Enhancing Underwater Images by Fusion

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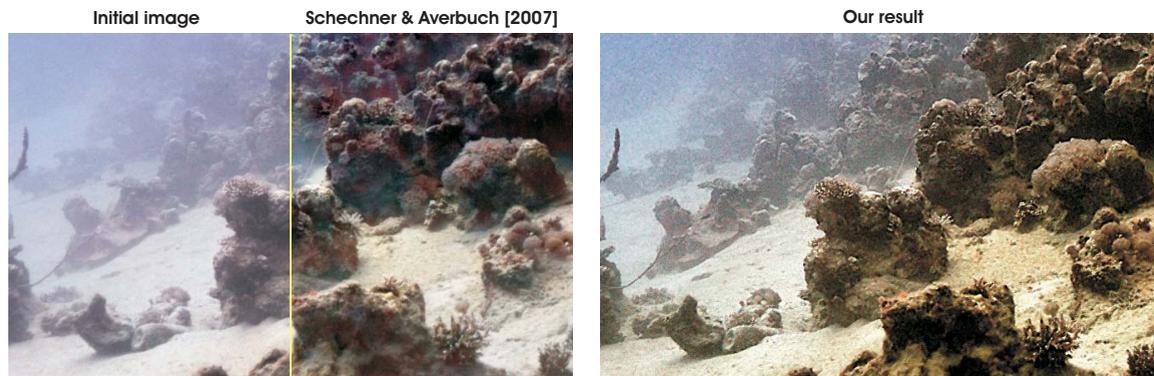Hasselt University, Belgium, firstname.lastname@uhasselt.be

Figure 1: *Considering the initial underwater image (left side of the first image) our strategy is able to enhance better the finest details compared with the specialized technique of [Schechner and Averbuch 2007].*

Introduction   When photographs are taken in underwater conditions the visibility of the scene is degraded significantly. This is due to the fact that the radiance of a point in the scene is directly influenced by the medium scattering. Practically, distant objects and part of the scene suffers from poor visibility, loss of contrast and faded colors. Recovering of such degraded visual information is important for applications such as oceanic engineering, mapping, research in marine biology, archeology, surveillance.

In general the existing specialized underwater techniques [Schechner and Karpel 2004; Schechner and Averbuch 2007] use several images of the same scene registered with different states of polarization. Moreover, although the recent single image dehazing techniques [Fattal 2008; Ancuti et al. 2010b; Ancuti et al. 2010a] shown some reliability in some particular cases, they are in general not able to restore accurately as well the underwater images.

Our approach   We propose a simple but effective strategy built on a multi-scale fusion technique. By defining properly several inputs and weights we demonstrate the utility of our fusion-based approach to enhance the underwater images.

The *first input* is defined by the white balanced version of the image. To obtain the color corrected image the algorithm searches to equalize the median values of the basic color channels. This step is important since the input color channels of the underwater images are rarely balanced. We perform a linear adjustment of the histogram, by stretching the original mean value to the desired mean value of the scene. Additionally, we have chosen that the mean reference value (default 0.5) should be increased with a small degree τ ($\tau = 0.15$) of the actual scene mean, in order to preserve both the gray values and to obtain the desired white appearance of the existing white objects in the scene.

The *second input* is obtained by applying the classical global min-max windowing method that aims to enhance the image appearance in the selected intensity window. This simple technique exploit effectively the object coherence by enhancing the contrast within a subrange of the intensity values at the expense of the remaining intensity values.

The weights of our algorithm are defined as following:

Luminance weight map controls the luminance gain in the final result. As a photograph is visually degraded, the general appearance tends to become flat. The weight values represents the standard deviation between every R,G and B color channels and the lightness of the original input image.

Contrast weight map yields high values to image elements such as edges and texture. To generate this map we rely on an effective contrast indicator built on the Laplacian filter computed on the grayscale of each image input.

Chromatic weight map is designed to control the saturation gain of the result. This map is a simple saturation indicator and computes for every pixel the distance between the saturation value and the maximum of the saturation range using a Gauss curve.

Saliency weight map is a quality map that estimates the degree of conspicuousness with respect to the neighborhood regions. This value is effectively computed based on the formulation introduced by Achanta et al. [Achantay et al. 2009].

Once the weight are obtained, we employed the normalized weight values by constraining that the sum at each pixel location of the weight maps to equal one. In the final step the inputs and the weights are merged by a multi-scale fusion process. To avoid haloing artifacts we opted for the widely-used multi-scale Laplacian pyramid decomposition. Practically, the final restored image is obtained mixing between the Laplacian inputs and Gaussian normalized weights at each scale level independently.

References

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