Underwater Depth Estimation and Image Restoration Based on Single Images

Paulo L.J. Drews Jr. ▪ *Universidade Federal do Rio Grande*

Erickson R. Nascimento ▪ *Universidade Federal de Minas Gerais*

Silvia S.C. Botelho ▪ *Universidade Federal do Rio Grande*

Mario Fernando Montenegro Campos ▪ *Universidade Federal de Minas Gerais*

In underwater environments, scattering and absorption phenomena affect the propagation of light, degrading the quality of captured images. A method based on a physical model of light propagation and the use of statistical priors can restore the visual quality of the images acquired in typical underwater scenarios.

An increasing number of real-world applications are related to underwater environments, including fisheries, environmental and structural monitoring and inspections, and oil and gas exploration. Petroleum and natural gas are still the most important energy sources in the world, and researchers have recently discovered relevant oil and gas reserves along the coasts of Brazil and Africa underneath what is known as presalt rock formations. Presalt layers of rocks in the earth's crust consist of petrified salt covering large areas on the ocean floor. Recent findings have unveiled that, over millions of years, large amounts of organic matter have been deposited beneath the layers of pressed salt between the west coast of Africa and the eastern shores of South America. This organic matter has been transformed into oil that in many areas is engulfed with gas.

In Brazil, the presalt area spans a range of about 800 kilometers along the coast. Geological studies have estimated that the oil and gas reserves in that area are on the order of 80 billion barrels, which would place Brazil as the sixth largest holder of reserves in the world, behind Saudi Arabia, Iran, Iraq, Kuwait, and the United Arab Emirates.

Exploring and working in the presalt reserves, however, present technological challenges that include the ability to perceive the underwater environment. Techniques based on machine vision can help humans monitor and supervise activities in these scenarios as well as allow us to carry out missions with autonomous robotic vehicles. In general, computer vision algorithms assume that the medium does not affect light propagation, but this assumption does not hold in scattering media such as underwater scenes. Indeed, scattering and absorption phenomena affect the propagation of light, degrading the quality of captured images.

Thus, efforts in the image processing and computer vision fields to improve the quality of underwater images may contribute to several applications, especially those related to the offshore oil and gas industry. In this article, we address the problems involved in image restoration, such as improving the visual quality of underwater images, and using a scene's depth estimation to extract geometrical information of the objects therein.

Image restoration and depth estimation are ambiguous problems because the available number of constraints is generally smaller than the number

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Related Work in Image Restoration of Underwater Images

Previous works have approached the problem of restoring images acquired in underwater scenes from several perspectives, such as using special-purpose hardware, stereo images, and polarization filters.[1] Although the improvements achieved by these approaches, they still present several limitations. For instance, methods that rely on specialized hardware are expensive and complex. The use of polarizers, for example, requires moving parts, and it is hard to implement in automatic acquisition tasks. In a stereo vision system approach, the correspondence problem becomes even harder because of the strong effects imposed by the medium. Methods based on multiple images require at least two images of the same scene taken under different environment conditions, which makes them inadequate for real-time applications. Thus, the problem of image restoration for underwater scenes still demands much research effort in spite of the advances that have already been attained.

In the past few years, a large number of algorithms for image restoration based on a single image have been proposed; the works of Kaiming He and his colleagues[2] and of Raanan Fattal[3] are the most cited in the field. Although these works have shown good performance in attempts to enhance the visual quality for outdoor terrestrial images, there is still room for improvement when they are applied to underwater images. As far as single-image methods are concerned, He and his colleagues have proposed one of the most popular methods called Dark Channel Prior (DCP). Liu Chao and Meng Wang,[4] John Chiang and Ying-Ching Chen,[5] and Seiichi Serikawa and Huimin Lu[6] have applied the DCP method to restore the visual quality of underwater images. However, these works do not address some of the fundamental DCP limitations related to the absorption rate of the red channel and do not discuss relevant issues with the basic DCP assumptions.

Unlike outdoor scenes, the underwater medium imposes wavelength-dependent rates of absorption, mainly in the red channel. Thus, Paulo Drews Jr. and his colleagues proposed a modified version of DCP to overcome this limitation for applications in underwater imaging.[7] Here we build on and extend that work, providing an extensive study about the prior with applications to image restoration and depth estimation. Furthermore, we provide new results of image restoration using qualitative and quantitative analysis.

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of unknown variables. One of the strategies most commonly adopted to tackle these problems in computer vision is to impose additional constraints that are based on some a priori knowledge about the scene, or *priors*. In general, a prior can be a statistical or physical property, an ad hoc rule, or even a heuristic assumption. Some of the widely used priors in image processing are smoothness, sparsity, and symmetry. Yet, an algorithm's performance is limited by the extent to which the prior is valid.

Inspired by the observation of Kaiming He and his colleagues that natural scenes tend to be dark in at least one of the RGB color channels,[1] we derived a new prior by observing the relevance of the absorption rate in the red color channel in underwater images. By collecting a large number of images from several image search engines, we tested our prior and validated its applicability and limitations on images acquired from real scenes.

The main contribution of the work we describe here is an extension of our previous work to deal with underwater image restoration called Underwater Dark Channel Prior (UDCP).[2] We present a deeper study of the method, including an extensive statistical experimental verification of the assumption following the guidelines described by He and his colleagues (see the related work sidebar for more details).[1] Additionally, we present a new application of UDCP for underwater image restoration and depth estimation. We performed qualitative and quantitative analyses on the algorithm using a new set of data, including images acquired off the Brazilian coast. The techniques presented here offer new opportunities to develop automatic algorithms for underwater applications that require high-quality visual information.

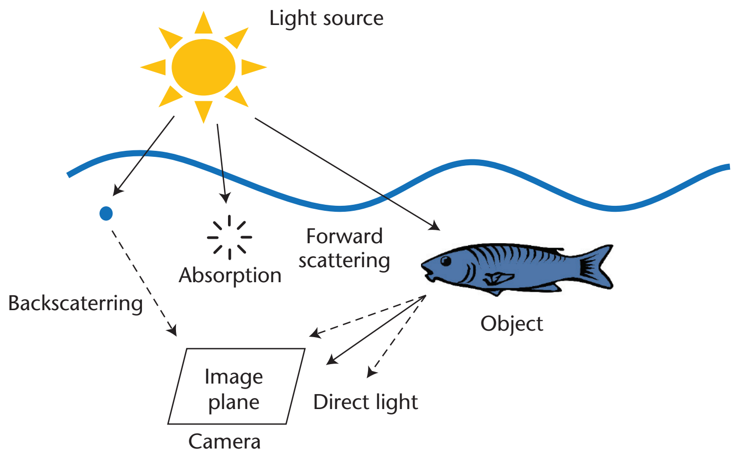


Figure 1. The underwater attenuation light model. The dashed lines show the forward scattering and backscattering effects. The scattering of light rays at small and large angles creates these effects, respectively. Direct light is the portion of light irradiated by the scene that reaches the image plane.

Underwater Attenuation Light Modeling

The formation of underwater images results from a complex interaction between the light, the medium, and the scene. A simplified analysis of this interaction is possible while still maintaining physical plausibility. To this end, first-order effects are forward scattering and backscattering—that is, the scattering of light rays at small and large angles. The absorption of light is associated with these two effects because they respond to contrast degradation and color shift in images. Figure 1 illustrates these effects.

According to Yoav Schechner and Nir Karpel,[3] backscattering is the prime reason for image contrast degradation, so the forward-scattering effect can be neglected. Therefore, the underwater attenuation light model is a linear combination of the direct light and backscattering. The direct light is defined as the fraction of light irradiated by the scene where a part is lost due to scattering and absorption. On the other hand, backscattering does not originate from the object's radiance; rather it results from the interaction between the environment's illumination sources and the particles dispersed in the medium. For a homogeneous illuminated environment, the backscattered light can be assumed to be constant, and it can be obtained from the image by using a completely haze-opaque region or by finding the farthest pixel in the scene. However, it is impossible to automatically acquire this information from a single image. Finding the brightest pixel in the dark channel is assumed an adequate approximation.

One important aspect of the linear model is the weight of the direct and backscattering components in the final image. The weight presents an exponential behavior in relation to the depth and the attenuation coefficient. In the literature, the exponential weight is called medium transmission. The depths in the scene are estimated up to a scale factor by applying the log operation to the medium transmission value.

The attenuation coefficient is an inherent property of the medium, and it is defined as the sum of the absorption and scattering rates. Because both rates are wavelength dependent, the attenuation coefficient is different for each wavelength.

Image restoration is performed by inverting the underwater attenuation light model. Assuming that we are able to estimate the medium transmission and the backscattering light, the restored image is computed by summing the backscattering light intensity and dividing it by the normalized color image.

Dark Channel Prior

The DCP is a statistical prior based on the observation that natural outdoor images on a clear day exhibit mostly dark intensities in a square patch of the image.[1] It was inspired by the well-known dark-object subtraction method from the remote sensing field. He and his colleagues considered that, in most of the nonsky patches in images of outdoor scenes, at least one color channel in the RGB representation would have some pixels with an intensity that was almost zero. This low intensity in the dark channel is due to three factors: shadows in the images, colorful objects or surfaces where at least one color has low intensity, and dark objects or surfaces. They collected a large number of outdoor images and built histograms, and with those, they showed that about 75 percent of the pixels in the dark channel had zero values and that the intensity of 90 percent of the pixels was below 25 on a scale of [0, 255]. Those results provide strong support for the DCP assumption for outdoor images. This prior lets us estimate an approximation of the amount of the medium transmission in local patches. He and his colleagues showed that DCP provided excellent results in hazy scenes.

The use of a local patch affects the performance of the medium transmission estimation. He and his colleagues proposed the use of a spectral matting method to refine the estimated transmission. Their method presents good results, but it requires a high computational effort to process the Laplacian matrix. Other works proposed approximate solutions to make it faster by using quadtrees, Markov random fields, or filtering techniques such as guided or bilateral filters.

DCP for Underwater Images and Their Variations

Because of the good results obtained by the DCP method for hazy scenes and the similarities in the modeling of hazy and underwater images, some previous works applied DCP to process underwater images. Liu Chao and Meng Wang were some of the first researchers to use DCP for underwater images.[4] Their reported results show a limited number of experiments where the visual quality of the results does not present a significant improvement, even for images with small degradation. John Chiang and Ying-Ching Chen also proposed an underwater image restoration method using DCP.[5] Their method obtained good results for real underwater images, but it was limited by the DCP method in underwater images and by the assumption that the image is predominantly blue. Recently, Seiichi Serikawaa and Huimin Lu proposed a variation of DCP that filters the medium transmission by using a joint trilateral filter.[6] Despite the improvement attained in the image restoration when compared with standard DCP, the limitation related to the red channel remains the same.

Kristofor Gibson and his colleagues proposed a variation of the DCP that replaces the minimum operator in an image patch with the median operator.[7] For their method, named MDCP, they chose the median operator because of its ability to preserve edges. Their approach could provide good estimation when the effects of the medium are approximately wavelength independent; in this case, the behavior tends to be similar to standard DCP.

Nicholas Carlevaris-Bianco and his colleagues proposed an underwater image restoration method using a new interpretation of the DCP for underwater conditions.[8] The proposed prior explores the fact that the attenuation of light in water varies depending on the light's color. The underwater medium attenuates the red color channel at a much higher rate than the green and blue channels. Unlike the standard DCP, that prior is based on the difference between the maximum in the red channel and each one of the other channels (G and B), instead of only the minimum, as in DCP. The method works well when the absorption coefficient of the red channel is large. That method shows some shortcomings, however, when estimating the medium transmission in shallow waters.

UDCP and Image Restoration

The statistical correlation of a low dark channel in haze-free images is not easy to test for underwater images because of the difficulty of obtaining real images of underwater scenes in an out-of-water condition. However, the assumptions made by He and his colleagues are still plausible—that is, at least one color channel has some pixels with an intensity that is close to zero. These low intensities are due to shadows; colored objects or surfaces having at least one color channel with a low intensity, such as fish, algae, or coral; and dark objects or surfaces, such as rocks or dark sediment.

Even though that dark channel assumption seems to be correct, some problems still arise from the wavelength independence assumption. There are many practical situations where the red channel is nearly dark, which corrupts the transmission estimate by DCP. Indeed, the red channel suffers an aggressive decay caused by the absorption of the medium, making it approximately zero even in shallow waters. Thus, the red channel information is not dependable.

To overcome this issue, our proposed UDCP considers just the green and blue color channels. This prior allows us to invert the model and obtain an estimate of the medium transmission. The medium transmission and the backscattering light constants provide enough information to restore the images.

We performed an experimental verification to evaluate the assumption of the new prior based on two assumptions:

- The main DCP assumption for outdoor scenes remains valid if it is only applied to the green and blue channels.
- The behavior of the UDCP histogram in underwater scenes is plausible.

Because the dataset collected by He and his colleagues is not publicly available, we created our own dataset following their proposed guidelines.[1] Our dataset consists of 1,022 outdoor landscape images greater than 0.2 megapixels (MPs) from the SUN database (see Figure 2 for image samples).[9] We also selected a subset of 274 images of natural scenes without any human-made object (see Figure 2a).

We next computed the distribution of pixel intensities, where each bin contains 16 intensity levels from an interval of [0, 255] (see Figure 3). We obtained the two set of histograms using only a subset of images acquired in natural scenes (274 images) and the full set of images. In Figure 3, each row depicts the results for the minimum operator in a small patch window using only the red, green, and blue channels; the DCP (dark channel in all channels), and the UDCP (dark channel in green and blue).

Figure 2. Sample images of our outdoor scenes dataset: (a) Natural scenes only and (b) scenes that include human-made structures and objects. (Images acquired from the SUN dataset[9]).

Even though our datasets and those used by He and his colleagues differ, they were collected using the same guidelines, and thus, some similarity is to be expected. Indeed, the histograms present similarities, but also important differences. The probability of the first bin (intensities between 0 and 15) is smaller than the one presented by He and his colleagues. They reported approximately 90 percent for the first bin in DCP, whereas the probability for our dataset is approximately 45 percent (see Figure 3). We can see that the highest probability, approximately 50 percent, is obtained for histograms of natural scenes (first and third rows in Figure 3), which is to be expected of typical underwater scenes.

The most important observation is related to the significance of each channel for the prior. The lower-intensity bins of the blue channel are dominant mainly in natural scenes. The red channel is still dark, but it is the most equalized histogram. The green channel presents similar behavior. Thus, the absence of blue color in the final composition of the scene represents the prevalence of this channel in both DCP and UDCP.

Figure 3 shows the similarities between the DCP and UDCP statistics in the histogram. We give the Pearson linear correlation coefficient in Table 1, which quantifies these similarities. The correlation coefficient range is [–1, 1], where a coefficient value close to 1 indicates that the relationship is almost perfect, and negative values indicate that data are uncorrelated.

One can readily see that there is a strong correlation between DCP and UDCP, which means that both methods are based on similar assumptions about the scene—that is, the presence of a low-intensity dark channel. The value of the correlation coefficients for the blue channel and DCP are approximately equal to 1, meaning that they are also strongly correlated. In the natural scenes, the correlation between the DCP and green channel is the smallest because of the presence of grass and trees in the scenes, which causes an increase in the intensities of this color channel.

We also created two datasets of underwater images to evaluate the influence of the medium and verify the UDCP assumptions. The datasets' creation again followed the guidelines of He and his colleagues. The first dataset (reduced) was created by extracting the images from a single Flickr user. This dataset contains 65 high-quality photos acquired with the same camera. The images, which include coral reefs, rocks, marine animals, and a shipwreck, were acquired during diving activities at several locations around of world (thus with different turbidity levels). Figure 4a shows sample images of the reduced dataset.

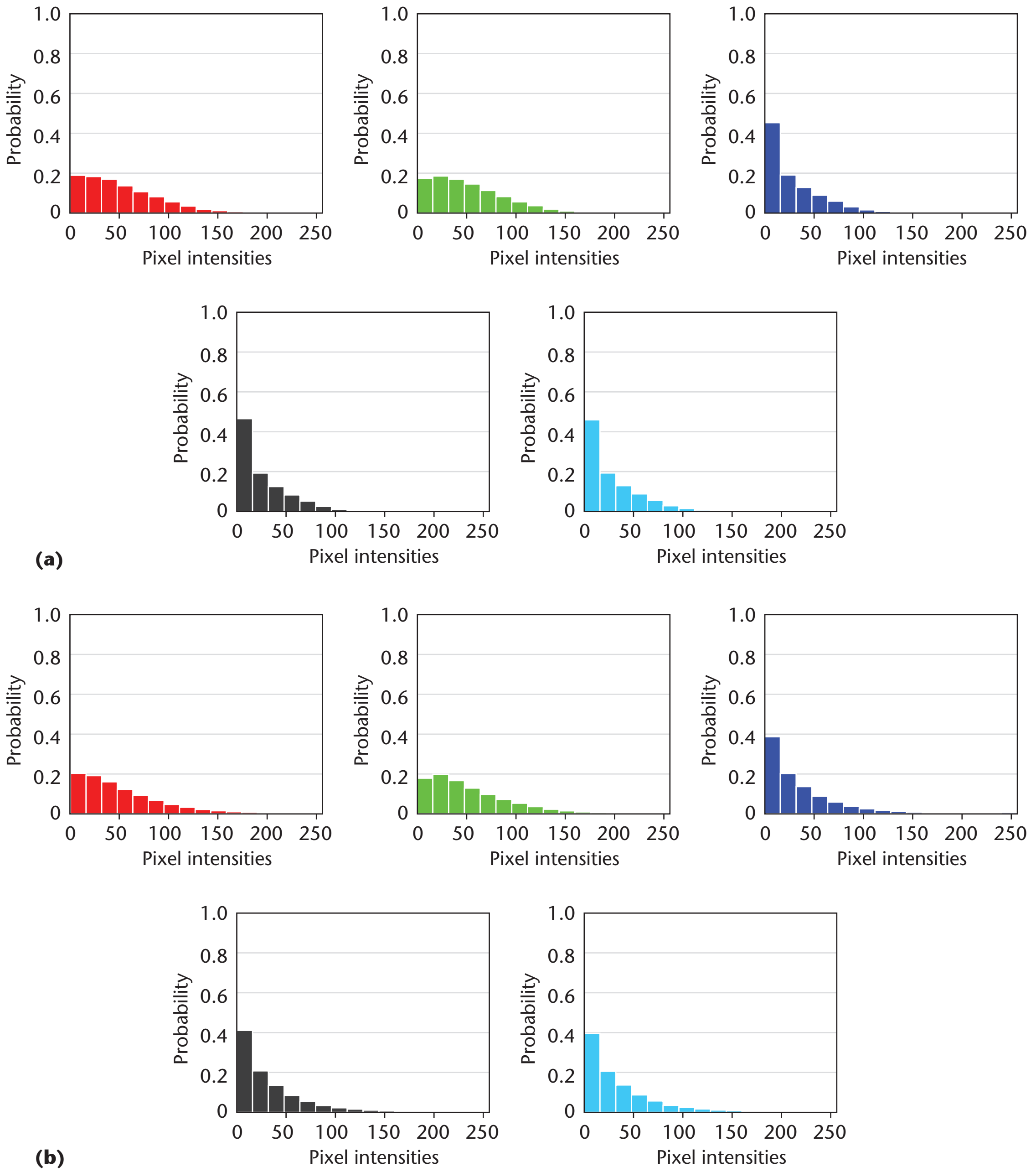


Figure 3. Distribution of pixel intensity of the dark channel for outdoor scenes: (a) Natural scenes only and (b) all images of the dataset. We show the histograms for the red, green, and blue channels, the DCP (in black), and the UDCP (in cyan).

Figure 4b shows sample images of the extended dataset, which we obtained by collecting images from several image search engines on the Internet. This dataset consists of 171 underwater images acquired under diverse media conditions, water depths, and scenes, which provides a rich source of information. All the images are approximately homogeneous illuminated.

Unlike the histograms of outdoor scenes, for the underwater images, approximately 90 percent of the pixels in the red channel are in the first bin (see Figure 5). This agrees with the UDCP assumption that the red channel has the highest absorption. As expected, the dark channel for the blue and the green channels are similar, but many values cover a broader range because of the effects of the interaction of light with the medium. The DCP histograms are somewhat consistent with what we would expect for nonparticipating media. Hence, DCP is not able to adequately recover the medium transmission. However, the bin values in the UDCP histograms are more evenly distributed,

Table 1. Pearson correlation coefficient between DCP and UDCP and the red, green, and blue channels.

Power	Subset of natural scenes	Dataset
UDCP	0.9999	0.9998
Red	0.8049	0.8856
Green	0.7680	0.8351
Blue	0.9998	0.9995

(a)

(b)

Figure 4. Sample images from the underwater datasets. (a) The reduced dataset includes images from a single Flickr user. (Courtesy of Rémi Forget) (b) The extended dataset contains images obtained from several image search engines. (Courtesy of Kristina Maze)

which indicates that UDCP is a better approach for estimating the medium transmission.

Experimental verification shows that the statistics for the UDCP assumption is a more general supposition than the DCP assumption. However, these results do not guarantee the quality of the estimated transmission. UDCP and DCP obtain similar histograms for natural scenes, as shown by the correlation analysis. These results indicate that both are based on similar assumptions.

Another important characteristic concerns the blue channel, which in natural scenes tends to be darker than the other channels. The underwater medium is typically blue, thus increasing the intensities of this color channel. This fact corroborates the UDCP assumption.

Experimental Results

Our experiments showed that the UDCP assumptions are valid, but it is also important to determine if UDCP outperforms the other DCP-based methods for restoring images. To evaluate the performance of UDCP, we applied the standard DCP to underwater images, as proposed by earlier work.[4,5] We also applied MDCP[7] to the underwater images, but with the refinement proposed by He and his colleagues.[1] We also obtained results for Bianco's prior (BP).[8]

Our evaluation includes both qualitative and quantitative analyses. Figures 6 and 7 show the qualitative results for the underwater images collected from the Internet.[10] Figure 8 shows a sample of images from three underwater videos that we captured, composed of 150, 138, and 610 frames, respectively. We acquired these videos in a coral reef at the Brazilian northeast coastal area at a depth of approximately 10 m.

In the quantitative evaluation, we used a metric called τ proposed by Nicolas Hautière and his colleagues[11] to analyze their method for weather-degraded images. We adopted this metric in the present work because of the similarities between

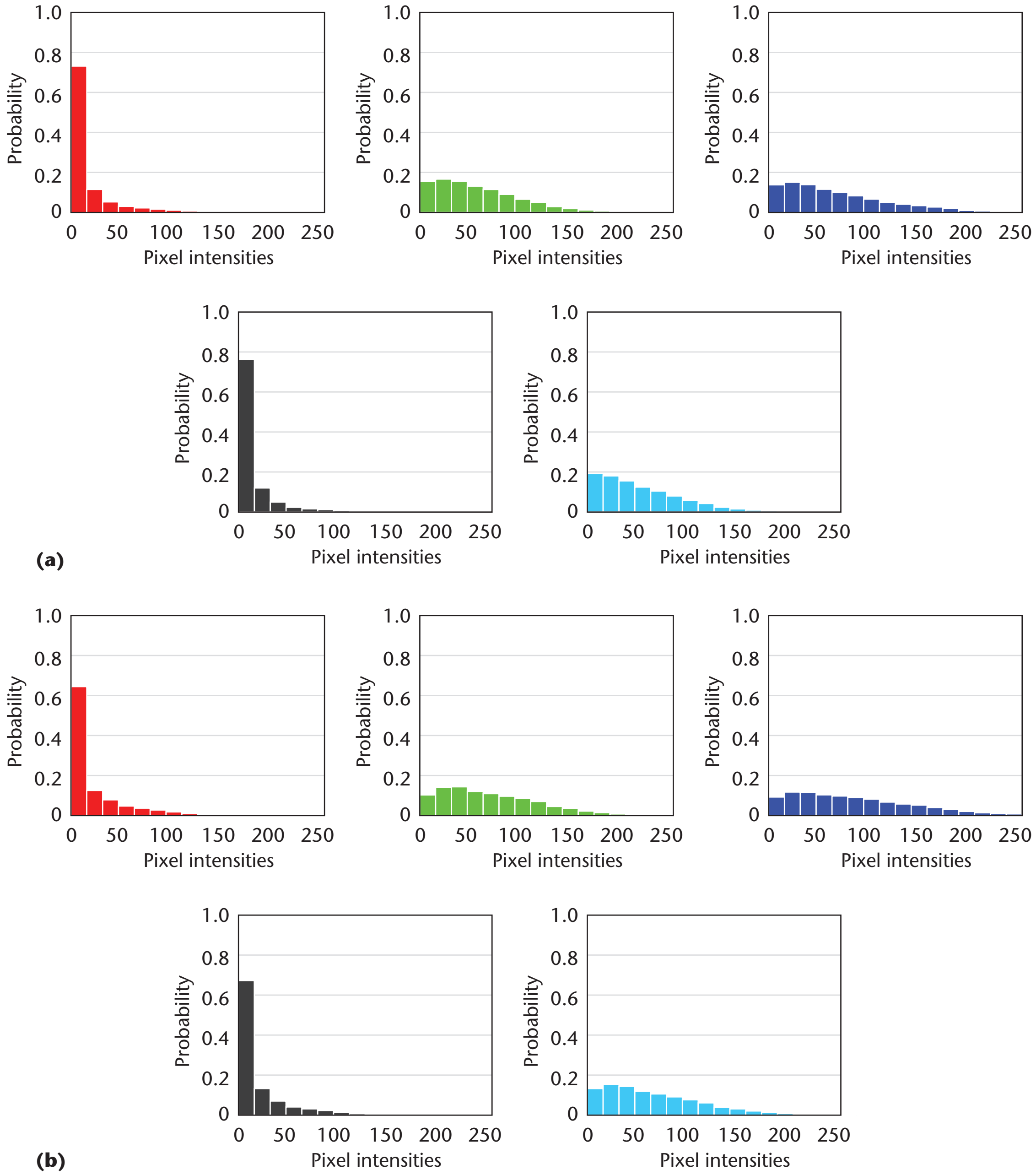


Figure 5. Distribution of pixel intensity of the dark channel for underwater scenes: (a) Reduced dataset and (b) extended dataset. We show the histograms for the red, green, and blue channels; the DCP (in black); and the UDCP (in cyan).

weather-degraded and underwater images. Three different indexes are defined in the τ metric: e, $\overline{r}$, and s. The value of e evaluates a method's ability to restore edges that were not visible in the degraded image but that are visible in the restored image. The value of $\overline{r}$ measures the quality of the contrast restoration; a similar technique was adopted by earlier work[3] to evaluate restoration in an underwater medium. Finally, the value of s is obtained from the number of pixels that are saturated (black or white) after the restoration method is applied but were not before. These three indexes allow us to estimate an empirical restoration score, $\tau = e + \overline{r} + 1 - s$, where larger values indicate better restoration.[11] Table 2 shows the obtained results.

Figure 6 depicts examples from these experiments, where Figure 6a shows the original image, Figure 6b shows the restored image, and Figure 6c shows the colorized depth maps obtained using the UDCP approach. We colorized the depth maps to aid the visualization, where bluish colors represent closer points and reddish colors represent points that are further away.

Figures 6 and 7 also show the results obtained by applying the methods proposed by other authors on images from the extended dataset. Figures 6a and 7a show underwater images with the backscattering light estimation. The estimation of the backscattering constant obtained by UDCP seems to be the most plausible—that is, near the farthest point in the image. The other methods fail in the estimation in at least one of the images. They

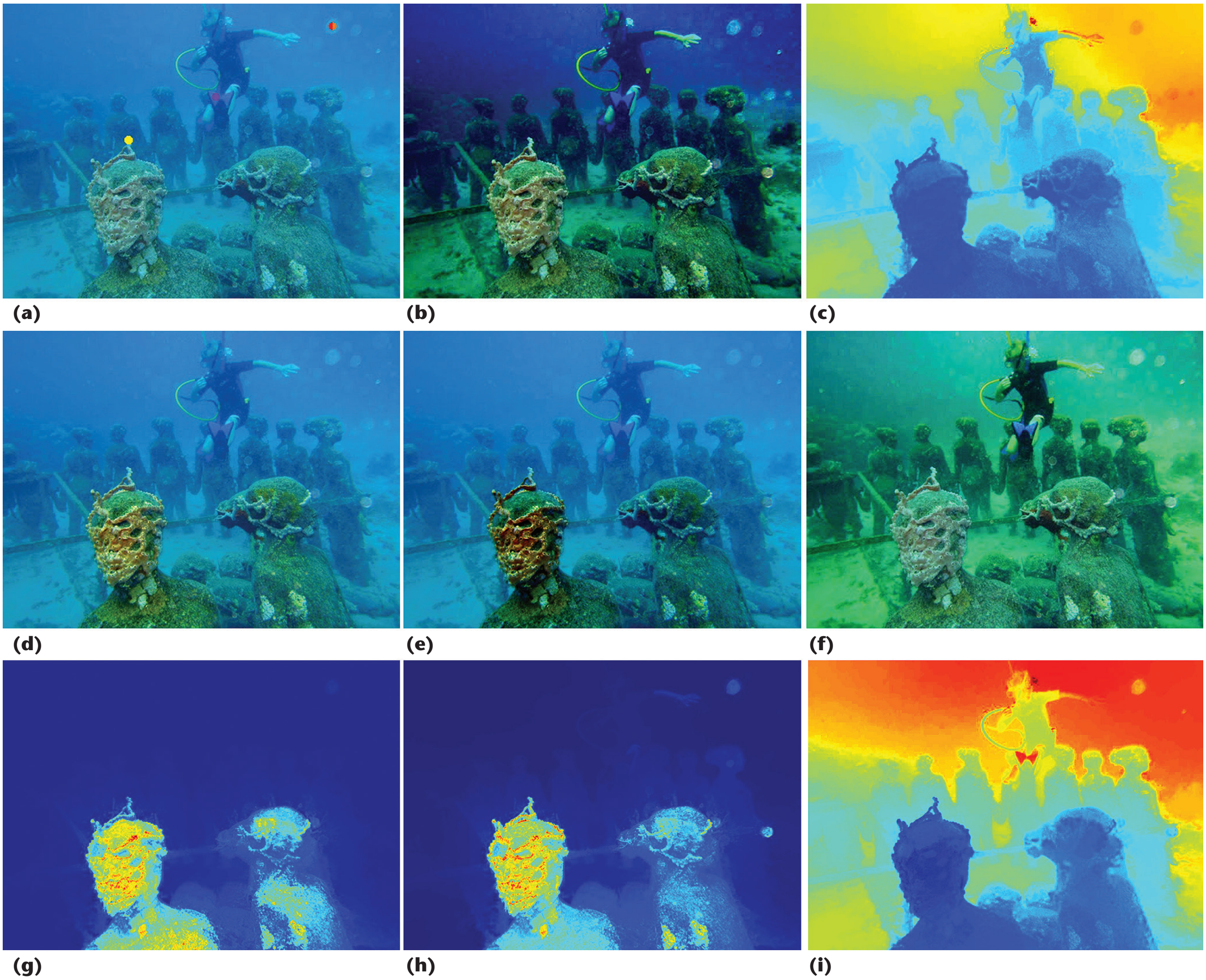


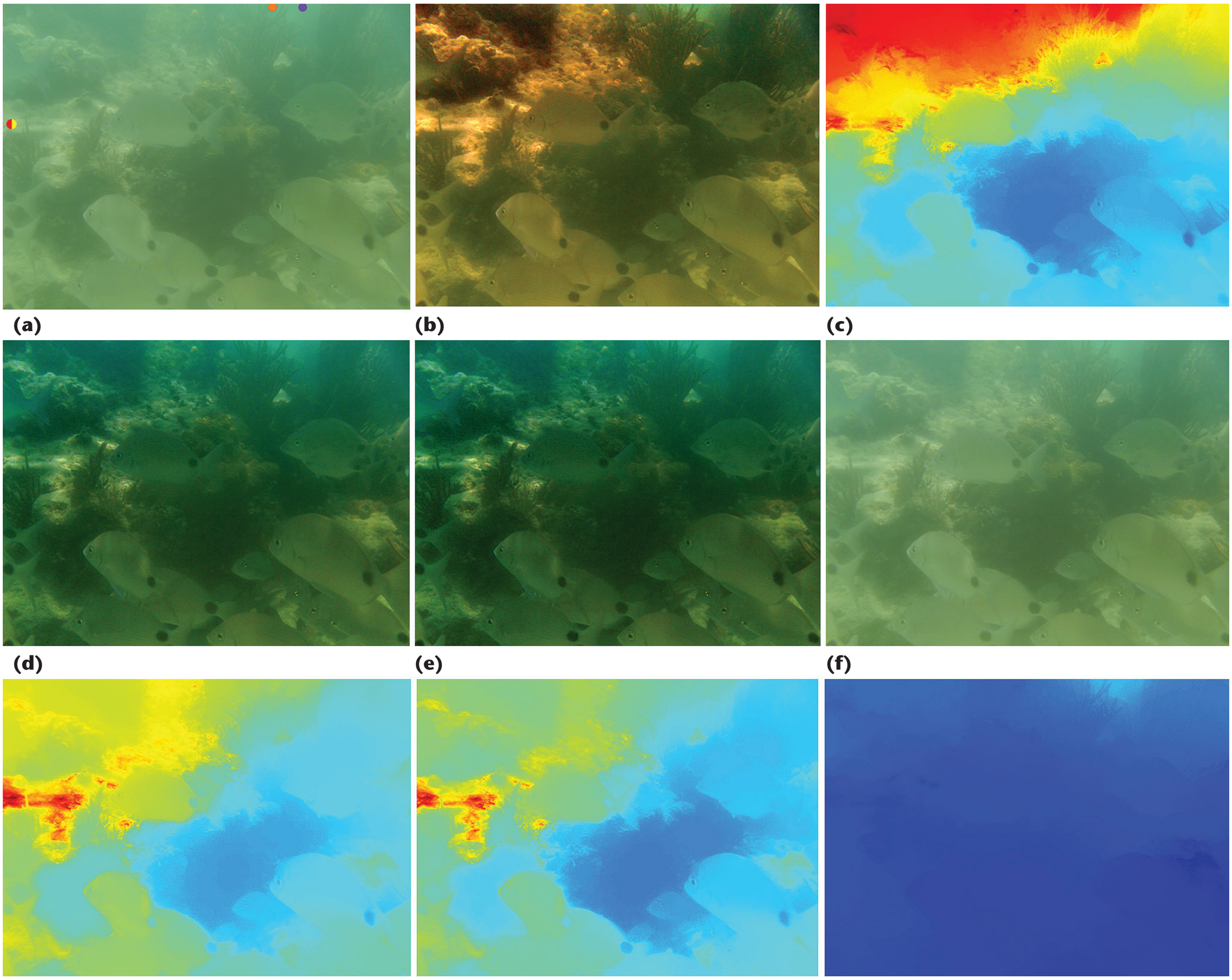
Figure 6. Restored image and depth estimation: (a) Underwater image with regions where the backscattering constant was estimated, using UDCP (orange patch), DCP (red patch), MDCP (yellow patch), and BP (purple patch). Restored images using (b) UDCP, (d) DCP, (e) MDCP, and (f) BP. Colorized depth maps obtained using (c) UDCP, (g) DCP, (h) MDCP, and (i) BP. (Original image courtesy of Kevin Clarke)

identify the backscattering light in bright surfaces of the scene instead of the farthest point.

The restored images using UDCP, Figures 6b and 7b, show that there was an improvement as far as contrast and color fidelity are concerned. The values in Table 2 show that the restoration using UDCP presented the best values for the τ metric for all experiments, including the extended dataset. In Figure 6, UDCP (Figure 6b) and BP (Figure 6f) presented the best results for contrast and visibility. However, BP fails to estimate the backscattering constant. It generates incorrect depth information shown by the colorization of the restored image. This is corroborated by the fact that the depth maps estimated by both methods are similar. We can also see an improvement in the estimation of the ocean floor in the image restored using UDCP. The improvement provided by DCP and MDCP is imperceptible because neither method could correctly recover the depth map.

The UDCP method obtained the best results in Figure 7 as well, and BP presented the worst results (see Figure 7f). The values in Table 2 also confirm this. This can be explained by the fact that BP underestimates the attenuation coefficient, limiting the quality of the map. This is because the red channel is not completely absorbed. The results obtained by DCP (Figure 7d) and MDCP (Figure 7e) are also related to this fact because both methods are able to provide good results for depth map and restoration.

Figure 8 shows the results obtained by applying the methods to the videos that we captured. We depicted one sample image from each video (see Figures 8a, 8b, and 8c). For these sample images, the backscattering constant is well balanced in all wavelengths due to the characteristics of the water



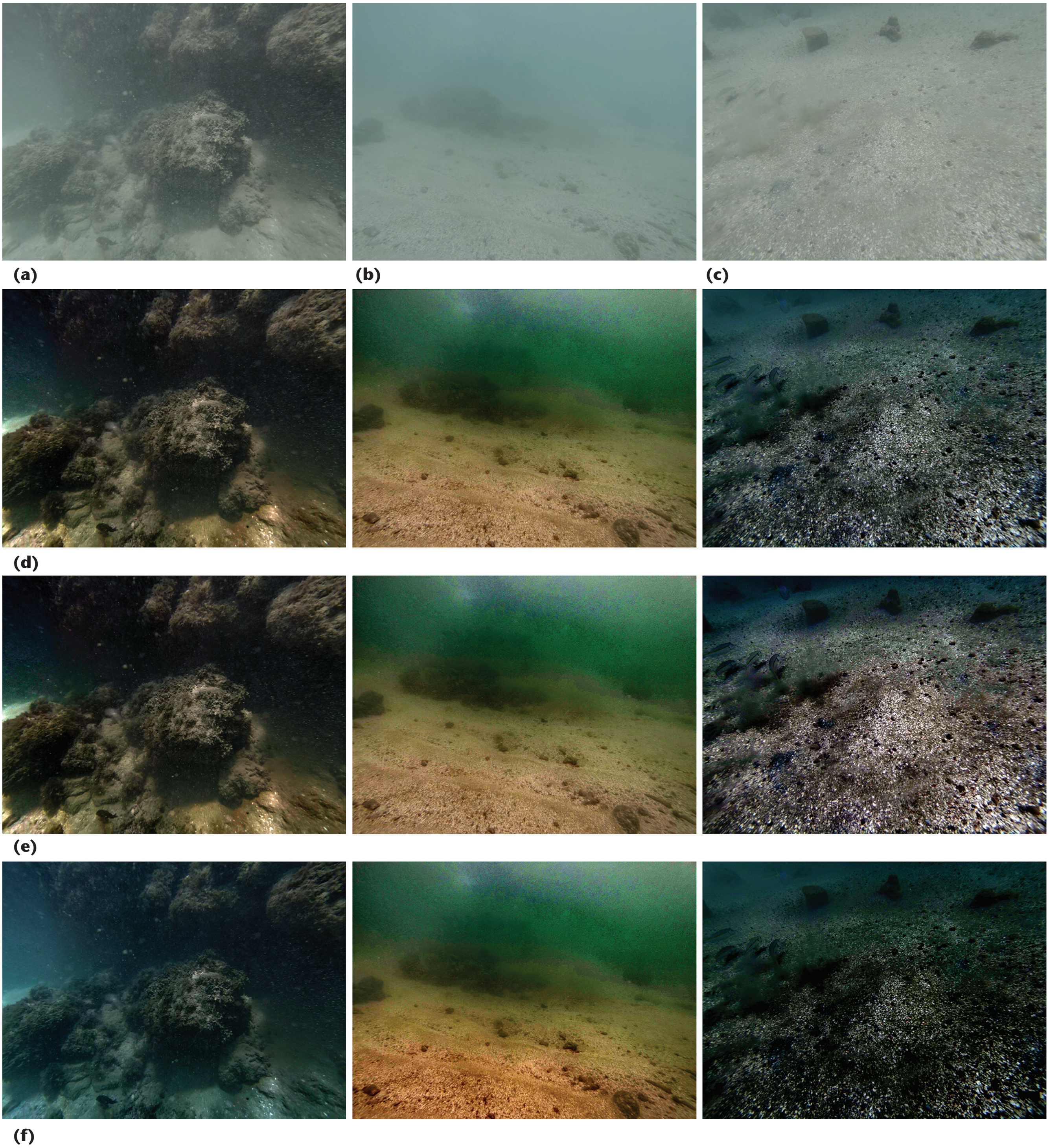
(a) (b) (c)
(d) (e) (f)
(g) (h) (i)

Figure 7. Second example of a restored image and depth estimation: (a) Underwater image with regions where the backscattering constant was estimated, using UDCP (orange patch), DCP (red patch), MDCP (yellow patch), and BP (purple patch). Restored images using (b) UDCP, (d) DCP, (e) MDCP, and (f) BP. Colorized depth maps obtained using (c) UDCP, (g) DCP, (h) MDCP, and (i) BP. (Original image courtesy of Cosmin Ancuti and colleagues[10]).

and shallow depth. In this case, DCP, MDCP, and UDCP present similar results in qualitative terms. The BP method fails to estimate the depth map, in a similar way as the one shown in Figure 7. Thus, we omit the results using BP because they are similar to those obtained by the underwater camera. UDCP attained the best results for scenes located farther from the camera, as the visibility of the rock in the top left of the restored image in Figure 8e shows.

Table 2 shows the average values for the videos illustrated by the sample images in Figure 8. We can clearly see that our method presents better results using the τ metric, especially due to its ability to improve edges. Table 2 also gives the average of the extended dataset, and the results are still favorable to UDCP. One can see that the τ metric presents large values for video associated with Figure 8a. This is because the number of edges in the underwater images are small, assuming the parameters adopted by Hautière and his colleagues.[11] The increase provided by the restoration is large, producing large values of the e metric and, as a consequence, the τ metric.

Although DCP is intuitive, it has shown limitations when applied to underwater conditions because of the high absorption of the red channel. The MDCP yielded results similar to DCP. The BP method presented good results in specific contexts, but it underestimates the medium transmission. Finally, UDCP presented the most significant results for underwater conditions, providing good restoration and depth estimation even in situations where other methods can fail.



(a) (b) (c) (d) (e) (f)

Figure 8. Image restoration of three underwater videos acquired in the Brazilian northeast coastal area. (a)–(c) A sample image from each video. The restoration results for these sample images obtained by (d) DCP, (e) UDCP, and (f) MDCP.

Even though UDCP presented meaningful results, it is lacking in terms of reliability and robustness due to the limitations imposed by the assumptions. On the one hand, using a single-image method to restore images can enhance quality, but on the other hand, it is susceptible to the variations in scene characteristics. Thus, one important direction for future work is to use the information provided by the image to estimate a confidence level, which would prove to be useful in practical applications, such as robotics. Another important direction to pursue is using image sequences to disambiguate the model parameters. Video acquisition is a common capability in almost all types of underwater cameras used by divers and remotely operated underwater vehicles. In this case, a single-image restoration method can be

Table 2. Quantitative evaluation of the underwater restoration methods using the τ metric.[11]

Source image	UDCP	DCP	MDCP	BP
Figure 6a	4.52	2.22	2.14	3.50
Figure 7a	60.43	41.44	56.97	3.01
Average of the extended dataset	3.68	2.77	2.75	3.01
Figure 8a	705.61	640.95	641.72	2.85
Average of video 1	3,460.2	1,500.0	1,942.8	2.79
Figure 8b	5.82	5.49	4.80	2.21
Average of video 2	32.02	23.09	24.09	2.30
Figure 8c	10.81	9.56	8.98	2.23
Average of video 3	90.37	69.56	73.11	2.36

used for initial estimation, which would be followed by successive refinements as other images become available. Finally, for several applications, it might be necessary to enhance the model to deal with images acquired under artificial illumination. It will enable us to deal with deep-water conditions.

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Paulo L.J. Drews Jr. *is an assistant professor at the Federal University of Rio Grande (FURG), Brazil. His research interests include robotics, computer vision, image processing, pattern recognition, and machine learning. Drews has a DSc in computer science from the Federal University of Minas Gerais (UFMG), Brazil. Contact him at paulodrews@furg.br.*

Erickson R. Nascimento *is a professor in the Department of Computer Science at the Federal University of Minas Gerais (UFMG), Brazil. His research interests include computer vision, pattern recognition, and visual computing. Nascimento has a DSc. in computer science from UFMG. Contact him at erickson@dcc.ufmg.br.*

Silvia S.C. Botelho *is an associate professor at the Federal University of Rio Grande (FURG), Brazil, and the vice director of the Centro de Ciencias Computacionais (C3-FURG). She is also the founder and director of the Robotics and Intelligent Automation (NAUTEC) at FURG. Her research interests in automation and computer science focus on sensor grids, intelligent systems, and robotics. Botelho has a PhD in robotics from the Laboratoire d'Analyse et d'Architecture des Systemes, Toulouse, France. She is a member of the Robotics Committee of the Brazilian Computer Society. Contact her at silviacb@furg.br.*

Mario Fernando Montenegro Campos *is a professor of computer vision and robotics in the Department of Computer Science at the Federal University of Minas Gerais (UFMG). He is also the founder and director of the Vision and Robotics Lab (VeRLab) at UFMG. His research interests include cooperative robotics, robot vision, and sensor information processing. Campos has a PhD in computer and information science from the University of Pennsylvania. He has been a distinguished lecturer with the IEEE Robotics and Automation Society. Contact him at mario@dcc.ufmg.br.*