithm is that the number of nodes added to the resulting polygon of a certain level depends of the resolution needed on the final image. Therefore two additional free parameter $d_{L1, 2}^{\max}$ and $d_{L2, 3}^{\max}$ were introduced, indicating that each time a node has to be added to the resulting

polygon of level 1, or 2, if the distance following a certain segment exceeds respectively d_{L1-2}^{\max} or d_{L2-3}^{\max} .

A summary of all free parameters, influencing the final result is given in table 1 with their corresponding values.

Parameter	Level 1		Level 2		Level 3
λ	0.35		0.35		0.4
Δ_{L_i}	10		8		5
N_{L_i}	500		1000		1500
d^{\max}		25		10	

Table I: Tuning parameters of the active contour algorithm with their corresponding values.

Subtraction of non-flooded from the flooded result: When the active contour algorithm is performed on the image taken during the flooded period and the one taken during the non-flooded period, both vectorized results are replaced on raster and subtracted from each other. This subtraction is performed such that only the flooded areas remain and not all kinds of permanent water bodies like lakes, canals, water sport areas, rivers,...

The disadvantage is that a reasonably recent image of a non-flooded period has to be available and that the whole active contour algorithm has to be performed once more over it. A zoom of the final flood result around the Schulen lake is shown in Fig. 4.

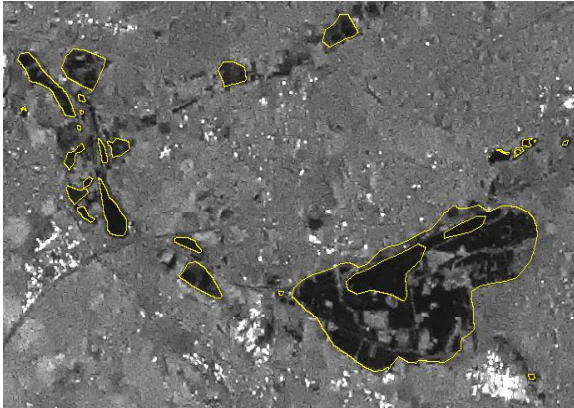


Fig. 4: Net flood result shown by the polygons on the ASAR image (Jan 2003) at the Schulens lake in Flanders using the Active Contour Algorithm.

Comparison both methods: When comparing the result obtained with the Object-Oriented Algorithm with that of the Active Contour Algorithm (Fig. 3 versus Fig. 4), one sees that the Object-Oriented algorithm typically delineates more precisely the black regions in the image, while the Active Contour algorithm tends to find the biggest region keeping the variance in color low. This means that both results are supplementary since the first method detects essentially only the water areas while the second method also tolerates for instance water areas with some structure in it, like trees, bushes, etc...

5. GEO-PORTAL

The geo-portal website ‘Geo-Vlaanderen’ is an existing website that has been developed and made operational by the support center GIS-Flanders. This website provides an interactive and dynamic way of informing a broad public about existing geo-

referenced governmental thematic data. From this site different thematic geo-portals can be consulted. Currently existing and fully operational thematic geo-portals are for instance the geo-portal ‘protected landscapes’, the geo-portal ‘regional zoning map’, the geo-portal ‘streets of Flanders’, the geo-portal ‘geographical statistics’, the geo-portal ‘nature areas’... A thematic geo-portal ‘flooded areas’ is now under development.

Once the flooded areas are extracted from the ENVISAT image, the delineations of the flooded areas can be put on the geoportal website ‘Geo-Vlaanderen’ on the internet so that local water managers can manually add some additional information (e.g. depth of water, source of flooding, date of flooding, photos, ...) for a certain location to the inundation database.

The website Geo-Vlaanderen can be consulted on <http://www.gisvlaanderen.be/geo-Vlaanderen>.

6. CONCLUSIONS AND PERSPECTIVES

The object-oriented method based on eCognition and the active contour method, both are capable of finding, on an automatic basis, the delineations of the floods. The complementary between both methods will be further investigated.

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8. REFERENCES

- [1] A. Pizurica, W. Philips, I. Lemahieu and M. Achery, ‘Despeckling sar images using wavelets and a new class of adaptive shrinkage estimators’, in *Proc. IEEE Conf. On Image Proc. (ICIP)*, Thessaloniki, Greece, Oct 2001.
- [2] A. Pizurica, ‘Image Denoising using Wavelets and Spatial Context Modelling,’ PhD thesis, University of Ghent, Faculty of Applied Sciences, Department of Telecommunications and Information Processing, June 2002.
- [3] C. Chesnaud, P. Réfrégier and V. Boulet, ‘Statistical Region Snake-Based Segmentation Adapted to Different Physical Noise Models’, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 21, No. 11, pp. 1145-1157, Nov 1999.
- [4] O. Germain and P. Réfrégier, ‘Optimal snake-based segmentation of a random luminance target on a spatially disjoint background’. *Optical letters*, vol. 2, pp. 1845-1847, 1996.