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Using a MRF-BP Model with Color Adaptive Training for Underwater Color Restoration

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***Abstract*—For underwater robotics applications involving monitoring and inspection tasks, it is important to capture quality color images in real time. In this paper, we propose a statistically learning method with an automatic selection of the training set for restoring the color of underwater images. Our statistical model is a Markov Random Field with Belief Propagation (MRF-BP). The quality of the results depends strongly on the trained correlations between the degraded image and its corresponding color image. However, it is not possible to have color ground truth data given the inherent conditions of underwater environments. Thus, we build a color adaptive training set by applying a multiple color space analysis to those frames that present a high change in its distribution from the previous frame and use only those frames for training. Experimental results in real underwater video sequences demonstrate that our approach is feasible, even when visibility conditions are poor, as our method can recover and discriminate between different colors in objects that may seem similar to the human eye.**

I. Introduction

Visual quality is fundamental for several underwater robotics applications, such as habitat and animal classification [1], mapping [2], 3D scene reconstruction [3], visualization [4], docking [5], tracking [6], inspection [7] and robot localization [8]. We are particularly interested in the monitoring of coral reefs. This type of ecosystems requires a cautious as well as a non-invasive monitoring of the possible changes in the coral's structure to assist research on marine biology. Therefore, to get quality data, the robot needs to get close to the targets of interest. Capturing the riot of colors that this type of ecosystems has is fundamental to be able to achieve an efficient inspection. From our previous investigations [9], we have noticed that color can be used as a robust visual cue to accomplish the above mentioned task. However, underwater environments typically present a "hazy" look in the captured images due to the absorption and scattering phenomena suffered by the light rays when interacting with large amount of suspended particles in the medium. As a result, we have a degraded image, *i.e.*, with lack of contrast, color loss, and non-uniform illumination. Unfortunately, the color cannot be recovered at a sufficient water depth. Firstly, the red light is lost at about $3-5$ meters of depth. After 5 meters of depth, the orange light disappears and, after 10 meters, most of the yellow color is gone. After 25 meters, only blue light remains [10]. Using artificial illumination may help recovering the color partially, at least in the limited area in which the source of light is directed to. However, as it was mentioned above, we do not want to affect the fragile marine life – it is well known the damage on the behaviour of aquatic organisms caused by artificial illumination [11].

In the last years, there has been a great number of research that focus on the color correction or color restoration of underwater images, which differs from the color enhancement problem. The first attempts to recover the "true" color of the scene while the second tries to enhance the color and other cues but not necessarily recovering the original tones. Most of the work reported in the literature in the color restoration problem rely on approaches that take the image formation process as its baseline. However, the fact that many of the variables involved in this process are constantly changing makes it hard to model, therefore some assumptions have to be made. Other approaches consider the use of image processing techniques that are applied directly on the values of the pixels in the image. There are few work that use statistical approaches that learn the correlations between a set of color depleted and color image patches in order to recover the color in new images. Furthermore, the use of suitable color space models has demonstrated to be crucial in the color restoration process.

We are interested in restoring the "true" color of underwater color-degraded video sequences. Our method uses a Markov Random Field (MRF) model, which, as in any statistical learning method, strongly depends on a training set. In our case, to estimate the missing color in a video sequence, the training set must capture, along the whole video sequence, the correlations between a color degraded image and its corresponding color. Since we could not directly obtain true-color training patches coming from the underwater scenes (*i.e.*, either these scenes where already taken or we are not allowed to use a source of light at any time due to habitat protection reasons), we first recover the color by applying a multiple color space analysis and processing stage in a previously selected image frame of the video sequence to be used as a seed (training set) in our MRF-BP model. The adaptive training is thought in terms of the way an image frame is selected at a given moment according to the occurrence of a change in the distribution of the channel values compared to previous distributions. Experimental results demonstrate that our approach is feasible, even when visibility conditions are poor, as our method can recover and discriminate between different colors in objects that may seem similar to the human eye.

The remainder of the paper is organized as follows: Sec. II describes the related works in terms of color restoration, and Sec. III presents the proposed methodology. Sec. IV evaluates the methodology using experimental field data. Finally, in Sec. V, we summarize the paper contributions and draw the future research directions.

II. Related Work

As manifested in the wide related literature, the problem of color degradation is due to physical phenomena such as light scattering and absorption. Both are wavelength/color of light dependent. For this reason, physics-based approaches are commonly adopted techniques to model the image formation process underwater. One of these models is the presented by Schechner *et al.* [12]. This approach exploits the polarization differences between two or more images of the same scene under different degrees of polarization.

However, this is not the unique existing approach, Schettini and Corchs [13] summarize several approaches until 2009, among which the work of Torres-Méndez and Dudek [9] stands out as it has the particularity of modeling the color correction problem as an energy minimization problem by using Markov Random Fields (MRFs). This work is based on the formulation presented by Freeman *et al.* [14], where the authors introduce an approach to train a MRF using a training set conformed by pairs of images, and the use of a Bayesian Belief Propagation algorithm to solve the model. However, one of the main drawback is that a suitable training set of the same scene is needed in order to obtain good correction of color.

More recently, the variety of approaches to tackle the color correction or color restoration problem has continued growing. Ancuti *et al.* [15] published a work that has been used as a reference in most of subsequent works. In that paper, the authors propose a color enhancement method that uses data fusion. Their method yields good results but with some limitations for deep images. Also, the authors present results of an illumination adjustment for the Gray-World assumption [16].

Several physics-based approaches using single image have been also proposed in the last years [17], [18], [19], [20], [21]. While they show good results on low turbidity images, their performance degrades in typical underwater scenarios. Recently, Drews *et al.* [4] have proposed a physics-based method that uses sequence of images to restore images with large variation on the scene depth. However, the method is based on a structure-from-motion technique that is constrained to textured scenes.

An approach that is gaining popularity for image enhancement is the Contrast Limited Adaptive Histogram Equalization (CLAHE) method [22]. An example of this method is the presented by Setiawan *et al.* [23], where the CLAHE algorithm is applied in RGB retinal images in order to improve the image quality. Another similar CLAHE approach with mixed color spaces is proposed by Hitam *et al.* [24]. The authors use a mix-CLAHE algorithm to improve the quality of underwater images, and they also propose and use a statistical analysis to evaluate the results of the color spaces mixture.

As in [24], the use of color spaces, different from the typical RGB, is gaining ground, specially those color spaces that are considered as perceptually uniform. One of the premises for using different color spaces in the image enhancement problem was established by Reinhard *et al.*, who in [25] use the Ruderman color space [26].

Early last year, Bianco *et al.*, proposed the idea of using the Ruderman color space for the specific problem of correcting color casts of underwater images. By using the radiometric model for image formation, which is typically used in color constancy formulations, the author proposed a Gray-World formulation defined in the $l\alpha\beta$ Ruderman's color space, which when complemented with a simple contrast enhancement based on histogram clipping yields a new color correction method for underwater imaging. One of the contributions of their work is the "White-World" (WW) assumption defined in the $l\alpha\beta$ color space. It was adapted here and extended to multiple frames using an online learning process.

III. Methodology

In this section, we describe our methodology which uses a Markov Random Field (MRF) model to restore the color of underwater video. The performance of any statistical learning method, such as MRFs, strongly depends on the initial training set given, as suitable correlations between their hidden and observation nodes must be captured in order to recover the missing information from current observations (in our case the color of underwater objects). Since we do not have ways to directly obtain true-color training patches from the underwater scenes (*i.e.*, either these scenes where already taken or we are not allowed to use a source of light at any time due to habitat protection reasons), we carry out a multiple color space analysis and processing stage to automatically recover the color in an image frame of the video sequence to be used as a training set in our MRF model. This stage must be adaptive and sensitive to changes in the distribution of the channel values of each image frame so a new training set can be obtained. In the following section the details are given.

A. MRF Model

A MRF is a graphical model with a set of nodes representing observation (input) and hidden (output) variables. These nodes are connected by undirected links, each of which only connects a pair of nodes. We particularly use a *Pairwise-MRF* model (also known as *Markov Network*) [14]. This pairwise model for the color restoration problem is depicted in Figure 1 where the variables y_i represent the observed color depleted nodes in the input images, and the variables x_i are their corresponding color hidden nodes [9].

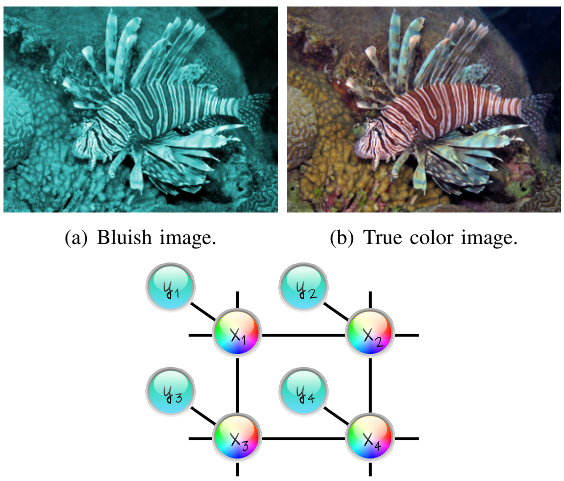
Formally, and supported by the Figure 1, let $A = \{a_i\}$ and $C = \{c_i\}$ the RGB input and output images, respectively, with $i = 1, \ldots, N$ where $N \in \mathbf{Z}$ is the total number of pixels in input/output image; a_i and c_i represent the i-th three-channel RGB pixel of their corresponding image. We consider for every pixel i, in both input and output image, an associated neighborhood whose size is a user-defined parameter. The patches conformed by every central pixel and its associated neighborhood in the image A are the y_i nodes in Figure 1, and analogously, the patches defined in the same way, but in the output image are the x_i nodes in the same graph.

To complete the pairwise model, two functions relating the nodes are considered, see Figure 2. The first, called potential function, denoted by ϕ_i, relates the local observations y_i with the hidden variables x_i. The second one is called the compatibility function and is defined between neighboring hidden nodes x_i and x_j, this function is denoted by ψ_{ij}.

Due to the Gibbs nature of MRFs and the *Hammersley-Clifford* theorem [27], the joint probability of the model can be written as

$$P(x, y) = \frac{1}{Z} \prod_{(i,j)} \psi_{ij}(x_i, x_j) \prod_i \phi_i(x_i, y_i), \qquad (1)$$

where Z is a normalization constant, also known as *partition function*. Then, the solution of the pairwise model is to find the state for every hidden node x_i that maximizes the joint probability (1). An alternative way to see the solution of the MRF model is by estimating the maximum a posteriori (MAP)



(a) Bluish image.

(b) True color image.

(c) Graph model.

Fig. 1. Pairwise MRF model for the color correction problem. a) An observed bluish image is represented in c) by the nodes y_i; b) The true color image is represented in c) by the hidden nodes x_i; and c) the graph model.

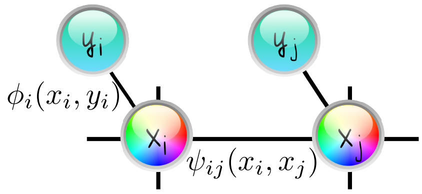


Fig. 2. Graphical representation of the potential and compatibility functions.

probability using a training set. This solution can be expressed as

$$\mathbf{x}_{MAP} = \arg\max_{\mathbf{x}} P(\mathbf{x}|\mathbf{y}), \qquad (2)$$

where

$$P(\mathbf{x}|\mathbf{y}) \propto P(\mathbf{y}|\mathbf{x})P(\mathbf{x}) \propto \prod_i \phi_i(x_i, y_i) \prod_{(i,j)} \psi_{ij}(x_i, x_j), \quad (3)$$

and $\mathbf{x} = x_i, \ldots, x_N, \quad \mathbf{y} = y_i, \ldots, y_N$ can be seen as a vector with all the central values of the patches in the output and input image, respectively. Due to the computational complexity of calculating the exact MAP in the MRF model, an alternative method to estimate an approximation is often adopted, in this case, we use the Bayesian Belief Propagation (BP) algorithm.

The BP algorithm is an iterative inference method based on passing messages between neighboring nodes, these messages are constructed using the potential and compatibility functions that are learned from a training set. Both, the potential and compatibility functions, are usually assumed with a Gaussian Distribution, and for the color restoration problem can be written as in [9]:

$$\phi_i(x_i, y_i) = e^{-|y_i - y_{x_i}|^2/2\sigma_i^2}, \qquad (4)$$

$$\psi_{ij}(x_i, x_j) = e^{-d_{ij}(x_i, x_j)/2\sigma_i^2}, \qquad (5)$$

where y_i is the i-th observed node in the input image, x_i a color corrected patch candidate in the training set, y_{x_i} denotes the corresponding color depleted patch for the x_i candidate, d_{ij} is an error metric between candidate patches i and j, usually this metric is assumed as an Euclidean norm that is not restricted to be defined in the RGB color space. Actually, in our implementation this norm is defined in the CIELab color space to exploit its perceptually uniform nature. Finally, σ is a user-defined parameter that models the standard deviation for the assumed Gaussian distribution, and e^s, $s \in \Re$ denotes the scalar exponential function.

The idea of the BP algorithm is to exchange messages that represent the probabilities for all the variables in the network, these probabilities are used to construct marginal probabilities that are called beliefs. For our pairwise color correction model, the messages have the sum-product form:

$$m_{ij}(x_j) = Z \sum_{x_i} \psi(x_i, x_j)\phi(x_i, y_i) \prod_{k \in N(i)-\{j\}} m_{ki}(x_i), \quad (6)$$

which can be read as the message sent from the node i to its neighboring node j, concerning the x_j candidate. In an analogous way, $m_{ki}(x_i)$ is the message, but in the previous iteration, between the k node in the neighborhood, $N(i)$, of the node i, excluding the node that is receiving the message, denoted j here. Then, using the BP approach, the MAP for the node i results:

$$x_{iMAP} = \arg\max_{\mathbf{x}_i} \phi(x_i, y_i) \prod_{j \in N(i)} m_{ji}(x_i). \tag{7}$$

We finish remarking that, in a strict way, BP provides an exact solution only for graphs without loops in it, however heuristic experimentations have shown that BP offers good results in loopy networks [14].

B. Automatic Color Adaptive Training

Our current, and in general, practical implementations of statistical learning models require training sets. As a contribution of this work, we propose an automatic way to generate a useful training set for a MRF designed to recover the color in a video sequence. Our approach is based on existing color restoration techniques reported in literature.

In a conceptual manner, our general approach is adaptive since we are interested in obtaining a dynamic training set that adapts itself to changes in underwater scenes. In order to do this, we assume that in a video sequence, the histograms of the scenes give us a hint to determine when a significant change in the chromatic channels a,b (of the color depleted frames) is present. Our algorithm can then use this event as an indicator to adapt the current training set and continue with the restoration of next batch of frames with similar chromaticity. Then, we use a similarity measure defined in terms of the statistical parameters of the chromatic-channels distributions:

$$S = \|Dist_t - Dist_{t-1}\|_2 \tag{8}$$

where $Dist_t = [\bar{a}, \sigma_a, \bar{b}, \sigma_b]$ is the statistical parameters vector at time t, with $\bar{a}$ the *"a"*-channel's mean, σ_a its standard deviation and, $\bar{b}$ and σ_b are the respective parameters but for the *"b"*-channel distribution. $Dist_{t-1}$ is the same vector but in the previous frame. The bigger the S, the less the chromatic similarity between frames and based on a threshold we can automatically adapt the MRF's training.

In the literature, albeit with some limitations, there exist several color correction algorithms which can be used as the base for our automatic adaptive training set generator. At the end, we are seeking to maximize the color restoration by using our MRF color correction model.

We start the training set generation process at every significant change of scene by first applying a gamma correction to the RGB color depleted frame and convert it to the $l\alpha\beta$ color space (also known as the Ruderman color space [26]). We use the $l\alpha\beta$ WW assumption formulated in [28] as:

$$A^{\star}_{l\alpha\beta} = A_{l\alpha\beta} - \bar{A}_{l\alpha\beta}, \tag{9}$$

where $A^{\star}_{l\alpha\beta}$ is the color corrected $l\alpha\beta$ image, $A_{l\alpha\beta}$ is the input image in Ruderman's color space and $\bar{A}_{l\alpha\beta}$ is the average of the image, computed only in the chromatic channels α, β.

We analyzed the results obtained in our tests and we found that the opposite nature of the Ruderman's space yields a color shifting effect as the pointed out by Ancuti *et al.* [15]. Similarly, we correct the scene illumination by using an adjusting parameter λ:

$$A_{I_{l\alpha\beta}} = \lambda \bar{A}_{l\alpha\beta}. \tag{10}$$

Note however that in comparison with the correction of the illumination proposed by Ancuti *et al.* [15], since we are working in the $l\alpha\beta$ color space and the center of its domain is $\{0, 0, 0\}$, the translation is not required and the domain of λ is not restricted to $[0, 0.5]$. This parameter is adjusted in a heuristic way. Note, also, that if we follow the straightforward deduction of the WW assumption, it is possible to include the correction term in the LMS color space [29], at this point the correction could have the form proposed by Ancuti *et al.* [15]. But we prefer the succinct expression reached if we apply this heuristic adjustment directly in the $l\alpha\beta$ color space, as in (10). Then, we can rewrite (9) as:

$$A^{\star}_{l\alpha\beta} = A_{l\alpha\beta} - \lambda \bar{A}_{l\alpha\beta}. \tag{11}$$

As an additional step to control the color shifting effect, the value of the adjusting parameter λ can be set different for every chromatic channel. This means that λ is set to one value for the channel with the color that is predominant in the scene, and the adjusting parameter for the left chromatic channel is not necessarily the same. Determination of the predominant color is obtained by finding the mean of the H channel for the input image in the HSV color space.

As it is suggested in [25], [28], the WW assumption can only be applied to the chromatic color channels α and β. Regarding the l (luminance) channel, we have only applied a histogram equalization using the CLAHE approach [22], this in order to improve the contrast of the restored image. CLAHE is only applied to the luminance channel seeking to avoid any color distortion in the generated training for the MRF model. After all these steps, the processed $l\alpha\beta$ image is transformed back to the RGB space to obtain an acceptable color corrected image which can be used to generate a new collection of depleted-color pairs, which in turn are used to adapt the current training set of our MRF model.

IV. EXPERIMENTAL RESULTS

In this section, we show our experimental results. Firstly, we show results of using the WW assumption with illumination adjustment (Eq. (11)) and CLAHE. These results are then processed using our adaptive approach to select only specific frames in the sequence to generate the automatic training set for the MRF. Furthermore, we show results of our color correction method using MRF model. For our test, we used some video sequences from the web and a C++ implementation using OpenCV library [30] to deal with the matrix manipulation and statistics functions.

A. Adapted White-World Assumption (WWA) Results

We start with the results of our adapted White-World approach with CLAHE and illuminant adjustment presented in the previous section. Since this approach is the base for

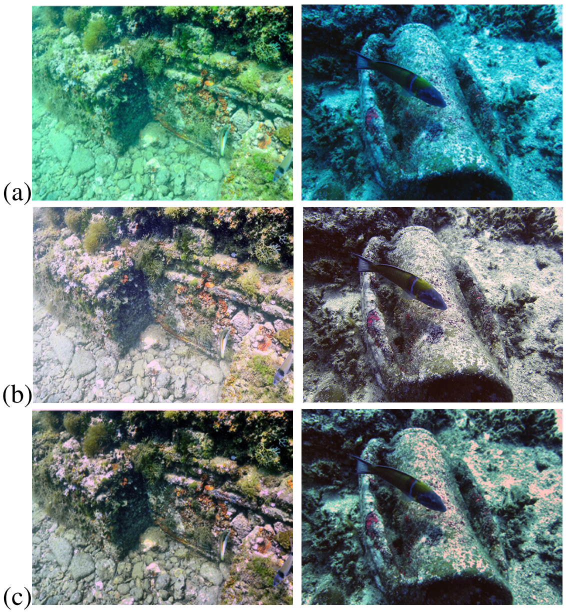


Fig. 3. Comparison between the our AWW method and the WW assumption. (a) underwater images; (b) output using WW-Assumption (taken from [28]); and our adapted WW-assumption (c).

building the training set of our MRF model, this constitutes by itself a color correction method. The color correction algorithm in [28] provides good results specially in removing the light source color (see Figure 3-b). However, some colors which are not due to the ambient light are lost, yielding grayish images in our experiments. Our extra considerations and adaptations described in section III-B help to preserve, visibly, a greater color variability, as depicted in Figure 3, in these cases and in all the results presented in this work we use the adjustment parameters as $\lambda_1 = 0.80$ for the channel with the predominant color in the scene, and $\lambda_2 = 0.75$ for the left chromatic channel.

Some others comparative results are shown in Figure 4, where the left column, (a), contains the input underwater color images, in the center column, (b), are the outputs for the WW assumption with the unique difference with respect to [28] that the luminance channel equalization was done by using CLAHE. The last column, (c), contains the results of using our adaptation of the WW assumption with illumination adjustment and CLAHE in the luminance channel. As we mentioned before, the color correction, achieved by using the original WW assumption, removes color that is not part of the ambient light, yielding grayish images.

The results of the right column represent a more realistic color achievement than the other. As a remark on this point, consider the images in the first row of the same figure, the ball that is hanging off from the hand of the diver, as it can be seen from the image obtained in the third column, has not the same color as the wet suit, the ball has a reddish tone, but in the center image both (the wet suit and ball) look black. This result is very important for color discrimination, for example, in robotic applications that involve the detection and/or recognition of objects and, more specifically, object tracking for long periods of time. Since the changes in the color of underwater objects may abruptly vary due to the local conditions from one place to another (even in few meters), this represents a real challenge.

B. MRF-BP Results

In this subsection, we demonstrate the feasibility of obtaining a useful training set for our MRF model by using the automatic color adaptive training described in Sec. III-B (setting the similarity threshold, $S > 0.01$). To make it clear, we have to point out that the training set is formed considering pairs of patches taken from the original color depleted frame, where the chromaticity change was detected, and its corresponding color corrected version produced by our adaptation of the WWA algorithm. Another remarkable fact is that the results shown here were obtained using the first assignment for every message of the BP algorithm, in our case equal to 1. To show the effectiveness of our color adaptive training, we took an underwater video sequence from the web and we processed it with our adaptive-training MRF model. Some results are shown in Figure 5. MRF-BP offers a way to recover the color of an image preserving the original color structure of the scene, this, even in regions where the original visibility conditions are really poor. To highlight this fact we can analyze the edge preservation of the reefs, fishes and background present in the results shown in Figure 5. A remarkable example of this is the lionfish at the back shown zoomed in Fig. 6, in which it is easy to distinguish the lines that are part of the fish texture and the difference between colors of its body and fins. Having a correct training is fundamental, and our approach has shown that it is possible to guarantee the availability of a feasible training for our model.

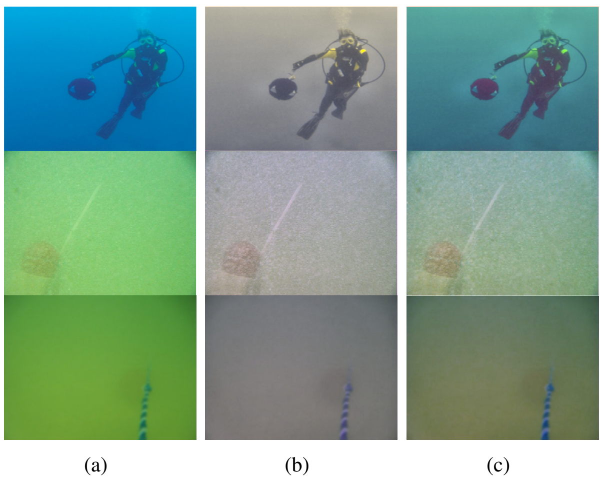
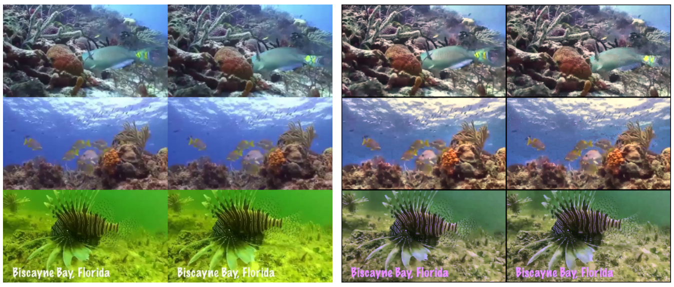


Fig. 4. Results for multiple real underwater images (a) in a variety of different conditions, including very challenging ones, (b) output by using the WW-Assumption (taken from [28]) and (c) results by using our adapted WW-assumption.



(a) Some frames of the input video. (b) Corresponding frames in the MRF output video.

Fig. 5. Results by using the MRF-BP model and the *Automatic Color Adaptive Training*, for every row our algorithm detected a significative scene change and therefore, the training set was updated.

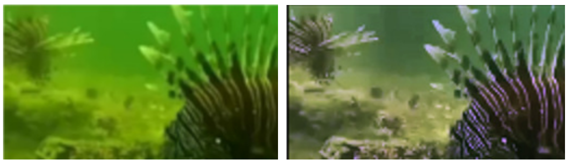


Fig. 6. Illustration of color structure and edges preservation in MRF output, even in poor visibility regions.

V. Conclusions and Future work

This paper proposed a Markov Random Field with Belief Propagation model for the color restoration problem. The novelty is in the automatic generation of a dynamic training set used in our model. The training set is enriched with new samples (*i.e.* frame patches) if an abrupt change in the distribution of the values in the chromatic channels occurs from one frame to the next. From the experimental results, we have observed that our MRF-BP model has a better performance, particularly in visual challenging situations, in which objects are not visible to the human eye. A specific example is the recovering of red color as it is the first color to be lost. Future work will be focused on evaluating color improvement in a quantitative form by defining a metric that includes the unfeasibility of gathering ground truth data.

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