Contributions to the Automatic Restoration of Images from Scenes in Participating Media

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Abstract. *This work deals with the problem of image restoration of monocular images acquired in participating media, i.e. media that interfere with light propagation. Specifically, the proposed work focus on the automatic restoration of images acquired in underwater and foggy/hazy scenes. The proposed restoration process requires at least a pair of images as input and produces images in which the medium effects are attenuated and the visibility improved. Differently from previous works, our method does not need additional equipment or information. We proposed a new model-based approach by estimating the depth map and the attenuation coefficient. We performed experimental evaluation in real and simulated environments with significant improvement in the quality of the images.*

1. Introduction

The computer vision and image processing fields have witnessed remarkable advances on a wide range of real world problems. Regardless of the advances, almost all of the techniques assumes that scene and camera are immersed in a non-participating medium, *i.e.* they assumed that the light rays travel through the medium without any alteration. However, there are some media that change the intensity and the direction of the light rays, called participating medium. Among them, the most important in practical terms are the water and haze/fog.

A myriad of problems need to deal with images acquired in participating media, *e.g* surveillance, mapping, autonomous robots and vehicles [Roser et al. 2014] to name a few. The effects of absorption and light scattering in participating medium decrease the overall contrast on images and causes color shifting, which reduce visibility on underwater scenes, for instance.

The main contribution is a new automatic method capable of restoring monocular sequences of images acquired in participating medium without any additional information. The method is based on temporal relation, three-dimensional structure and medium properties. The main steps of our approach are depicted in the outline in Fig. 1. The method is initialized by using a new transmission prior that provides an initial estimation of the scene depth which allow us to compute the optical flow. Structure from motion techniques based on a novel optical flow model provide an estimation of the depth map, which is used for computing the attenuation coefficient and subsequently to restore the image sequence. The obtained results shows significant improvements in several quantitative metrics.

The techniques presented in this work open new opportunities to use the legacy computer vision and image processing methods in participating medium. Thus, the proposed work impacts in recent technologies such as autonomous car, underwater robotics and surveillance.

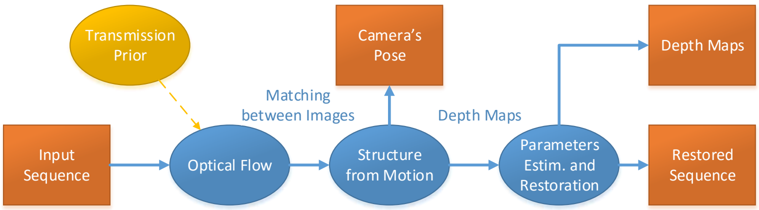

Figure 1. Outline of our image restoration methodology. We estimate a transmission map based on priors. This map allows us to compute the optical flow. Then, depth maps are predicted using structure from motion techniques. Finally, the medium parameters and the restored images are estimated. The orange boxes are the inputs/outputs data, the blue ellipses are the proposed steps, and the yellow ellipse is the prior that provides the optical flow initialization.

The results of this work were partly published in international conferences and an international journal[1]. The works also received two awards[2]. Furthermore, some papers are under submission/review[3]. The code of the UDCP is freely available[4]

2. Related Works

Several approaches have been proposed to tackle the problem of restoring images acquired in participating media, namely, specialized hardware, polarization filters and stereo images [Roser et al. 2014]. Although the high quality of the reported results using specialized hardware, most of these methods are expensive and require complex setup. The use of polarizers is cumbersome, even though images acquired with them present good results. The main drawback of this technique is the need to identify the maximum and

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minimum polarization states. In the case of stereo systems, the correspondence problem is also difficult to solve due to the effects imposed by the medium.

Several methods based on single images have been proposed in the literature, e.g. [He et al. 2011, Kim et al. 2012]. While they show good results on foggy images, their performance degrades in underwater scenarios. The main issue of these methods is the estimation based on heuristics, which may hold true only for restricted conditions.

Very few studies have addressed the problem of image restoration of a sequence of images. In the work of [Zhang et al. 2011], a method to estimate the medium transmission based on priors and optical flow is presented to enhance the visibility of hazy images. Despite the interesting results, it is based on assumption of brightness constancy that does not hold true on partipating media. The temporal coherence is taken into account to estimate the transmission map in the work of [Kim et al. 2012], however this method also can fail in typical situation due to the same assumption. A large review of the state-of-the-art is presented in Chap. 2.

Differently from the aforementioned works, our approach is based on temporal relation, three-dimensional structure and medium properties. These information are fused to provide a more robust image restoration method.

3. Methodology

In this work we present a new automatic methodology to restore images acquired in participating media. Assuming the model previously described, the problem of image restoration may be reduced to the problem of estimating the medium parameters and the depth map.

Our methodology is composed of three main steps: the dense correspondence between images by estimating the optical flow, the 3D structure estimation, and parameter estimation and image restoration. Fig. 1 depicted the proposed methodology.

Firstly, we estimate a transmission map based on a new prior. Recently, several priors for single images have been proposed. They enable us to estimate the medium transmission, and, consequently, the depth map up to scale. Among them, the most successful prior is the Dark Channel Prior (DCP) [He et al. 2011]. Although the dark channel assumption sounds acceptable in underwater medium, the wavelength independence is clearly false in most of the cases. Therefore, we proposed a new prior called Underwater DCP (UDCP). The method only uses the green and blue channels due to the difficult to modeling the behavior of the red channel. This phenomenon is mainly related to the high absorption effect in the red channel which imposes it to be near zero in many situations. The methodology and a experimental verification of the method is found in Chap. 3.1.

This map allows us to compute the optical flow. However, the majority of state-of-the-art in terms of optical flow methods assumes constancy in the brightness patterns in the image, but this assumption does not hold true for participating media. Therefore, we proposed the Generalized Optical Flow Model (GOFM). GOFM assumes that the brightness in the image is not constant because of the effects of the medium. Nevertheless, it assumes that the scene radiance is approximately constant. More details are provided in Chap. 3.2.

Depth maps are predicted using structure from motion techniques. We adopted a set of state-of-the-art techniques as detailed in Chap. 3.3.

Finally, the attenuation parameter and the restored images are estimated (details in Chap. 3.4). The restoration is achieved using an algebraic inversion of the simplified light propagation model (Chap. 2.1). A new interpretation from the model allows us to estimate the attenuation coefficient based on the depth maps in two consecutive frames. Assuming the same 3D point in the scene. This approach is highly dependent on the quality of the depth maps and, mainly, the optical flow. Thus, we imposed a new constraint inspired in the work of [Roser et al. 2014] to improve the robustness of our approach. The new cost function imposes several constraint that enable us to estimate the coefficient using a robust optimization method.

In addition to the restored images, our method also produces an estimation of the depth maps, the camera's pose and the attenuation coefficient of the medium, which can be used in specific applications such as automatic obstacle avoidance, surveillance or localization.

4. Experimental Results

We obtained results using simulated and real datasets, all of them with qualitative and quantitative evaluation. We compared our approach with the single image methods DCP[He et al. 2011]/UDCP and two enhancement techniques: histogram equalization and contrast-limited adaptive histogram equalization (CLAHE). Simulated results are just shown in Chap. 4.3.

Quantitative results are obtained using the metric proposed by [Hautière et al. 2008]. They define three different indexes: e, $\overline{r}$ and s that evaluates the number of edges, the overall contrast and the number of satured pixels. These three indexes allow us to estimate an empirical restoration score $\tau = e + \overline{r} + (1 - s)$, where larger values mean better restoration. We also perform quantitative results by matching SIFT [Lowe 2004] descriptors. It allow us to evaluate the ability of the descriptor to identify and match features from a raw and restored image.

4.1. Real Results

We show real results in two scenarios. Firstly, we captured underwater images in the Brazil's Southeast Coast with depth ranging from $12m$ to $20m$ using an underwater robot, the Seabotix LBV300-5, equipped with a color camera. Furthermore, we captured a sequence from a residential area in a foggy day.

For the underwater sequence, the estimated attenuation coefficient is $\eta = [0.0335, 0.0331, 0.0289]$ for each RGB channel, respectively. 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, and they are similar to each other due to the water characteristics and depth of the image acquisition.

Fig. 2(a) is a sample underwater image with limited visibility and significant color distortion. Fig. 2(b) shows restored image by our method, where the quality is improved. Results obtained using CLAHE are shown in Fig. 2(d), where the contrast and the noise are increased, and the colors are distorted. Restored images using histogram equalization and UDCP are shown in Fig. 2(c) and 2(e), respectively.

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

(f) (g) (h) (i) (j)

Figure 2. Qualitative comparison using a sample image acquired in naturally lit shallow oceanic water and in a foggy day: original image (a,f), restored using our method (b,g), histogram equalization (c,h) , CLAHE (d,i), UDCP (e), and DCP [He et al. 2011] (j).

Table 1. Comparative study using the average of the restoration score τ [Hautière et al. 2008] and SIFT matching [Lowe 2004] for the sequences in Fig. 2. The best and second best results are highlighted in blue and light blue letters, respectively.

	Underwater Sequence					**Foggy Sequence**				
	e	$\overline{r}$	τ	Match.	Pts.	e	$\overline{r}$	τ	Match.	Pts.
UDCP/DCP	1.7089	1.2591	3.9678	1	18	1.4185	0.7877	3.2063	10	30
Hist. Eq.	**2.5430**	2.4544	**5.9885**	10	197	**1.5540**	**1.8267**	**4.3667**	**70**	**286**
CLAHE	1.8821	**2.8494**	5.7315	**11**	**391**	0.4996	1.5081	3.0077	65	265
Our Method	**2.7057**	**2.6493**	**6.3488**	**33**	**375**	**1.5804**	**1.9689**	**4.5430**	**78**	**360**

Table 1 shows qualitative evaluation for the underwater sequence. Our method outperforms the others in term of the τ metric. Our method obtains improvement in terms of contrast and slightly smaller values in terms of new edges. CLAHE obtains the largest values of $\overline{r}$ because of the increase in the overall contrast, however with some color distortion and increasing the noise. Our approach also provides the largest number of correct matches using SIFT [Lowe 2004]. However, the number of detected keypoints for the CLAHE method is the largest. This results is expected since the restoration obtained by CLAHE presented a large $\overline{r}$. However, this restoration is not stable, thus it does not increase the number of correct matches. Our method is able to significantly improve the number of matches, as well as the number of detected keypoints. It is also corroborated by the improvement in terms of contrast, $\overline{r}$.

A foggy sequence is also shown in Fig. 2. Fig.2(f) shows a sample image that presents limited visibility and color distortion. Fig. 2(g) shows our restoration. The visibility and the color are improved, mainly in the houses (bottom left). The buildings in the center of the image are under a strong "haze" layer, thus limiting the capability of restoration due to the loss of information. However, the contours of the buildings are recovered by our approach. The result for histogram equalization (Fig. 2(h)) is similar to our result. One important difference can be noted in the largest tree that our method is able to improve. The result produced by CLAHE (Fig. 2(i)) is imperceptible. DCP fails to estimate the global light (Fig. 2(j).), thus the image becomes darker with limited restoration.

The estimated attenuation coefficient for the foggy sequence is $\eta = [0.1752; 0.2026; 0.1882]$. Differently to the underwater sequence, the red channel is the smallest attenuation coefficient while the green channel presents the largest value. These three coefficients are relatively similar ($\approx 15\%$) as expected.

Table 1 also shows qualitative evaluation for the foggy sequence. Our method outperforms the others in term of the τ metric. Our method obtains similar results to histogram equalization method. However, our method presents a small advantage in all metrics. The results of CLAHE technique is limited, presenting a small improvement. Therefore, CLAHE obtains the smallest values in the number of edges and the τ metric. DCP distorts the colors, but this fact is not taken into account by this metric. Our method obtains the largest number of correct matches using SIFT [Lowe 2004], as well as detected keypoints. More results are shown in Chap. 4.

5. Conclusions

This work proposed a new methodology to restore sequences of images acquired in participating media. We explore the temporal relation between the images that allow us to estimate structure of the scene, camera's pose and depth maps. The relation is obtained by a new optical flow formulation adapted for participating media that depends on the knowledge of the medium transmission, which is computed by UDCP/DCP. Finally, we developed a new robust methodology to estimate the most critical parameter of the medium: the attenuation coefficient. Qualitative and quantitative results in real images show the quality of the restoration obtained by our approach. The estimated depth maps is still limited, but enough to the restoration task. The proposed method to estimate the attenuation coefficient is robust even in the presence of outliers.

Future work will focus on investigating the structure from motion method to improve the depth map estimation and the inclusion of artificial illumination in the scene. Furthermore, a new method to quantitatively evaluate the image restoration methods will be investigated.

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