

# Mosaicing Deep Underwater Imagery

## SUPPLEMENTARY MATERIAL

In this supplementary material we give additional results and some of the intermediate images generated while performing enhancement and mosaicing.

In Fig. S1, we show the impact of our channel-wise illumination compensation on the final restored results obtained after dehazing. Fig. S1 (a) is the result of dehazing directly on the non-uniformly illuminated image. It still possesses high non-uniformity across the image. The values in darker regions are either too dark or blue. However, the result in Fig. S1 (c) contains clear scene information even in peripheral areas of the image. Moreover, the uniformity of intensity in Fig. S1 (c) resembles that of terrestrial images which makes it more suitable for feature-point based stitching as compared to Fig. S1 (a). Fig. S1 (b) shows the result of dehazing on the image through an illumination compensation which gives equal importance to all channels. Undesired color artifacts present in Fig. S1 (b) clearly indicates the need for a channel-wise illumination compensation.

Fig. S2 displays the results of alignment of input images from the experiment 1 of the main paper, using our proposed approach. As can be observed from Fig. S2 (d-f) alignment is not a global homography based, but is composed of local homographies. A similar observation can be made from Fig. S3 (d-f), which displays the aligned images for the case of experiment 2 in the main paper.

Results for enhanced image mosaics obtained from another set of images are shown in Fig. S4. Here we have used 4 input images (Fig. S4 (a-d)). Fig. S4 (e-h) shows the results after restoration using channel-wise illumination compensation and dehazing. All restored images are warped onto a common canvas to obtain the aligned images shown in Fig. S4 (i-l). Image mosaics produced by the proposed method is shown in Fig. S4 (m). Fig. S4 (n) and (o) shows the results from [30] and Autostitch [4]. As can be clearly seen proposed method lead to better alignment and almost no blur in the overlapping region as compared to other methods.

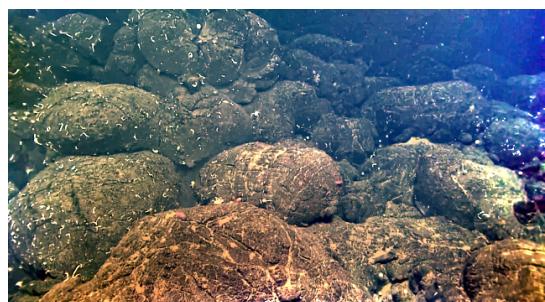
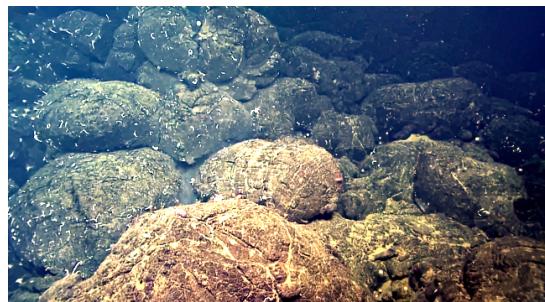
## S1. DISCUSSION

ACM acknowledges that this contribution was authored or co-authored by an employee, contractor or affiliate of a national government. As such, the Government retains a nonexclusive, royalty-free right to publish or reproduce this article, or to allow others to do so, for Government purposes only.

*ICVGIP '16 Guwahati, Assam India*

© 2016 ACM. ISBN 978-1-4503-4753-2/16/12...\$15.00

DOI: <http://dx.doi.org/10.1145/3009977.3010029>

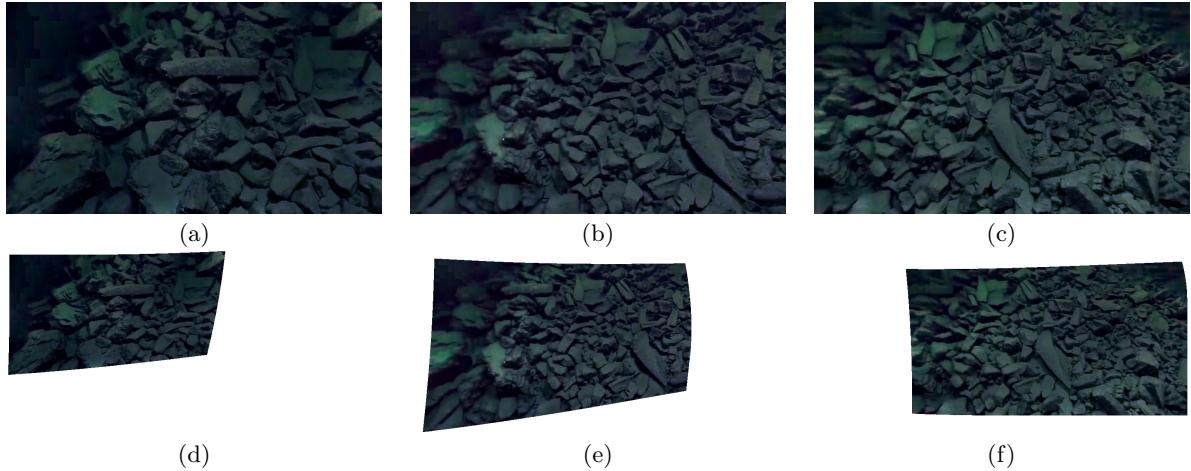


(b)

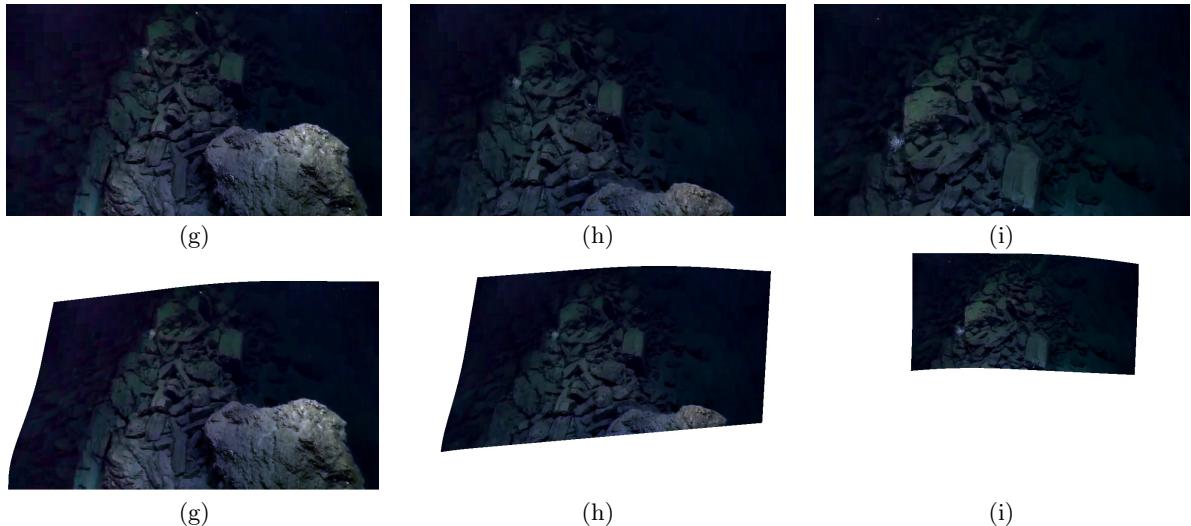


(b)

Figure S1: Results after removing haze from a (a) non-uniformly illuminated image, (b) directly illumination compensated image, and (c) channel-wise illumination compensated image respectively.



**Figure S2:** Intermediate images from experiment 1 in the main paper. The first row (a-c) shows the three images obtained by doing the enhancement via illumination compensation and dehazing. (d-f) Registered forms of (a-c) onto a common canvas.



**Figure S3:** Intermediate images from experiment 2 in the main paper. (a-c) Restored forms of input images. (d-f) Aligned images using the proposed local homography warps.

While our mosaicing pipeline is robust to small errors in depth estimates, large errors in depth can affect accuracy of our results. Our approach is not designed to handle dynamic scenes (a typical limitation in most mosaicing algorithms).

Existing approaches do not handle haze, illumination variations and stitching all within a single roof. However, for each of these modules, our approach is as fast as the state-of-the-art ([29], [10], [30]) methods. Run time (in seconds) on per-image basis on a PC with Intel i7 CPU and 16GB memory, using MATLAB, and for input images of size 640 x 360 is 0.79 for Illumination compensation, 54.78 for Dehazing and 28.89 for Depth-aware stitching (4 images).

To measure the loss of local information due to blurring, the outputs are evaluated on two no-reference quality metrics: Cumulative Probability of Blur Detection (CPBD) [19] and Entropy, since standard reference image based quality metrics such as PSNR and SSIM cannot be used. In regions where the outputs from ours and competing methods are vis-

**Table S1: Quantitative Comparisons.**

Figure No.	Proposed Method	[30]	[4]
Figure 4 [CPBD]	0.34	0.26	0.26
Figure 4 [Entropy]	6.13	6.06	5.77
Figure 5 [CPBD]	0.49	0.45	0.47
Figure 5 [Entropy]	5.91	5.66	5.76
Figure S4 [CPBD]	0.30	0.27	0.24
Figure S4 [Entropy]	6.17	6.04	5.25

ibly different, qualitative comparison suffices. Where qualitative evaluation becomes difficult, these measures help in objectively evaluating mosaicing performance. In table S1, we list the values of CPBD and Entropy for the 3 experiments shown in our main paper and supplementary material. We computed average values of these metrics over several  $80 \times 80$  patches of the output. Higher values indicate better quality.

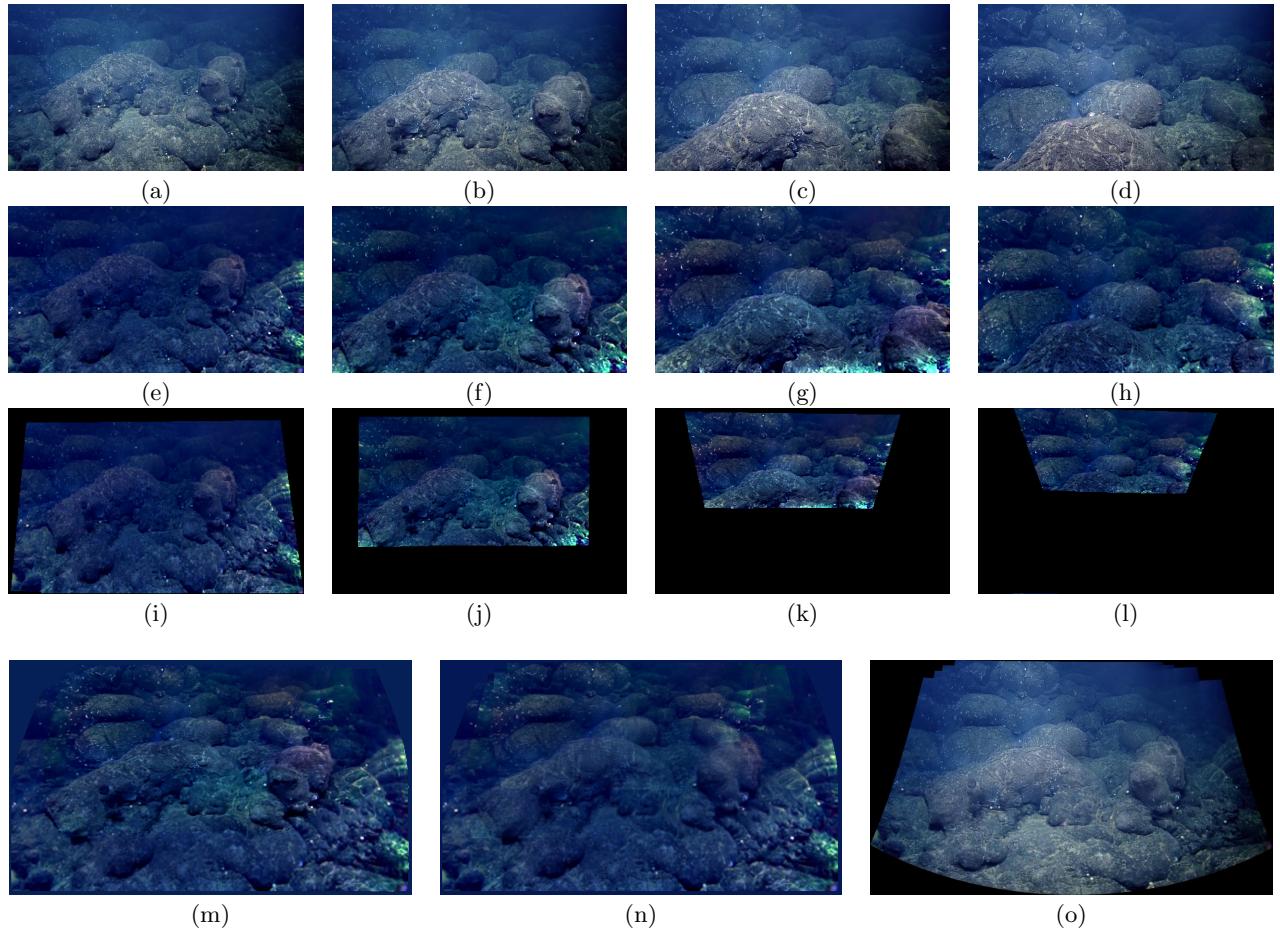


Figure S4: Results obtained for experiment 3. (a-d) Input images, (e-h) Restored forms of (a-d) using our method. (i-l) Aligned forms of (e-h). Mosaics obtained using (m) proposed method, (n) [30], and (o) AutoStitch [4] respectively.