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Coastline extraction from SAR images and a method for the evaluation of the coastline precision

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Abstract

The coast area is a vital and highly dynamic environment whose multiple geophysical parameters are worth monitoring. At present the current coastline extraction operations made through high-resolution aerial images consist of the visual photo-interpretation. This performance, which mainly finds cartographic applications, is rather slow in comparison to the possibilities of remote sensing and image processing techniques.

The aim of this paper is to describe the development and testing of an innovative algorithm able to extract semi-automatically the coastline by means of remote sensed images.

The approach proposed is based on fuzzy connectivity concepts and takes into account the coherence measure extracted from an InSAR (Interferometric Synthetic Aperture Radar) couple. The method combines uniformity features and the averaged image that represents a simple way of facing textural characteristics. The results are then quantitatively evaluated through the comparison with optical aerial images. An automatic procedure is proposed for the evaluation of results, which makes use of distance measurements between the satellite and the aerial result, even though there is a considerable difference in space resolution.

Keywords: Interferometric synthetic aperture radar (InSAR); Coherence; Coastline detection; Segmentation; Fuzzy connectedness

1. Introduction

Monitoring the evolution of the coastline is an important task in several applications such as cartography and the environmental management of the entire coastal zone. The development of new and reliable algorithms for the automatic and semi-automatic extraction of this parameter is well accepted even if such algorithms are far from a current practical application. Such a task is usually performed manually by experts using photo-interpretation techniques. The paper describes the work performed for the development and testing of an innovative algorithm based on fuzzy connectivity concepts, able to extract semi-automatically the shoreline from remotely sensed images and to compare results derived from two different acquisition modalities. In particular the research

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activities have been focused on the exploitation of SAR (Synthetic Aperture Radar) interferometric images, this kind of data being particularly attractive for several reasons such as the possibility of acquisition regardless of weather conditions and future planned satellite missions with high spatial resolution SAR sensors. At the state of the art (Mason and Davenport, 1996; Lee and Jurkevich, 1990) several research studies have been performed for the extraction of the coastline from remotely sensed images. Most of them exploit methodologies and algorithms related to the grey-level feature of the images concerned. This is not always useful when considering SAR images because the sea is generally not characterised by uniform grey levels. The approach proposed considers that SAR images are characterised by a heavy textural information due to both backscatter properties and natural surface properties. In these images the sea shows a texture that is different from the land area.

An original aspect of the method proposed consists of the simple integration of different image parameters taking into account the coherence measure extracted from an InSAR (interferometric SAR) couple. Coherence information is always a powerful discriminant between land and sea. The simplicity of the method consists of the small number of parameters and thresholds values applied that, in contrast to other existing methods, originate an objective, robust, and repetitive method.

The proposed algorithm gives good results from satellite images that are evaluated by means of the other acquisition modalities, i.e. aerial optical photo-images. In addition, a method for the evaluation of the quality of the results obtained is proposed. The shoreline extracted from a high-resolution aerial image has been exploited as a reference to measure the precision of the results from SAR data. This has been possible even though there is a great difference in spatial resolution between the SAR and aerial images (i.e., 20 and 1 m, respectively). Finally, the evaluation of the results has been obtained by overlapping the coastline extracted from SAR on the aerial coastline, while taking into account some uncertainty within the extraction of the latter.

2. Previous work

The current coastline extraction method is the visual photo-interpretation of high-resolution aerial images. This task is mainly performed for cartographic applications. In particular, cartographic maps are developed at 1:5000 and 1:10,000 scales. The methodology exploited is composed of three main steps: the acquisition of data from aerial platforms, the geometric correction of such data to a map, and the ground checking of some points in the aerial images. These techniques require specific working tools and are affected by several errors, mainly derived from the manual interpretation and extraction of the coastline from the images acquired. Objective evaluation and repeatability represent two weak aspects of such a traditional approach, even though some uncertainty in the results is tolerated. As reported in the paper by Niedermeier et al. (2000), the error that is considered to be acceptable for governmental agencies maps on a beach slope of 1:100 is equivalent to 30 m in shoreline position.

In the past few years (e.g., Schwabisch et al., 1997; Lee and Jurkevich, 1990) the extraction of the shoreline has been an important research issue and many algorithms have been developed on the basis of different kinds of image processing methodologies. This because, as previously described, the current method is performed manually with high costs due to the high involvement of experts. Some methods have been proposed which rely on the region growing approach integrated with the output of edge detectors (Le Moigne and Tilton, 1995) or on the separation between textured and non-textured regions (Palmer and Petrou, 1997).

However, when dealing with SAR data, one has to face the problem of the presence of various textures in all image regions. The works presented by Mason and Davenport (1996) and by Niedermeier et al. (2000) have focused on the extraction of the coastline through SAR images. Mason and Davenport have developed a semi-automatic algorithm mainly aimed at the construction of a digital elevation model of an intertidal zone using SAR images and a hydrodynamic model output. Within this work a coarse to fine resolution processing approach has been employed in which sea regions are in the first instance detected as regions of low edge density in a low-resolution image; then image areas near the shoreline are subjected to a finer processing at a higher resolution using an active contour model. With the methodology described more than 90% of the shoreline appears to be visually correct, but no precise quantitative evaluation of the results is stated (Mason and Davenport, 1996). In addition, as stated in the paper, the authors "aim for higher (single-pixel) positional accuracy without necessarily extracting a continuous interface".

Referring to Niedermeier et al. (2000), a number of different methods is applied in a sequence with the possibility of manual intervention and a few post-processing steps. In this approach an edge-detection method suggested by Mallat and Hwang (1992) and Mallat and Zhong (1992) is first applied to SAR images to detect all edges above a certain threshold. A blocktracing algorithm then determines the boundary area between land and water. A refinement is then achieved by local edge selection in the coastal area and by propagation along wavelet scales. Finally, the refined edge segments are joined by an active-contour algorithm. In this case, the error is estimated by comparing the results achieved with a model based on visual inspection: the mean offset between the final edge and the model solution is estimated to be 2.5 pixels (Niedermeier et al., 2000).

In both cases, as a result of the number of steps applied, the number of the parameters and threshold values affecting processing robustness is considerable.

3. Dataset

The dataset used in the present work for the extraction of the coastline is composed of SAR images acquired by ERS-1 and ERS-2 in September 1995. Table 1 identifies the images.

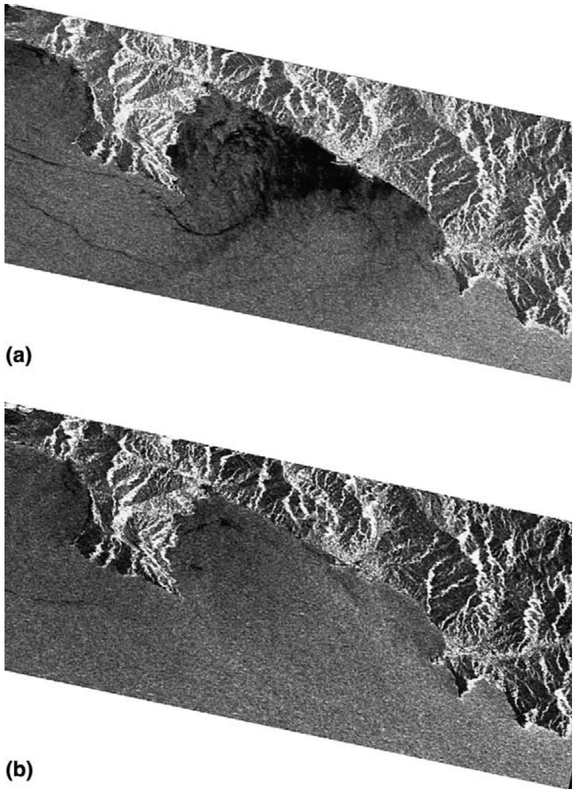

Fig. 1. SAR images acquired by ERS-1 and ERS-2 September 1995 representing the eastern Ligurian coast, near Genova, Italy.

Such images (Fig. 1a and b) are characterised by a spatial resolution of 20×20 m. Exploiting data with such a low resolution can be seen as a drawback, considering the fact that the aim of the research activities is to provide a valuable coastline extraction method for monitoring purposes. Moreover, traditional methodologies provide a much higher resolution compared to the SAR data. Nevertheless, the research activities have been focused on SAR images, as in the near future

Table 1
SAR images exploited for the extraction of the coastline

	Satellite	Date of acquisition	Baseline	Orbit	Frame/track
Master	ERS-1	11 September 1995	51 m	02066	2709-208
Slave	ERS-2	12 September 1995	51 m	21739	2709-208

Fig. 2. High-resolution images acquired from aerial platform during 1998 representing the eastern Ligurian Coast, near Genova, Italy.

satellites provided with a few meters resolution SAR sensors will be launched. In particular, COSMO SkyMed will provide high-resolution SAR data for marine applications especially for the Mediterranean Sea. As already mentioned, SAR data are attractive because they allow data acquisition regardless of weather conditions. This facility is particularly important for applications such as the coastline monitoring, as most relevant changes are related to bad weather conditions and sea storms. The high-resolution data (Fig. 2) used for the evaluation of the results have been acquired from an aerial platform during 1998. These images are in the visible spectrum and they are characterised by a spatial resolution of 1×1 m.

4. Methodology

The methodology proposed for the extraction of the coastline is based on an analysis of the remote sensing SAR data, taking textural and multitemporal aspects into account at a same time. In fact, image intensity and textural properties are both exploited with the feature of interferometric coherence derived from the correlation of the InSAR couple.

This method has the main steps shown in Fig. 3:

- a preliminary pre-processing for the extraction of the coherence image from the input InSAR couple;
- a second pre-processing step to face the presence of texture, that generates the homogeneous average image;
- a segmentation process applied in parallel to the coherence image and the average image, resulting in a weighted connectivity map that is thresholded to extract the coastline.

Registration of the SAR images and aerial photos is a preliminary step for the processing and the consequent comparison between the extracted shorelines.

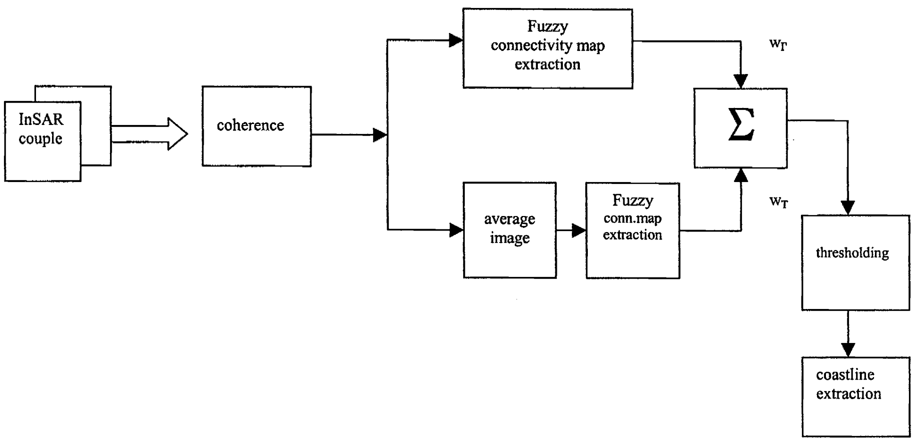

Fig. 3. Functional processing scheme.

4.1. Interferometric coherence image

The coherence image can be extracted from an InSAR couple of complex images I_1 and I_2 by applying the classical formula that involves the use of the statistical expectation operator (E):

$$\Gamma = \frac{E[I_1 \cdot I_2^*]}{\sqrt{E[|I_1|^2] \cdot E[|I_2|^2]}} \tag{1}$$

The coherence measure extracted for each image point p, $\Gamma(p)$, is particularly interesting within our scope, because it contains information concerning changes in the investigated area within a known period.

Earthview software (see reference) has been exploited to obtain such images as shown in Fig. 4.

As clearly shown in the image, the sea is characterised by a low level of coherence, due to its continuous changes. In order to obtain a correct coherence image it is necessary to exploit two different images properly registered; otherwise within the coherence image several regions could be characterised by low levels of coherence.

4.2. Pre-processing step

In order to define textures in an image we must describe the spatial variability of pixel grey levels within a predefined moving window centred on each pixel (Ulaby et al., 1986; Jain and Farrokhnia, 1991). Many techniques have been proposed in the literature for the characterisation of textures, one of the most widely used in remote sensing applications (Bruzzone et al., 1997; Baraldi and Parmigiani, 1995) being the computation of the *grey level co-occurrence matrix* (*GLCM*) (Haralick et al., 1973).

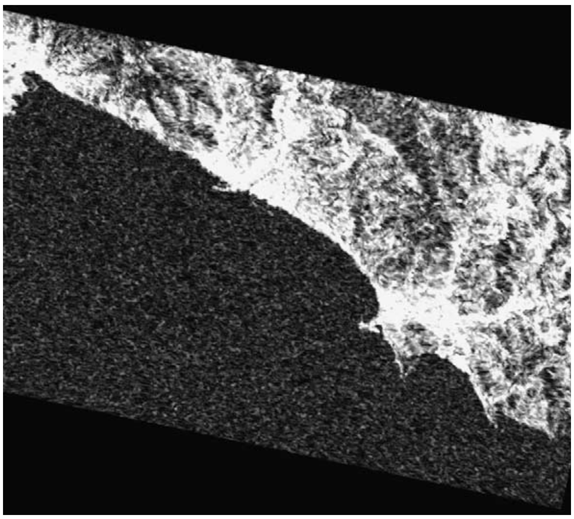

Fig. 4. Coherence image of SAR images.

The most well known GLCM features, for instance variance, energy, and contrast, have proved not to be so discriminant in the present case. On the contrary, the simple feature of local average, as computed at an appropriate window size, allows the generation of a feature image that is homogeneous in the sea land.

As a consequence, the second pre-processing step of the method—shown in the low branch of Fig. 3—consists of the extraction of the average image, by applying a simple moving average filter. For the current images the window size is fixed at 4 pixels so as to contain a satisfying number of pixels for statistical characterisation of the texture under analysis, that is, for the extraction of a homogeneous image.

4.3. Segmentation process for shoreline extraction

In the literature many semi-automatic or automatic segmentation techniques devoted to the extraction of regions of interest from various kinds of image sources, have been proposed and developed (Chen, 1999). In remote sensing applications a possible approach is the supervised one, in which a priori knowledge about class features is available before processing. The Markov random field (MRF) approach applies the Bayesian theory considering contextual information through the iterative analysis of local neighbourhood. It has been successfully applied in the SAR image analysis by Rignot and Chellappa (1991) and Smits and Dellepiane (1997) but it requires a high computational load.

Typical segmentation difficulties arise from the spatial heterogeneity of images and from the presence of high textural features due to both natural and acquisition properties. The methods described in the literature often tend to apply preor post-processing to improve segmentation results. This effort usually shows a drawback consisting of suppressing important fine details present in an image.

To face these fundamental problems we suggest that the theory of fuzzy sets proposed in the iso-contour method presented in (Dellepiane et al., 1996) should be adopted. In that case connectivity is exploited to consider spatial relationships between neighbouring pixels. Given a fuzzy field H describing the normalised intensity values $\eta(p)$ of each pixel p, the definition of fuzzy intensity-connectedness refers to a path $P(q,p)$, 8-connected path of points from a pixel q to a pixel p. We can define the degree of connectedness from q to p as the "*χ-connectivity*" or "*intensity-connectedness*" associated with a generic seed point a by applying the formula:

$$\mathrm{conn}(X^a, a, p) = \max_{P(a,p)} [\min_{z \in P(a,p)} X^a(z)] \tag{2}$$

The modified field X^a is extracted from the original field H by applying, with reference to the point a, the following:

$$X^a(p) = 1 - |\eta(p) - \eta(a)| \tag{3}$$

The approach proposed is a semi-interactive segmentation based on a seed-growing process. The growth starts from the seed point selected by the user as surely belonging to the object searched for. Then it follows the best paths in terms of connectivity, thus guaranteeing the extraction of a connected structure and of its fine details.

Due to the fuzzy nature of the algorithm, the final result is not hard but fuzzy. The final image, called the connectedness map, is characterised by membership values that indicate to what extent each pixel is connected to the seed point. This means that the user can easily choose the best result by thresholding the connectedness image.

The method is mainly data-driven and makes use of some information it can extract from the selected seed point. It could therefore be considered partially supervised.

In comparison with the traditional supervised maximum likelihood (ML) and minimum distance (MD) methods, the application of the isocontours method allows one to better locate objects of interest that are very heterogeneous, like the sea land.

Fig. 5. Segmentation result from the coherence image.

The use of the coherence image only does not allow the correct detection of the coastline, since the presence of the texture in the sea area is responsible for a too fragmented result, as one can appreciate in Fig. 5. On the other hand, the use of the average image only is responsible for the loss of important details. Fig. 6 shows such a result.

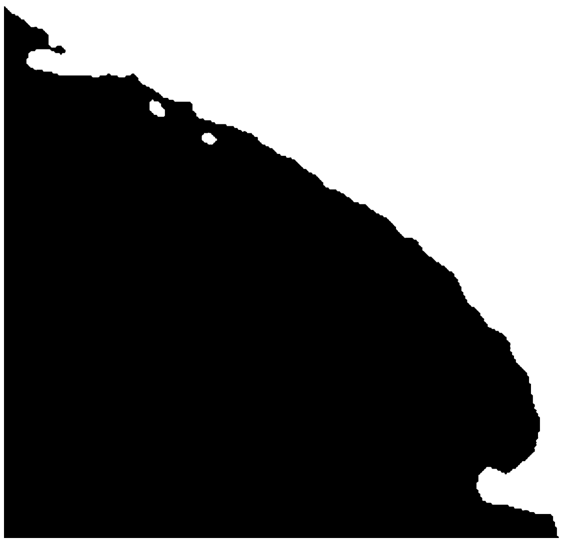

Fig. 6. Segmentation result from the average of coherence image.

Given the pre-processing and the filtering computation time, the proposed segmentation approach has a slightly higher price in terms of user interaction, as compared with the MRF approach, but a much faster computation time. A fuzzy connectivity map can be extracted starting both from the coherence image and from the averaged image. As in Fig. 3, the equation of the fuzzy connectivity (Eq. (2)) is applied to field connectedness, Γ, and to the average image, that plays the role of a texture image, namely field T, as indicated respectively by the upper branch and the second block of lower branch. The combination of the two information sources is made at a connectivity level. This allows us to apply a very simple weighted average by the following equation:

$$\begin{aligned}\mathrm{conn}_{\mathrm{weighted}}(p) &= W_\Gamma \cdot \mathrm{conn}(\Gamma, a, p)\\ &\quad + W_T \cdot \mathrm{conn}_T(T, a, p)\\ W_\Gamma, W_T &= (1 - W_\Gamma) \in [0, 1] \end{aligned} \tag{4}$$

where Γ and T means respectively *grey level* and *textural average*. At present, the proper values for weights W_Γ and W_T are predefined on the basis of experimental results, and remain the same for every pixel in the image.

Finally, a simple interactive thresholding step allows the identification of the most suitable threshold for extracting the coastline from the weighted connectivity map. During the threshold selection, a user-friendly interface helps the user. The method is a region-based approach, able to segment sea with respect to non-sea area. The final step of the coastline extraction shown in Fig. 3 is responsible for the extraction of the line from the region-segmented result.

The result shown in Figs. 7 and 8 refers to the combination of the two measurements, by means of Eq. (4). W_Γ and W_T values are 0.7 and 0.3, respectively. Computation time is about 1 s, on an image of 380×380 pixels, by using a Pentium III, 1 GHz, 1 GB RAM.

In the case of the aerial images, the extraction of the shoreline has also been carried out using the local average as a texture information. The results are presented in Figs. 9 and 10.

5. A method for the evaluation of the coastline precision

Even if it is not so precise, the extracted line from the aerial data can be considered as the real position of the shoreline, given that 1 m resolution is one order of magnitude finer than 20 m resolution (i.e., the resolution which defines SAR data).

The comparison of images with two different resolutions is not a trivial task as it is impossible to overlap the images without adapting them to each other. Therefore preprocessing of the aerial image has been carried out by sub-sampling it; in particular the initial information contained in the aerial image has been transposed to a new image with 20×20 m resolution. This operation has been performed preserving the geographical information of the whole image.

In order to evaluate quantitatively the results obtained, the selection of the best parameter which describes the differences between two lines is necessary. Such difference is well described by the mean offset between the two lines, although such a parameter is not enough to evaluate the overall quality of the results. It is therefore necessary to introduce an additional parameter in order to describe the variability of the distance between the two lines. This is due to the fact that two different results, each represented by an extracted coastline, may have the same mean offset with respect to the correct coastline but may differ greatly. For example, while one may be completely parallel to the correct coast, the other may not even be similar to it in the shape.

A specific module in IDL language has been implemented within ENVI (see reference) in order to perform the following steps:

- Extraction of a distance image from the resized aerial image;
- Normalisation [0,1] of the coastline extracted from the SAR images;
- Masking of the distance image with the normalised SAR coastline. In particular from this step, a line is obtained in which each pixel represents the distance between the two lines;

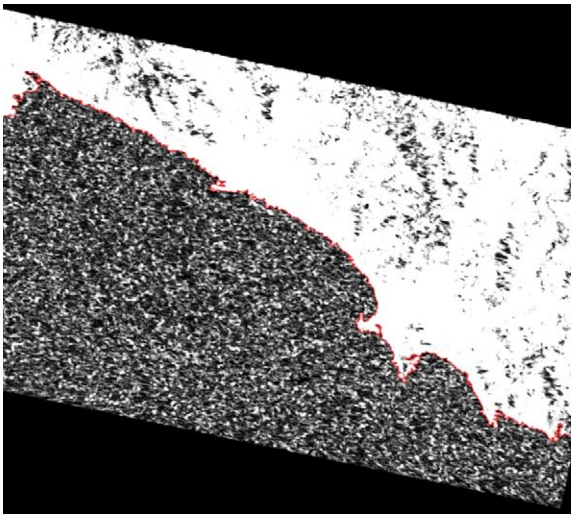

Fig. 7. Extracted coastline.

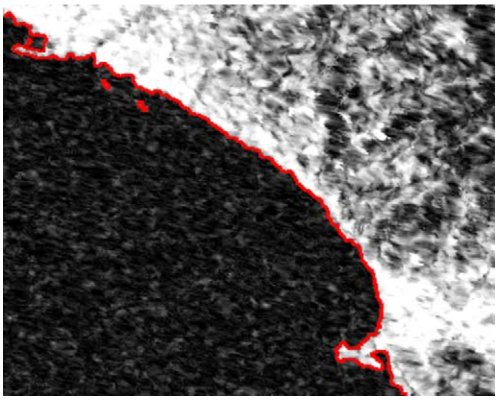

Fig. 8. Detail of the extracted coastline from the image in Fig. 7.

- Computing of the mean offset and standard deviation parameters for each of the pixels of the line derived from the previous masking.

Using this method, the evaluation of the results of the coastline extraction from SAR images has been carried out. The results of this evaluation process are shown in Figs. 11 and 12; in particular the result obtained along the sandy shoreline can be considered good as the values of the mean offset and standard deviation are low. In particular, the

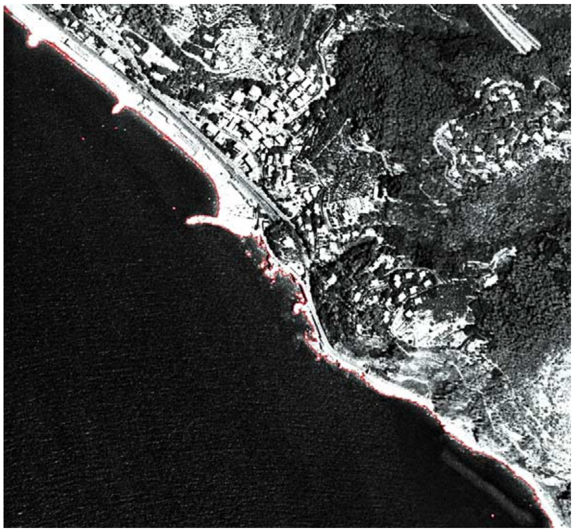

Fig. 9. Extracted coastline from the aerial image representing the eastern Ligurian coast, near Genova, Italy.

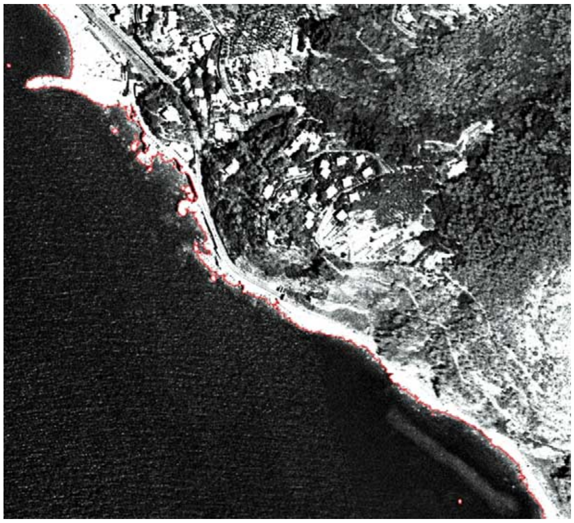

Fig. 10. Detail of the previous image, showing the extracted shoreline.

average error within this portion of territory (5.5 km long) is equal to 3.5 pixels, the variance is equal to 4.6, and the maximum value is 12 pixels. In other regions the algorithm fails in retrieving the exact position of the shoreline; this is due to

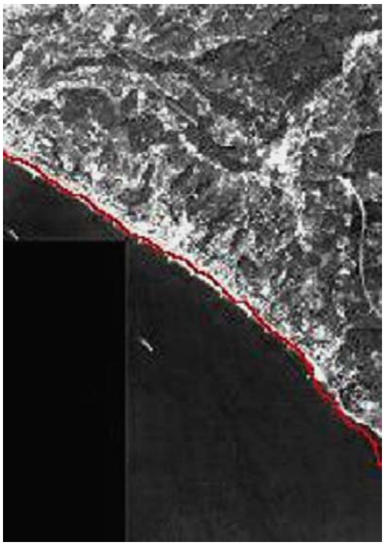

Fig. 11. Results obtained from the coherence image superimposed to the aerial image for the coastline characterised by the presence of sand and pebbles.

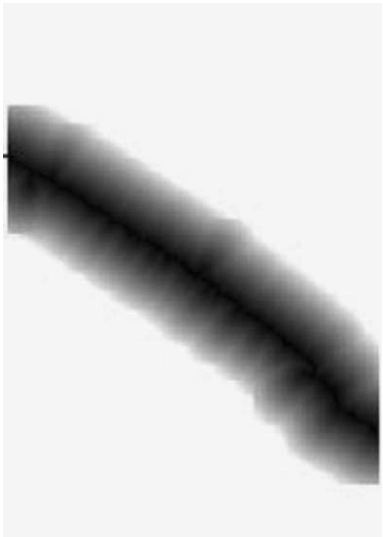

Fig. 12. Image of distance obtained from aerial image.

the fact that the coherence values of both land and sea are low. Nevertheless, the overall results obtained from the coherence image are quantitatively better than the ones obtained from the original SAR images. For this reason this derived image is preferred.

6. Conclusions

The work done has focused on the development and evaluation of an algorithm for the extraction of coastlines through SAR data and has proved that the coherence image represents a powerful feature in separating land and sea. The error evaluation is based on a model that has been derived semi-automatically from an aerial image, reducing in this way the subjective analysis that often occurs in the more traditional evaluation approach.

As previously demonstrated, the results obtained can be considered quantitatively promising, especially for portions of land where sand and pebbles are present on the coast. The evaluated error is comparable with the one reported by Niedermeier et al. (2000) (i.e., 3.5 pixels mean offset in our case, as compared with 2.5 pixels in their case). Let us consider that no paper takes into account the imprecision associated with the reference model. The model solution used by Niedermeier is based on visual inspection, and is extracted from a very smooth shoreline 'where both the algorithm and the human eye have difficulties determining the correct position of the coastal edge'.

On the other hand, the presented method relies on a fuzzy processing and on a trivial data combination. These aspects allow the method to consider the inaccuracy and reduces the dependence on threshold and parameter values as much as possible. As a result of this, the method is more robust and more likely to be automatic in comparison to the ones presented in the literature which apply complex sequences of carefully tuned algorithms.

Finally, an added value of the developed methodology is that the results do not depend on the spatial resolution of the data considered. Therefore, it can be presumed that the proposed methodology will be useful for monitoring the coastline when higher resolution data are available.

Acknowledgements

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