Coastline change-detection method using remote sensing satellite observation data

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Coastal zones are not only the fundaments for local economics based on trade, shipping and transport services, but also a source of food, energy, and resources. Apart from offering diverse opportunities for recreation and tourism, coastal zones provide protection against storms and other meteorological disturbances. Environmental information is also essential because of the direct influence on a country's maritime zones, which are territorial sea and exclusive economic zones. Keeping local communities and ecosystems healthy requires monitoring and assessing of all the vital changes of territorial sea and its baseline. The paper presents a method and a concept of a system that provides an efficient means of automatic analysis of spatial data provided by satellite observation systems (optical Landsat 8 and SAR Sentinel 1) in order to monitor, and detect, changes in the coastline. The proposed methodology is based on a set of algorithms that enable one to trace and detect changes in coastline shape, and eventual damage to marine infrastructure, such as breakwaters and harbours, relying on high resolution satellite observational products.

Keywords: coastal monitoring, SAR, Sentinel, Landsat, background subtraction, image processing

1. Introduction

Monitoring of shoreline changes is essential for coastal communities and economies. It is also a crucial concern in the context of the national border security, and ecosystem monitoring. The availability of high resolution satellite observational products from the European Space Agency (ESA) Sentinel satellite missions has increased the possibilities in the field of remote monitoring in such areas [1][2].

Remote sensing applications belong to numerous research fields; including physics, geology, oceanography, meteorology and climatology. The field of Earth observation has a wide range of data processing and analysis methods [3], which are used, among many other monitoring purposes [4][5], for detection of shoreline changes [6][7][8]. The proposed method of shoreline monitoring consists of shape and change-detection algorithms. Preliminary shoreline detection uses solutions from basic image processing, which are: thresholding, Gaussian and Sobel filters. Coastal zone change-detection uses a “Running Average” method of background subtraction [9] in satellite image sequences. The results were evaluated using radar Sentinel 1 (ESA) and optical Landsat 8 (NASA) data.

2. Radar S-1 SAR and Landsat 8 input data

Sentinel satellite missions are one of the most important ESA projects. They are a vital part of the Copernicus programme, whose goal is to provide a platform for complete Earth remote observation and monitoring of the environment. Each Sentinel mission focuses on a different type of satellite data [10] [11].

Sentinel-1 (S-1) mission consists of satellites equipped with synthetic aperture radar (SAR) data. The increase of virtual antenna size, and as a result the increase of data resolution is achieved by sending and receiving probing signals using a sensor on a moving platform. Since the system is equipped with active sensors, various surfaces deflect radar signals differently, depending on signal polarization, which is utilized in a wide range of detection algorithms. SAR sends probing signals with different polarizations, vertical (V) or horizontal (H) linear polarizations during transmit and receive, which results in obtaining VH, HV, VV and HH output datasets [1].

Each satellite is equipped with an SLC-C sensor, which is working in the microwave (radar) band. Radar waves are weather and day/night independent. Time of revisit to the same area is currently 12 days. SAR data used in this paper is from pre-processed Ground Range Detected (Level-1 GRD) product, in which data were projected on an Earth model, and radar speckle effect is minimised. As a result, it is more suitable for image processing and change-detection. GRD data were acquired in Interferometric Wide Swath mode (IW) and the ground resolution is 21m [12]. Images used as input data are shown in Fig. 1.

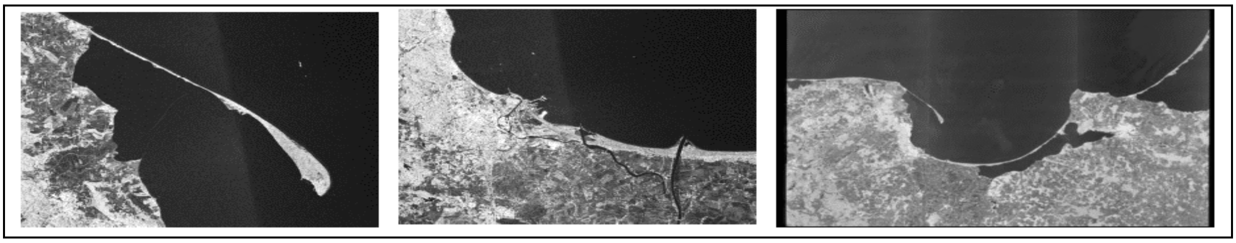

Fig. 1. SAR S-1 GRD images of Hel Peninsula, fragment of Gdansk and Northern Poland.

One of the main disadvantages of SAR data, comparing to optical data, is the radar speckle effect. It results in difficulties during image classification, and detection of features. It is caused by spatial variability of the adjacent pixels' brightness. Noise reduction is performed in order to improve radar images’ quality. These effects are minimised by averaging a number of signal samples, and image synthesis - the results of this process are shown in Fig. 2. It greatly improves the radiometric resolution at the expense of spatial resolution, and image features and edges are preserved [13] [14].

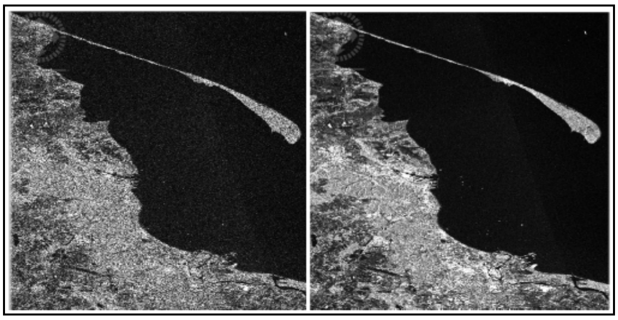

Fig. 2. Original SAR S-1 image with Hel Peninsula, Gdynia, Sopot and Gdansk before and after speckle effect minimisation.

Landsat 8 is the eighth satellite in the NASA, and the United States Geological Survey (USGS), Earth observation program. It is equipped with an Operational Land Imager (OLI) sensor, which works in the optical band. It is weather and day/night dependent, as seen in Fig. 3. The time of revisit is 16 days. Input data was acquired in band 8 panchromatic mode, with 15m ground resolution [15].

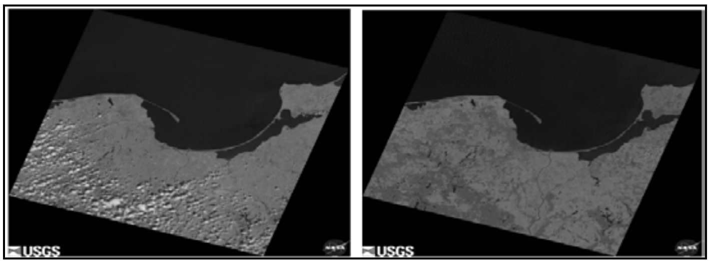

Fig. 3. Landsat 8 optical images of Northern Poland. Weather dependency visible on the first image.

3. Shoreline shape-detection using Sobel filter, Gaussian filter and thresholding

The preliminary processing is based on detection of a boundary line between land and sea on larger satellite image sets. It is based on a set of image filters. Firstly, input data must be processed properly in order to start the detection. Satellite photos and respective masks (in TIF format) must both be grayscale. The mask is used to exclude all the irrelevant elements, land and sea areas, which do not belong to the coastline. In the next step, the colour values of analysed area satellite image are normalised in the range of 0 to 255. It is then subjected to a thresholding (with selected colour values of 50-70) and a Gaussian filter (with matrix unit of 3x3 size) in order to sharpen the image. Sobel filtering is then used for basic edge (coastline shape) -detection. To highlight it even further, the subsequent thresholding is performed with a selected colour value of 180. This process detects all the pixels in the image which belong to the coastline. The scheme presenting the consecutive steps of this method is presented in Fig. 4.

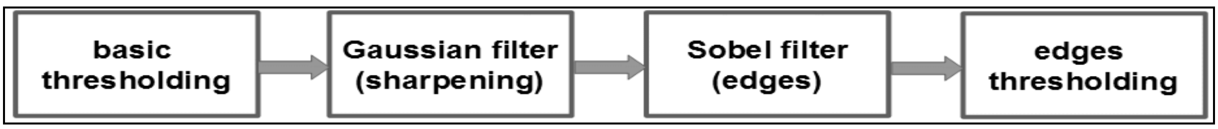

Fig. 4. Graph of preliminary coastline shape-detection using graphical filters.

4. Coastline change-detection using background subtraction

Detection of moving or changing objects in image sequences is a very significant part of image processing research. One of the most popular solutions in this field is background subtraction, which originated from detection of moving objects in video stream processing [16]. There are a few different algorithms for performing subtraction of the fixed background, and detection of changes in sequences of images. After subtracting the invariable background (or with minimal changes) of the image, the pixels that have changed throughout the succeeding images can be determined [17] [18]. This article presents the use of a background subtraction algorithm to detect changes in the sequence of satellite images of the analysed area.

Detection of changes in the coastline is achieved by analysis of the series of satellite images of the same area in 3-month intervals. Distinction between pixels, whose values have changed, and background (unchanged pixels) is implemented according to the Running Average (RA) method of background subtraction [9]. Throughout the sequence of images the comparison of successive images of the given area with the background image of the area (average of the unchanged pixels from previous dates) is made; in order to find which fragments of the area are subject to changes on the current and previous images. In order to find the pixels that were changed the following formula is used:

$$Fg_i(x,y) = \begin{cases} 1, & |F_i(x,y) - B_i(x,y)| > A \\ 0, & |F_i(x,y) - B_i(x,y)| < A \end{cases}$$

where:

Fg_i – *the table of the pixels that includes a change in the coastline,*

F_i – *the table of the pixels of the currently-analysed image,*

B_i – *the table of unchanged pixels (currently averaged background),*

A – *threshold value.*

The threshold value is the pixel colour value difference representing a substantial pixel change. If the difference of pixel colour value of the current image from the sequence, and the averaged background (from previous images) exceeds the threshold value, the pixel is marked as a pixel which includes a significant change in the coastline. Otherwise, this pixel is marked as invariable background, and is copied (using an averaging coefficient) into the averaged background, which is done in the second step, by using the formula:

$$B_i(x,y) = \alpha \cdot F_i - {}_1(x,y) + (1-\alpha) \cdot B_i - {}_1(x,y)$$

where:

B_i – *the table of the unchanged pixels (currently-averaged background),*

B_{i-1} – *the table of previous values of the averaged background,*

F_{i-1} – *the table of pixels of the previously analysed (last) image,*

α – *averaging coefficient.*

When the averaging coefficient equals from 1% to 5%, the averaged background includes changes from previous images. If the coefficient equals 50% or more, the averaged background mainly includes differences from the last image. The graph of this method is presented in Fig. 5.

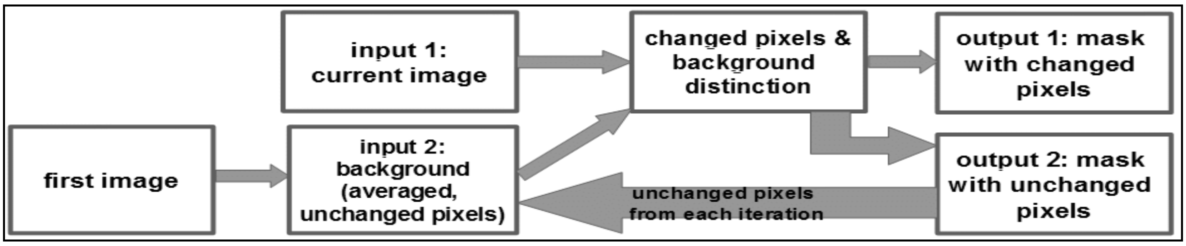

Fig. 5. Graph of coastline change-detection using background subtraction.

5. Results

Preliminary shoreline-detection was successfully implemented using a Sobel filter, a Gaussian filter, and the thresholding process. The results were used to detect visible substantial coastline changes during the preliminary area selection for background subtraction analysis. Selected results are shown in Fig. 6 and Fig. 7. Preliminary detection using the filters is more difficult when using SAR data, because of the speckle effect, and optical data is more suitable for this process (Fig. 8).

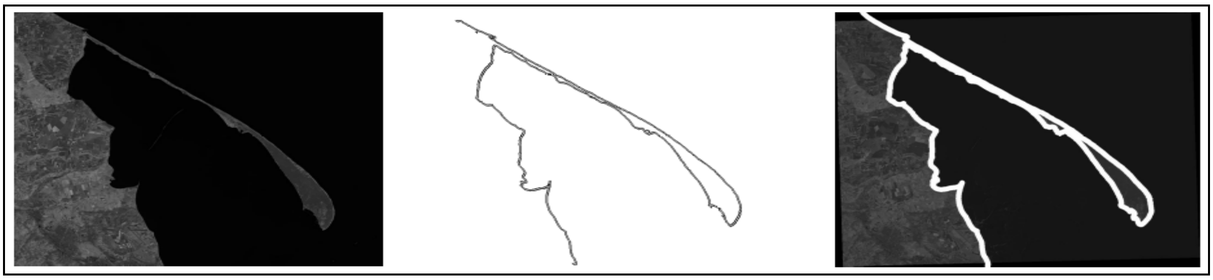

Fig. 6. Preliminary shoreline shape-detection results - Hel Peninsula.

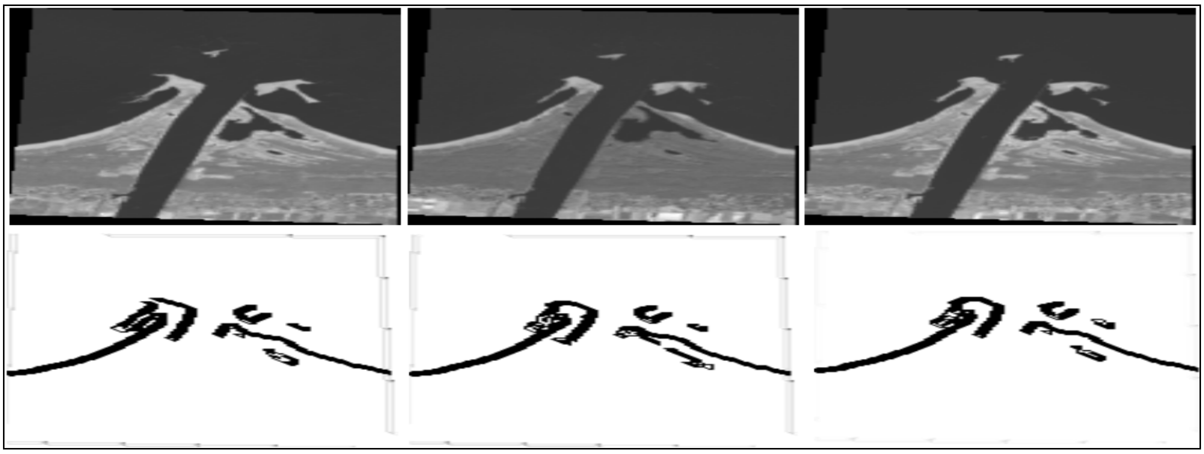

Fig. 7. Preliminary shoreline shape-detection results -Vistula river mouth on the Baltic coast.

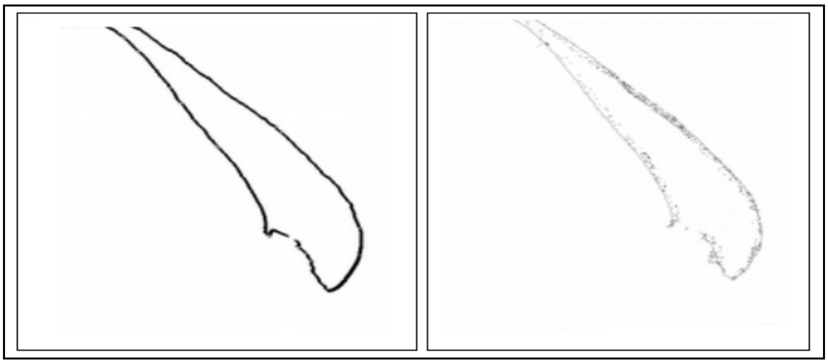

Fig. 8. Preliminary shoreline-detection using filters with optical and SAR input data – Hel Peninsula

More detailed detection of changes in the coastline is achieved by the implementation of the RA method of background subtraction. It successfully detected changes in the coastline, regardless of the light and weather conditions, when using SAR input data. Detection of changes using Landsat 8 data causes false detections, because of the weather and day/night data dependency. Results are shown in Fig. 9 and Fig. 10. In each figure, the first background subtraction result is from the first two images (left side) from the sequence, and the next two images (right side) result from the end of the sequence. It can be observed that, when the background is averaged from a few images, the detection of changes is more precise and detects lesser changes in the land, important changes are located along the coastline.

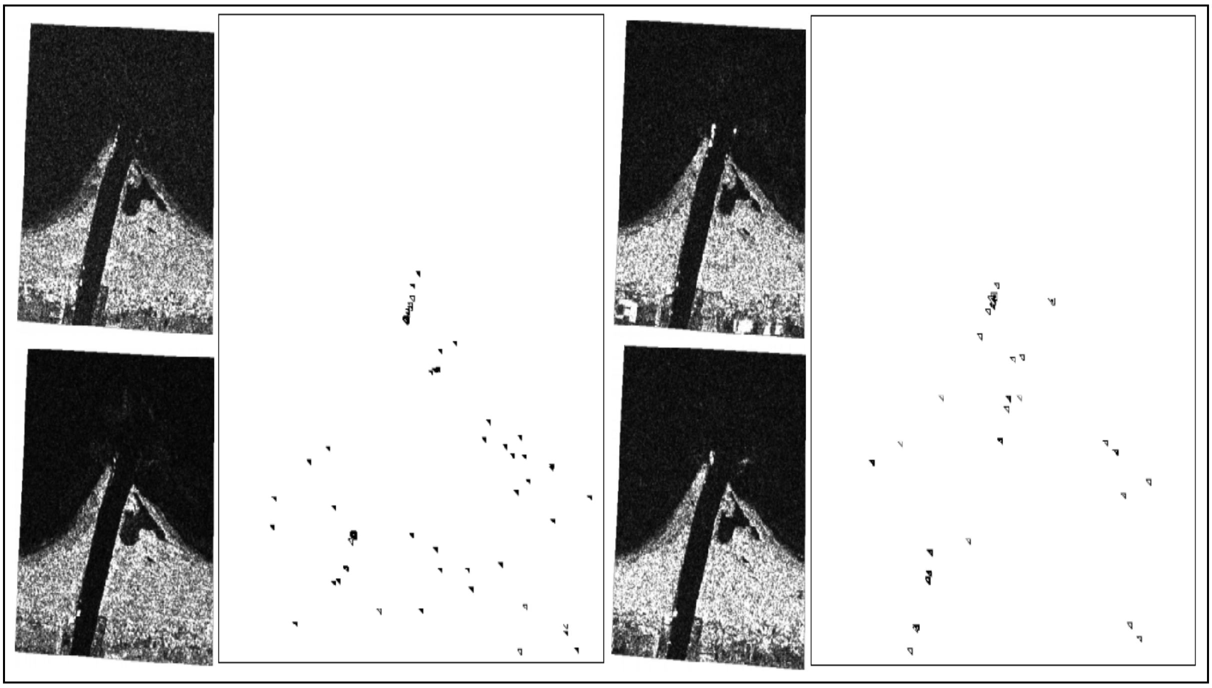

Fig. 9. Results of change-detection method using background subtraction – Vistula river mouth on the Baltic coast.

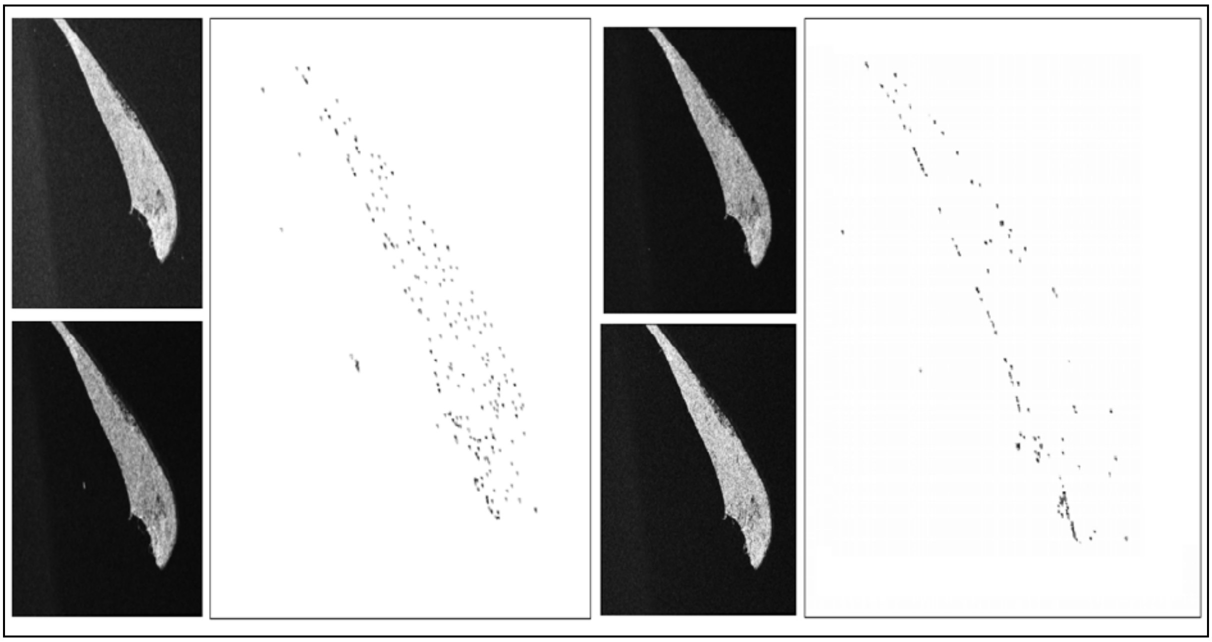

Fig. 10. Results of change-detection method using background subtraction – fragment of Hel Peninsula.

Background subtraction has been successfully used in detection of moving, or changing, objects in image sequences [19] [20], including satellite data [21] [22]. Presented results show that this technique is also applicable in detection of changes in SAR images.

6. Conclusions

Each type of satellite data, optical or radar, proved effective for achieving different detection goals in coastline remote monitoring. Optical data are not subjected to speckle effect, so as a result this kind of data is more suitable for shape-detection, but the optical data availability is significantly limited because of the weather and light dependency. This dependency also results in false detections of changes in the background subtraction process.

SAR data speckle effect caused difficulties in shape-detection, but because of the weather and day/night independence of radar data, it proved more effective as input data in change-detection analysis.

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