Small Scale Underwater Change Detection

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Abstract - *Automatically detecting changes between images is nowadays of common use in remote sensing. Change detection algorithms require highly accurate geometric and photometric registrations. For that reason, they have never been used with underwater imagery in the past. In this paper, we present a method to detecting changes in sequences of underwater images. First, the geometric registration is performed taking into account the relief of the seafloor, modeled using a structure from motion algorithm. Next, a new photometric registration technique is used. Once the images coming from different sequences are accurately registered, standard change detection algorithms are applied on each pair of images. Finally, all the change images are merged together in one single view.*

Keywords - *Change detection, underwater.*

I. INTRODUCTION

The study of benthic areas benefits from recent progress in underwater technology, allowing the deployment of optical cameras for systematic surveying. However, the underwater environment can significantly degrade the quality of the acquired images. Scattering effects and non-uniform lighting result in different intensity levels of the same scene point in the images. Moreover, because of the rapid attenuation of light and the scattering effects, the images have to be taken at short range, and the area of interest cannot generally be acquired in one single view. Therefore, it is necessary to acquire a sequence of images covering the interest area and stitch them into a common frame referred to as photo-mosaics to gain a global perspective of the sea floor. Unfortunately, acquiring images at short range also emphasizes the parallax effects of the 3D relief. Also, the source of artificial light in deep water or the sun flickering in shallow water makes the illumination of the scene non-uniform. These constraints are in opposition with the requisites of the change detection algorithms. Indeed, such algorithms require highly accurate geometric and photometric registrations [1, 4].

In this paper, we present a method to deal with the constraints of the underwater medium for automatically finding changes between sequences of underwater images. Several underwater application fields would benefit from automatic change detection, e.g., benthic habitat monitoring, deep water geological exploration, mapping of archaeological sites, supervision of geothermal and volcanic activities, or area monitoring after sudden impacts from natural or human activities.

II. METHODOLOGY

Our approach for change detection takes two images sequences as input. It comprises the following steps detailed in the rest of this section. A 3D model is constructed from one sequence. This model is used for accurate geometric registration of images between the two sequences. Once geometrically registered, the images are photometrically registered using a new method of local histogram matching. A standard change detection method is then applied. Finally, all detected changes are merged into one single view. Unfortunately, due to inaccuracies of the 3D model used for registering the images, some misalignments might appear between images. Changes are then detected in these areas where the scene could not be properly modeled. We developed a method that evaluate the precision of the 3D model in order to discard the changes detected over the areas where the model fails to be accurate.

A. Geometric Registration

Registering the images using a simple, flat model is not possible due to the important relief of the scene with respect to the altitude at which the images are acquired. Therefore, the 3D structure is estimated from a sequence of images, hereafter called *model sequence*, using Structure From Motion (SFM) [2]. The 3D structure is composed of a set of 3D vertices characterized by the local image descriptors resulting from feature tracking. SFM also estimates the poses of the camera with respect to this 3D structure.

The images that need to be compared with the model sequence are called *target images*. For each target image, the pose of the camera with respect to the estimated 3D structure needs to be computed. This is done by matching local image features with the 3D vertices through their descriptors. The textures of the model images are then projected on the 3D structure and new images are generated as seen from the point of view of the target images. This registers all the model images with each target image.

Sometimes, it might happen that there is too many small changes such as habitat growing that the descriptors of the same scene points between two sequences are too different to be matched. Also when the changes are present in a big part of the target image, it is not possible to match them with the model. A solution for finding the camera pose of target images that cannot be matched with the model is to match two 3D structures. A second model is generated from the target sequence. Both models are then matched using their descriptors and a joint optimization is performed on the two models to merge them. This gives the poses of all the target images with respect to the structure generated from the model sequence. The poses are more accurate when they are close to correspondences between the two structures. However, if they are far from correspondences, they are not as constrained in the optimization process and they might drift from their real positions. In this case, it is not possible to register the images and they are then discarded.

B. Photometric Registration

The different sequences are likely to have different illumination conditions and different sensor responses if they are acquired from different cameras. This results in different intensity values of the same scene points. A photometric matching technique is then needed to correct these differences.

A local histogram specification between the target image and its corresponding registered model images is applied. The histogram of a sub-window of the target image is extracted and this histogram is imposed in the same region of the registered model images. The sub-windows have overlapping areas in which a weighted average is computed to avoid abrupt changes between the tiles.

C. Change Detection

Change detection algorithms generally generate a change image that represents the quantification of changes for each pixel. As each target image is compared to several model images, different change images are generated. These change images are combined by averaging them. This combined change image is more representative of true changes than the individual ones. Effectively, some changes are triggered because of moving objects such as fishes or local misregistrations due to the inaccuracies of the 3D model. These kinds of changes are generally detected at different positions of the registered model images. Therefore, averaging the individual change images makes their contributions less important.

D. Mosaicing of changes

Generating a change image for each target images is already a big step in analyzing the data. It is easy to look at them and identify the changes in the target image. However, having a single view of the changes of the whole scene is easier and faster to analyze. As the 3D structure and the poses of the target images are known, the change images are projected on the 3D model and averaged in the areas where they are overlapping. This also increases the consistency of detected changes, as unwanted changes due to moving objects or misregistrations are generally detected in different parts of the target images.

E. Detection of model inaccuracies

The performance of our change detection technique depends on the accuracy of the 3D model. However, it is not possible to generate a perfect 3D model. Changes are detected in the areas where the scene was not properly modeled. Indeed, in these areas, the model images are not correctly registered with the target images. False changes are triggered and even if they are averaged with different change images, they might still have a big weight in the final mosaic of changes. The detection of these changes cannot be avoided, but the areas where the scene was not properly modeled can be detected.

The texture of model images are projected on the 3D structure and back-projected from the target pose in order to generate the registered model images. If the model is accurate, The registered model images look similar. If the model is not accurate, the texture of model images will be projected in wrong places. This means that where the model is not accurate, there is some displacement between the texture of the registered model images. The area where the model is not good are then detected by finding changes within the sequence of registered model images. These changes can also be merged in one single view of the whole area.

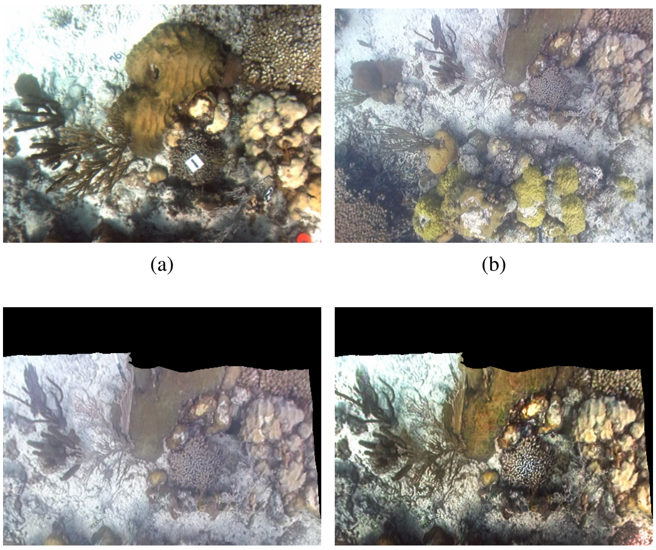
III. RESULTS

In order to test the method described in the previous section, two sequences of images from a coral reef were used. The sequences were acquired with different cameras and ten months apart. Both cameras were calibrated and the images were corrected for radial distortion. The scene presents an important 3D relief that produces parallax effects and makes it impossible to detect changes directly from 2D image alignment. Figure 1 shows one sample of model image registered geometrically and photometrically with a target image.

After applying the change detection algorithm, the individual changes images are merged to generate one change image per target image (see figure 2a). Also, changes are detected within the set of registered model image in order to estimate the accuracy of the 3D model. In figure 2b, it can be seen that the model is not accurate in the bottom left of the image. This is due to moving algae that could not be modeled since the SFM algorithm is only able to model rigid scenes.

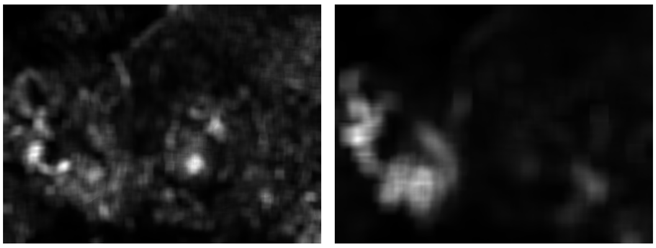
The area that are detected as changed are delimited by applying a threshold on the change images. A threshold is also applied to determine the areas not properly modeled. Figure 3 shows a target image and one of its registered model image. The areas that are detected as changed are outlined in red and the areas in which the model is not good are delimited in green.

When processing the whole sequence, very few target images would be matched with the 3D structure and therefore, we could not generate a single view of all the changes of the



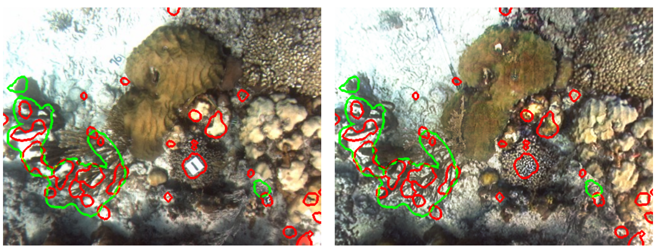
(a) (b) (c) (d)

Figure 1: One target image (a) and on of the model images (b). The model images is first registered geometrically (c) and then photometrically (d).



(a) (b)

Figure 2: The change image (a) corresponding to target image show in figure 1a and the corresponding model accuracy assessment (b)



(a) (b)

Figure 3: The target image (a) and one of its registered model image (b) with the changes detected outlined in red and the areas where changes detected can be discarded outlined in green

whole scene. However, we tried this part of the method on two other sequences of rocks. In the second sequence, one rock has been moved (2 changes), one rock and one leaf have been removed (2 changes) and one rock has been added (1 change). Figure 4 shows the mosaics of target images and model images, the detected changes and the area where the scene is not properly modeled. Figure 4e shows the substraction between the detected changes and the area not well modeled. In this final change mosaic, it can be seen that the five changes were properly detected. It can also be seen that changes are triggered on a rock in the bottom of the image. This change was not intentional but it appeared because the rock moved while stepping on it.

IV. CONCLUSIONS AND FUTURE WORKS

We have developed a method to deal with the constraints of the underwater environment in order to detect changes in sequences of images. Results show that using information about the 3D relief of the scene allows to register the images even if the parallax effect is important. The proposed algorithm incorrectly detects changes in the areas of the images that could not be correctly modeled or that could not be modeled at all. This can happen when moving objects like fishes or algae are present in the scene. In some sequences of images the light source is also moving, resulting in moving shadows. Fortunately, it is possible to detect those areas by finding the changes within the sequence of registered model images, and thus discard the changes that are detected in these areas.

There are several ways to improve the results of this method. One direction is to improve the accuracy of the 3D model since it has a direct impact on the accuracy of the registration. The 3D modeling algorithm can be improved by using a dense matching approach or using stereo vision.

In this paper we used a standard change detection algorithm which produced good results for the test sequences. However, other more sophisticated algorithms such as the neural network algorithm proposed in [3] need to be implemented and tested.

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Figure 4: Mosaics of both target (b) and model (a) images, the changes detected (c), the inaccuracies of the 3D model (d) and the final changes in which the inacuracies of the 3D model haves been removed.

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