Adaptive UW Image Deblurring via Sparse Representation

F. Farhadifard and M. Radolko

Computer Science Faculty, University Rostock, Germany
Fraunhofer Institut für Grafische Datenverarbeitung (IGD) Rostock, Germany

Abstract

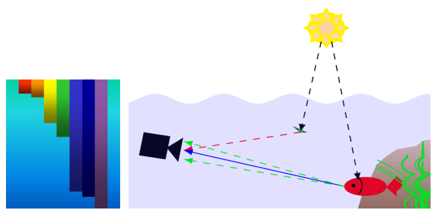
We present an adaptive underwater (UW) image deblurring algorithm based on sparse representation where a blur estimation is used to guide the algorithm for the best image reconstruction. The strong blur in this medium is caused by forward scatter and is challenging since it increases by camera scene distance. It is a common practice to use methods such as dark channel prior to estimate the depth map, and use this information to improve the image quality. However, we found it not successful in the case of blur since these methods are based on haze phenomenon. We propose a simple but effective algorithm via sparse representation which establishes a blur strength estimation and uses this information for adaptive deblurring. Extensive experiments manifest the effectiveness of our method in case of small but challenging blur changes.

Categories and Subject Descriptors (according to ACM CCS): I.4.3 [Image processing and computer vision]: Enhancement—

1. Introduction

Underwater (UW) imaging is challenging due to the physical properties of this environment. In contrast to common images (in air), underwater images suffer from poor visibility due to light attenuation. The light is attenuated while traveling in the water. It increases exponentially by the camera scene distance and depth. The light energy reduces by going deeper in the water which leads to low contrast and colors drop based on their wavelength (Fig. 1(a)). Objects appear blurred which is due to refraction of light from the object of interest to the camera, so-called forward scatter (Fig. 1(b)). Light is reflected to the camera from water or floating particles before it even reaches to the object of interest which, leads to the hazy appearance. This component is called backward scatter and has no information about the scene (Fig. 1(b)). Practically, in common sea water, the objects at a distance of more than 10 meters are almost indistinguishable while the colors are faded. Therefore, capturing a clear scene underwater is not a trivial task, so underwater image preprocessing algorithms are demanded to provide sufficient quality for further advanced image processing and understanding.

There are plenty of UW image enhancement algorithms towards solving mentioned challenges, such as color correction, deblurring and dehazing [IOJ*10] [AAHB12] [CC12]. Based on our best knowledge, none consider the small yet challenging blur changes in this medium. There are methods such as [CC12] [YCH*11], where the depth map is estimated using dark channel prior [HST11] and relative information are used to enhance the quality of UW images. Dark channel is designed based on haze effect caused by backward scatter. Thus, It assumes that for any given point x in an outdoor image, there is at least on pixel with a near zero brightness value close by. However, in case of UW blur where haze is not dominant, it fails.



(a) (b)

Figure 1: (a) Light attenuation. (b) Light scattering, direct component (solid blue), forward scatter (dashed green), backward scatter (dashed red).

In this paper, we propose an UW image deblurring algorithm according to the blur estimation of the image. As it was mentioned above, forward scatter is one of the challenges for UW imaging systems. This component is caused by light refraction on its way from the object to the camera with very small angle and it increases by the camera scene distance. Thus, different parts of an UW image can have different blur rates according to the image depth map. Dictionary learning algorithms have shown good results in applications such as super resolution [ZEP12] [FZvL15], reconstruction [YWHYM08] and denoising [EA06]. Although, they are not capable of learning a dictionary with multiple degradation models. This means that, each single dictionary has atoms with the same degradation model, in our case all atoms have the same level of

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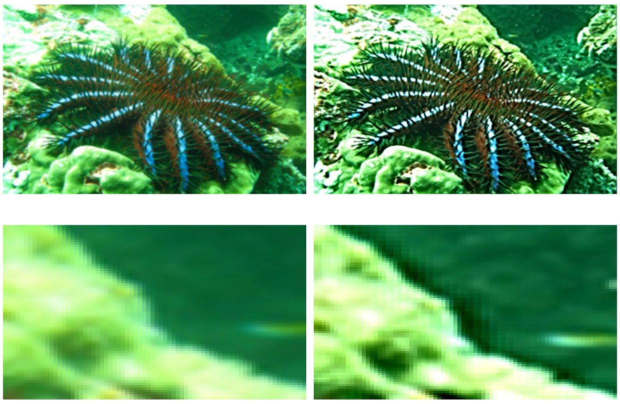


Figure 2: First column is the blurred input image and second column is deblurring result using a single dictionary. Second row shows a zoom perspective where the halo effect appears in output due to over sharpening.

blurriness. Therefore, in case of UW images where several levels of blurriness can be seen in a scene, it is not sufficient to use a single dictionary for all parts of the image. In order to compensate this shortcoming of dictionary based methods, it is necessary to use several dictionaries with different blur levels. For this, we calculate the blur rate of each individual image patch based on its sparse representation and estimate a blur map of the whole image. Later, using this map together with proper dictionaries learned by different degradation models, the blurry image is recovered.

2. Our Approach

In this paper, we propose a guided approach towards deblurring underwater images by obtaining an estimation of the blur level for each image patch. According to the UW blur model proposed in [TOA06], the blur effect caused by forward scatter is a function of camera scene distance:

$$B \approx Ke^{-cR_c\omega}, \tag{1}$$

where B is the degradation model in frequency domain, K is a constant weight, c is the attenuation coefficient and R_c is camera scene distance. (The reader is referred to [TOA06] for more on UW blur model). Therefore, objects in farther distance to the camera appear more blurred than those which are close to the camera. This knowledge leads us to the idea of adaptive deblurring since each part of the scene needs to be sharpened differently. For this purpose, our first attempt is to estimate the blur map of the input image and in the second step, use this information to sharpen the image. Our approach is learning based and profits from the advantages of sparse representation in both, the blur estimation and deblurring steps. In the next two subsections, we give an detailed description of our approach.

2.1. Blur Map Estimation

How blur map estimation can help deblurring? Dictionary learning based algorithms work reasonably well as long as the blur effect

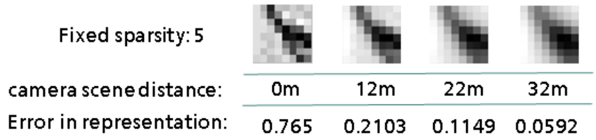
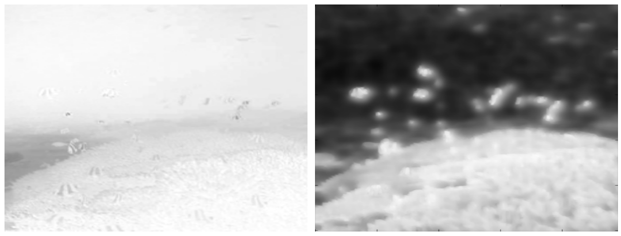


Figure 3: A sharp image patch (left) and three increasingly blurred versions of this patch can be seen. The representation of these patches over a blurred dictionary with sparsity five, is always erroneous. However, the error decreases drastically as the blurriness increases.



(a) (b)

Figure 4: An example of blur map estimation using dark channel prior (a) and our proposed method (b). As it can be seen, our method gives more detailed map. Specially, at the parts where water is dominant, dark channel prior fails in case of blur estimation.

is considered to be constant over the whole image. However, applying it on an image where some parts are more blurred than the rest, some artifacts appear. This is due to the incapability of these methods to learn a dictionary with multiple blur models. In this case, regions with lower blur ratio would contain unwanted oversharpening artifacts such as ringing or halo. An example is given in Fig. 2. The output image contains halos at the edges where are not as blurred as the rest. In this case, if local blurriness level, can be measured, we can apply the proper dictionary with a lower blur level in the sharp regions (to avoid artifacts) and a dictionary with a higher blur rate in the less sharp regions (to enhance sharpness). Since UW blur is a function of camera scene distance, it is essential to consider small but challenging blur changes to avoid artifacts. In order to get a sufficient quality all over the image, we need to use the proper dictionary with appropriate blur effect for each part of the image based on its blur map.

In order to estimate the blur map of a single image without any prior knowledge, we use the sparse representation theory and defined a metric to differentiate between different levels of blurriness. We employed the same logic as [SXJ15]. A blur dictionary has different abilities to represent a sharp patch than a blurred one. To be more precise, consider a dictionary containing atoms learned from a blurred image data set. Using this dictionary, to represent a sharp image patch x of size $n \times n$ as accurate as possible, one need to use a big number of atoms. It can reach to the patch dimension (n^2). It is due to the fact that, a sharp patch has sharp edges and in order to decompose it using blurred dictionary atoms, we need a large number of atoms with their corresponding weight coefficients. In

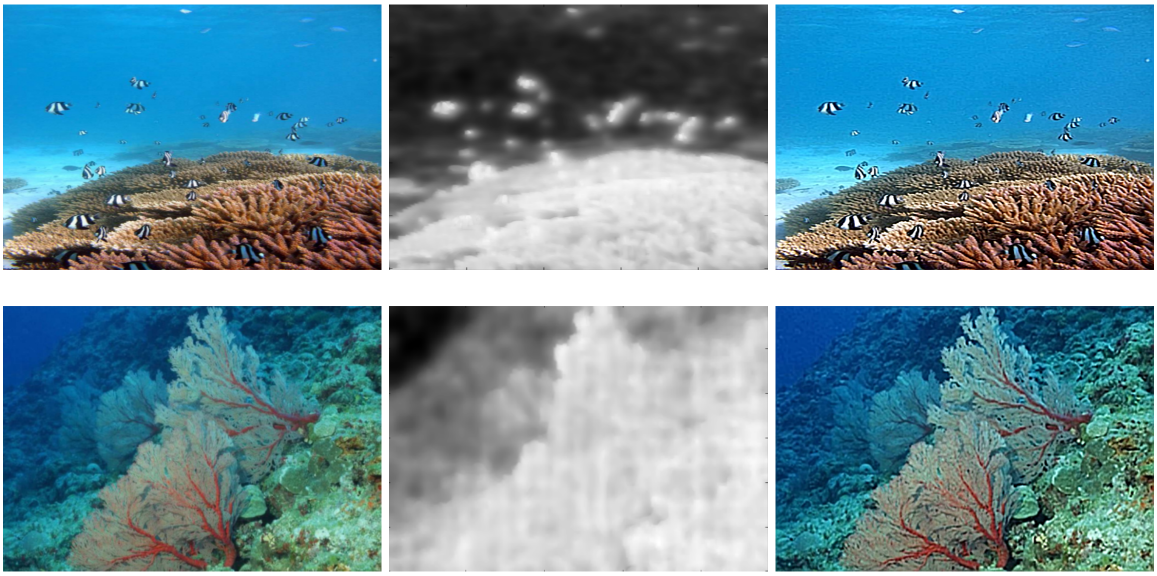


Figure 5: Results of deblurring algorithm together with blur estimation: First column is original image, second column is blur map estimation and last column shows our results.

contrast, to represent a blurred image patch y with the same size, it is possible to get the same accuracy by using fewer atoms in the dictionary. This illustrates that with a fixed sparsity of $T \ll n^2$, we have bigger error in representation of a sharp image patch than a blurred one. We apply this simple fact to estimate a blur map of a single image. For this, we use a blur dictionary to represent all patches, blurred and sharp, over it. Once we have the dictionary (D) with the desired blur level, a test set of image patches containing sharp and blurred ones are represented over it. We set the sparsity to the fixed integer five and calculate the error in representation. We choose sparsity five, since based on our experimental results we can get sufficient quality in reconstruction while obtaining a low computational complexity. The error in representation reflects if the input is blurred and how strong it is (Fig. 3):

$$\|z - D\alpha\|_2^2 \quad s.t. \quad \|\alpha\|_0 \leq 5, \tag{2}$$

where z is the vectorized image patch, D is the dictionary and α is the sparse coefficient vector. The constrain on $\|.\|_0$, enforces the sparsity.

To learn the dictionary, first of all, we collect some clear and sharp UW images. Then, using the degradation model proposed by Trucco and Olmos [TOA06], the blurred images are conducted. The dictionary is learned over degraded images using equation (1) with camera scene distance, R_c, 32m. We use a blur dictionary and not a sharp one since in a blur dictionary we do not have sharp atoms. Therefore, decomposition of a sharp image patch with fixed sparsity leads to a bigger error in comparison to the blurred one. In contrast, if we use a sharp dictionary, there may exist some flat and smooth regions which are sufficient to represent a blurred patch with the same sparsity. So a sharp dictionary will have similar ability to represent a sharp and blurred image patch with almost the same error in the representation.

In summary, a clear image patch with sparsity five, over the blurry dictionary gives bigger error in representation. By increasing the blur level of the image patch, since less number of atoms are needed to represent it, so the error of the representation decreases. The trend can be obtained: bigger error in representation, the sharper the image patch is. We thus use this clue as our blur map estimation.

2.2. Deblurring Algorithm

In proposed deblurring algorithm, we are given a single blurry UW input image and asked to recover it with proper dictionaries. For this purpose, we use the blur map estimation obtained from the last section to cluster the patches into groups with similar blur level. Later, we calculate the sparse coefficients of each cluster using the proper blur dictionary. Once we have the sparse coefficients of each group, the corresponding clear dictionary is used together with the same sparse coefficients to recover the blurry image patches. This strategy is used in several applications such as image restoration and super resolution [ZEP12] [YWHYM08] [FZvL15].

During the blur map estimation of our test data, we could set a limit for the number of blur levels between two to five layers. The decision is made based on the range of blur estimation of each image. Thus, we consider at most, five levels of blurriness for our test data set. Therefore, we learn five pairs of dictionaries using the degradation model explained in [TOA06] with different camera scene distances. Dictionaries are learned offline. For this, we use our clear training set and produce five blurred image sets with different blur levels. Using dictionary learning algorithm such as KSVD [AEB06] and sparse coding methods such as orthogonal matching pursuit (OMP) [PRK93], we learn a blur dictionary for

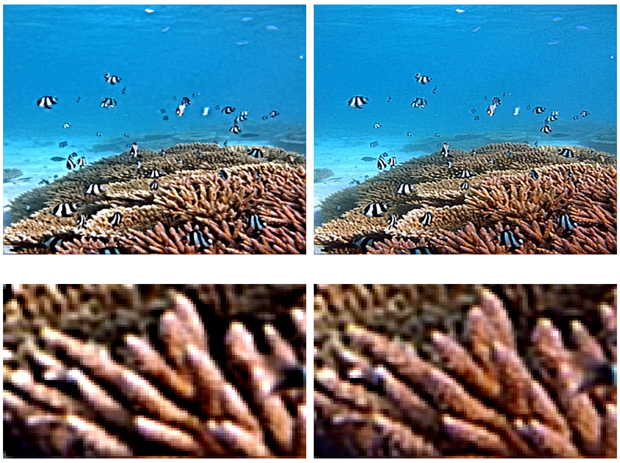


Figure 6: First column is the result of a single dictionary approach [FZvL15] and second column is our results, over compensation can be seen in zoom in view of their result, where due to this problem some details are destroyed.

each training set:

$$\min_{D_l,A} \|Y - D_l A\|_F^2 \quad s.t. \quad \forall i, \|\alpha_i\|_0 \leq T, \tag{3}$$

where D_l stands for blur dictionary, A is the matrix of sparse coefficients and Y is a matrix containing image patches of each cluster. Once we have all blur dictionaries, the corresponding clear dictionary D_h is calculated for each pair:

$$D_h = X(A^T)(AA^T)^{-1}, \tag{4}$$

where X is the matrix of clear image patches. For each cluster j, having the pair of dictionaries $(D_l, D_h)_j$ and input image patches Y_j, we represent Y_j over the blur dictionary $(D_l)_j$ and calculate the sparse coefficients A_j, $Y_j = (D_l)_j A_j$. Then, using the same sparse coefficients of each cluster together with the clear dictionary corresponding to that group $(D_h)_j$, the sharpened image patches are calculated, $X_j = (D_h)_j A_j$. At the end, we merge the image patches and conduct the output image.

3. Results and Discussions

In this paper, we propose an adaptive deblurring algorithm for UW images. We define a measure to detect the blur level of the image patches and categorise them into several clusters and deblur each cluster via the proper dictionary pair. We applied our method on several underwater images with different camera scene distances and taken in different depths. As long as objects are distinguishable the blur estimation is successful and an acceptable image quality is obtained (Fig. 4). By applying this method, we avoid the small yet important problems such as over compensation and halo effects in our results. An example can be seen in Fig. 5, where the results of our method is compared to the previous work, where only one single dictionary was used to enhance the sharpness of the image [FZvL15]. The recovered image using single dictionary, shows a good quality overall but after a zoom in, the halos around the edges are clearly visible while overcompensation destroys some details there. It illustrates that, by applying the blur map estimation, not only we get the same sharpness as single dictionary but also we save the fine details in the image where in previous work they are lost due to over compensation.

Acknowledgment

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