

COLOR BALANCE AND FUSION FOR UNDERWATER IMAGE ENHANCEMENT

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ABSTRACT: We introduce an effective technique to enhance the images captured underwater and degraded due to the medium scattering and absorption. Our method is a single image approach that does not require specialized hardware or knowledge about the underwater conditions or scene structure. It builds on the blending of two images that are directly derived from a color-compensated and white-balanced version of the original degraded image. The two images to fusion, as well as their associated weight maps, are defined to promote the transfer of edges and color contrast to the output image. To avoid that the sharp weight map transitions create artifacts in the low frequency components of the reconstructed image, we also adapt a multiscale fusion strategy. Our extensive qualitative and quantitative evaluation reveals that our enhanced images and videos are characterized by better exposedness of the dark regions, improved global contrast, and edges sharpness. Our validation also proves that our algorithm is reasonably independent of the camera settings, and improves the accuracy of several image processing applications, such as image segmentation and keypoint matching.

Index Terms– Underwater, Image fusion, White-balancing.

1. INTRODUCTION

With the fast advance of technologies and the prevalence of imaging devices, billions of digital images are being created every day. Due to undesirable light source, unfavorable weather or

failure of the imaging device itself, the contrast and tone of the captured image may not always be satisfactory. In fact, image enhancement algorithms have already been widely applied in imaging devices for tone mapping. For example, in a typical digital camera, the CCD (Charge Coupled Device) or CMOS (Complementary Metal Oxide Semiconductor) array receives the photons passing through lens and then the charge levels are transformed to the original image. Usually, the original image is stored in raw format, with a bit length too big for normal displays.

In this project the image enhancement approach adopts a two step strategy,

- White-balancing
- Image fusion

Combining white-balancing and image fusion, to improve underwater image without restoring. In this approach white-balancing aims at compensating for color cast caused by the selective absorption of colors with depth and image fusion is considered to enhance the edges of the image. Here, we aim for a simple and fast approach that is able to increase the scene visibility in a wide range of underwater images.

White-Balancing

Because of the undesirable illuminance or the physical limitations of inexpensive imaging sensors, the captured image may carry obvious color bias. To calibrate the color bias of image, we

need to estimate the value of light source, the problem of which called color constancy. Using a suitable physical imaging model, one can get an approximated illuminance, and then a linear transform can be applied to map the original image into an ideal one.

White balance determines color rendition of digital photography's, here it is a typical example for the effect of different white balance settings show in the below Figure 1.3.1. White-balance is an aspect of photography that many digital camera owners don't understand, so for those of you have been avoiding white balancing.

Adjustment of White Balancing

Different digital cameras have different ways of adjusting white balance. Many digital cameras have automatic and semi-automatic modes to help you make the adjustments. White balance basically means color balance. It is a function which gives the camera a reference to "true white". It tells the camera what the color white looks like, so the camera will record it correctly.

Image Fusion

Image fusion is a procedure of fusing two or more images of same scene to form single fused image which displays vital information in the fused image. Image fusion technique is used for removing noise from images. The advantages of image fusion includes image sharpening and feature enhancement.

2. EXISTING SYSTEM:

- Image enhancement
- Histogram

3.2.1. Basic Steps of Image Enhancement

The basic steps of image enhancement, if we are taking the any input image, the image is then specify application pre-processing method will be performed on those image after this method the image quality is increased.

Input Image: In this first an image will be taken as an input. These images can be medical images, blur images, remote sensing images machine vision, the military applications etc.

Perform Pre-processing on the Image:

Images that will be taken as input can be blur image or noisy image so the various pre-processing methods will be performed on those images before applying enhancement technique.

Applying Domain Techniques: After applying pre-processing method on input images then image quality will be enhanced by using Image enhancement domain techniques such as spatial or transformation.

Output Enhanced Image: In this the output image will be get which is an enhanced image.

3. PROPOSED SYSTEM:

Underwater environment offers many rare attractions such as marine animals and fishes, Different from common images, underwater images suffer from poor visibility resulting from the attenuation of the propagated light, mainly due to absorption and scattering effects. The absorption substantially reduces the light energy, while the scattering causes changes in the light propagation direction. They result in foggy appearance and contrast degradation making distant objects misty. Practically, in common sea water images, the objects at a distance of more than 10 meters are almost unperceivable, and the colors are faded because their composing wavelengths are cut according to the water depth.

There have been several attempts to restore and enhance the visibility of such degraded images. Since the deterioration of underwater scenes results from the combination of multiplicative and additive processes traditional enhancing techniques such as gamma correction, histogram equalization appear to be strongly limited for such a task. Works that are the problem has been tackled by tailored acquisition strategies using multiple images, specialized hardware or polarization filters. In contrast, this paper introduces a novel approach to remove the haze in underwater images based on

a single image captured with a conventional camera.

Our approach builds on the fusion of multiple inputs, but derives the two inputs to combine by correcting the contrast and by sharpening a white-balanced version of a single native input image. Our approach builds on the fusion of multiple inputs, but derives the two inputs to combine by correcting the contrast and by sharpening a white-balanced version of a single native input image.

Light Propagation in Underwater

For an ideal transmission medium they received light is influenced mainly by the properties of the target objects and the camera lens characteristics. This is not the case underwater. First, the amount of light available under water, depends on several factors. The interaction between the sun light and the sea surface is affected by the time of the day (which influences the light incidence angle), and by the shape of the interface between air and water (rough vs. calm sea). The diving location also directly impacts the available light, due to a location-specific color cast: deeper seas and oceans induce green and blue casts; tropical waters appear cyan, while protected reefs are characterized by high visibility. In addition to the variable amount of light available under water, the density of particles that the light has to go through is several hundreds of times denser in seawater than in normal atmosphere.

As a consequence, sub-sea water absorbs gradually different wavelengths of light. Red, which corresponds to the longest wavelength, is the first to be absorbed (10-15 ft), followed by orange (20-25 ft), and yellow (35-45 ft). Pictures taken at 5 ft depth will have a noticeable loss of red. Furthermore, the refractive index of water makes judging distances difficult. As a result, underwater objects can appear 25% larger than they really are.

The comprehensive studies have shown that the total irradiance incident on a generic point of the image plane has three main components in underwater mediums: direct component, forward scattering and back scattering.

The direct component is the component of light reflected directly by the target object onto the image plane. At each image coordinate x the direct component is expressed as

$$E_D(x) = J(x) e^{-\eta d(x)} = J(x) t(x) \quad q.1$$

Where $J(x)$ is the radiance of the object, $d(x)$ is the distance between the observer and the object, and η is the attenuation coefficient. The exponential term $e^{-\eta d(x)}$ is also known as the transmission $t(x)$ through the underwater medium.

Besides the absorption, the floating particles existing in the underwater mediums also cause the deviation (scattering) of the incident rays of light. Forward-scattering results from a random deviation of a light ray on its way to the camera lens. Back-scattering is due to the artificial light (e.g. flash) that hits the water particles, and is reflected back to the camera. Back-scattering acts like a glaring veil superimposed on the object. Mathematically, it is often expressed as shown below in Eq.2 and Eq.3.

3.1. Underwater White Balance

In our approach, white balancing aims at compensating for the color cast caused by the selective absorption of colors with depth, while image fusion is considered to enhance the edges and details of the scene, to mitigate the loss of contrast resulting from back-scattering. We now focus on the white-balancing stage.

White-balancing aims at improving the image aspect, primarily by removing the undesired color castings due to various illumination or medium attenuation properties. In underwater, the perception of color is highly correlated with the depth, and an important problem is the green-bluish appearance that needs to be rectified. Since the scattering attenuates more the long wavelengths than the short ones, the color perception is affected as we go down in deeper water.

In practice, the attenuation and the loss of color also depends on the total distance between the observer and the scene. To compensate for the loss of red channel, we build on the four following observations/principles: The green channel is relatively well preserved under water, compared to the red and blue ones. Light with a long wavelength, i.e. the red light, is indeed lost first when travelling in clear water. The green channel is the one that contains opponent color information compared to the red channel, and it is thus especially important to compensate for the stronger attenuation induced on red, compared to green. Therefore, we compensate the red attenuation by adding a fraction of the green channel to red. We had initially tried to add both a fraction of green and blue to the red but, using only the information of the green channel allows to better recover the entire color spectrum while maintaining a natural appearance of the background (water regions).

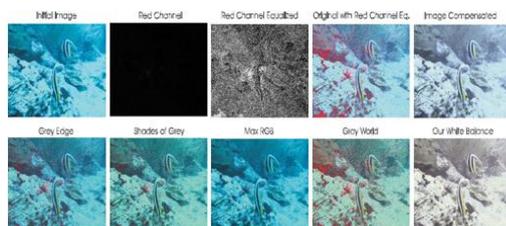


Figure.1. Underwater White-Balancing

The compensation should be proportional to the difference between the mean green and the mean red values because, under the Gray world assumption (all channels have the same mean value before attenuation), this difference reflects the disparity/unbalance between red and green attenuation.

To avoid saturation of the red channel during the Gray World step that follows the red loss compensation, the enhancement of red should primarily affect the pixels with small red channel values, and should not change pixels that already include a significant red component.

In other words, the green channel information should not be transferred in regions where the information of the red channel is still significant. Basically, the compensation of the red channel has to be performed only in those regions that are highly attenuated telling that if a pixel has a significant value for the three channels, this is because it lies in a location near the observer, or in an artificially illuminated area, and does not need to be restored. Mathematically, to account for the above observations, we propose to express the compensated red channel I_{rc} at every pixel location (x) as follows

$$I_{rc}(x) = I_r(x) + \alpha \cdot (\bar{I}_g - \bar{I}_r) \cdot (1 - I_r(x)) \cdot I_g(x) \dots \text{(Eq.4)}$$

Where I_r, I_g represent the red and green color channels of image I , each channel being in the interval $[0, 1]$, after normalization by the upper limit of their dynamic range; while \bar{I}_r and \bar{I}_g denote the mean value of I_r and I_g . Each factor in the second term directly results from one of the above observations, and α denotes a constant parameter. In practice, our tests have revealed that a value of $\alpha = 1$ is appropriate for various illumination conditions and acquisition settings. To complete our discussion about the severe and color-dependent attenuation of light under water, it is worth noting the works in, which reveal and exploit the fact that, in turbid waters or in places with high concentration of plankton, the blue channel may be significantly attenuated due to absorption by organic matter. To address those cases, when blue is strongly attenuated and the compensation of the red channel appears to be insufficient, we propose to also compensate for the blue channel attenuation, i.e. we compute

$$I_{bc}(x) = I_b(x) + \alpha \cdot (I_g - I_b) \cdot (1 - I_b(x)) \cdot I_g(x) \dots \text{(Eq.5)}$$

Our white-balancing approach reduces the quantization artifacts introduced by domain stretching (the red regions in the different outputs). The reddish appearance of high intensity regions is also well corrected since the red channel is better balanced, our approach shows the highest robustness compared to the other well-known white-balancing techniques. In particular, whilst being conceptually simplest, in cases for which the red channel of the underwater image is highly attenuated, it outperforms the white balancing strategy introduced in our conference version of our fusion-based underwater dehazing method.

3.2. Multi-Scale Fusion

Inputs of Multi Fusion

Since the color correction is critical in underwater, we first apply our white balancing technique to the original image. This step aims at enhancing the image appearance by discarding unwanted color casts caused by various illuminants. In water deeper than 30 ft, white balancing suffers from noticeable effects since the absorbed colors are difficult to be recovered. As a result, to obtain our *first input* we perform a gamma correction of the white balanced image version. Gamma correction aims at correcting the global contrast and is relevant since; in general, white balanced underwater images tend to appear too bright.

To compensate for this loss, we derive a *second input* that corresponds to a sharpened version of the white balanced image. Therefore, we follow the unsharp masking principle, in the sense that we blend a blurred or unsharp (here Gaussian filtered) version of the image with the image to sharpen.

The typical formula for unsharp masking defines the sharpened image S as $S = I + \beta (I - G * I)$, where I is the image to sharpen (in our case the white balanced image), $G * I$ denotes the Gaussian filtered version of I , and β is a parameter. In practice, the selection of β is not trivial. A small β fails to sharpen I , but a too large β results in over-saturated regions, with brighter highlights and darker shadows. To circumvent this problem, we define the sharpened image S as follows:

$$S = (I + N \{ I - G * I \}) / 2, \quad \dots(\text{Eq.6})$$

With $N \{ \cdot \}$ denoting the linear normalization operator, also named histogram stretching in the literature. This operator shifts and scales all the color pixel intensities of an image with a unique shifting and scaling factor defined so that the set of transformed pixel values cover the entire available dynamic range.

The sharpening method defined is referred to as normalized unsharp masking process in the following. It has the advantage to not require any parameter tuning, and appears to be effective in terms of sharpening. This second input primarily helps in reducing the degradation caused by scattering. Since the difference between white balanced image and its Gaussian filtered version is a high pass signal that approximates the opposite of Laplacian, this operation has the inconvenient to magnify the high-frequency noise, thereby generating undesired artifacts in the second input.

Weights of the Fusion Process: The weight maps are used during blending in such a way that pixels with a high weight value are more represented in the final image. They are thus defined based on a number of local image quality or saliency metrics.

Laplacian contrast weight (W_L): estimates the global contrast by computing the absolute value of a Laplacian filter applied on each input luminance channel. This straightforward indicator was used in different applications such as tone mapping and extending depth of field since it assigns high values to edges and texture. For the underwater dehazing task, however, this weight is not sufficient to recover the contrast, mainly because it cannot distinguish much between a ramp and flat regions. To handle this problem, we introduce an additional and complementary contrast assessment metric.

Saliency weight (W_S) aims at emphasizing the salient objects that lose their prominence in the underwater scene. This computationally efficient algorithm has been inspired by the biological concept of center surround contrast. However, the saliency map tends to favour highlighted areas (regions with high luminance values). To overcome this limitation, we introduce an additional weight map based on the observation that saturation decreases in the highlighted regions.

Saturation weight ($W_{S_{at}}$) enables the fusion algorithm to adapt to chromatic information by advantaging highly saturated regions. This weight map is simply computed (for each input I_k) as the deviation (for every pixel location) between the R_k , G_k and B_k color channels and the luminance L_k of the k^{th} input. We explain this observation as follows. The exposedness weight map had been introduced to reduce the weight of pixels that are under- or over-exposed. Hence, this weight map assigns large (small) weight to input pixels that are close to the middle of the image dynamic range. In our case, since the gamma corrected input tends to exploit the whole dynamic range, the use of the exposedness weight map tends to penalize it in favour of the sharpened image, thereby inducing

some sharpening artifacts and missing some contrast enhancements.

Naive Fusion Process Given the normalized weight maps, the reconstructed image $R(x)$ could typically be obtained by fusing the defined inputs with the weight measures at every pixel location (x) Where I_k denotes the input (k is the index of the inputs - $K=2$ in our case) that is weighted by the normalized weight maps W_k . In practice, the naive approach introduces undesirable halos. A common solution to overcome this limitation is to employ multi-scale linear or non-linear filters.

Multi-Scale Fusion Process The pyramid representation decomposes an image into a sum of band pass images. In practice, each level of the pyramid does filter the input image using a low-pass Gaussian kernel G , and decimates the filtered image by a factor of 2 in both directions. It then subtracts from the input an up-sampled version of the low-pass image, thereby approximating the (inverse of the) Laplacian, and uses the decimated low-pass image as the input for the subsequent level of the pyramid. In this equation, L_l and G_l represent the l^{th} level of the Laplacian and Gaussian pyramid, respectively. To write the equation, all those images have been up-sampled to the original image dimension. However, in an efficient implementation, each level l of the pyramid is manipulated at native sub sampled resolution. Following the traditional multi-scale fusion strategy, each source input I_k is decomposed into a Laplacian pyramid while the normalized weight maps W_k are decomposed using a Gaussian pyramid. Both pyramids have the same number of levels, and the mixing of the Laplacian inputs with the Gaussian normalized weights is performed independently at each level.

4. BLOCK DIAGRAM

In this project, two images are derived from a white-balanced version of the single input and are merged based on a multi-scale fusion algorithm. Block diagram is shown in the Figure 2.

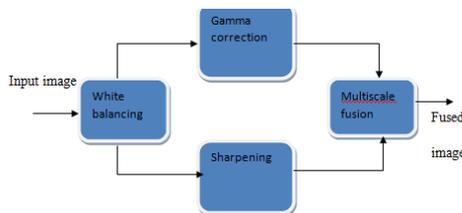


Figure 2. Block Diagram of Project
Image enhancement approach adopts a two step strategy, combining white-balancing and image fusion. White-balancing aims at compensating for the color cast caused by the selective absorption of color with depth, while image fusion is considered

to enhance the edges and details of the scene. Color correction is critical in underwater so first we apply white balancing technique to the original image. This step aims to enhance the image.

5. DESIGN AND IMPLEMENTATION

In this paper our white-balancing aim at compensating for the color cast caused by selective absorption of color with depth. Primarily by removing the undesired color casting due to various illumination or medium attenuation properties. Image fusion is to improve underwater images without restoring. Here the results are executed in MATLAB software .Image processing toolbox is used to perform analysis and algorithm development which perform image segmentation, image enhancement and noise reduction.

SYSTEM ARCHITECTURE:

In this paper a single image is given as input image and our white-balancing approach derived into two images one is the input 1 and input 2 as shown in the Figure using gamma correction and edge sharpening and the two input images are used as inputs of the fusion process. Multi-scale fusion approach is here to examine with three levels by weight maps calculation.

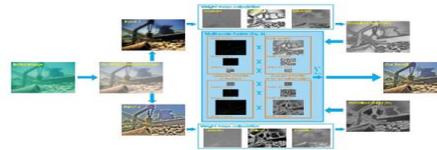


Figure 3. System Architecture Diagram

The weight maps tends to amplify some artifacts such as ramp edges of our second input and to reduce the benefits derived from the gamma corrected image in terms of image contrast. This second input corresponds to a sharpened version of the white balanced image. Second input primarily helps in reducing the degradation caused by scattering. The weight maps are used during blending in such a way that pixels with high weight value are more represented in the final image.

6.. OUTPUT SCREENS:

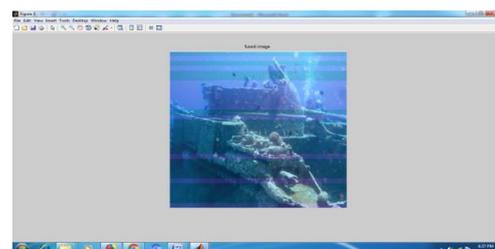


Figure 4. Fused Image

As shown in the Figure 6. Fused image builds on the set of inputs and weight maps derived from single image. This fused image is defined based on number of local image quality. In this Figure we can see the difference between the input image and fused image as the fused image is clear with color and quality of the image. Finally we calculate and get the values of MSE and psnr to know the quality of the image.

7. CONCLUSION

In this paper, we have presented an alternative approach to enhance underwater images. Our strategy builds on the fusion principle and does not require additional information than the single original image. We have shown in our experiments that our approach is able to enhance a wide range of underwater images (e.g. different cameras, depths, light conditions) with high accuracy, being able to recover important faded features and edges. Moreover, for the first time, we demonstrate the utility and relevance of the proposed image enhancement technique for several challenging underwater computer vision applications.

8. FUTURE SCOPE:

Our future scope is focused on patch segmentation fusion. An image is first split into small patches and the segmentation is performed on each patch. Here, sharpening method is used to smooth the edges to increase the visibility of the underwater image in wide range. Our future scope is focused on patch segmentation.

REFERENCES:

- [1] G. L. Foresti, "Visual inspection of sea bottom structures by an autonomous underwater vehicle," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 31, no. 5, pp. 691–705, Oct. 2001
- [2] Y. Kahanov and J. G. Royal, "Analysis of hull remains of the Dor D Vessel, Tantura Lagoon, Israel," *Int. J. Nautical Archeol.*, vol. 30, pp. 257–265, Oct. 2001
- [3] A. Ortiz, M. Simó, and G. Oliver, "A vision system for an underwater cable tracker," *Mach. Vis. Appl.*, vol. 13, pp. 129–140, Jul. 2002.
- [4] A. Olmos and E. Trucco, "Detecting man-made objects in unconstrained subsea videos," in *Proc. BMVC*, Sep. 2002, pp. 1–10.
- [5] S. G. Narasimhan and S. K. Nayar, "Contrast restoration of weather degraded images," *IEEE Trans. Pattern Anal. Mach. Learn.*, vol. 25, no. 6, pp. 713–724, Jun. 2003.

[6] C. H. Mazel, "In situ measurement of reflectance and fluorescence spectra to support hyperspectral remote sensing and marine biology research," in *Proc. IEEE OCEANS*, Sep. 2006, pp. 1–4.

[7] M. D. Kocak, F. R. Dalgleish, M. F. Caimi, and Y. Y. Schechner, "A focus on recent developments and trends in underwater imaging," *Marine Technol. Soc. J.*, vol. 42, no. 1, pp. 52–67, 2008.

[8] B. A. Levedahl and L. Silverberg, "Control of underwater vehicles in full unsteady flow," *IEEE J. Ocean. Eng.*, vol. 34, no. 4, pp. 656–668, Oct. 2009.

[9] R. Schettini and S. Corchs, "Underwater image processing: state of the art of restoration and image enhancement methods," *EURASIP J. Adv. Signal Process.*, vol. 2010, Dec. 2010, Art. no. 746052.