Automatic Restoration of Underwater Monocular Sequences of Images

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Abstract—Underwater environments present a considerable challenge for computer vision, since water is a scattering medium with substantial light absorption characteristics which is made even more severe by turbidity. This poses significant problems for visual underwater navigation, object detection, tracking and recognition. Previous works tackle the problem by using unreliable priors or expensive and complex devices. This paper adopts a physical underwater light attenuation model which is used to enhance the quality of images and enable the applicability of traditional computer vision techniques images acquired from underwater scenes. The proposed method simultaneously estimates the attenuation parameter of the medium and the depth map of the scene to compute the image irradiance thus reducing the effect of the medium in the images. Our approach is based on a novel optical flow method, which is capable of dealing with scattering media, and a new technique that robustly estimates the medium parameters. Combined with structure-from-motion techniques, the depth map is estimated and a model-based restoration is performed. The method was tested both with simulated and real sequences of images. The experimental images were acquired with a camera mounted on a Remotely Operated Vehicle (ROV) navigating in a naturally lit, shallow seawater. The results show that the proposed technique allows for substantial restoration of the images, thereby improving the ability to identify and match features, which in turn is an essential step for other computer vision algorithms such as object detection and tracking, and autonomous navigation.

I. INTRODUCTION

Over the past decades Autonomous Underwater Vehicles (AUVs) have been deployed in a growing number of aquatic environments, including the observation of benthic habitats, shallow reefs, near-shore mangroves and marinas. The images thus acquired by AUVs are being used for a variety of applications such as animal and habitat classification, 3D mapping and reconstruction of scenes [1], inspection [2], obstacle avoidance [3] and robot localization [4], to name few. However, due to the complex interaction of light rays with the water, it becomes quite a difficult task to extract the full scene information from underwater images.

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In underwater environment, light is absorbed and scattered by the medium before reaching the camera. These effects become a serious issue since it reduce the overall contrast on images and produce color shifting, directly impacting on the reduction of the visibility. This degradation worsens exponentially with distance making it impossible to acquire meaningful information from images of scenes with large distances. The present paper focuses on the restoration of underwater images. The purpose of restoration methods is to obtain the true scene appearance, i.e., the appearance that a scene would have whether it was not underwater.

Several approaches have been proposed to tackle the problem of restoring underwater images, including the use of specialized hardware [5], stereo images [6], [7], [3] and polarization filters [8], [9]. Despite the quality of the results, methods that rely on specialized hardware are expensive and require complex setup, which make them hard to be used in unstructured underwater environments. In the case of stereo systems, solving the correspondence problem is made harder due to the effects imposed by the medium, and often a stereo pair is not available in underwater vehicles. The use of polarizers is also cumbersome, even though images acquired with them present very good results. The main drawback of this technique is the need to automate the identification of maximum and minimum polarization states. In summary, in spite of the advances that have already been attained, the problem of image restoration of underwater scenes still requires more research effort.

Dehazing algorithms based on single outdoor images have been proposed in the literature [10], [11], [12]. While they show good results, their performance degrades in underwater scenarios [13]. One key aspect for high quality image restoration is the estimation of the transmission map, which pro-
vides information about the scene structure and the turbidity of the medium. Transmission map is the exponential function of the depth map scaled by the attenuation coefficient [14].

The main contribution of this paper is a novel underwater restoration methodology based on monocular sequence of images that uses the temporal relation, geometric and environmental information to achieve the image restoration. The main steps of our approach is depicted in Fig. 1. In the first step, the method is initialized by using transmission map priors that provide an initial estimation of the scene depth which is used to compute the optical flow from the images. Structure-from-motion techniques based on the tracking information from optical flow provide an estimation of the depth map, which is then used to compute the attenuation coefficient of the medium and subsequently to restore the image sequence. Another contribution of this work is the development of a robust technique to estimate the attenuation parameter based on insights provided by the underwater light attenuation model.

The remainder of the paper is structured as follows. Initially, Sec. II described the physical underwater light attenuation model. Sec. III describes the proposed underwater restoration method, and Sec. IV presents an evaluation of the proposed approach based on simulated data. Sec. V evaluates the methodology using experimental field data collected by a ROV. Finally, Sec. VI summarizes the paper and discusses future directions.

II. PHYSICAL UNDERWATER LIGHT ATTENUATION MODEL

Underwater images can be modeled as a complex interaction of the light rays travelling through the medium and the scene. One such a model was proposed by Jaffe-McGlamery [15], [16], one of the most widely used in the literature. It is composed of three components: direct illumination \( E_d \), forward-scattering \( E_{fs} \) and backscattering \( E_{bs} \), as shown in Eq. 1:

\[
E_T = E_d + E_{fs} + E_{bs}. \tag{1}
\]

Part of the light that radiates from the scene is wasted due to scattering and absorption phenomena, and the portion that reaches the image plane is called the direct illumination. According to [8], backscattering is the prime reason for image contrast degradation, and thus the forward-scattering, \( E_{fs} \), is usually neglected. After simplifications and following the terminology adopted by [12], the direct component can be defined as:

\[
E_d = J e^{-\eta d} = J t_r, \tag{2}
\]

where \( J \) and \( d \) are the scene radiance and depth, respectively, \( \eta \) is the attenuation coefficient (also termed \( c \) in the literature), and \( t_r \) is the medium transmission modeled as the exponential term. The term \( t \) refers to the time and the transmission of the medium is described by \( t_r \).

In underwater scenes, the attenuation coefficient \( \eta \) is composed of the scattering coefficient, \( \beta \), and the absorption coefficient, \( a \). Both are wavelength dependent [14].

The backscattering component does not originate from the scene’s radiance, but results from the interaction of the ambient illumination sources with particles dispersed in the medium. Therefore, a simplified model is given by:

\[
E_{bs} = A(1 - e^{-\eta d}) = A(1 - t_r), \tag{3}
\]

where \( A \) is the global light in the scene, also called \( B_\infty \), a scalar that is also wavelength dependent.

The constant \( A \) can be estimated in different ways, such as calibration procedures [6], finding the brightest pixel in the image [10], [11] and estimating the brightest pixel in the dark channel [12]. For the non-uniform illumination case, the \( A \) parameter may be modeled as a function of each pixel, and estimated using a simple calibration process [9].

Therefore, an enhanced model describing the image formation in an underwater medium can be posed as:

\[
I(x) = J(x) t_r(x) + A(1 - t_r(x)), \tag{4}
\]

where \( x \) is the pixel coordinate and \( I \) is the underwater image. It is assumed that this model is valid for naturally lit, homogeneous media.

III. UNDERWATER RESTORATION METHOD

This work proposes a novel methodology to restore an underwater sequence of monocular images. By using the model previously described, the problem of image restoration may be reduced to the problem of estimating the medium parameters and the scene depth. The overall approach is depicted in Fig. 1, where arrows indicate the data flow. In addition to the restored images, our method also produces an estimation of the depth map and the attenuation coefficient of the medium. Red arrows show the loop that allows to improve the restored image in an iterative way. Differently from previous work, we combine the temporal relation, geometric and environmental information provided by the monocular sequence of images to achieve the restoration.

A. Transmission Prior

Although, priors of the scene and medium can be used to estimate the transmission map and to provide meaningful information of the scene, these may hold true only for restricted conditions. Thus, priors cannot be adopted as a definite solution for the image restoration problem. We adapted the method for outdoor scenes called Dark Channel Prior (DCP) [12] to underwater environments, and we call it Underwater DCP (UDCP) [17], which differently from [12], it can provide a rough initial estimate of the medium transmission for underwater scenes.

The Dark Channel Prior is a statistical prior based on the observation that haze-free outdoor images frequently have a mostly dark square patch somewhere in the image, i.e. there is a patch in at least one color channel whose pixels have very low intensity values. This statistical correlation, as assumed by [12], is not easy to be verified in underwater environments due to the difficulty of obtaining real underwater images in an out of water condition. However, the main assumptions are still plausible, i.e at least one color channel has some
pixels whose intensities values are close to zero. These low intensities may be due to: a) shadows; b) objects or surfaces where at least one color is of low intensity, e.g. fishes, algae or corals; c) dark objects or surfaces, e.g. rocks or dark sediment.

Although the dark channel assumption seems to be acceptable, the wavelength independence is clearly false in most cases, i.e. the method assumes that the behavior of the medium is independent of the light wavelength. Due to the high absorption rates of the light in typical oceanic conditions, our UDCP method assumes that the red channel cannot be used to estimate the medium transmission. Considering Eqs. 4 and the aforementioned assumption, we isolate the transmission in a local patch $t_r$ as in the standard DCP. By applying the minimum operation to both sides, we can estimate $t_r$ based on the image $I$ and the global illumination $A$:

$$t_r(x) = 1 - \min_{y \in \Omega(x)} \left( \min_{c \in G, B} \frac{I_c(y)}{A_c} \right). \quad (5)$$

The global illumination $A$ is estimated by finding the brightest pixel in the underwater dark channel. The estimated transmission $t_r$ contains some block effects since the transmission is not always constant in a patch $\Omega(x) = 15 \times 15$ pixels [12]. Furthermore, we refine it employing the guided filter [18].

B. Generalized Optical Flow Model

The problem of obtaining dense correspondence between pixels in a sequence of underwater images is challenging, since the main assumption of brightness constancy is invalid. In spite of advances in optical flow, virtually all methods do not work well for underwater images. As described by the model in Eq. 4, for underwater images the brightness in the image $I$ is not constant due to transmission effects. Nevertheless, one may assume that the radiance $J$ is approximately constant due the characteristics of the medium. Considering this assumption, it is possible to derive a generalized model [19], which we call the Generalized Optical Flow Model (GOFM). This is defined as:

$$(I_c^u u + I_c^v v + I_c^e) + (I_c^e - A_c)(D_x^e u + D_y^e v + D_t^e) = 0, \quad (6)$$

where the derivatives of function $D(x, y, t) = -\log t_r(x, y, t)$ with respect to $x$, $y$ and $t$ are defined as $D_x$, $D_y$ and $D_t$, respectively, and the derivatives of the image function $I(x, y, t)$ with respect to $x$, $y$ and $t$ are defined as $I_x$, $I_y$ and $I_t$, respectively. The index $c$ represents each channel in the RGB color space. In underwater environments, the spectral absorption characteristics of the medium can significantly influence the contents of the three channels, and this can be used to provide valuable information for optical flow estimation.

C. Structure-From-Motion Technique

This step estimates depth maps from a pair of images. It is assumed that the intrinsic parameters of the camera have been previously estimated by calibration, and that the temporal correspondences between pixels have been estimated using optical flow. The methodology is based on essential matrix and triangulation [20]. We adopted a robust estimation of the essential matrix based on MSAC [21] because of its capability to deal with data outliers.

Although camera calibration in underwater images has its own issues, the perspective camera model is the most applied for underwater images because of its simplicity [22], as it approximates the refractive effect by parameter calibration. In [23] the authors show that a camera calibrated underwater approximates the refraction effect using focal length and radial distortion. [24] shows that principal point and camera pose absorb some of the model error in addition to focal length and radial distortion. Hence we adopted the perspective camera model, but with the camera being calibrated in the underwater medium (i.e. the images of the classic chessboard are acquired in the underwater environment).

After the triangulation, a bundle adjustment optimization [20] is applied to compute a reliable set of 3D points. We compute the distance between the 3D points and the optical center of the camera, which enables us to obtain the distance in the line of sight (LOS) for each pixel. Although the correspondences between points obtained by optical flow are dense, they are prone to outliers and missing values. Therefore, the depth maps have several discontinuities and gaps. We applied two algorithms in order to solve these problems. Firstly, the inpainting approach [25] is used to fill the gaps in the generated depth maps. After that, we used the guided filter method [18] to smooth the depth maps and to improve edge discontinuities.

D. Parameter Estimation and Restoration

The final steps of our method estimate the attenuation coefficient and restore the image. The attenuation coefficient is estimated in an automatic and robust way as follows. The underwater light attenuation model, Eq. 4, provides insights that allows us to compute the attenuation coefficient, $\eta$, based on the depth maps and the intensity images. Assuming the same 3D point in the scene and a small displacement between images, the model is given by:

$$I^t - A = (J - A) e^{-\eta \Delta d},$$
$$I^{t+1} - A = (J - A) e^{-\eta (d + \Delta d)}, \quad (7)$$

where $I^t$ is the image acquired in time $t$, and $\Delta d$ is the depth variation between time $t$ and $t + 1$. Dividing one equation by the other, we obtain:

$$\frac{I^{t+1} - A}{I^t - A} = \frac{e^{-\eta (d + \Delta d)}}{e^{-\eta \Delta d}} = e^{-\eta \Delta d},$$
$$\eta \Delta d + \ln \frac{I^{t+1} - A}{I^t - A} = 0. \quad (8)$$

The problem is reduced to line fitting, because the attenuation coefficient is assumed to be a constant for the entire image. In this case, we are interested in the slope of the line. Since the estimation of the correspondence between points, i.e. optical flow, and the resulting depth maps are subject to noise and error, the line fitting needs to be robust to outliers.
We adopted a classic RANSAC line fitting method [26] to estimate the attenuation coefficient.

One interesting point is related to the estimation of $\Delta d$. The depth maps can be obtained up to a single scalar [27], and the same is true for the difference of depth maps. Therefore, the RANSAC algorithm allows us to recover the attenuation coefficient up to scale:

$$\eta' = -\frac{\ln(I^{t+1} - A) - \ln(I^t - A)}{\lambda \Delta d} = \frac{\eta}{\lambda}$$  \hspace{1cm} (9)

where $\lambda$ is the universal scale and $\eta'$ is the attenuation coefficient up to scale. This estimated coefficient compensates the scale factor of the depth values. Thus, the model remains valid.

Following the model defined in Eq. 4, the restored image $J(x)$ is close to zero when $t_r(x)$ is small. Thus, we restrict the transmission $t_r(x)$ by a lower bound $t_0$, i.e., we preserve a small amount of scattering in strongly degraded regions.

The final restored image $J(x)$ for each color channel is given by:

$$J(x) = \frac{I(x) - A}{\max(t_0, t_r(x))} + A,$$  \hspace{1cm} (10)

where a typical value of $t_0$ is 0.1 [12].

IV. SIMULATION RESULTS

One of the challenges with validating underwater methodologies is the difficulty of acquiring images of underwater scenes with reliable ground truth. To tackle with this problem, we chose to validate our method by using the sequence freiburg1_xyz from the RGB-D SLAM dataset [28], which includes the sequence of images and their respective depth maps.

We perform artificial degradation of the images by simulating the effects of an underwater vehicle navigating at a depth of 5m. We simulated the attenuation coefficient $\eta$ and the global illumination $A$ as proposed in [14] and [3], respectively. We assumed a strong turbidity with the medium being contaminated with a chlorophyll concentration $C = 2.0mg m^{-3}$ [14]. Since the depth maps provided by the dataset are not perfect, we also performed inpainting [25] and guided filtering [18].

Fig. 2 shows the achieved results to estimate the attenuation coefficient by our methodology. Since estimated depth maps are prone to errors and gaps, mainly because of the noise, occlusion and the movement of the camera, i.e. some part of the imaged scene in one camera’s pose may be out of the field of view of the other camera’s pose. Furthermore, the structure-from-motion technique and the attenuation coefficient estimation are based on MSAC and RANSAC, i.e. these estimation are stochastic. Thus, we performed one thousand running of the algorithm for a random selected pair of images. The statistics are shown in Fig. 2a, where the crosses and the colored bars show the mean and the standard deviation, respectively.

Fig. 2b shows the statistics of the Root-Mean-Square Error (RMSE) for the attenuation coefficient estimation. Although the mean of the estimated values tends to the ground truth, the standard deviation of the error is much smaller than the standard deviation of the estimated coefficient. Despite the robustness of the method to outliers, the estimation is still quite sensible to noise. It is due to a fairly small values of the attenuation coefficient and the large number of outliers, which lead to a smaller standard deviation for the RMSE. The number of inliers in all executions is almost constant, but the estimated attenuation coefficient shows some variability.

Qualitative results for the restoration of this pair of images are presented in Fig. 3. We compared our approach with the UDCP [17] and two classical enhancement techniques:
histogram equalization [29] and contrast-limited adaptive histogram equalization (CLAHE) [30]. Original and simulated images are shown in Figs. 3a-3b and Figs. 3c-3d, respectively.

The results of our method are presented in the second row with two different attenuation coefficients. We set the attenuation coefficients as: ground truth (Figs. 3e-3f) and estimated coefficient (Figs. 3g-3h). The restored images are not perfect, even for the ground truth coefficient, because of the error in the estimated depth maps obtained from our methodology. Furthermore, the improvement of the images is notable.

Histogram equalization (Figs. 3i and 3j) and CLAHE (Figs. 3k and 3l) improve the contrast but with limited restoration in terms of visibility and color fidelity. CLAHE presents the worst restoration result. Results obtained by UDCP (Figs. 3m-3n) show improvement in terms of visibility, but the method distorts the colors. One can see the color distortion by observing the white desk, where red halos appear.

We show the quantitative results obtained by using the image quality assessment (IQA) measures where three state-of-art metrics are employed [31], [32]. IQA methods are well established in the literature and aim to use computational models to measure the image quality consistently with subjective evaluations. The IQA metrics compare two images using values in the interval [0, 1], where one means the best quality while zero means the worst quality.

The first metric, called FSIM [31], is based on the fact that the human visual system responds to an image mainly according to its low-level features, specifically the phase congruency and the gradient magnitude. Secondly, [31] also proposed an extension called FSIMc that uses the chrominance information in the YIQ color space. The third metric adopted is called SR-SIM [32]. This metric is based on the spectral residual visual saliency and the hypothesis that an image’s visual saliency map is closely related to its perceived quality. This last method is only applicable to grayscale images.

Table I shows the results for each pair of restored images. One can readily see that our methodology produces the best results. CLAHE produces better results than the classic histogram equalization and than UDCP. Artificial underwater images produced the worst values, as expected.

V. EXPERIMENTAL RESULTS

Real underwater image sequences were obtained with an underwater vehicle, the Seabotix LBV300-5, equipped with a color camera (Fig. 4). Our method was applied to a sequence of images acquired in Brazil’s Southeast Coast, specifically in the Parcel do Carpeinteiro, a reef with irregular bottom topography formed by rocks, gravel and sand. The reef is located approximately 17 nmi from the coast, and has depths ranging from 12m to 20m.

The sequence was acquired with overlaid on-screen information (OSD), and the resolution of the captured images is 640 × 480 pixels. All pixels in the OSD area were discarded.

The radial distortion was corrected, and as a result the OSD information is distorted in the images.

Fig. 5 shows the results for the attenuation coefficient for each color channel on a sample pair of images shown in Fig. 6. Due to the estimation error, a robust approach is adopted to remove outliers, shown by black dots in Fig. 5. We also show the inlier points and the attenuation coefficient, i.e. as a line in this space. The total number of valid points is ≈ 8000 points. Points associated with missing values in the depth maps and pixels near zero in the normalized images were removed from the estimation process.

The attenuation coefficient is estimated as [0.1442, 0.1424, 0.0907], for each RGB channel respectively. These parameters are called total beam attenuation coefficient [14]. The blue channel typically has a smaller attenuation value while the red channel has a larger value as shown in the results. It is worth noting that this coefficient is obtained up to a scale factor due to the depth map estimation.

Fig. 6 shows the qualitative comparison of our restoration method for a sample pair of images acquired in naturally lit shallow water. Fig. 6a is a sample image acquired by the
TABLE I: Comparative study using the IQA metrics for the images shown in Fig. 3.

<table>
<thead>
<tr>
<th>Method</th>
<th>FSIM II</th>
<th>FSIMc II</th>
<th>FSIM II</th>
<th>FSIM II</th>
<th>SR-SIM II</th>
<th>SR-SIM II</th>
</tr>
</thead>
<tbody>
<tr>
<td>Underwater</td>
<td>0.8092</td>
<td>0.7110</td>
<td>0.8583</td>
<td>0.7312</td>
<td>0.8482</td>
<td>0.8995</td>
</tr>
<tr>
<td>UDCP</td>
<td>0.9171</td>
<td>0.8491</td>
<td>0.8978</td>
<td>0.8178</td>
<td>0.9380</td>
<td>0.9238</td>
</tr>
<tr>
<td>Hist. Eq.</td>
<td>0.9077</td>
<td>0.8764</td>
<td>0.8903</td>
<td>0.8611</td>
<td>0.9242</td>
<td>0.9175</td>
</tr>
<tr>
<td>CLAHE</td>
<td>0.9227</td>
<td>0.8441</td>
<td>0.8949</td>
<td>0.8124</td>
<td>0.9362</td>
<td>0.9321</td>
</tr>
<tr>
<td>Our Method</td>
<td>0.9646</td>
<td>0.9516</td>
<td>0.9327</td>
<td>0.9034</td>
<td>0.9778</td>
<td>0.9628</td>
</tr>
</tbody>
</table>

ROV, with limited visibility and significant color distortion. Fig. 6b show the images restored by our methodology, where the quality is clearly improved. The results obtained using adaptive histogram equalization are shown in Fig. 6d, where the contrast and the noise are improved, but the colors are distorted. The restored images using histogram equalization are shown in Fig. 6c and using UDCP in Fig. 6e. Fig. 6f shows the optical flow estimated using the GOFM approach. The method is able to correctly estimate the flow mainly in textured areas in the center of the image, and in the bottom right corner.

Quantitative results are obtained using the metric proposed by [33]. This metric was developed for weather-degraded images, but it was applied here due to the similarities with underwater images. It defines three different indexes: $e$, $\tau$ and $s$. The value of $e$ evaluates the ability of a method to restore edges which were not visible in the degraded image $I$, but are visible in the restored image $J$. The value of $\tau$ measures the quality of contrast restoration by the proposed method; a similar technique was adopted by [8] to evaluate restoration in an underwater medium. Finally, the value of $s$ is obtained from the proportion of the number of pixels which are saturated (black or white) after applying the restoration but were not before. These three indexes allow us to estimate an empirical restoration score $\tau = e + \tau + 1 - s$ [33], where larger values mean better restoration.

Our method outperforms the others in term of the $\tau$ metric. It achieves the best improvement in terms of new edges in the image, although it is not the best in terms of contrast. CLAHE obtains the best value of $\tau$ because of the increase in contrast in the entire image, including the seabed and the horizon area. The contrast is an interesting metric of the quality of the restored image but it is sensible to noise, a typical problem in restoration techniques.

We also perform quantitative results by matching SIFT [34] descriptors. In this experiment we evaluate the ability of the descriptor to identify and match features from a raw and restored image. Table III presents the results obtained for the restored images shown in Fig. 6. For each pair of images, we show the number of keypoints detected in both images and the number of correct matches. We adopted the MATLAB implementation provided by the SIFT’s author in order to compute the values.

Results show that our approach provides the largest number of correct matches, while the number of detected keypoints for the CLAHE method is larger. This is due to the increase in contrast and, mainly, to noise. This larger number of detection is expected since the restoration obtained by CLAHE (Table II) presented the larger $\tau$. However, this restoration is not stable, thus it does not increase the number of corrected matches. Figs. 6g-6h show that the matches obtained by our approach cover a larger area of the image than those obtained from CLAHE.

VI. CONCLUSION

In this paper we proposed a novel underwater restoration methodology based on monocular sequence of images that uses the temporal relation, geometric and environmental information to increase the quality of visual features for underwater images. The approach is based on robust estimation of the depth map and of the most critical parameter of the medium, namely the attenuation coefficient. The depth estimation is achieved using an adapted optical flow and structure-from-motion techniques. The proposed method estimates the attenuation coefficient using a new derivation of the underwater light attenuation model into the RANSAC framework. Our method shows better restoration results in quantitative and qualitative terms, both for simulated and real monocular sequences, when compared to other methods such as UDCP and histogram equalization techniques. Future work will focus on investigating multiple view structure from motion approaches to improve the depth map, and the inclusion of artificial illumination in the scene.

REFERENCES

TABLE II: Comparative study using the restoration score $\tau$ for the images shown in Fig. 6.

<table>
<thead>
<tr>
<th></th>
<th>$e_1$</th>
<th>$s_1$</th>
<th>$P_1$</th>
<th>$e_2$</th>
<th>$s_2$</th>
<th>$P_2$</th>
<th>$\tau_1$</th>
<th>$\tau_2$</th>
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<tbody>
<tr>
<td>UDCP</td>
<td>1.7259</td>
<td>0.0001</td>
<td>1.2682</td>
<td>1.6918</td>
<td>0.0001</td>
<td>1.2499</td>
<td>3.9940</td>
<td>3.9416</td>
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<tr>
<td>Hist. Eq.</td>
<td>2.7595</td>
<td>0.0115</td>
<td>2.3023</td>
<td>2.3265</td>
<td>0.0064</td>
<td>2.6665</td>
<td>5.9266</td>
<td></td>
</tr>
<tr>
<td>CLAHE</td>
<td>1.9001</td>
<td>0.0048</td>
<td>1.2862</td>
<td>1.8640</td>
<td>0.2068</td>
<td>2.9126</td>
<td>5.7766</td>
<td></td>
</tr>
<tr>
<td>Our Method</td>
<td>2.8621</td>
<td>0.0005</td>
<td>2.4676</td>
<td>2.6277</td>
<td>0.0006</td>
<td>2.7266</td>
<td>6.3537</td>
<td></td>
</tr>
</tbody>
</table>

TABLE III: Comparative analysis using the image descriptor SIFT for the images shown in Fig. 6.

<table>
<thead>
<tr>
<th></th>
<th>Correct Matches</th>
<th>Keypoints I1</th>
<th>Keypoints I2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original</td>
<td>0</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>UDCP</td>
<td>1</td>
<td>18</td>
<td>18</td>
</tr>
<tr>
<td>Hist. Eq.</td>
<td>10</td>
<td>151</td>
<td>243</td>
</tr>
<tr>
<td>CLAHE</td>
<td>11</td>
<td>359</td>
<td>422</td>
</tr>
<tr>
<td>Our Method</td>
<td>17</td>
<td>176</td>
<td>322</td>
</tr>
</tbody>
</table>


Fig. 6: Qualitative comparison between our methodology, UDCP and histogram equalization techniques using a sequence of images acquired in naturally lit shallow water. (a) original image, (b) restored by our methodology, (c) restored using histogram equalization, (d) restored using CLAHE, and (e) using UDCP. (f) shows the optical flow estimated using GOFM, and (g, h) the SIFT matching in restored images using CLAHE and the proposed method, respectively.