Single Image Marine Snow Removal based on a Supervised Median Filtering Scheme

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Abstract: Underwater image processing has attracted a lot of attention due to the special difficulties at capturing clean and high quality images in this medium. Blur, haze, low contrast and color cast are the main degradations. In an underwater image noise is mostly considered as an additive noise (e.g. sensor noise), although the visibility of underwater scenes is distorted by another source, termed marine snow. This signal disturbs image processing methods such as enhancement and segmentation. Therefore removing marine snow can improve image visibility while helping advanced image processing approaches such as background subtraction to yield better results. In this article, we propose a simple but effective filter to eliminate these particles from single underwater images. It consists of different steps which adapt the filter to fit the characteristics of marine snow the best. Our experimental results show the success of our algorithm at outperforming the existing approaches by effectively removing this phenomenon and preserving the edges as much as possible.

1 INTRODUCTION

Underwater (UW) images are mainly characterized by poor visibility due to light interaction with water and its inherent particles. Light interacts with water via attenuation which increases by travelling deeper in water or by expansion of the object-camera distance. It is caused by two factors: light absorption and scattering. As a result, visibility UW is limited at a distance of about twenty meters in clear water and five meters or less in turbid water (Bazeille et al., 2006). This is due to color cast, haze, blur and low contrast.

Naming distortions for UW imaging, one of the degradation sources which is not well-researched and mostly neglected from image processing algorithms, is the presence of floating particles. Floating particles are composed of dead material and dissolved organic matter slowly drifting downward. These particles, so-called marine snow, are highly variable in shape, size and concentration. In some cases such as biology, marine snow can be an important subject to be researched. In contrary, for image processing algorithms, marine snow is mostly considered as a source of noise and should be removed. Light reflection on marine snow creates white bright spots that lead to an inhomogeneous medium. Not only scattering and absorption are increased due to this phenomenon, but also as their luminance is high, they may appear dominant enough to reduce the scene perception.

There are many approaches towards UW image enhancement and restoration which address blur, haze and color cast such as (Trucco and Olmos-Antillon, 2006)(Chiang and Chen, 2012)(Ancuti et al., 2012). Fewer approaches tackle denoising UW images e.g. (Arnold-Bos et al., 2005)(Shanmugasundaram et al., 2013). These methods consider that every kind of present noises can be defined as one of the additive noises. Thus Gaussian, speckle and salt and pepper noises are considered as UW noise and with this assumption authors provide a solution. However, none of these approaches are directly designed to eliminate marine snow and their main assumptions do not accomplish its characteristics. Removing marine snow is not a trivial task since an actual object in the image is introduced as noise and should be discarded.

Based on our knowledge only one paper has directly addressed the elimination of this phenomenon (Banerjee et al., 2014) which is based on a probabilistic approach and median filtering. It is a patch-based approach which checks the probability of existence of marine snow. This is done by looking for high luminance pixels in a patch using a predefined threshold

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and calculating the probability as follows:

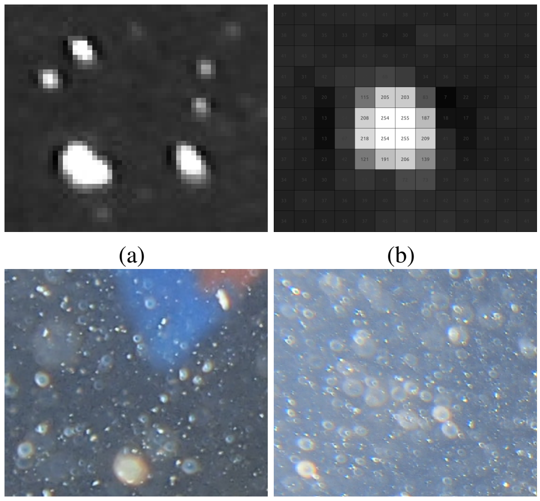
$$P(MS) = 1 - \frac{N_{HL}}{N} \quad (1)$$

where N_{HL} and N stand for number of high luminance pixels and total number of pixels in the current patch respectively. A double checking is done to avoid misclassification of true objects as marine snow. To this end, keeping the same center pixel, they increased the window size by 2 and calculate the probability one more time. If the probability of having marine snow in the patch is still high (low number of high luminance pixels) then the center pixel is replaced by the median value of the local patch. However, cross checking in this approach may fail in the case that marine snow is at a corner of window and has a structure big enough to fit partially in the window. Thus number of high luminance pixels increases at the cross checking and results in misclassification. This is not considered in this approach since they assumed that marine snow has a structure of two or three pixels. Although depending on the image resolution, marine snow can sometimes reach size of 50×50 pixels. Moreover, the approach is only applied on luminance channel which could result in false detection of similar structures with different colors.

To address above mentioned shortcomings, first we investigate the real characteristics of marine snow and provide our solution accordingly. The aim is to clean an UW image from the presence of this phenomenon and preserve the edges of the desired objects as much as possible. For this, we design a filter which examines each pixel in all possible extracted patches to detect marine snow. Once defected pixels are defined, their intensity is replaced by a new value which is calculated and set according to a voting algorithm. We build our algorithm based on a supervised noise detection and concept of median filtering. Our approach is a patch-based method in a multiscale manner. It is a simple but effective method which show promising results where marine snow is almost completely removed and even small details are preserved.

1.1 Proposed Approach

One of the most common used filters in cases similar to marine snow such as impulse noise and dust and scratches is median filtering (Wang and Zhang, 1999)(Hwang and Haddad, 1995)(Abreu et al., 1996)(Bergman et al., 2007). The simplicity and efficiency of these filters besides successful results motivate us to address our source of noise with a similar filter. To this end, we first investigate the characteristic of marine snow and propose an adaptive filter accordingly.



(a) (b) (c) (d)

Figure 1: Illustration of marine snow characteristics.

1.2 Characteristics of Marine Snow as a Noise

As plants and animals near the surface of the ocean die and decay, they fall toward the sea floor, just like leaves and decaying material fall onto a forest floor. The decaying material is referred to as marine snow, because it looks like snowflakes. These particles grow as they fall, some reaching several centimetres in diameter. In addition to dead animals and plants, marine snow also includes faecal matter, and other inorganic dust.

In an image, this phenomenon appears as white bright spots randomly distributed in the image. These bright spots have specific properties as follows:

1. Size: They appear in different sizes depends on the image resolution and the camera scene distance. Usually between 3 by 3 pixels to 50 by 50 pixels (Figure 1(a)). It is not necessarily symmetric so can have different hight and width.
2. Intensity: Since this is an object and not additive noise due to the sensor or so, they have both high and low frequencies. It consists of a high peak somewhere in the middle and intensity the surrounding area decreases proportional to the distance to the peak location. In most cases, a dark area around the marine snow highlights its intensity (Figure 1(b)).
3. Shape: Its shape can be roughly estimated as a Gaussian distribution in all directions although the high intensity peak is not always in the middle so its not symmetric. (Figure 1(b)).
4. Distribution: In contrary to additive noise, marine

snow is present in all layers of an image and therefore, it can have a highly overlapped and non-uniform distribution over the image (Figure 1(c)).

5. Reflection: The most challenging fact about this phenomenon is that in case of an artificial light, they scatter the light to the camera and appear as circle shaped reflections. This leads to further distortion since they superimpose themselves in front of the scene (Figure 1(d)).

1.3 Marine Snow Removal - Supervised Median Filtering

Taking into consideration most of aforementioned characteristics, we propose an algorithm based on median filtering to remove marine snow effect from single UW images. Our algorithm is a supervised approach. First it detects the potential corrupted pixels. The candidate pixels are those that are highly dissimilar than their neighbors and are therefore suspected to be part of defect. Dissimilarity is defined as an unusual higher intensity area in a patch. The Dissimilar Pixel Values (DPV) are replaced by the mid value of the rank-ordered remaining values in the current patch. This process is repeated for the whole image.

We extract the patches highly overlapped; this means each pixel can be in $n \times n$ possible patches (where n is the patch size) except for the pixels at the border of the image with less possibilities. Therefore for each pixel marked as DPV several filtered candidates could be obtained. Next a voting algorithm based on a predefined threshold is used to make the final decision. This is when edges of objects are preserved and noise is eliminated. The threshold is defined according to the size of window and naturally number of candidates for the processing pixel. At last, to robust our algorithm to different size of marine snow, the algorithm is repeated for different patch sizes.

To be more precise, consider the corrupted image X of size $N \times M$ where $X(i,j)_c$ for $c \in (R,G,B)$ denotes the intensity value at pixel location (i,j) and channel c. Let Ω be the extracted patch of size $n \times n$ centered at $X(i,j)_c$. The detection, and filtering of the proposed algorithm is explained in two following subsections.

1.4 Coarse Filtering

At this step, we extract all possible patches of the image and for each and every patch the following conditions are checked to detect all dissimilar pixel values. Firstly, we mark the pixels with a very high intensity values compared to the neighbours in a local patch. A pixel candidate p has to satisfy the following inequality:

$$\|p - \mu(\Omega)\|_2^2 > W_1 \cdot \sigma(\Omega) \quad p \in \Omega, \tag{2}$$

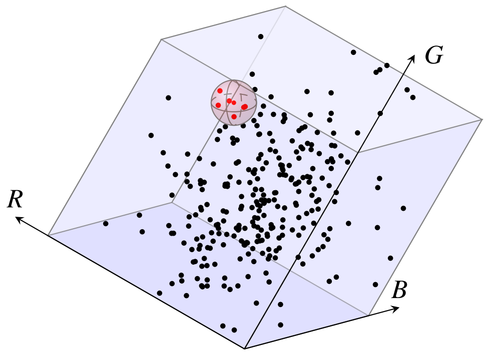


Figure 2: The pixels of current patch are visualized as points in RGB color space. The purple sphere demonstrates the search environment for the density calculation.

here W_1 is an empirical weight, $\sigma(\Omega)$ is the standard deviation and $\mu(\Omega)$ denotes the mean value of the local patch Ω. Secondly, to find the general outliers we apply the idea of (Gutzeit et al., 2010). By considering the RGB color space as an Euclidean space, we calculate the density of pixels in a specific area to identify the outliers. For each suspected pixel, a sphere covering an area surrounding it is explored (see Figure (2)). The number of pixels within this sphere is defined as follows:

$$\#\{v \in \Omega \mid \exists p \in \Omega : \|p - v\|_2^2 < W_2 \cdot \sigma(\Omega)\}, \tag{3}$$

which together with the volume of sphere and number of pixels in the patch gives us the density. The radius of the sphere is defined dynamically based on the weighted standard deviation of Ω to make the approach adaptive. We consider marine snow in an image to have colors with low saturation and high value which is mostly the case. Therefore, to avoid taking into account the objects with the same properties as marine snow but different colors, we discard the pixels with high saturation by applying the following inequalities

$$|p_c - p_l| < T \quad \forall c,l \in \{R,G,B\} \ \wedge \ c \neq l. \tag{4}$$

Thereby, we limit dissimilar pixel values to have colors close to white using a predefined threshold T.

Once all pixels which satisfy three aforementioned equations are detected, we discard them from the patch Ω, and sort the remaining pixel values (RPV), the mid value of this list is derived as the initial filter value:

$$\Omega_f(i,j) = \begin{cases} med(RPV), & \text{if } \Omega(i,j) \in DPV \\ \Omega(i,j), & \text{otherwise} \end{cases} \tag{5}$$

where Ω_f indicates the corresponding filtered patch. Before initial filtering, the pixels surrounding the one in DPV list are examined if there is a sudden low intensity, these pixel values are discarded from the median calculation. The reason for such a selection is to discard the halo-like shadows around the high intensity of marine snow (see property 2 in section 1.2). Therefore, not only a very high bright spots but also a very dark surrounding defines this phenomenon and should be filtered out.

1.5 Fine Filtering

We use fine filtering to avoid removing objects' edges since in coarse filtering step all pixels clustered as DPV are filtered, this is regardless of noise or objects. This may happen when the patch is placed on the edges of an object which can satisfies all conditions in the last step. To prevent such a false detection, we employ a voting algorithm to make the final decision. For this, we extract the patches in highly overlapped fashion, accordingly, each pixel is checked in $n \times n$ patches. This means if a pixel is defined as DPV in several patches, then we have several filtered values for it. Here is where our voting algorithm decides about that pixel. If it is marked as DPV in more than 80% out of $n \times n$ possible patches (highly voted to be noisy), then it is replaced with the median value of all initial filtered values correspond to that pixel. On the other hand, if the pixel is not marked as DPV in such a big majority then it will keep its original value in the final result. To clear the idea behind such a strategy, consider a patch which is placed at the edge of an object, therefore the pixels correspond to that part of object are marked as DPV. Now moving the patch fully overlapped surrounding those pixels, there will be the situation that the object is not only in the corner of the patch but covering a big part of the patch and finally the whole patch. In this situation those pixels which were clustered as DPV at first, won't satisfy the conditions mentioned in the last section and won't be clustered as DPV anymore. Figure (3) illustrates the ambiguity. Thus, the voting algorithm can avoid destroying the objects' edges which are marked as DPV in minor number of patches out of $n \times n$ possible patches.

To take care of different sizes of noise, we have used different patch sizes. Based on our experiments the maximum patch size in an HD image should be 19×19. For that reason, our method is applied in several iterations until all pixels have been tested and the noise in different layers is filtered out.

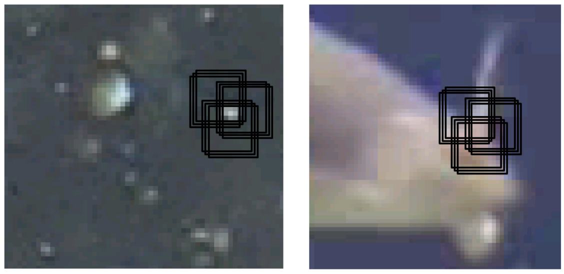
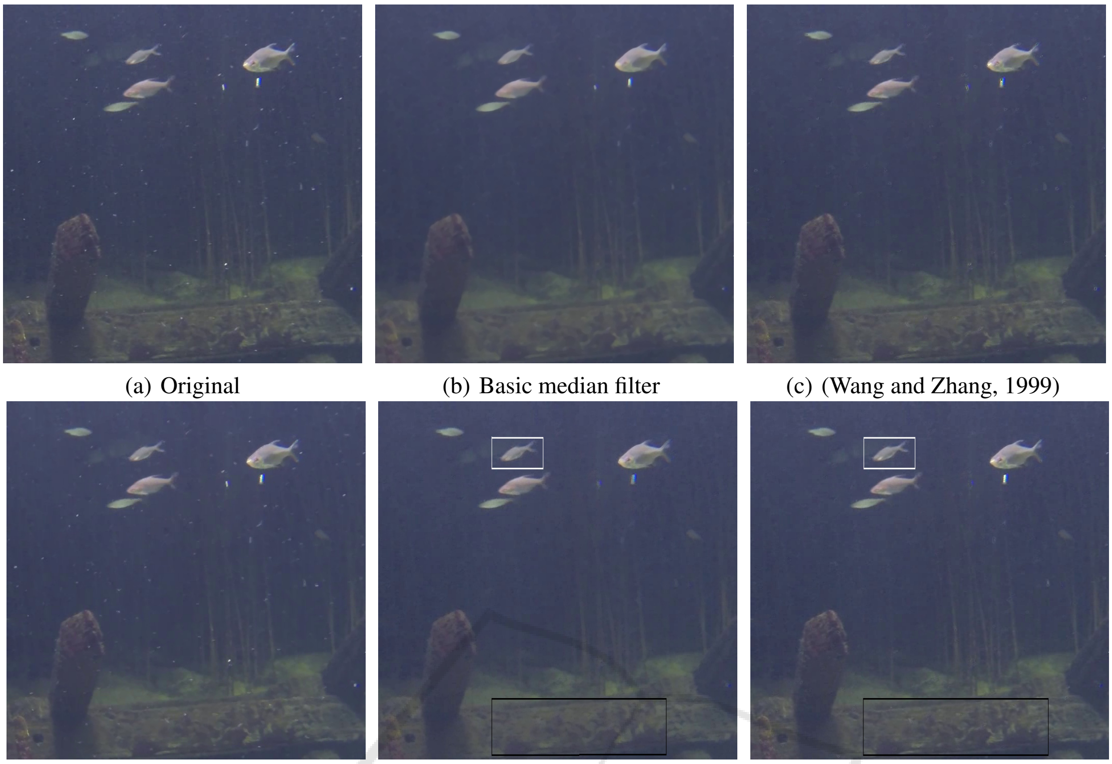


Figure 3: Marine snow detection, shows overlapping patches for marine snow (left) versus a true edge (right).

2 SIMULATION RESULTS AND DISCUSSIONS

Our proposed method is applied on several UW images taken in both sea and pool in presence of marine snow. In some images such as the one which is taken at Ozeaneum Stralsund (Figure (4)), we did not use any artificial light UW, but the ones which are taken in see or river (Figure (5) and (7)) due to depth, an artificial light is used. Artificial illumination causes more degradation where the marine snow is dominant, since the reflection of strong light on these particles introduces bright transparent circles which superimpose themselves in front of the scene as a small veiling area (Figure 1(d)). This introduces a new and very complicated issue which needs to be tackled in a different perspective since it has different characteristics than marine snow itself. In these cases we ignore the reflections and only focus on removing marine snow itself.

Figure (4(a)) illustrates a relative simple example of an UW scene with marine snow and the result after applying the proposed algorithm (4(f)). The main focus in our algorithm is to remove noise while preserving the objects' edges as much as possible. As it can be seen, marine snow is removed effectively while even the small details of the background structure are preserved. Furthermore, we have compared our method to the similar existing ones based on median filtering. Our method outperforms the three different versions of median filters. This is when basic median filter with window size 5 smoothed the image too much which destroyed all the details (Figure 4(b)), the progressive median filtering (Wang and Zhang, 1999) cleaned the marine snow but obviously destroyed the edges of the objects (fishes) (Figure 4(c)). Decision based median filtering (Srinivasan and Ebenezer, 2007) failed at removing marine snow which is explainable due to different criteria at detecting noise (Figure 4(d)). The only competitive one is (Radolko et al.,) which is an improved version of



(a) Original (b) Basic median filter (c) (Wang and Zhang, 1999)

(d) (Srinivasan and Ebenezer, 2007) (e) (Radolko et al.,) (f) Proposed method

Figure 4: The original image (a) and results after applying basic median filter (b), (Wang and Zhang, 1999) (c), (Srinivasan and Ebenezer, 2007) (d), (Radolko et al.,) (e) and our proposed method (f). Areas assigned with rectangles shows how (Radolko et al.,), (Banerjee et al., 2014) smoothed the true edges of the image details which are preserved in proposed method.

(Banerjee et al., 2014) with few changes which are applied to increase the accuracy of noise selection and filtering steps in (Banerjee et al., 2014). For this, they check if the center pixel has a high luminance value compared to its neighbours, if yes then they double check it with a bigger window. If in both cases center pixel is defined as being noisy, then it is replaced by the median value of the local window discarding the center pixel itself. For further enhancement, instead of only luminance channel, they applied it on each color channel separately. At the first glance, (Radolko et al.,) (Figure 4(e)) shows competitive results but as we pay more attention to the detail, it can be seen that a lot of details at the background (e.g. black rectangle) and also high frequencies at the foreground's objects are smoothed (e.g. white rectangle).

Figure (5) shows the results of our method and (Radolko et al.,) for a more challenging case, where marine snow is more dominant and contains some reflections. This leads to more difficulty where reflections overlap with marine snow and prevent the method from detecting and removing them completely. Despite big reflections which are still present, our method could remove marine snow while very small details of marine creature are retained. At last we have tested our method on a very difficult case (Figure 7) which is highly corrupted with marine snow. The proposed approach could clean the marine snow effectively, although, due to using artificial light source, reflection of marine snow is dominant enough to disturb the visibility of image further. This image can illustrate how intensive marine snow is involved in all layers of the scene.

Furthermore, we test the ability of proposed method at removing marine snow quantitatively. For this, two important parameters namely Mean Square Error (MSE) and Peak Signal to Noise ratio (PSNR) are employed. PSNR is mainly used to measure the quality of noise free reconstructed image. Generally it is shown in terms of logarithmic decibel scale due to high dynamic range of images and is derived as follows:

$$PSNR = 20 \times log[\frac{\mathrm{Max}^2}{\mathrm{MSE}}] \quad (6)$$

here MAX denotes maximum pixel value of the image. MSE represents the variance between image after reconstruction $\hat{X}$ and the original image X and is

Table 1: Comparison of Marine Snow Removal Methods using PSNR and MSE Metrics.

		Level 1	Level 2	Level 3
PSNR	(Radolko et al.,)	38.644	37.801	37.460
	Proposed Method	43.595	41.538	41.150
MSE	(Radolko et al.,)	8.884	10.787	11.668
	Proposed Method	2.841	4.563	4.989

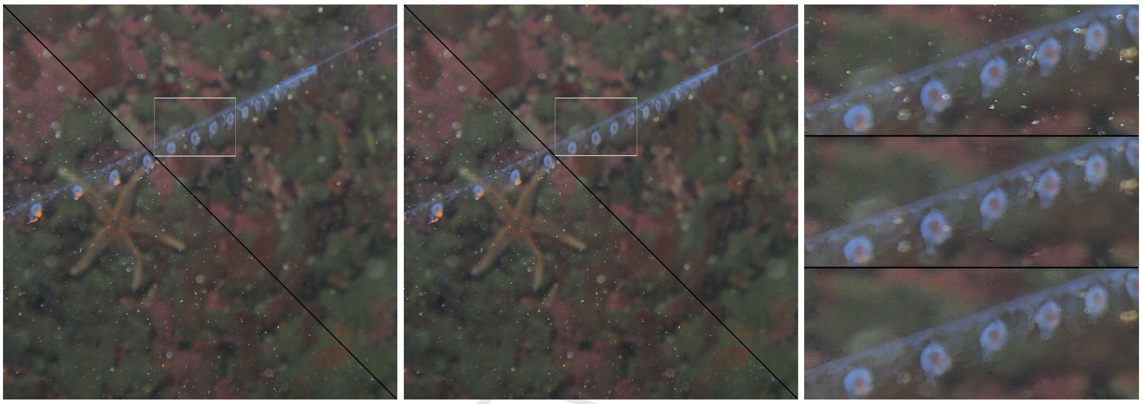


Figure 5: From left to right: result after applying (Radolko et al.,), our approach (both in comparison to the original image). The last image is a close-up of the original image, (Radolko et al.,) and proposed method from top to bottom respectively. Underwater image is provided by Eik Deistung.

computed as:

$$\mathrm{MSE} = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{m-1}|\hat{X}(i,j) - X(i,j)|. \qquad (7)$$

For both aforementioned metrics, besides the result after denoising, the original noise free version of the image is also needed. However, in UW case mostly we do not have access to the original image except when a target image is used. A common solution is to simulate the degradation model over a high quality and clear image. However, simulation of marine snow is still a subject under investigation (Slade et al., 0011). Nevertheless a simple way to model marine snow would be to generate salt and pepper noise on the original image such as (Shanmugasundaram et al., 2013). Although, earlier in this paper we have discussed that marine snow is not an additive noise and behaves differently, thus, it is not a valid assumption and cannot be used to evaluate the proposed method.

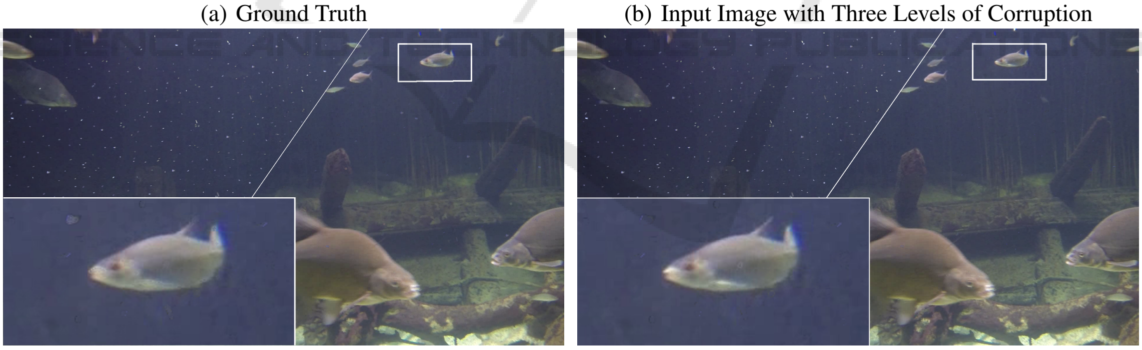
To this end, we have came up with a different strategy. First we provide a realistic ground truth from a scene containing marine snow. For this, we choose a test image from the scene 4 and remove all the marine snow particles by a human expert. This gives us a ground truth image that should be recovered by the algorithm. Second, we extract the marine snow from another frame of the same scene and place them by hand in the ground truth image. Thereby, we can freely decide on the amount of marine snow we want to have in the image and at the same time we have the exact ground truth data available. In addition, since the extracted marine snow patches are real samples from the very same scene, we obtain very realistic simulated image which matches the size and the resolution of marine snow the best. We create three images of the same scene with different levels of corruptions, level 1 (low corruption), level 2 (medium corruption) and level 3 (highly corrupted). Each level differs from the other ones by the number of marine snow placed in it.

Table 1 compares the value of PSNR and MSE of the result after applying (Radolko et al.,) and proposed method on three images. The results illustrate that proposed method achieves higher PSNR (about 5 and 4 db at level 1 and levels 2 and 3 respectively) and lower MSE in all three levels. This is where perceptually (Radolko et al.,) shows more convincing result for level 1, although numbers indicates that it is only due to smoothness which is a drawback of (Radolko et al.,) and (Banerjee et al., 2014) algorithms. Figure 7 demonstrates the qualitative comparison of results after applying (Radolko et al.,) and proposed method on simulated data. To give a better insight, we have provided a zoom in image of the results of image level 3. It can be observed that (Radolko et al.,) failed at completely removing marine snow with a relative bigger size and falsely removed the high frequencies of the true object (fish) by over smoothing it.

(a) (Radolko et al.,) / Original (b) Proposed method / Original

Figure 6: Results after applying (Radolko et al.,) (a) and proposed method (b) on a highly corrupted image. The results are shown compared to the original image which is the courtesy of Eik Deistung.

(a) Ground Truth (b) Input Image with Three Levels of Corruption



(c) Input Image (Level 3) / (Radolko et al.,) (d) Input Image (Level 3) / Proposed Method

Figure 7: Comparison between the simulated data (level 3) and the results of (Radolko et al.,) (first column) and proposed method (second column). The close up shows the ability of proposed method at preserving the object's detail while eliminating marine snow compared to (Radolko et al.,).

3 CONCLUSIONS

UW images suffer from unique distortions due to light absorption and scattering. Some of them can be addressed via solutions for similar challenges for in air images such as blur, haze, low contrast. Although they have their own characteristics. However, there are some imaging defects that are unique to this medium and should be tackled specifically considering their properties such as color cast or marine snow. In this report we have addressed removing marine snow from UW images as a source of noise. This phenomenon is defined as bright spots which are the reflection of light on the surface of aggregate matters. Not much literature has addressed this challenge due to its complexity. Usually it is considered as salt and pepper noise, due to the appearance similarity. Although it is not a valid assumption since marine snow is an object which disturbs the scene's visibility and is undesired in our case. In addition, it is not a single pixel noise like salt and pepper, in contrary, it has a structure of several pixels with both high and low intensity pixel values.

In this paper, we have discarded the circle shaped lower intensity reflections of marine snow which usually appear when an artificial light is used at the time of photography. Despite that, we have considered most of the characteristics of marine snow and proposed a simple and effective method towards removing this phenomenon. Our method consists of a selective noise detection process and a novel voting algorithm which prevents misclassification of objects as noise. Results have shown the superior of our method compared to several median filters such as (Wang and Zhang, 1999)(Srinivasan and Ebenezer, 2007) and (Radolko et al.,).

As our future work, we are concerned about taking into account the circle shaped light reflection of marine snow caused by using an artificial light. These reflections appear as small veiling areas and lower the visibility by hiding the scene. This is more challenging to deal with since they have bigger structure than marine snow itself and therefore bigger distortion.

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