Underwater Image Restoration: Effect of Different Dictionaries

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Abstract. Ocean engineering has a strong need for clear and high quality underwater images. Capturing a clear scene underwater is not a trivial task since color cast and scattering caused by light attenuation and absorption are common. The poor quality hinders the automatic segmentation or analysis of the images. In this work, an image restoration based on compressive sensing is reported which tackles with blurring caused by light scattering and provides better structural details. Furthermore, the effects of different dictionaries on the quality of restoration is studied. The aim is to use a single degraded underwater image and improve the image quality without any prior knowledge about the scene such as depth, camera-scene distance or water quality.

Key words: Underwater image restoration, Compressive sensing

1 Introduction

Digital imaging and image processing have been established in a wide range of challenging topics, in surveillance tasks, industrial quality assurance, inspection applications and exploration. Autonomous Underwater Vehicles (AUV) and Remotely Operated Vehicles (ROV) are usually employed to explore the deep sea. These robots can reach to the depths where divers cannot operate safely and effectively.

Imaging systems underwater, give poor visibility results. This is due to the light interaction with water and its inherent particles. Light attenuation is an exponential function as it travels in water, and results in a poor contrasted and hazy scene. Visibility in this medium is limited by the light attenuation at distance about twenty meters in clear water and five meters or less in turbid water. The overall performance of underwater imaging system is influenced by the absorption and scattering which are the reasons of light attenuation. Forward scattering is the light which is deviated from its way from the object to the camera and generally leads to blur of the image features. On the other hand, backscattering which is a fraction of light that is reflected back to the camera by water or floating particles before it even reaches to the object, and generally limits the contrast of the images, generating a characteristic veil that superimposes itself on the image and hides the scene.

Furthermore, the amount of light reduces by traveling deeper into water, and colors drop off depending on their wavelengths. According to the selective absorption of water, colors with longer wavelength are much easier to be absorbed, so red light will be absorbed before colors with shorter wavelengths such as the blue and green. On the other hand, based on Rayleigh scattering theory, scattering intensity is inversely proportional to the fourth power of wavelength, so that shorter wavelengths of violet and blue light will scatter much more than the longer wavelengths of yellow and especially red light. As a conclusion, water absorbs the longer wavelength of red and scatters the blue and violet when visible light disseminates in it. Absorption and scattering effects are not only due to the water itself but also due to the components such as a dissolved organic matter so-called marine snow. Although, the visibility range can be increased with artificial illumination of light on the object, but it produces non-uniform of light on the surface of the object and producing a bright spot in the center of the image with poorly illuminated area surrounding it. So, underwater images suffer from limited range of visibility, low contrast, non-uniform lighting, blurring, bright artifacts, color diminished and noise. (The reader is referred to [1] for more on scattering and absorption).

A possible approach to deal with mentioned challenges is to consider the image transmission in water as a linear system [2] and recover the image using some priority knowledge. Image restoration aims to recover the original image $X(i,j)$ from the degraded image $Y(i,j)$ using a model of the degradation and of the original image formation; it is essentially an inverse problem.

Several techniques have been proposed to handle the restoration of underwater images from different perspectives. E. Truco et.al [3], considered the forward scattered component of light as the main reason of degradation and proposed a self tuning restoration filter using a simplified version of the well-known Jaffe-McGlamery image formation [4] [1] by eliminating the backward scattered component. X. Wu and H. Li [5], followed the same fundamental but considered that water made of lots of layers which scatter the same amount of light to take into consideration the relationship between the components of the light that enters into the camera. On the other hand, some methods considered the backward scattered component as the main problem and using statistical approaches, attempted to recover the clear image from hazy version[6][7][8]. For this, using dark channel prior, the depth map of each image is estimated. Once the depth map is calculated, the foreground and background is segmented, then the presence of artificial light is determined and finally, the haze phenomenon will be corrected by considering the effect of artificial light.

In this work, we use a learning based algorithm based on compressive sensing which is proposed [9], in order to recover the blur free underwater image using the simplified image formation of Jaffe-McGlamery presented at [5]. The main goal is to do a study about the results of this method using dictionaries learned by two different image data sets and also two different degradation models in order to find the best combination. We used two image sets, including underwater images and in air images and as degradation model we applied Gaussian blur and blur model proposed at [5].

The rest of this report is structured as follows, first some preliminaries are given in two subsection: compressive sensing and underwater degradation model. In section 3, the approach is explained in details. Simulation results and the study discussion are reported at section 4 and then at last conclusion is placed.

2 preliminaries

Before further proceeding, we will give some preliminaries which are needed to proceed to the algorithm.

2.1 Compressive Sensing

Compressive sensing (CS) has received considerable attention in different fields such as computer science, electrical engineering and mathematics. It suggests that it is possible to surpass the traditional limits of sampling theory. The fundamental of CS is built based on sparse representation of a signal which says a signal can be represented with only a few non-zero coefficients in a suitable domain if the signal is sparse in that domain. Using nonlinear optimization, the recovery of such a signal from very few measurement is possible.

CS enables a potentially large reduction in the sampling and computation costs for sensing signals that have a sparse or compressible representation. While the Nyquist-Shannon sampling theorem states that a certain minimum number of sampling is required in order to perfectly capture an arbitrary bandlimited signal, when the signal is sparse in a known basis we can vastly reduce the number of measurements that need to be stored. The basic idea of CS is that rather than first sampling at a high rate and then compressing the sampled data, we would like to find ways to directly sense the data in a compressed form, (at a lower sampling rate).

This field grew out of the work of Candes, Remberg and Tao and of Donoho who showed that a finite dimensional signal having a sparse or compressible representation can be recovered from a small set of linear, nonadaptive measurements [10][11][12][13].

2.2 Underwater degradation Model

The Jaffe-McGlamery [4][1] underwater imaging model, shows a complete and comprehensive statement of light interaction with water and the corresponding components of light which enters into the camera. McGlamery stated that the total irradiance enters into the camera is the line superposition of the three components, direct, forward scattered and backward scattered.

$$E(i,j) = E_d(i,j) + E_{fs}(i,j) + E_{bs}(i,j) \tag{1}$$

Since the aim is to recover the blurry images and it caused by forward scattered component, therefore, the backward scattered component which has no information about the scene can be ignored and only the relation between the direct component and forward scattered one is considered.

$$E(i,j) = E_d(i,j) + E_{fs}(i,j) \tag{2}$$

where

$$E_{fs}(i,j) = E_d(i,j) * g(i,j/R,G,c,B) \tag{3}$$

and

$$E_d(i,j) = e^{-cR} E_d(i,j,0) \tag{4}$$

where G and B are empirical coefficients, c is the attenuation coefficient and R is the scene-camera distance. Thus, the formation of $g(i,j/R,G,c,B)$ is the key to restore the clear underwater image.

In frequency domain we have:

$$E(f) = S(f)E_d(f) \tag{5}$$

Because of sea water complexity, it is not trivial to come up with an accurate model. The most authoritative model is proposed by Jaffe [4] as the following:

$$S(f) = (e^{-GR} - e^{-cR})e^{-Bzf} + e^{-cR} \tag{6}$$

After some simplifications and optimization proposed at [5], the final degradation model which represent the blurriness caused by forward scattered component is obtained as:

$$E(f) = (1 + k\frac{1-e^{-bf}}{f})E_d(f) \tag{7}$$

where $E(f)$ represents the spatial form of blurry image, and $E_d(f)$ states for spatial form of direct component which represent the clear underwater image.

3 Image Restoration

In the problem of restoration, we are given a degraded image Y and asked to recover the original image X using a prior knowledge such as degradation model. In this report, we are going to make a study about the recovery of blurry underwater images using a learning based algorithm proposed at [9], which is based on compressive sensing theory. The fundamental of the algorithm will be explained first and then the results of study will be discussed.

The method has two stages, first a pair of dictionaries is learned. Dictionaries are linked to each other by the degradation function and have corresponding atoms. Then using the dictionaries together with sparse representation theory, the sparse coefficients are calculated and afterwards, the clear image is recovered using the same sparse coefficients and the dictionary of clear images.

To be more precise, consider degraded underwater image Y which is blurred version of desired clear image . And assume that there is an over-complete dictionary $D_h \in R^{n\times k}$ of k bases which is a large matrix learned using high quality and clear image patches. Then the vectorized patches of image X, $x \in R^n$ can be sparsely represented over dictionary D_h. So the high quality and clear patch x can be represented as $x = D_h\alpha_0$ where $\alpha_0 \in R^n$ is a vector with very few nonzero elements ($\ll k$). The relationship between a high quality and clear image patch x and its degraded counterpart y can be expressed as:

$$y = Lx = LD_h\alpha_0 \tag{8}$$

Note that L represents the blurring model. Substituting the representation for the high quality and clear patch x into (Eq. 8) and noting that $D_l = LD_h$, one gets:

$$y = LD_h\alpha_0 = D_l\alpha_0 \tag{9}$$

Equation (9) implies that the degraded image patch y will also have the same sparse representation coefficients α_0. Now given the degraded image patches, one can obtain the representation coefficients using a vector selection such as OMP[14]. After obtaining the sparse coefficients, one can reconstruct the high resolution patch x.

$$x = D_h\alpha_0 \tag{10}$$

The sparse representation problem (vector selection) has the formulation as an optimization problem which results in finding the sparse coefficient α using dictionary D_l. For obtaining the sparse representation coefficients for the degraded image patch y, one solves the following optimization problem:

$$\min_{\alpha_0} \|y - D_l\alpha_0\|_2 \quad s.t. \quad \|\alpha_0\|_0 < T \tag{11}$$

where T is a threshold which is used to control the sparseness of the representation. The l_0 norm is used to identify the number of nonzero elements of the vector α_0. The level of sparsity can vary depending on the complexity of test signal, higher sparsity can give more accurate representation. An error based formulation of the vector selection problem can also be employed. In order to represent the signal of interest, a suitable dictionary and a sparse linear combination of the dictionary atoms is needed. The sparse representation problem subject to find the most proper selection of those linear combination vectors from an over-complete dictionary D_l. To find such a representation different pursuit algorithms can be used such as OMP[14] and the over-complete dictionary can be formed using K-SVD[15].

3.1 K-SVD approach

As it was mentioned previously, an over complete dictionary together with the sparse coefficients are needed to represent a signal. The joint dictionary learning and sparse representation of a signal can be defined by the following optimization problem:

$$\min_{D,\alpha} \|X - DQ\|_F^2 \quad s.t. \quad \forall i, \|\alpha_i\|_0 < T \tag{12}$$

Consider a set of over-complete basis vector f, and an initial dictionary which is formed by choosing its elements from the set randomly, D. In order to find the sparse coefficients of such a set over the dictionary, once the dictionary is assumed to be fixed and then the sparse coefficients are calculated using OMP by solving following optimization problem for each and every input signal

$$\|y_i - D\alpha_i\|_2^2 \quad s.t. \quad \min_{\alpha_i} \|\alpha_i\|_0 \quad i = 1, 2, ..., N \tag{13}$$

Since the K-SVD algorithm attempts to update dictionary by replacing one atom at a time to reduce the error in representation, thus in every iteration, the dictionary and effective sparse coefficient vectors are considered to be fixed and just one atom in the dictionary is questioned to be replaced and the corresponding sparse coefficient is calculated.

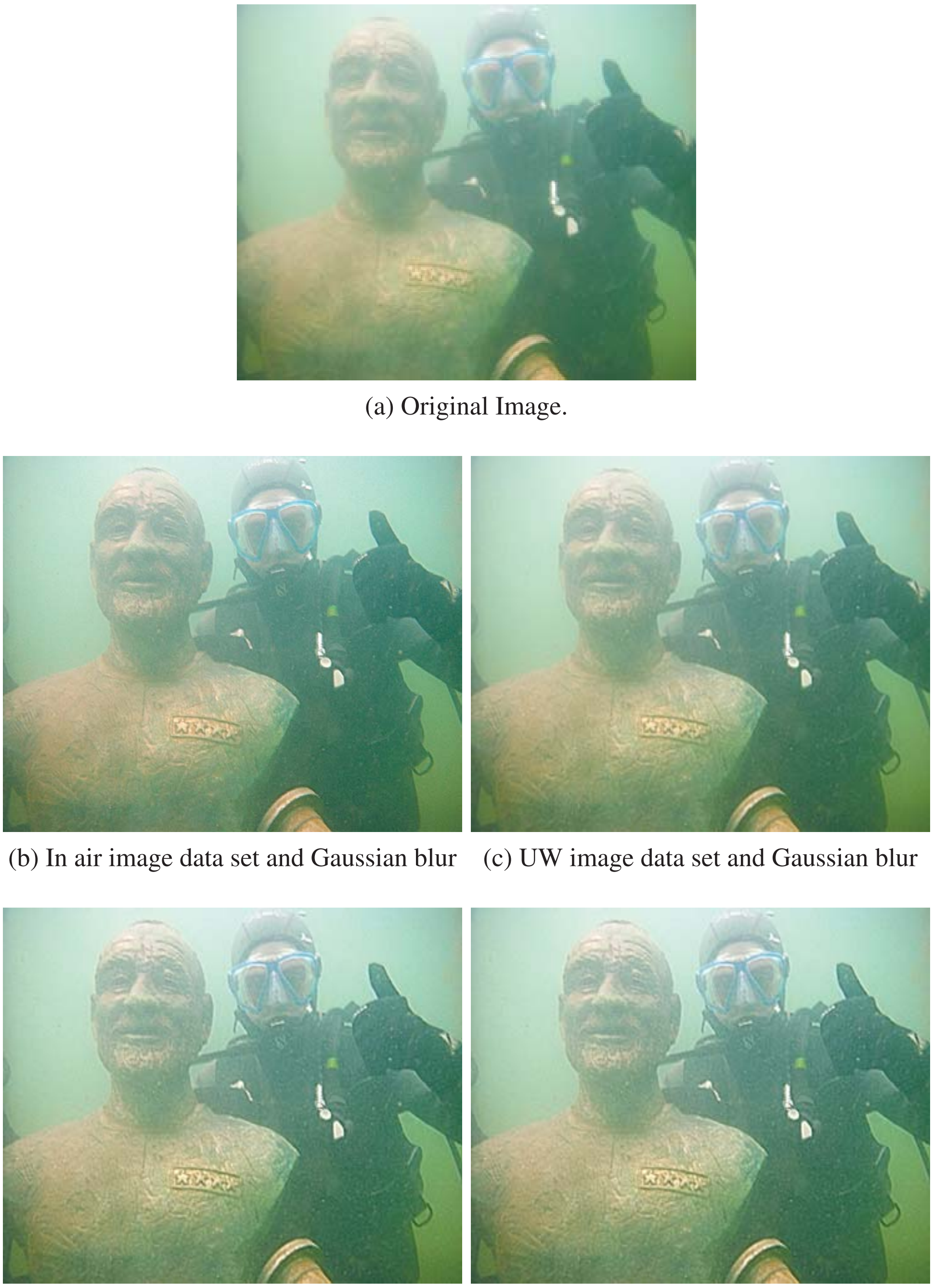
3.2 Orthogonal Matching Pursuit (OMP)

As it was mentioned before, finding an exact sparse representation of a signal is not easily achievable. As the result, many researchers have aimed to find the best approximate solution. Among all the methods Orthogonal Matching Pursuit (OMP) has been the main choice. OMP is a simple method which, enjoys fast running time. Given a dictionary, OMP as a greedy algorithm, aims to find sparse representation of the signals of interest over that dictionary. It is an iteratively algorithm which updates the basis vector in every iteration and as the result reduces the error in the representation. According to this scheme, the dictionary atoms with the largest absolute projection on the error vector are selected. This results into selection of atoms which contain maximum information and consequently reduce the error in the reconstruction.

4 Simulation Results

In order to evaluate the method, we used several underwater images which, were taken in different seas and unknown depths and try to recover the blur free images. Some of the test images are the same as those used in [9]. For this purpose, we learned four different pairs of dictionaries. We used two training sets, one contains in air images and the second one, underwater (UW) images. Then using two possible blur models, Gaussian blur and UW blur model explained above, four possible pair of dictionaries are trained. Once we have all dictionaries, the quality of restored images are studied over some test images which are independent from training data sets. Qualitative comparison is provided to evaluate the results. We did not provide any quantitative comparison such as SNR, since the ground truth data are not available.

As it can be seen in both Fig. 1 and Fig. 2, the reconstructed images using the both training sets where Gaussian blur is used as the degradation model, show almost the same quality (almost identical). Both provide good quality at recovering blur free and detail enhanced images. Experimental results show that, we can achieve better reconstruction if the degradation model is designed specially for underwater situation. Training dictionaries using the UW blur give results with sharper edges and better contrast while the details are more enhanced (Fig.3). But this does not apply for results of the dictionaries with in air training set. Fig. 4, shows that clearly by the artifacts, and overcompensation which gives an unnatural appearance to the image.



(a) Original Image.

(b) In air image data set and Gaussian blur

(c) UW image data set and Gaussian blur

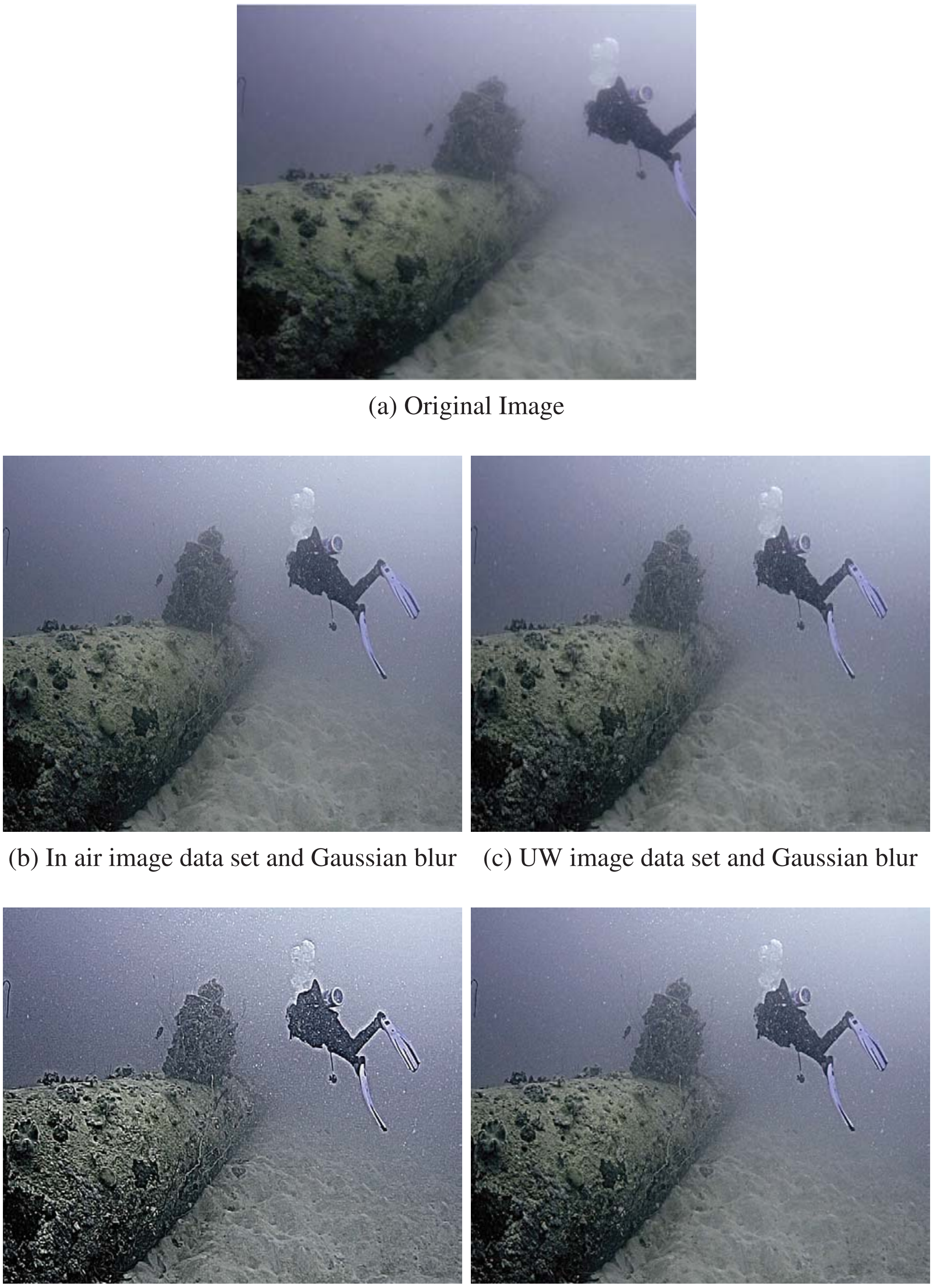
(d) In air image data set and UW blur

(e) UW image data set and UW blur

Fig. 1: Comparison of the results using different dictionaries and degradation models. Original image is Courtesy of C. Ancuti et al. [16]

5 Conclusion

In this paper, we reported an underwater image restoration method based on compressive sensing and further, studied the effects of different dictionaries in the final result.



(a) Original Image

(b) In air image data set and Gaussian blur

(c) UW image data set and Gaussian blur

(d) In air image data set and UW blur

(e) UW image data set and UW blur

Fig. 2: Comparison of the results using different dictionaries and degradation models.

Based on experimental results, we can recover a blurry underwater image without any knowledge about the depth or camera-scene distance while the local contrast is enhanced and better structural details are provided. The study illustrates that, when we learn dictionaries using UW image data set which have similar statistical nature as in-

(a) Original Image

(b) In air image data set and Gaussian blur

(c) UW image data set and Gaussian blur

(d) UW image data set and UW blur

Fig. 3: Zoom-in view of the results

(a)

(b)

Fig. 4: Zoom-in view of results by in air data set and UW blur model.

put and specific blur model caused by forward scattered light, the best reconstruction can be achieved while UW images keep their natural appearance.

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