match ${}^{k}x_j$ and the projection of its point ${}^{k}x_i$ in the image frame *j* and r^{k}_{LBL} is the difference between the camera position and its LBL reading. W_{PM} and W_{LBL} are weights that account for the different accuracies of the point-match and the acoustic position.

3. Results

Results are presented on challenging deep-sea image set. This set was acquired during the LUSTRE'96 cruise over the Lucky Strike hydrothermal vent field by Woods Hole Oceanographic Institution. This vent is located in the Mid-Atlantic Ridge and covers an area over 1 square km. The survey pattern comprised large sparse transects, where more than 20.800 images were captured. The navigation file contains sparse positioning and angular sensor reading, every 60 seconds. Using this initial data, the camera pose at each frame is interpolated to estimate the initial 3D trajectory.

4. Conclusions

A weight tuneable optimization technique to globally align photomosaics has been designed to obtain a locally aligned and globally coherent mosaic. This method is applied on a challenging deep-sea data set. Due to the large extent of the data set, initial tests have focused on creating sub-mosaics (Fig. 1) that can be subsequently aligned as rigid blocks.

5. Future Work

Ongoing work addresses the use of multiple iterations of image matching and optimization in order to improve the results.

The estimation process uses a cost function which is being extended to other sensor information, such as vehicle inclination or fiducial points, in future data sets.

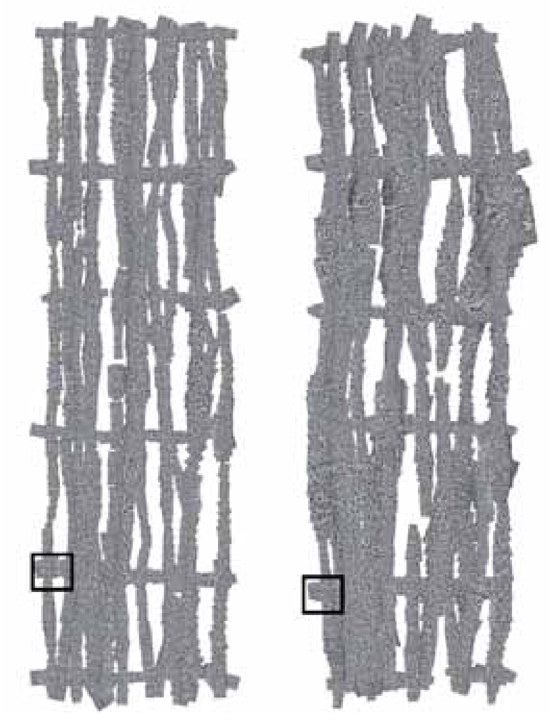

Figure 1. Section of the optical survey comprising 1.240 images. The initial mosaic (left) was obtained using only the navigation data and was refined using bundle adjustment with point and matches between images and LBL priors (right). The black squares refer to the areas that are enlarged in Fig. 2.

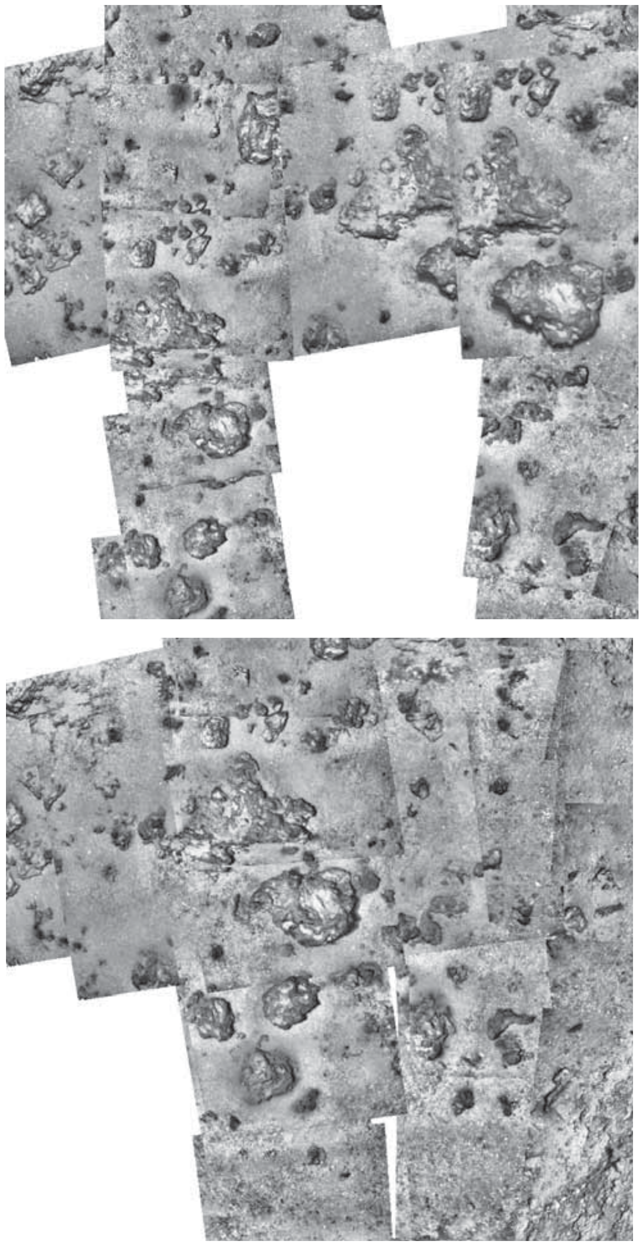

Figure 2. Inaccuracies in the navigation data result in image misalignments. On the top image, the arrows plotted in the same color point to the same rock. Bottom image shows the resulting alignment after the bundle adjustment.

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proaches. (c)-(g) show blending results using (c) Multi-resolution Splining, (d) Energy Minimization Multi-resoltion Splining (applied only on straight lines), (e) Interactive Digital Photomontage, (f) Graph Cut Seam based on Watershed Segmentation, (g) proposed hybrid method.

3. Conclusions

The reviewed and obtained results demonstrate that transition smoothing methods are adequate for image mosaicing presenting an accurate registration, when moving objects or significant geometrical inconsistencies do not appear in the scene. The vignetting problem is well solved. Energy Minimization Multiresolution Splining is especially valuable to reduce the perception of large photometric inconsistencies Neverthe-less, the blurring on the overlapping region stills being sometimes noticeable.

Finding the optimal seam allows reducing the visibility of misalignment problems in the regis-tration. These methods are not able to solve by themselves the photometric inconsistencies, but actually reduce their visibility.

In the proposed hybrid method, Graph Cut based seam estimation allows to reduce the visibility of geometrical misalignments, while the application of this method on the Watershed segmentation increases the speed of the whole process, making it feasible for large images. Gradient Domain Image Blending, based on the imposition of boundary conditions to the gradi-ent belonging to the seams boundary, allows recovering the images through the Poisson equations, forcing the intensity of differently exposed mosaic areas to have the same lumi-nance level.

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CREATING LARGE AND ACCURATE MOSAICS OF THE MID-ATLANTIC RIDGE

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1. Introduction

Seafloor imagery is a rich source of data for the study of biological and geological processes. Among several applications, sea-floor imagery can be used to construct image composites referred to as photo-mosaics. Photo-mosaics provide a wide-area visual representation of the benthos, and find applications as diverse as geological surveys, mapping and detection of temporal changes in the morphology of biodiversity and autonomous vehicle navigation.

The characteristics of the underwater environment offer several challenges for image mosaicing, mainly due to the significant attenuation and scattering of visible light. Moreover, light attenuation does not allow images to be taken from a large distance. Therefore, in order to gain global perspective of the surveyed area, mosaicing techniques are needed to compose a large number of images into a single one. Obtaining high quality mosaics requires a good harmony of the different steps, namely: motion estimation between overlapping images, detection of the non-consecutive overlapping image pairs, and global alignment. We present an approach for creating image mosaics using navigation data consisting on 3D position estimates provided by sensors such as LBL available in deep water surveys. A central issue with acoustic 3D positioning is that the accuracy is far too low compositing the images within reasonable accuracy.

2. Approach

We parameterize the camera trajectory in the most general terms using 6-DOFs (3D position and orientation), using unitary quaternions to represent the camera rotation in order to prevent singularities. The bundle adjustment step will optimize these poses to minimize a defined cost function.

As an input, we consider an image sequence captured at close range above the sea-floor, with sufficient overlap to allow automatic pairwise registration, plus its corresponding navigation data. Image-to-ground plane mappings are used to estimate planar homographies which allow for a simple definition of the error terms [1].

The algorithm starts with a coarse estimate of the trajectory given by the navigation data. This estimation allows detecting loops in the trajectory, and defining which sets of nonconsecutive images are likely to overlap.

Planar motion between consecutive and nonconsecutive image pairs is estimated using SURF [2] matches. Every pair of images is locally aligned according to the SURF result. Then, we extract Harris corners [3] in one of the images, and their correspondences are detected through correlation in the other image. If correspondences are not found, this motion is rejected. The new correspondences and the LBL camera readings are used as input observations for the minimization algorithm.

An initial 3D camera trajectory is computed from the navigation data and then used as the starting point for the non-linear minimization. The minimized cost function is defined as the weighted squared sum of the point-match and the LBL reading residuals:

$$\min \left(W_{PM} \sum_{k=1}^{n} \left({}^{k}r_{ij}^{2} + {}^{k}r_{ji}^{2} \right) + W_{LBL} \sum_{k=1}^{n} {}^{k}r_{LBL}^{2} \right)$$

where ${}^{k}r_{ij}$ r is the difference between the point ${}^{k}x_{i}$ and the projection of its match ${}^{k}x_{j}$ in the image frame i , ${}^{k}r_{ji}$ is the difference between the