A methodology for water boundary detection using high-resolution remote camera images

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Abstract. A methodology to address hazards affecting coastal zones was developed, providing important information on the beach hydrodynamics and monitoring inundation events, using data from complex models and real-time sensors. Herein, we present our monitoring approach that uses remote camera images.

Keywords: camera, coastline, high-resolution, detection.

1. INTRODUCTION

Coastal flooding and overtopping due to a combination of energetic wave conditions, storm surges and spring-tide high water levels are one of the major hazards affecting coastal zones [1],[2]. A combination of real-time data, model predictions and risk indicators at each coastal stretch can be used to anticipate severe hazardous events, thus supporting effective and timely coastal management [3]. Better detection methodologies are still needed to process complex data and translate them into indicators of flooding and related issues that can be shared with end-users.

A methodology to quantify these hazards was developed [3], that consists in applying a cascade of numerical models and procedures to determine the offshore wave generation and propagation, the combined wave/circulation at an intermediate scale (10-100 km) and the hydro- and morphodynamics at the beach scale [4]. The offshore conditions are modelled with WW3 and SCHISM, the intermediate scale is modelled with SCHISM and the nearshore and beach with model XBEACH [4]. Real-time observations, field campaigns data and satellite data are then used to improve the daily forecasts of hydro- and morphodynamics.

The installation of remote monitoring cameras can improve coastal monitoring. On the beach, they provide real-time images to surfers and bathers about wave and rip current conditions, and additional information to external entities such as maritime police or civil protection. Herein, the cameras' images are used to detect several water boundary lines like the breaking waves line, the wet/dry interface line and the runup line. We demonstrate a new water lines detection approach using 4 MP remote camera images that enriches the information on the beach hydrodynamics and monitors inundation events.

2. COASTLINE DETECTION

2.1 Methodology and Results

The methodology consists in processing remote camera images using Python 3 (a scripting language), OpenCV (module for video and image analysis), numpy (mathematical module) and scikit-learn/scikit-image (modules for image processing and machine learning). The methodology follows three steps: 1) image averaging and masking, 2) lines extraction and 3) image rectification. The averaging procedure filters out the variability associated with wind waves, making the data readily comparable to phase-averaged wave models. Processing the images before their rectification is expected to minimize errors. This issue will be further investigated in the future by switching steps 1 and 3, and validating with field data.

First, images are averaged over 20 minutes intervals. The image bank is composed of all images obtained between 10 minutes before and 10 minutes after a specific time. Figure 1 illustrates an average image from the S. Pedro Moel camera, at daylight with a temporal resolution of 1 minute. Then, features that can complicate line detection are eliminated using a mask created by the user specifically for these images (Figure 2).

Secondly, we determine the wet/dry interface, the runup and the breaker lines (which indicate the position of submerged bars over which waves break). The RGB image is converted to the HSV (Hue-Saturation-Value) colorspace, and the K-Means algorithm is applied for image segmentation and feature classification (Figure 3). K-Means is an unsupervised machine learning algorithm that defines (randomly) the class' centroid values of each of the K clusters. Pixels are classified by calculating the difference of the centroid value with the pixel value, choosing the cluster class that has the nearest/smallest difference as the candidate, and iterating until the convergence of the cluster values. For the clustering, the color component(s) of the image must be specified a-priori, in this case Hue from HSV. In Python, images are arrays of values, each array representing a color component, and K-Means needs one array as input, so we choose the color components, and aggregate their arrays as input to run K-Means.

Extracting the water lines requires the determination of the K-Means classes on the image for wet sand, dry sand, water, and wave foam. These classes are used to define the corresponding boundary lines: two classes for the wet/dry boundary line (dry sand, wet sand); three classes for the runup line (wet sand, runup wave and runup middle); and one class for the breaker lines (wave foam). For each boundary detection, an image is generated with the chosen classes. To detect the wet/dry boundary and runup lines, we apply OpenCV's morphology to close loose pixels and the Canny algorithm as edge detection to generate the lines. To detect and distinguish the breaker lines, which use the same class, we define the corresponding areas on the image to indicate where to extract each one, and apply the skeletonize algorithm from scikit-image to generate them (Figure 3).

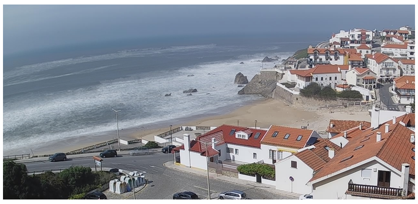

Figure 1. Average RGB image obtained on March 11, 2020, from S. Pedro Moel remote camera

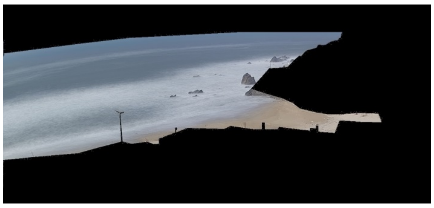

Figure 2. Average Image filtered with mask and applied K-Means in HSV colorspace

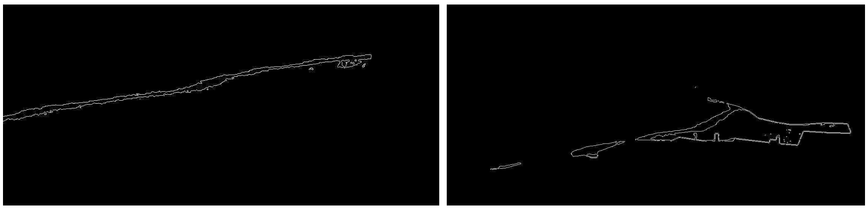

Figure 3. Images of detected breaker line (left) and wet/dry (right) boundary line

The last step consists in applying the undistortion and rectification algorithms of the images, using the software proposed in [5]. For that purpose, the camera was set up beforehand in a strategic position and angle to capture coastline and shoreline, and an in-situ calibration was performed with a checkerboard panel to determine and set the parameters on the software to correct the image distortion/skew.

3. CONCLUSIONS AND FUTURE WORK

The methodology proposed herein provides some encouraging results in a test case. Some problems arise with the K-Means algorithm and further efforts are necessary to fully automate the procedure. Choosing an adequate colorspace image and the correct color components for the K-Means clustering to classify the features correctly is a major challenge. The present method applies the HSV because it separates the Intensity (luminance) from the color information (chromaticity) [6]. K-Means was also found to be inconsistent in determining the classes for each image, two images will have different class numbers for a feature we want to use for extraction (for instance sand). This behavior complicates automatic detection. Possible solutions could involve using another clustering algorithm, such as KNN, with a fixed list of K classes and respective values, or using ISODATA [7] clustering, an iterative split-and-merge technique algorithm.

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