THE APPLICATION OF ACTIVE CONTOURS FOR THE LOCALIZATION OF VARYING-CONTRAST EDGES IN SYNTHETIC APERTURE RADAR IMAGES

Benjamin Seppke and Leonie Dreschler-Fischer

University of Hamburg, MIN-Faculty, Department of Informatics,
Cognitive Systems Laboratory
Vogt-Kölln-Str 30
D-22527 Hamburg
Germany

Email: {seppke;dreschler}@informatik.uni-hamburg.de

ABSTRACT

Over the last years, active contour methods have become a basic tool in computer vision. They have proven to be efficient for various image processing applications, like reconstruction of the edges inside images or the tracing of image features. However, when applying the basic snake technique to synthetic aperture radar (SAR) remote sensing images, the reconstruction of edges may not be satisfying. This is caused by the special imaging technique of SAR that may tend to produce varying-contrast edges and the commonly known speckle noise.

In [4] we proposed the use of asymmetric external energy terms to cope these problems. In this paper we will summarize the lessons learned in the previous work, where we applied the technique to detect edges of tidal creeks using an ENVISAT ASAR image. These creeks can e.g. be found in the UNESCO World Heritage Site ”Wadden Sea” located at the German Bight (North Sea). In addition, we describe the challenges and opportunities that could be achieved when using hi-resolution TerraSAR-X data instead of the ASAR data. We have just applied for some TerraSAR-X hi-resolution images and are looking forward to practically demonstrate the advantages for this special class of images.

1. INTRODUCTION

Active contour algorithms can be seen as a model-based segmentation approach. Contrary to commonly known pixel-based approaches, they provide an efficient tool for the localization and tracking of linear features at a sub-pixel accuracy. The can be defined as parametric curves that move within an image during defined energies at an optimization process. This behavior may be the reason for their synonym: “snake”. The energies are usually defined such that the snake will iteratively fit to image edges or other features of interest inside the image during the optimization process (see [2]).

The aim of this work is to accurately localize the tidal creek shorelines in synthetic aperture radar (SAR) imagery of the German UNESCO Heritage Site “Wadden Sea”. In the ENIVSAT ASAR image we used, the edge of the tidal creek is formed by a homogeneously imaged water surface on one hand and a heterogeneous silt surface on the other hand. Thus, we cannot use common edge detectors like the canny edge detector or texture based methods (cf. [3]). Moreover, the structure of these edges does not allow for the use of classical SAR shoreline detection algorithms due to the strong speckle noise along the edges of varying-contrast (see [5]).

According to their definition, snakes are capable to bridge those gaps in the image gradient information. This is achieved by an energy term, that favors smooth, connected curves and thus penalizes to much bending. In past research, we have found that the energy definitions that have been used widely for the localization of edges did not seem to be adequate for the localization of varying contrast edges in SAR images. Thus, we introduced a new asymmetric external energy definition for the snakes in [4].

1.1. Region of interest

The UNESCO world heritage “German Wadden Sea” is an intertidal flat area located at the German Bight (North Sea). The task presented herein is the accurate localization of tidal creek shorelines in the Wadden Sea using space borne

SAR images. Thus, the main question is: What characterizes such shorelines in a SAR image and how can they be localized?

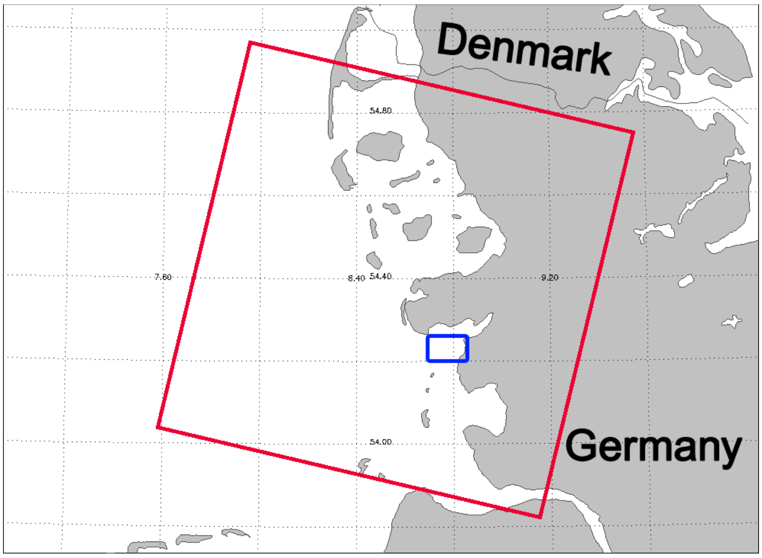


Figure 1: The large red region denotes the complete SAR image taken by the ENVISAT ASAR sensor. The smaller blue region is the ROI, where we applied the algorithm.

The intertidal flat area of the “German Wadden Sea” is interesting in many aspects and for various kinds of researches. As the interactions of land and water are very strong during each tidal cycle, a highly branched system of tidal creeks is evolving and spreading through the entire landscape. These creeks have been carved by the water and turn this area into a very dangerous place for hikers. When the water comes back, hikers can be trapped on a piece of land or get drown. Additionally the exact position is very important for boats and ships inside this area.

1.2. Image data

We will now present some results obtained using snakes with an asymmetric energy term on a SAR image. The image was captured by the ASAR sensor aboard the ENVISAT satellite in October 2007 covering an area of approx. $105 \times 105\,km^2$ (see Fig. 1). Further information about the image properties can be found in Tab. 1.

Platform and Sensor	ENVISAT ASAR (C-Band)
Sensor	ASAR (C-Band)
Acquisition Mode	Image Mode
Date and Time	2007/10/18 09:55 UTC
Polarization	VV
Incidence Angle	22.5°

Table 1: Satellite sensor and image acquisition information for the used data.

The image was taken during low-tide, showing some dry fallen areas in front of the coastline. These areas appear heterogenous compared to the surrounding water surface (see Fig. 2). This heterogeneity may be caused by various sources, e.g. wind- and wind-water interactions, incidence angle and direction. In addition, we notice that strong speckle noise is affecting nearly all edges. Thus, the signatures from the radar backscatter are hard to interpret, even for domain experts. In general, SAR images can provide valuable information about mainly cloud covered areas, like the German Bight.

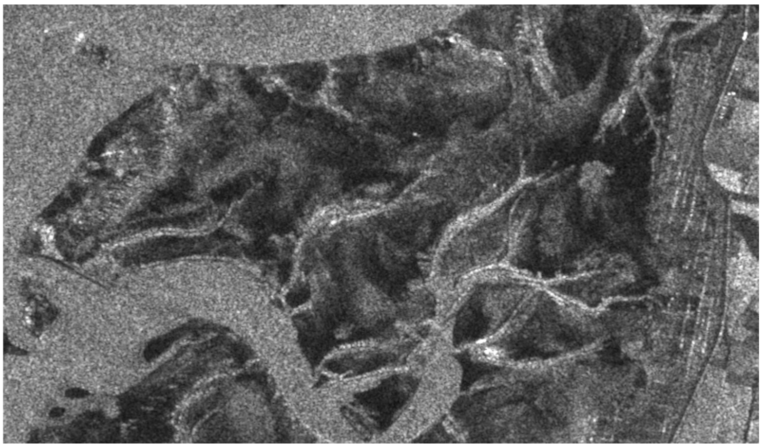


Figure 2: The ROI of the ENVISAT ASAR image. Darker patches denote dry-fallen areas, whereas (noisy) light gray areas denote the surrounding water.

2. ACTIVE CONTOURS

Active Contours or snakes are a common tool for the modeling, localization and tracking of contours in computer vision research. The following definitions are according to [4] but have been summarized for this paper. We start with the definition of an active contour by a parametric curve:

$$\vec{s}(p)=[x(p), y(p)] \quad \text{with} \quad p\in[0,1] \tag{1}$$

For the implementation, we used a B-Spline approximation of the parametric curve defined above. This approximation has some advantages over other methods (see [1]). Complementary to the parametric curve, an energy functional is defined:

$$E(s)=\int_0^1 E_i(p)+E_e(p)dp\ , \tag{2}$$

where E_i is the internal energy of the snake itself and E_e denotes the external energy that is determined solely by the image. This functional is usually minimized iteratively, which results in a contour, that refers best to the image edge of interest.The minimization of both parts along the curve causes the snake to move with respect to certain shape- and image constraints at the same time. The role of the different energy parts is described in the following two subsections.

Besides this brief introduction, further basics of modeling snakes can be found in [2]. In the current implementation, the optimization algorithm of the snake is based on a multi-resolution coarse to fine gradient back-step algorithm. The gradient is computed by a variation of the control points' coordinates and a recording of the change of the energy. Although this may be much slower than using a dedicated gradient calculation method, it is the most general approach possible and allows for easy adaption of other energy terms in our experimental setup.

2.1. Internal energy

The internal energy term represents the intrinsic energy of the snake. Hence, it does not depend on any image information. We propose to divide the internal energy E_i into two internal energy parts:

$$E_i=a_s E_s+a_c E_c \tag{3}$$

To weight the different energy terms against each other, there are two coefficients a_s, the spacing coefficient, and a_c, the linearity coefficient, which controls the strength of the curvature dependent term. The internal spacing energy E_s is given by:

$$E_s=\sum_{i=0}^{n-2}\left(\frac{|\vec{d}_i|}{l}-1\right)^2 \tag{4}$$

where the vectors $\vec{d}_i$ denote the differences between two neighbored control points $\vec{c}_{i+1}$ and $\vec{c}_i$. There are *n* control points, which yield $n-1$ difference vectors; *l* gives the goal length for the segments. This segment length is a parameter of the snake as well and may be set programmatically. By default it is set to the average segment length and is calculated only once during the snake's initialization.

$$l=\frac{\sum_{i=0}^{n-2}|\vec{d}_i|}{n-1} \tag{5}$$

Obviously, E_s will be zero if and only if all the segments have a length of *l*. E_s will approach $n-1$ if the snake shrinks to a point and will grow with the square of the length of the snake as it is stretched further and further. The curvature dependent term E_c is given by:

$$E_c=\sum_{i=0}^{n-3}\left(1-\frac{\vec{d}_i\cdot\vec{d}_{i+1}}{|\vec{d}_i||\vec{d}_{i+1}|}\right) \tag{6}$$

This energy will be in the range $[0,2(n-2)]$. A value of zero signals a straight line and the more the snake is bent the higher this energy becomes.

2.2. External energy

For the localization of varying-contrast boundaries in a SAR image, we propose the use of two different image dependent energy terms. The first one detects edges; the other one punishes differences in the image intensity on the waterside of the snake. The edge detector is the complement of the two dimensional Gaussian bell function differentiated in the *y*-direction (see Fig. [3]).

$$E_g=\sum_{i=0}^{n-1}\nabla I_s(\vec{s}(p_i))^2 \tag{7}$$

where $\nabla I_s(\vec{s}(p_i))$ denotes the image gradient perpendicular to the snake direction at position $\vec{s}(p_i)$.

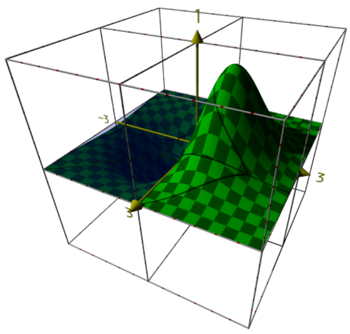


Figure 3: The kernel that is used to determine the image gradient based external energy.
The value at a kernels position is plotted at the *z*-axis.

This edge detector is applied to the image at all points of the snake and rotated to match the snake's direction. All filter responses are squared and summed up to obtain the edge related energy term E_g. This allows the snake to find dark/bright as well as bright/dark edges.

2.3. Asymmetric external energy term

In empirical studies we found that the squared gradient magnitude alone is not sufficient to determine boundaries of varying contrast in SAR images. The variation of the contrast along these edges is very heterogeneous. Therefore, we introduced a second external energy term in [4]:

$$E_v = \frac{1}{n-1} \sum_{i=0}^{n-1} \left(\nabla I_v(\vec{s}(p_i)) - \overline{\nabla I_v(\vec{s}(p_i))}\right)^2 \tag{8}$$

where $\nabla I_v(\vec{s}(p_i))$ is defined as the image convolved with the kernel k_v perpendicular to the snake direction at position $(\vec{p_i})$. The kernel k_v is the same where the image gradient is positive and it is set to zero otherwise (see Fig. 4).

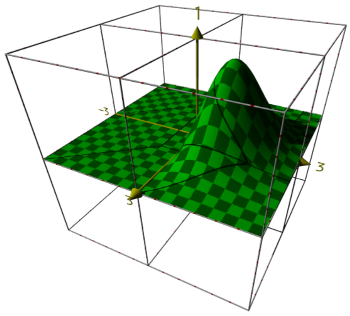


Figure 4: The kernel that is used to weight the variance of the image for the asymmetric energy term The value at a kernels position is plotted at the *z*-axis.

Thus its response is proportional to the image intensity of a small region on one side of the snake. Note that, instead of summing up the responses, we use their variance to determine the second energy term E_v. The rationale behind this is that water appears quite smooth in a SAR image since the wind and hence the waves do not change on a small scale. It follows that a strong variance of the intensities on the waterside is a sure sign that the snake does not follow an edge of a tidal creek. For the two image-related energies to be weighted a third parameter needs to be introduced: α sets the relative weight of the variance term in the image energy.

$$E_I = \alpha E_v + (1-\alpha) E_g \tag{9}$$

If α is set to zero, only the edge detecting energy will be used. Contrary, a value of one leads to a use of only the variance dependent term. In the later case it will not be likely to find an edge at all, but simply seek a featureless location.

3. RESULTS

Before running the algorithm, we manually set the initial control points of the snake. After this initialization, we start the algorithm with three different parameter sets. First, we set $\alpha = 0$:

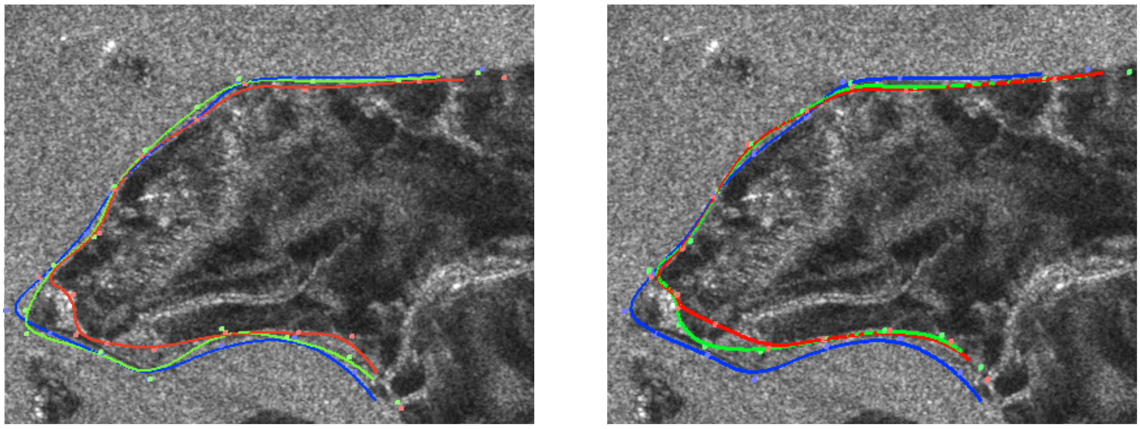
$$E = E_g + 500\, E_s + 500\, E_c\,, \tag{10}$$

which results in a snake optimization that is purely affected by the image's gradient magnitude and the internal snake energy. This case corresponds to the classical definition of a snake and is shown in Fig. 5 (left panel, red graph and right panel, green graph). For the second run, we set the parameter $\alpha = 0.9$, which leads to a combination of both external energy terms:

$$E = 0.9\, E_v + 0.1\, E_g + 500\, E_s + 500\, E_c \tag{11}$$

The result of this run is shown in Fig. 5 (left panel) in green color. We see a better approximation to the real tidal creek border. Note that it is hard to determine the real position of an edge of a tidal creek, although we assume that the dark areas in Fig. 5 all belong to dry-fallen areas and thus must not be crossed by edge detecting snakes. Additionally we selected a intermediate value of $\alpha = 0.5$ which results in the third test setting, where both external energy terms are weighted equally:

$$E = 0.5\, E_v + 0.5\, E_g + 500\, E_s + 500\, E_c \tag{12}$$

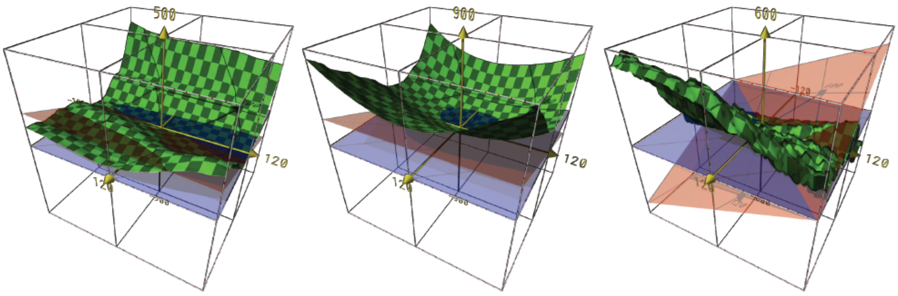


initial snake, α=0.0, α=0.9 *initial snake, α=0.5, α=0.0*

Figure 5: Results using the same initialization and different parameter settings.

4. CONCLUSIONS

Traditional snakes are a reliable base for contour localization. They can be extended to work on new image domains like SAR imagery. The analysis of complex "edges" may profit from asymmetric energy terms by means of localization results. We also performed empirically observation of the local energy distributions around control points (see Fig. 6). From the different distributions it can be observed that the right weighting choice determines the existence of local energy minima.



$a_S = 0, a_C = 0, \alpha = 1$ $a_S = 500, a_C = 500, \alpha = 0.9$ $a_S = 0, a_C = 0, \alpha = 0$

Figure 6: Local energy distributions at one control point for different parameter settings.

The first results look very promising, even when applied to non hi-resolution SAR data like the ENVISAT ASAR image presented herein. We hope for improvement of the results but are also estimating new challenges when working with TerraSAR-X very high-resolution data, e.g. provided by the new DTeddie project. Currently, we are extending our framework to allow for a knowledge based initialization of the snakes (e.g. by means of Electronic Nautical Charts) and for a better interpretation and understanding of the resulting contours.

For the future, we are planning several enhancements, like the implementation of faster optimization strategies and the combination with more higher knowledge about the imaged scene. We will also apply the algorithm on more ENVISAT ASAR images and on high-resolution TerraSAR-X data in future. Another issue will be the comparison with ground truth about the location of the tidal creeks' edges. The determination of such lines requires a lot of domain and remote sensing knowledge and thus has to be carried out by domain experts like oceanographers.

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