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Optical Image Blending for Underwater Mosaics

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Abstract- Typical problems for creation of consistent underwater mosaic are misalignment and inhomogeneous illumination of the image frames, which causes visible seams and consequently complicates post-processing of the mosaics such as object recognition and shape extraction. Two recently developed image blending methods were explored in the literature: "gradient domain stitching" and "graph-cut" method, and they allow for improvement of illumination inconsistency and "ghosting" effects, respectively. However, due to the specifics of underwater imagery, these two methods cannot be used within a straightforward manner. In this paper, a new improved blending algorithm is proposed based on these two methods. By comparing with the previous methods from a perceptual point of view and as a potential input for pattern recognition algorithms, our results show an improvement in decreasing the mosaic degradation due to feature doubling and rapid illumination change.

I. INTRODUCTION

In the recent years, mosaics created from individual images acquired underwater are attracting more and more attention from marine geologists and biologists. Applications can be clearly divided into two categories: those targeting extraction of quantitative information (distances, sizes, shapes, etc.), and those attempting to create a consistent continuous image, possibly at the expense of minor local distortions. (A special category, aiming at accurate recovery of three-dimensional information about the seafloor, is capable of achieving both goals, but requires principally different approach, and has substantially higher level of complexity.)

In reality, due to limited visibility underwater, artificial and, as a consequence, spatially inhomogeneous illumination, and the parallax issues, most underwater images are fuzzy and difficult to process. In this paper, we are not concerned with the ability to measure distances and sizes as accurately as possible. Algorithms for object recognition and shape extraction are typically tolerant to scaling and insignificant distortions, but can be easily confused by feature doubling and rapid changes in illumination. Our goal is to diminish the effects of inhomogeneous illumination, which are almost always present in the case of artificial lighting, and to combine individual image frames into a single mosaic in some optimal way. Note that "optimal" may have different meanings depending on intended consumer: scientist, trying to deduce large-scale interrelationships; computer program, extracting shapes according to some specific rule; or a high-school student learning about a deep-sea environment.

Current blending techniques can be divided in two main categories, assuming that the images have already been aligned: One approach is an optimal seam algorithm [1-3] that searches for a curve in the overlap region on which the differences between two overlapping images are minimal, and then each image is copied to the corresponding side of the seam. One simple and commonly used method is the minimum cut method which employs dynamic programming [1], but it works well only when two images are involved. As opposed to this "memoryless" approach, the graph-cut method [4, 5] was proposed that can be applied when more than two images are needed to be mosaiced. However, the seam may still be visible where brightness of neighboring original images differs dramatically.

Another category is aiming at smoothing the transition between two images. Most common blending techniques employ simple averaging of images in the overlapping regions. This results in ghosting artifacts, blurring, and visible seams that degrade the mosaic. Some improvement of this method were proposed, such as feathering or alpha blending [6] which employs the special weighting functions, multi-resolution blending [7-9] which takes advantage of the characteristics of different sub-bands, and gradient domain stitching [10-12,16], which is designed to remove sharp changes of brightness across the frame boundaries. However, blurring and ghosting effects could not be avoided due to misalignment of the underwater imagery.

In our paper, the methods mentioned above are explored in application to underwater images. Due to the complexity of underwater imagery, the defects of these methods are more apparent, and thus other practice should be considered in order to get higher quality mosaics for either post-processing or simple viewing. Our proposed blending method is using advantages of the graph-cut technique and gradient domain stitching method, and has achieved a significant improvement over the existing algorithms.

II. THEORETICAL BACKGROUND

In this section, methods of gradient domain stitching and graph-cut are highlighted and application details are introduced.

A. Gradient Domain Stitching

Computation in the gradient domain was recently used in compression of dynamic range [12], image editing [11], image inpainting [13] and separation of images to layers [14]. In [10], two approaches were proposed for image stitching in the gradient domain, and the previous spatial methods (such as feathering, pyramid blending and optimal seam) performed in gradient domain of the images were compared with their original methods. Results show an improvement in overcoming the photometric inconsistencies and small geometric misalignment between the stitched images. Performance here is similar to image editing [11], which suggests editing images by manipulating their gradients. One of the editing applications concerned is the object insertion, where an object is selected and cut from an image, and inserted into a new background image. The insertion process is done by solving the Poisson equation in the gradient field of the inserted patch, with boundary conditions defined by the background image.

Mathematically, the gradient of a two-variable function (here the image intensity function I) is at each image point a 2D vector with the components given by the derivatives in the horizontal and vertical directions, that is:

$$\nabla I = (\partial I / \partial x, \partial I / \partial y). \tag{1}$$

With some additional assumptions, the derivative of the continuous intensity function can be calculated as a function of the sampled intensity function, i.e. the digital image. For example, the gradient for digital images approximated by the forward difference:

$$\nabla I(x,y) \approx (I(x+1,y) - I(x,y), I(x,y+1) - I(x,y)) \tag{2}$$

In order to reconstruct the pixel values, integration should be performed, however, the conservativeness can rarely be achieved in this case [11]. Other methods were proposed to solve this problem such as Fourier basis function algorithm [15] which orthogonally projects the gradient values onto a finite set of ortho-normal basis functions spanning the set of integrable vector fields; another method is to search the function over the space of all 2D potential functions whose gradient is closest in the sense of least-squares. As proved in [11], the second method is equivalent to solving of the following Poisson equation:

$$\nabla^2 I = divG, \tag{3}$$

where Laplacian values of I is expressed as:

$$\nabla^2 I = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2} \tag{4}$$

and the divergence of gradient vector G is:

$$divG = \frac{\partial G_x}{\partial x} + \frac{\partial G_y}{\partial y} \tag{5}$$

Approximating them with the standard finite differences yields a linear system of equations, where the Laplacian of I is expressed as:

$$\nabla^2 I = I(x+1,y) + I(x-1,y) + I(x,y+1) + I(x,y-1) - 4I(x,y) \tag{6}$$

and the divergence of G is:

$$divG = G_x(x,y) - G_x(x-1,y) + G_y(x,y+1) - G_y(x,y-1) \tag{7}$$

In solving the Poisson equation, boundary conditions were reported to be chosen differently according to the applications.

B. Graph-cut method

The graph-cut method [5] is designed to find a boundary between two images in such a way that the seam is the least noticeable. This search is formulated in terms of finding the minimum of a certain energy function. The graph-cut algorithm is based on the principles of combinatorial optimization, and has attracted a lot of attention recently due to its ability to solve problems of this type extremely effective.

Principally similar, dynamic programming method was first proposed in [1], which also incorporate seams finding process. However, specifics of implementation impose restrictions on the ways the seam is allowed to follow. This may lead to missing of good seams that cannot be modeled within the imposed structure. In addition, dynamic programming is "memoryless" and cannot explicitly improve existing seams. This gives limitations when appending new images to the existing images. Graph-cut technique overcomes these disadvantages by treating each pixel uniformly and is also able to place patches over the existing images.

Specifically, let x and y be two adjacent pixel positions in the overlap region. Let $A(x)$ and $B(y)$ be the pixel values in the same color channel coming from original and new images, respectively. The matching quality cost E can be defined between the two adjacent pixels x and y that are copied from patches A and B to be:

$$E(x,y,A,B) = \|A(x) - B(x)\| + \|A(y) - B(y)\|, \tag{8}$$

where $\|*\|$ denotes an appropriate norm.

III. PROPOSED METHOD

The method proposed in this paper is overcoming the defects of the single graph-cut technique, which would have apparent seam when two images have inhomogeneous illumination, and the single gradient domain stitching, which can still cause blurring in a misaligned case. As mentioned in the previous sections, our method is based on the graph-cut in the gradient domain. Different from the method of optimal seam in gradient domain [10], which is the dynamic programming based method, graph-cut here is performed on the overall image values, and is more flexible in defining the "cut" area.

The procedure is as follows, assuming that two images I_D, I_B have already been aligned and we take only one color channel for illustration:

1) Following the formula of (4), we calculate the gradient values of two images, I_D, I_B, obtaining G_D, G_B.

2) According to the overlapping area (which in general is an irregular polygon), a boundary box is obtained, which is composed of three parts: overlapping area, and parts that have contributions from only one of the images.

3) Within the boundary box, execute the graph-cut technique and get the graph-cut mask, using weighting function to smooth the boundary cut and obtaining the final mask.

4) Fill in the boundary box with gradient values according to the mask matrix, and use it as a source term of the Poisson equation. Boundary values of the boundary box are from the original pixel values of two images given the boundary of the mask.

5) Reconstruct the spatial values of the boundary box by solving the Poisson equation with Dirichlet boundary conditions.

6) Put the corresponding reconstructed values back in the final mosaic.

In practice, the images are part of a sequence, for example, captured from a video tape. Transformations relating consecutive images are either deduced from the navigation data, or estimated from the imagery. Frames are added sequentially to already existing mosaics.

IV. EXPERIMENTS

In this section, the proposed method is applied and results are shown, then experiments using different methods and results are compared from the perceptual point of view.

In our case, size of the mosaic can rapidly grow so that a typical desktop computer cannot handle it. Addition of a new individual image frame to an existing mosaic is described in terms of interaction between two images: one, represented by a rectangular footprint, and another, bounded by a complex polygon, which in general may consist of several disjointed parts, be concave, and have holes. For simplicity of comparison, our experiments are performed on two overlapping gray-level frames the video footage courtesy of Dr. R. Vrijenhoek, MBARI.

A. Results of the proposed method

Below are the results following the performance procedures introduced in the previous section: first, the original images overlapping I_D and I_B are given in Fig. 1, then the position and dimension of boundary box is illustrated on the image of mosaics in Fig. 2. Graph-cut matrix with the narrow weighting function (Here, we give the result of three pixel wide band) is shown in Fig. 3. The mask, which is filled by the source gradient values and boundary conditions are in Fig. 4. In this case, the light gray stands for the gradient values from G_D, and the darker gray stands for the values from G_B, while the black

values in the bottom are the gradient values from G_B, but not out of the overlapping area. Efficient solution of the Poisson equation can be achieved by a variety of methods. We have chosen the direct solver from the INTEL Math Kernel Library, v.8.01.

B. Results from other methods

For comparison, we performed the following blending methods on the same images, and their results were given in Fig. 5-10:

1) the direct averaging blending method,
2) feathering method,
3) feathering in gradient domain,
4) direct graph-cut method,
5) graph-cut method in gradient domain without weighting function methods.

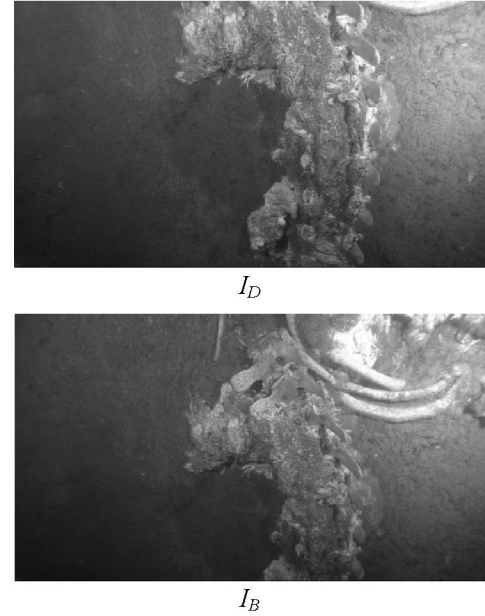I_D

I_B

Fig. 1. Original Images I_D and I_B.

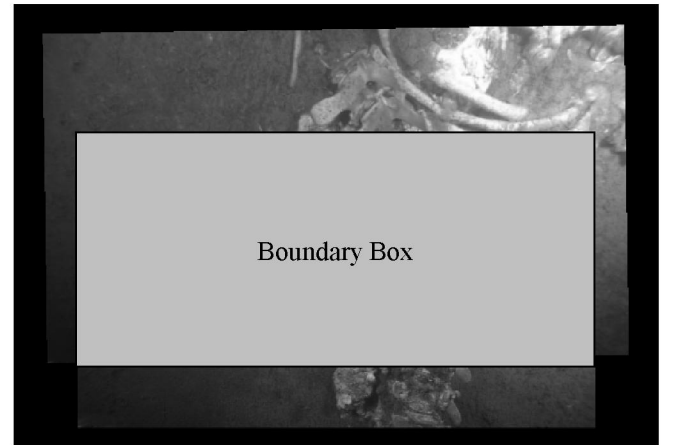

Boundary Box

Fig. 2. The position of the boundary box.

Fig. 3. Graph-cut mask of the boundary box

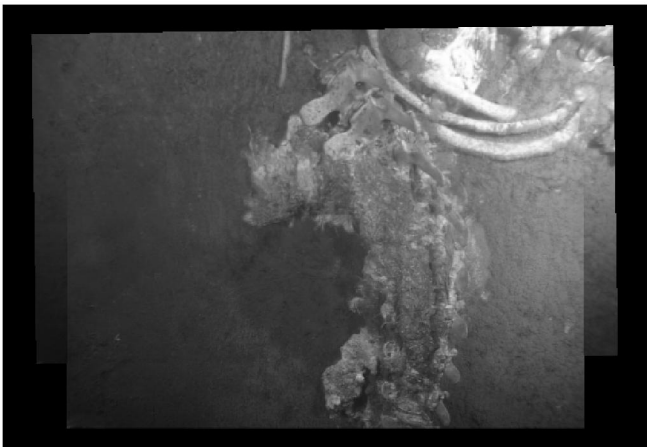**Fig. 4.** Mask for gradient values filling.

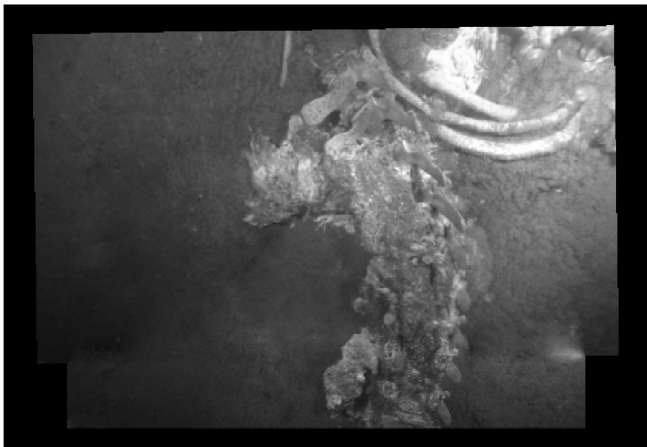**Fig. 7.** Feathering blending method.

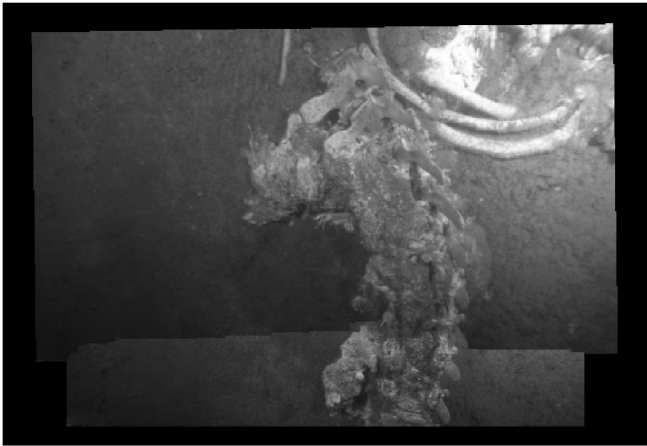**Fig. 5.** Graph-cut in gradient domain with a weighting function.

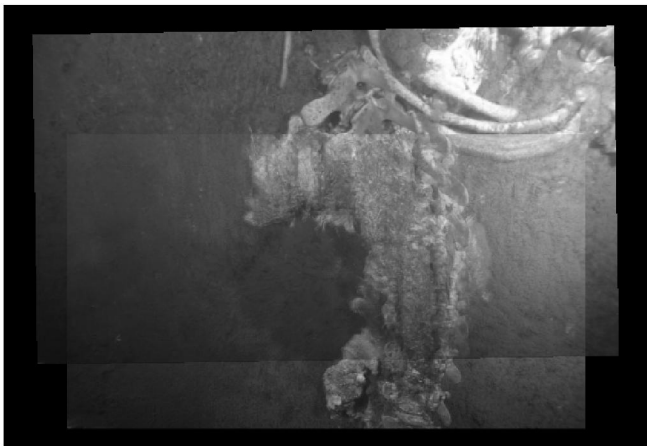**Fig. 8.** Direct graph-cut method.
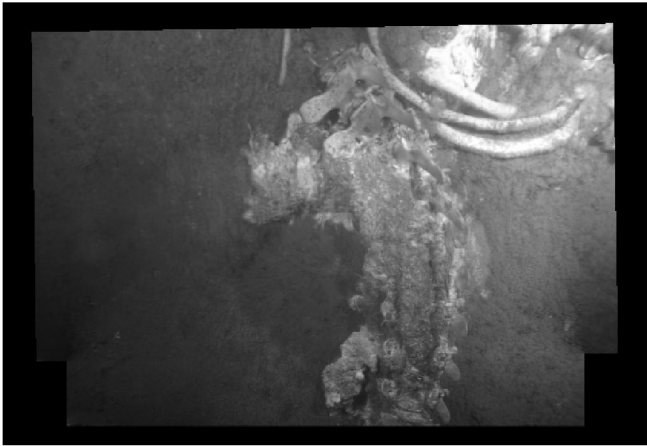

Fig. 6. Averaging blending method.

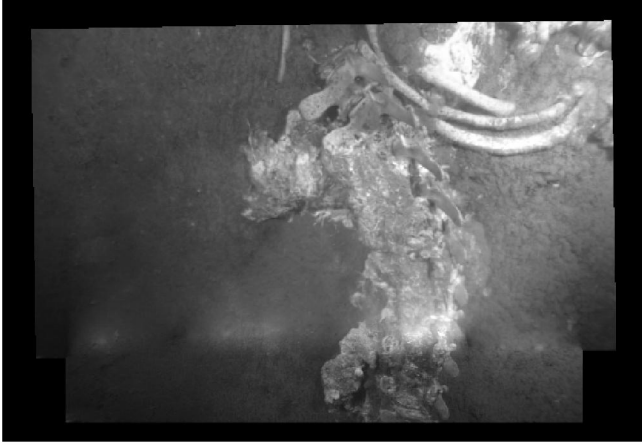**Fig. 9.** Feathering in gradient domain method.

Fig. 10. Graph-cut in gradient domain without weighting function.

From Fig. 6, it can be observed that direct averaging method give rise to apparent blurring and doubling, in addition, it does not improve the illumination difference in two images. In Fig. 7, the weighted averaging seems to be improved in sense of both of these two disadvantages above, still, the seam due to the illumination difference is apparent on the right of the mosaic. In terms of decreasing the blurring and ghosting effects, graph-cut technique in Fig. 8 gives a good result, however, the seam is more apparent because, in this case, the difference of illumination is large and the seam cannot be hidden among the complex texture of the images. Fig. 9, which performs in the gradient domain with weighting function make the whole mosaic more homogeneous in illumination, however, comparing with the original images, details are blurred and not as distinctive as in the direct graph-cut method. Fig. 10 which employs graph-cut mask in the gradient domain, the mosaic illumination is more homogeneous comparing with direct graph-cut method, while the details are clearer compared to the gradient domain feathering. But there are some blocks of white along the region of cut, which are apparent artifacts. It might be due to the inconsistency of the source term along the seam. In our experiment, when using the weighting function along the cut, the effect is less apparent, as shown in Fig. 5.

V. CONCLUSIONS

Due to the artificial lighting and 3D content of imaged terrain, imagery taken underwater almost always suffers from inhomogeneous illumination and feature misalignment, when mosaiced. This causes degradation of the final product and makes it more difficult to post-process. Often used mean value averaging blending technique can hardly satisfy the demand of post processing such as feature extraction or human view leisure.

These days, a lot of blending techniques were explored in the area of image processing. Most of them fail when it comes to the underwater images, which have different specifics. We reviewed the existing popular methods and combined them in a way to facilitate in post-processing of underwater mosaics. Specifically, we have combined the graph-cut method designed to improve on image blurring and ghosting, caused by local misalignments, and the gradient domain stitching technique, which helps with lighting inhomogenities and exposure artifacts. Employing the graph-cut in the gradient domain eliminates their defects with the weighting band. Experimental results show the effectiveness of the proposed methods, comparing with other existing methods such as special averaging, feathering, graph-cut, and feathering, graph-cut in gradient domain. The reason for artifacts, occasionally occurring in the reconstructed process, requires further investigation.

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