WEAKLY SUPERVISED IMAGE SEGMENTATION: APPLICATION TO MAPPING AND MONITORING OF SALT MARSH VEGETATION IN THE MONT-SAINT-MICHEL BAY FROM HIGH RESOLUTION IMAGERY

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ABSTRACT

Quantitative information about shoreline position is fundamental for coastal resource management and environmental monitoring. Land planners are interested on up-to-date coastline information for managing human activities, for inventorying natural resources, for delineating areas exposed to coastal hazards. The automatic acquisition of this information is complex, difficult and time consuming when using traditional ground survey techniques. It is also highly dependent on the morphological characteristics of the coastline. Rapid and replicable techniques are required to monitor coastline retreat or aggradation and update coastline maps. In this paper, we propose a user-friendly image segmentation method, which needs only a low intervention from the expert to drive the segmentation process, and to easily adapt it to the coastal environment under study. We illustrate the performance of this segmentation tool by using it to map and monitor the extension of the salt marsh vegetation formation in the tidal zone of the Mont-Saint-Michel Bay, which is the European coastal system experiencing the highest tides.

***Index Terms*—** Image segmentation, Weak supervision, High resolution optical imagery, Coastline extraction, Salt Marsh vegetation monitoring, Mont-Saint-Michel Bay

1. INTRODUCTION

Quantitative information about shoreline position is fundamental for coastal resource management and environmental monitoring. Land planners are interested on up-to-date coastline information for managing human activities (settlements and roads, recreational resorts), for inventorying natural resources, for delineating areas exposed to coastal hazards [1].

The automatic acquisition of this information is complex, difficult and time consuming when using traditional ground survey techniques. It is also highly dependent on the morphological characteristics of the coastline (sandy beaches, rock cliffs, etc) [2]. Rapid and replicable techniques are required to monitor coastline retreat or aggradation and update coastline maps. Thus we propose in this paper a new image segmentation method, which is not fully automatic but rather relies on a low intervention of the expert to drive the segmentation process. This method takes benefit from both the marker-based watershed transform (a standard image segmentation method from the mathematical morphology framework) and a supervised pixel classification. The user inputs only consists of some spatial and spectral samples which are defined depending on the coastal environment to be monitored.

2. STUDY SITE AND DATA SOURCE

We considere here as a case study the Mont-Saint-Michel Bay (Normandy, France), which is the European coastal system experiencing the highest tidal range (approximately 15m) because of its geological, geomorphological and hydrodynamical contexts at the estuary of the Couesnon, Sée and Sélune rivers. It is also an important touristic place with the location of the Mont-Saint-Michel Abbey, and an invaluable ecosystem of wetlands forming a transition between the sea and the land. Since 2006, engineering works are performed with the objective of restoring the maritime character of the Bay. These works will lead to many changes in the spatial dynamics of the Bay which can be monitored with two indicators: the sediment budget and the wetland vegetation (Fig. 1).

Multitemporal high resolution satellite images (Spot 4 and 5, Aster, Landsat) are used in order to analyse the development of salt marsh over the period 1996–2006 (Tab. 1). These images are acquired in low tide periods. The objective is to show how a weakly supervised segmentation method may help to highlight the extension of salt marshes.

3. METHOD

3.1. Marker-based watershed segmentation

The watershed transform is a very popular image segmentation method, as it is computationally efficient and does not

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require any parameter. However it has also some drawbacks, such as the sensitivity to noise and above all oversegmentation (i.e., where each object-of-interest is split in many meaningless regions). To counter these limits and to increase the accuracy and relevance of the results, it is possible to consider prior knowledge. This is most often achieved by providing number and positions of expected regions through the definition of some markers, thus resulting in the marker-based watershed [3]. In the following, we consider the flooding paradigm [4] to identify watershed lines: the image to be segmented is considered as a topographic surface f which is flooded from some initial locations defined by the set of markers M; dams are built to prevent merging water from different catchment basins in order to produce a segmentation map.

3.2. Spectral marker-based watershed segmentation

In the definition of the marker-based watershed given previously, only the spatial information brought by the set of markers is used. But when the expert defines a marker corresponding to an object-of-interest, it also provide a spectral knowledge which is worth being involved in the segmentation process. The new segmentation scheme is the following.

Let us first modify the definition of the markers, considering from now a collection $M = \{M_i\}_{1 \leq i \leq c}$ of c markers. Each individual marker is a set of points $M_i = \{p\}_{1 \leq p \leq n}$, thus resulting in either one or several connected components. These points may be characterized by various features (we rely here on spectral signature, but intensity, colour, or texture features may be also used). We associate to each marker M_i a class C_i and we apply then a given supervised (soft or fuzzy) pixel classification, using M_i as the learning set for the class C_i. The supervised classification procedure will return a set of probability values $\{w_i(p)\}$ where $w_i(p)$ represents the probability a pixel p would belong to the class i. From the content of a given marker M_i, we have then generated a new image w_i where high values represent pixels which most probably belong to M_i. To fit the watershed paradigm, we define the functions $f_i = (1 - w_i) \cdot f$ where pixels with high probability w_i will have their relative input surface f lowered whereas pixels with low probability will be kept unchanged.

The watershed algorithm (either standard or marker-based) relies on a grayscale image f. Here the supervised classification procedure results in a set of c images f_i. A standard way to combine these images is to compute a given norm (such as the euclidean norm) as in [5]. In the context of marker-based watershed segmentation, it is not necessary to merge all f_i images into a single one, and we rather consider a different image f_i for each marker M_i. So the usual algorithm [4] cannot be applied directly and should be adapted to our case. More precisely, we consider here that each catchment basin, initially defined from a given marker M_i, will grow relying mainly on the surface f_i built from M_i. Several topographic surfaces f_i will be involved only in case of borderline pixels which could be assigned to different catchment basins. In other words, each pixel p is given the label of the marker M_i (or catchment basin) which reaches it first (i.e., before the other markers or basins). See [6] for a more complete description of the algorithm. This segmentation algorithm is able to consider regions of heterogeneous spectral content if markers are adequately chosen by the user and well represent the regions to be segmented. A reliable result can then be achieved by integrating both spatial and spectral information and by taking into account the user knowledge, as shown in Sec. 4. Moreover, only a few markers are needed from the expert, thus we call this method *weakly supervised*.

3.3. Application to coastline extraction

The experimental setup for extracting coastline from high-resolution imagery is the following. First, the expert has to provide some markers (e.g. samples) for each object-if-interest he/she would like to delineate. We recall that markers are used both as spatial initialisations of the segmentation algorithm and as learning sets of the supervised fuzzy classification procedure. Thus markers have to be spectrally and spatially significant. To illustrate, Fig. 2 shows 5 markers of similar shape (squares of 10x10 pixels). The two first markers are associated to the tidal zone: M1 for the slikke and M2 for high reflectance zones representative of shell banks. The two following markers are associated to salt marshes: M3 for those with high level of chlorophyll, dense and reached only by highest tides; M4 for those on the pioneer line (lower density and but higher humidity). Finally, the last marker (M5) also denotes a salt marsh zone. It is set on the East part of the Couesnon and is needed since this area is not connected to the salt marsh area located on the West part of the Couesnon.

The computation time needed by the segmentation process is very low. To illustrate, with a baseline laptop and a Java implementation which could still be optimized, the average segmentation time for the multispectral images considered in this study varies from 200–300 to 1000–2000 milliseconds, depending on the spatial resolution (i.e., from 691$\times$192 pixels for Spot 20m to 1382$\times$384 pixels for Spot 10m). Thus it allows the user to interact with the system and to provide a more discriminative and/or complete set of markers if the result is not satisfying. Let us observe that the fuzzy supervised classification step is the actual bottleneck of the approach, and that the computation time may be decreased if the classification is performed on a subsampled image and membership maps are subsequently interpolated. The remaining parameters are the following: the classification algorithm in use is a 5 nearest neighbours (but any other classification algorithm may be used), and the gradient operator to be combined with membership maps is obtained after computing the euclidean norm of the morphological gradient applied marginally on each spectral band.

4. RESULTS AND DISCUSSION

4.1. Quantitative and qualitative evaluation

In order to evaluate the quality of the proposed method, we apply the same 3-step protocol for all types of images (Fig. 2): (1) the expert selects the markers depending on the objects to be identified (e.g., slikke, salt marsh); (2) based on these markers, the proposed segmentation method perform object extraction and delineation; (3) result is evaluated using qualitative and quantitative indicators.

The qualitative evaluation consists in comparing the detected coastline with a ground-truth reference digitized by a visual photo-interpretation. The quantitative assessment relies on a criterion measuring the shift (in pixels) between the reference and the extracted lines. This measure is then normalized by the length of the reference line to ensure invariance against coastline length and image size. Thus the measure may be interpreted as an average location error in each pixel. For instance, an error of 1 means that each detected pixel is (on average) only distant of one pixel from the ground-truth (corresponding to a distance of 20m if the spatial resolution of the image is 20m). Tab. 2 indicates a detection error equals of a half-pixel for images with a 20m spatial resolution (corresponding to a gap of 10 m between the detected line and the reference line). For satellite images with a finer spatial resolution (10 to 15 m), the average location error is higher but still lower than one pixel.

In summary, the proposed method allows to detect a line between the slikke and salt marshes with an error lower than one pixel on average. The qualitative evaluation allows to understand results more deeply and to locate the detection errors. The main errors are located near tidal stream or on the pioneer line characterized by scattered salt marsh patches. Indeed, in these areas spectral responses are confused with the slikke (mudflat). Thanks to the method accuracy (Fig. 2), a reliable multi-temporal analysis may be achieved.

4.2. Multi-temporal analysis

The multi-temporal analysis between 1986 and 2006 highlights that in 1986 where the study area is 5300 ha, salt marshes cover 34% and the mudflat (slikke) and the arable land represent respectively 47% and 19% of the area. In 2006, salt marshes represent 2200 ha. Then, in twenty years, salt marshes have increase in average of 19 ha/yr. Three periods can be identified (Fig. 3): (1) the 1986–2000 period characterized by an increase lower than the average (15 ha/yr) with a stability period from 1995; (2) the 2000–2002 period with a high development of salt marshes (66 ha/yr); and (3) the 2002–2006 period with a lower development of salt marshes (11 ha/yr).

The location of the salt marshes evolution allows to define accretion sectors and regression sectors. For instance, in the 2000-2002 period, some regression sectors are locally detected. The increase of salt marshes observed on the West sector is partly explained by the presence of shell banks. Highly dynamic sectors are also detected near the Mont with both regression sector near the Couesnon stream and accretion sector in the South.

5. CONCLUSION

In this paper, we have dealt with (semi-)automatic feature extraction from high resolution imagery. We have shown how a weakly supervised segmentation method, which asks the user to provide only a few markers, may be used to perform mapping and monitoring of salt marshes lines, thus helping to understand a dynamic and complex system such as the Mont-Saint-Michel Bay. This method is inspired from the standard marker-based watershed transform, but it also relies on spectral information brought by the user markers.

In the future, we will consider more advanced segmentation and classification schemes to improve the method accuracy and to offer a more efficient user interaction. In particular, we are planning to involve advanced machine learning strategies (e.g., active learning, semi-supervised learning, etc.). Indeed, is has been shown recently that machine learning may improve notably the performance of watershed-based segmentation [5]. Moreover, we think this method may be useful in a wide range of earth observation problems where a low user intervention is possible and expected, and we are currently looking for additional application cases.

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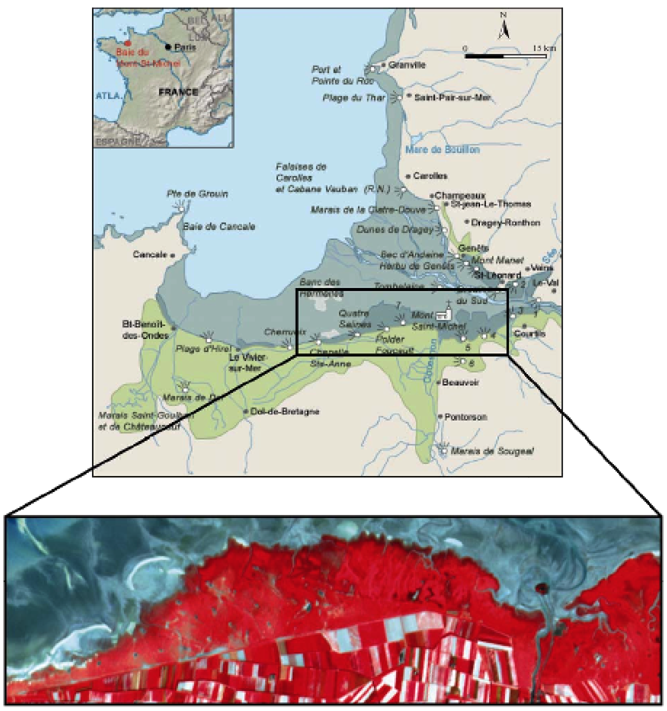

Fig. 1. Study zone

Sensor	Date	Image properties
Spot 1	09/06/1986	XS 20m (G – R – NIR)
Spot 3	28/08/1991	XS 20m (G – R – NIR)
Spot 3	22/08/1995	XS 20m (G – R – NIR)
Aster	07/04/2000	MS 15m (G – R – NIR)
Spot 5	24/09/2002	MS 10m (G – R – NIR)
Aster	09/09/2004	MS 15m (G – R – NIR)
Spot 4	20/09/2006	XS 20m (G – R – NIR)

Table 1. Satellite images available from the Ecosgil project (2005–2008).

Date	Average error (in pixels)	Spatial resolution (in meters)
09/06/1986	0.4	20m
28/08/1991	0.5	20m
22/08/1995	0.5	20m
07/04/2000	0.9	15m
24/09/2002	0.6	10m
09/09/2004	0.6	15m
20/09/2006	0.5	20m

Table 2. Quantitative evaluation of segmentation results.

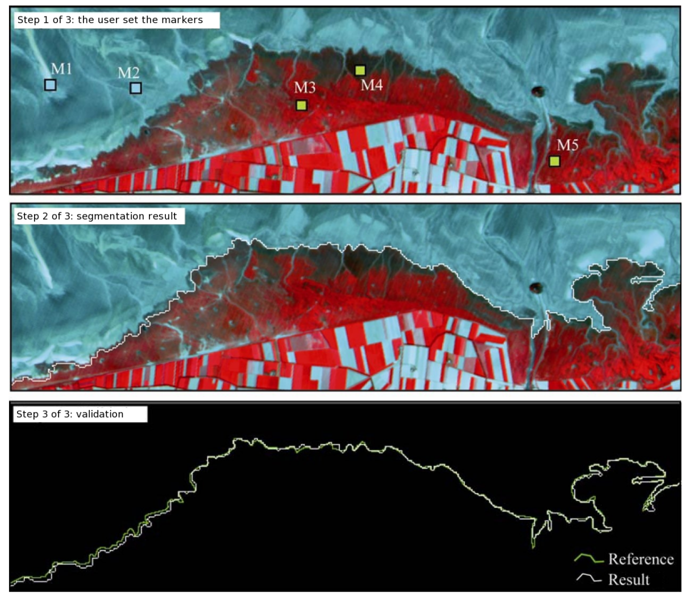

Fig. 2. Test protocol in 3 steps applied on satellite images between 1986 and 2006.

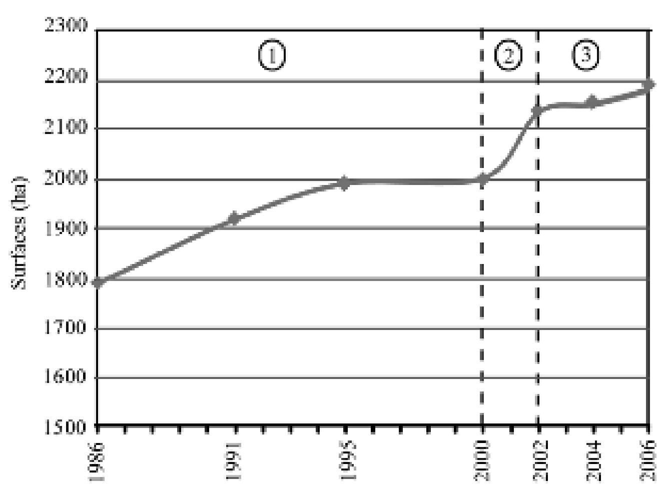

Fig. 3. Surface evolution of salt marsh vegetation between 1986 and 2006.