Marine Snow Removal in Underwater Images

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Abstract: In this paper two methods of marine snow detection in underwater images are presented. The proposed techniques are based on the pixel corruption measures which enable the identification of clusters forming the marine snow. As the detection of marine snow contaminating the images must be followed by an inpainting step, various techniques which allow to restore the images with missing regions were evaluated. The experiments revealed that the restoration quality of applied inpainting techniques is dependent on the image structure and the size of regions needed to be restored and that their overall efficiency is comparable. Therefore, the faster algorithms should be preferred. To asses the quality of marine snow removal techniques, a database of images with 5 levels of contamination was created. The experiments performed on this database showed that the proposed marine snow detection techniques coupled with fast inpainting methods yield very satisfactory results, superior to the techniques already known from the literature.

1 INTRODUCTION

Due to numerous factors contributing to the degradation of underwater images, the problem of their enhancement has received a lot of attention. Poor lighting conditions frequently have a negative impact on underwater image acquisition. The underwater images can be of low contrast, they are frequently blurry or hazy, have severely distorted chrominance channels, or even have completely lost their color. The natural occurrence of so called *marine snow* (MS), which is an accumulation of biogenic material falling down from the upper layers of the water column, is also a significant source of underwater images distortions.

As plants and animals perish and decompose, marine snow grows as a result of the aggregation process up to several centimeters in diameter. The particles are made up of faecal matter, sand, soot and other inorganic materials and the reflected light appear as bright spots obscuring the underwater image scene (Dörgens et al., 2015; Alldredge and Silver, 1988).

Marine snow is typically regarded as a source of noise that should be eliminated from the image to prevent a decline in the efficiency of image processing operations like object segmentation, classification or recognition. Due to the fact that the floating particles frequently resemble the seabed's structures, such as small stones and the textures of plants and animals, the problem of MS detection and removal is challenging. In addition, the pixels that represent the detected snowflakes should be eliminated in a way that prevents artifacts from being introduced and rendering image analysis systems less effective.

In this work, two effective techniques for detecting marine snow are described and the efficacy of various image inpainting methods which are used to replace the noisy pixels are examined. The proposed techniques of underwater image enhancement affected by marine snow proved to be reliable and effective and can be used in real-time applications.

2 MARINE SNOW REMOVAL

Marine snow varies in size, shape and brightness. However, mostly it appears as bright, almost white spots, randomly distributed over the image. The spots can be of different size, but usually they are represented by circular clusters of up to 50×50 pixels, depending on the image resolution. Their shape resembles to some extent the Gaussian distribution, with intensity decreasing with the distance to the peak location. However, the maximum of intensity can be also located outside of the spot center and very often the snowflakes are surrounded by a dark area which highlights their intensity.

The process of marine snow removal can be divided into two steps: detection of snow particles and their replacement, preferably using a suitable image

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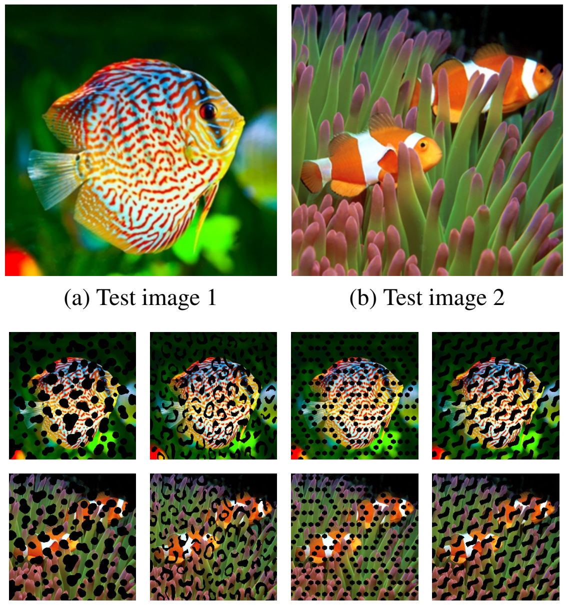
inpainting method. An efficient algorithm of marine snow removal should be accurate, computationally efficient and should not create artifacts which could affect the performance of computer vision analysis.

A straightforward method of marine snow removal can rely on the reduced vector ordering. Using this approach, for each pixel in the local filtering window, the distance in a chosen color space, to other samples from this window is calculated. Then the cumulated distances assigned to each pixel are sorted and the pixel for which the sum of distances is minimized, replaces the central sample of the filtering window (Astola et al., 1990). Defined in this way Vector Median Filter, (VMF) is able to remove outliers and clusters of pixels like marine snow particles, which are treated as impulsive noise. However, as the central pixel is uniformly replaced by a pixel from the local window, this procedure leads to loss of details and overall image blurring. Additionally, if large spots of pixels are to be filtered out, a sufficiently large processing window is needed to ensure that the vector median, which is replacing the central pixel of the window, does not belong to the unwanted structures.

Quite often, instead of the vectorial processing of the image structures, channelwise (marginal) methods are applied. In this way, instead of the vector median, the pixel whose components are medians of the respective channel values of the samples from the processing window is declared as the filter output. As the correlation between color channels is neglected, the marginal median filter output generally does not belong to the set of pixels from the filtering window, which means that a new color is created. Such a procedure can generate artifacts, especially at the edges of image objects, however it can be advantageous in the case of Gaussian noise which affects all image pixels.

To decrease the amount of pixels which are unnecessarily changed by the median filter, a switching procedure can be applied. First, the outlying pixels are detected and then they are replaced by the local median. A simple measure of pixel corruption is the difference between the intensity of the central pixel of a filtering window and the median or weighted median value (Sun and Neuvo, 1994). If the absolute difference exceeds a predefined threshold, the pixel is declared as noisy. When all image pixels are analyzed, the noisy pixels in a filtering window are replaced with the median of uncorrupted samples in the processing window, otherwise they remain unchanged. This procedure can be applied iteratively, especially if the noise contamination intensity is high (Zhou Wang and Zhang, 1999).



(a) Test image 1 (b) Test image 2

(1) (2) (3) (4)

(c) Test images with missing regions

Figure 1: Color test images used for the evaluation of the efficiency of inpainting methods.

To alleviate the problems caused by direct application of image denoising algorithms, filtering methods dedicated to marine snow removal were proposed. In (Banerjee et al., 2014) a patch-based Adaptive Probabilistic Approach (APA) was presented. First, the image is converted from RGB into YCbCr color space. Then the luminance channel is processed and the pixels which intensity exceeds an adaptive threshold, based on local mean and variance, are detected and the probability of MS occurrence is computed. In the sequel, to avoid object misclassification, the processing patch is enlarged and the calculations are repeated. If the existence of marine snow spot within the processing window is confirmed, the central pixel is replaced with the local marginal median. Finally, the image with reconstructed luminance channel is converted back into the RGB color space.

Another approach, based on a Supervised Median Filtering scheme (SMF), is focused on removing marine snow utilizing the characteristics of snowflakes and applying a voting mechanism (Farhadifard et al., 2017a). In the first step, the algorithm detects the pixels belonging to a snowflake, analysing the distance in the RGB color space to the remaining pixels of a processing window. When the initial candidates are found, then their local density is determined. The detected pixels, which are grouped in clusters of low-saturated pixels are declared as parts of a snowflake. Pixel classification is repeated for different window sizes and finally the color pixels recognized as marine snow are replaced with the marginal median of the samples from the local area detected as background.

When comparing SMF to APA, this procedure offers slightly better results, but still it does not solve the problem of removing circle-shaped light reflections caused by artificial illumination reflected from marine snow particles. It also requires predefining thresholds and is time consuming due to window resizing and voting scheme used for the pixels classification. Therefore, an improved method of marine snow removal was proposed in (Farhadifard et al., 2017b). The detection step remained unchanged, however to replace the pixels detected as belonging to the marine snow, instead of median filtering, an inpainting method based on the Field of Experts concept (Roth and Black, 2005) was utilized.

3 INPAINTING METHODS

The aim of image inpainting methods is the reconstruction of its lost or damaged parts. Inpainting is being used in many applications including removing inscriptions and logos from images, eliminating the red eye effect and restoration of old, damaged photographs, among many others. In this work we use various inpainting methods to replace the image pixels detected as marine snow and we also validate their performance in terms of objective quality measures.

The most computationally complex, but very effective technique, is the Annihilating filter based Low-rank Hankel structured matrix completion approach, known as ALOHA (Jin and Ye, 2015). It is a patch-based method which exploits the annihilation property between a shift-invariant filter and image data, observed in many inpainting algorithms.

Among the existing methods, there are many which are based on Partial Differential Equations (PDEs) of different order. An example is an optical flow based inpainting method called Absolutely Minimizing Lipschitz Extension (AMLE) (Caselles et al., 1997). This technique solves PDE on the Riemannian manifold for recovering missing values. Harmonic Inpainting via a Discrete Heat Flow algorithm (HARI) (Shen and Chan, 2002) is also a method based on solving a PDE.

Another technique called INAS belongs to a set of algorithms based on sparse linear algebra and like the mentioned algorithms it solves discrete PDEs (D'Errico, 2004). Using this approach only horizontal and vertical neighbours of the processed pixel are considered. In the case of small missing elements, this inpainting method works fast, however the processing of each of the image channels is performed separately.

Inpaitning via Iterative Process (INPAI) is a method based on Discrete Cosine Transform (DCT) and was created for automatic smoothing of multidimensional incomplete data. It was adopted for the purpose of supplementing large datasets of medical or satellite images (Garcia, 2010). This procedure is using the penalized least square (PLS) regression formulated in terms of DCT. A statistical model is created and the modeling process is completely controlled by one smoothing parameter.

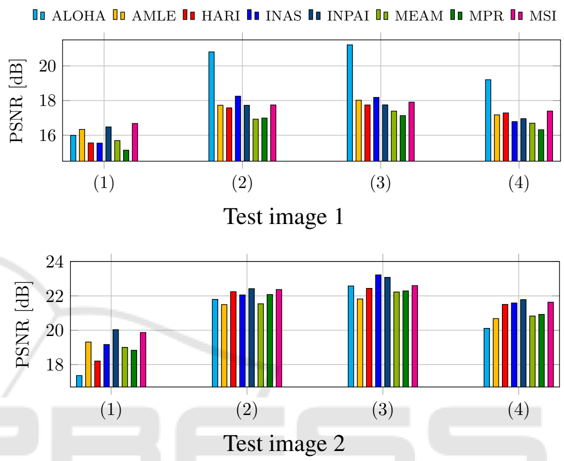


Figure 2: Comparison of inpainting results in terms of PSNR quality measure using corrupted versions of test image 1 and 2 shown in Fig. 1 c).

Modified Planar Rotator Model for Missing Data Prediction (MPR) (Žukovič and Hristopulos, 2018) is anticipating the unknown values in the spatial data using Gibbs Markov Random field. This model assumes the use of spin interaction between closest neighbors and is suitable for data sets of big sizes.

The Mumford-Shah Inpainting with Ambrosio-Tortorelli Approximation (MSI) (Esedoglu and Shen, 2002) belongs to a group of variational models simulating the unique macro-inpainting mechanism. The reconstruction of damaged parts of an image is performed iteratively solving the Euler-Lagrange equations.

To increase the computational efficiency of the inpainting procedure, a fast algorithm which recursively fills in the missing pixels with the average of the pixels with known values contained in the sliding processing window was proposed (Smolka and Mendrela, 2020). The elaborated Mean based Method (MEAM) can be seen as a generalization of the fast image inpainting algorithm proposed in (Oliveira et al., 2001).

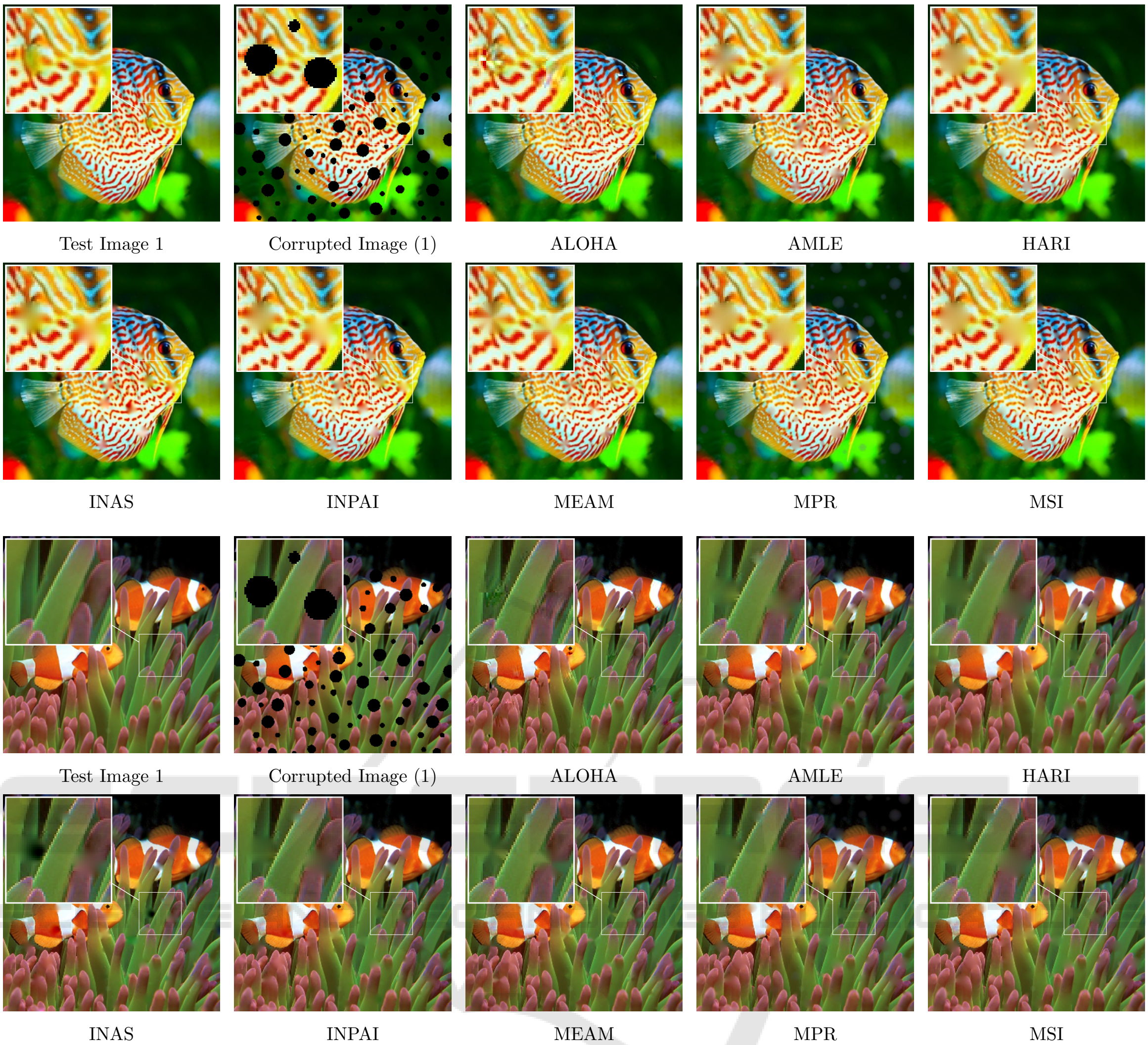


Figure 3: Efficiency of the inpainting results using the color test images corrupted by pattern (1) shown in Fig. 1.

We conducted a study based on two images shown in Fig. 1 of size 300×300, from which some parts were removed. The regions of removed pixels, forming 4 various patterns are marked with black color in Fig. 1c). The most important, potentially decisive factors were preservation of the natural appearance and recovery of image details. In addition to the visual assessment, the inpainting results were analyzed using the widely used PSNR image quality measure.

The efficiency of the evaluated methods in terms of PSNR has been summarized in Fig. 2. It is worth noticing that the differences in objective restoration measures depend not only on the image structure but also on the shape of the missing regions. The restoration efficiency of the proposed method can be also assessed visually in Fig. 3.

As can be observed very good results were obtained using the ALOHA inpainting when restoring the test images. The differences in the restoration quality were smaller in case of the second test image, which indicates that the efficiency of inpainting methods is dependent on the image structure and also on the size of image regions which have to be filled. The drawback of ALOHA is its huge computational complexity which renders this method unsuitable for real time applications. In contrast, the very fast MEAM and INAS techniques proved to yield results comparable with those offered by much more computationally expensive methods.

Figure 4: Exemplary images with increasing Marine Snow Intensity Level (MSIL).

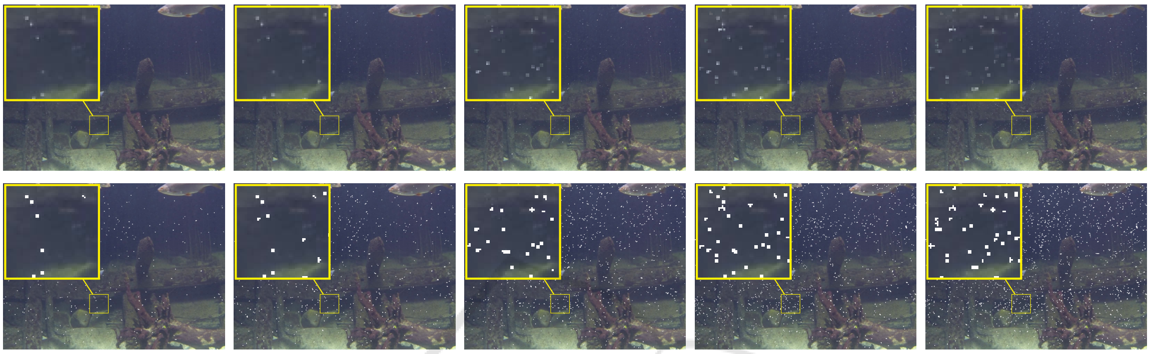


Figure 5: Marine Snow test images.

4 MARINE SNOW REMOVAL

As the ground truth images corrupted with marine snow are not available, we marked manually all pixels depicting the MS particles in 15 carefully chosen, representative images with resolution of 640×480 pixels. Figure 5 shows 3 exemplary images from the dataset. These images were extracted from a video sequence from the *Dataset of Marine Snow* available at http://underwaterchangedetection.eu, which contains more than 1000 frames. In this way a set of 15 images with carefully marked marine snow particles was created.

To obtain the ground truth images needed to perform experiments which aim was to reveal the efficiency of the various inpaiting methods, the missing regions were restored using the ALOHA algorithm, choosing parameter settings offering visually satisfying results. In this way, the restored images were used as a reference set, which enabled to perform both the objective and visual evaluation of the available inpainting techniques.

The images with marked regions of marine snow were used to simulate pictures with increasing contamination intensity. To this end, the marked regions (marine snow flakes) from all images from the dataset were superimposed on each of the 15 pictures restored with ALOHA. In this way we created $15 \times 15 = 225$ images with added marine snowflakes.

To further increase the intensity of the marine snow, we created a database consisting of images with artificially superimposed MS regions taken from 2 different images from the dataset. The sources of MS were randomly chosen 3 times for each image, so that 45 noisy images were prepared. Additionally, for each reference image, 3 corrupted sources containing noise from 3, 4 and 5 other images from the dataset were composed. In this way, we created a dataset of 5 marine snow contamination intensity levels, composed of $225 + 4 \times 45 = 405$ images, with overlaying marine snow. These images can be treated as contaminated by MS noise with available ground truth, so that various denoising techniques can be evaluated. Figure 5 depicts examples of images with increasing marine snow intensity levels. Below, for each noisy image the superimposed snowflake regions are marked with white color.

The results of the restoration of images corrupted by marine snow obtained using the analyzed inpainting techniques are depicted in Fig. 6, which shows the PSNR values of the enhanced images with increasing amount of the marine snow. Again, the fast INAS and

MEAM technique proved to yield results comparable with the competitive inpainting techniques.

Having a database of images corrupted by artificially created marine snow, we were able to create and evaluate methods of its detection. The first of the elaborated MS detection techniquess is based on the Ranked Order Absolute Difference (ROAD) statistic (Garnett et al., 2005), which is used for determining the degree of image pixels corruption. This method will be referred to as ROAD based Algorithm for Marine Snow detection - RAMS.

The ROAD technique calculates the Euclidean distance in the RGB color space between a processed pixel and its neighbors contained in a filtering window. Then the distances are sorted and a sum of a specified number of smallest distances serves as a measure of pixel similarity to its local neighborhood. In this way the outlying pixels can be easily detected and increasing the size of the filtering window, clusters of outliers can be identified. In this way, the pixels which compose the marine snow are treated as small pixel clusters which can be localized analyzing the ROAD values.

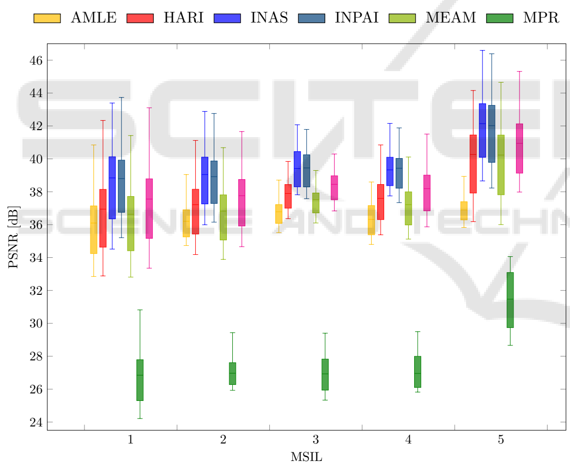


Figure 6: Efficiency of the inpaiting methods applied to restore the underwater images corrupted with increasing Marine Snow Intensity Levels (MSIL) expressed with PSNR.

To increase the discriminating properties of the proposed detector, the obtained map of pixel contamination was subjected to the morphological Top-Hat operation, which enables to diminish the influence of image texture on the final marine snow detection result. The detection step needs a thresholding value which was obtained using the triangle binarization method (G. Zack, 1977).

In this way, if the result of the Top-Hat operation performed on the image depicting the ROAD values exceeds the automatically determined threshold, then a pixel is considered as belonging to a cluster of pixels that make up a snowflake, which should be restored using an inpainting technique. Otherwise, the pixel is classified as background and is left unchanged. The proposed method needs 2 parameters: the size r of the processing window containing $r \times r$ pixels and the number of smallest distances denoted as α, taken for the calculation of ROAD based dissimilarity. The performed experiments showed that satisfactory results were obtained using $r = \alpha = 7$.

The second method used for the detection of marine snow is based on the distance transformation and will be called Distance Transform based Algorithm for Marine Snow - DITAMS. This method determines for every image pixel the minimal cost of a digital path joining it with the boundary of a sliding processing window.

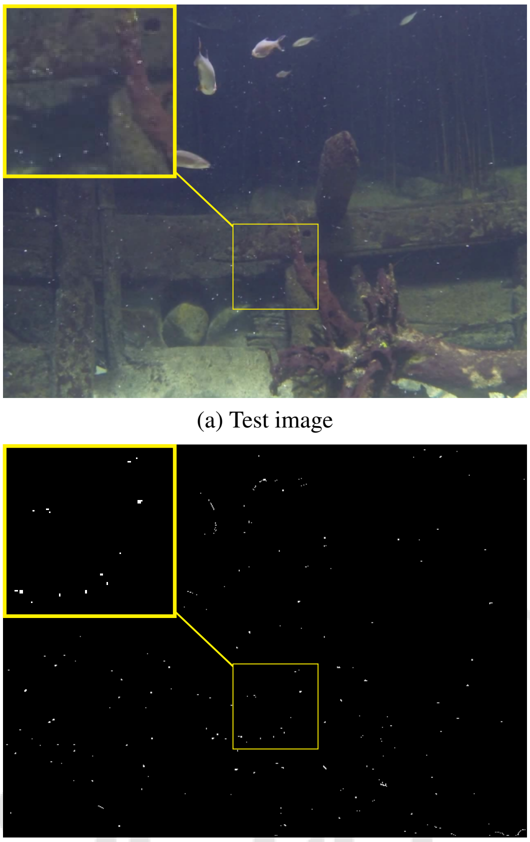
The path cost is calculated as the sum of transitions between adjacent pixels expressed through the Euclidean distance in the RGB color space. Pixels belonging to a cluster of pixels which differ significantly from their surrounding are not connected by a low-cost path and therefore they can be easily detected using the triangle binarization technique. To speed up the process of distance transform calculation, a two-pass algorithm proposed by Rosenfeld and Pfaltz has been applied (Rosenfeld and Pfaltz, 1968).

Figure 7 shows a test image and the binarization result using the triangle algorithm. The results obtained using the RAMS method are visually very similar. The performed experiments revealed that satisfying efficiency of the proposed DITAMS scheme was obtained for the window size $r = 7$, which makes the proposed scheme fast enough to be applied in real time MS detection systems.

Figure 8 compares the Accuracy, Precision, Recall and Specificity of the APA, SMF, RAMS and DITAMS marine snow detection techniques. To describe the efficiency measures, the following notation is used: Q - total number of image pixels, P - number of noisy pixels, N - number of undisturbed pixels (Q=P+N), TP - pixels correctly classified as noise, TN - pixels correctly classified as uncorrupted, FP - pixels which were not correctly classified as noise.

Accuracy is a basic measure, which refers to the ratio of the number of correctly classified pixels in an image to their total number - (TP+TN)/Q. The Accuracy values are high for all of the analyzed methods but the best results were obtained using DITAMS and RAMS.

Precision specifies the ratio of the number of pixels correctly classified to the class of noisy pixels in relation to all pixels classified as noise, which includes misclassifications as well - TP/(TP+FP). The experiments showed that the DITAMS was the most



(a) Test image

(b) Binarized distance map

Figure 7: Binarization of the output of the distance transform based marine snow detector.

precise among the evaluated methods. It can be also concluded that the APA and SMF methods are not the best choice if high precision of MS detection is required.

Next measure describing the efficiency of the proposed techniques is Recall, which specifies the ratio of the number of pixels correctly classified as noise to all noisy pixels in the image - TP/P. The highest value of this parameter is obtained for the RAMS algorithm. The APA method is not much worse and is followed by SMF and DITAMS. The lower values of this parameter is caused by the high number of incorrectly classified pixels, which means that in the detection stage, there are a lot of pixels which belong to the marine snowflakes but are classified as background.

Last measure of the efficiency of the compared methods is the Specificity, (true negative rate) - TN/N, which specifies the ratio of the pixel number correctly classified as not belonging to the MS to the number of background pixels. For all the compared techniques, specificity measure achieves very high values. For the DITAMS detection method it is almost equal to 1 which indicates that in this respect the algorithm

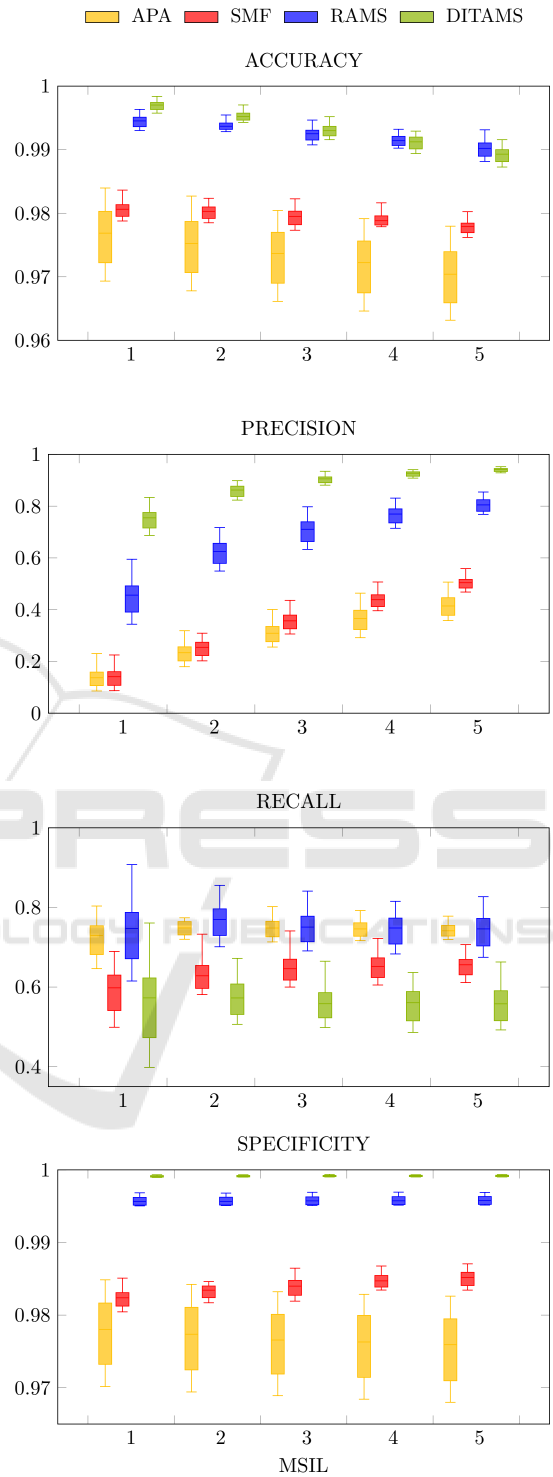


Figure 8: Boxplots summarizing the performance of 4 detection methods for the increasing marine snow intensity levels (MSIL).

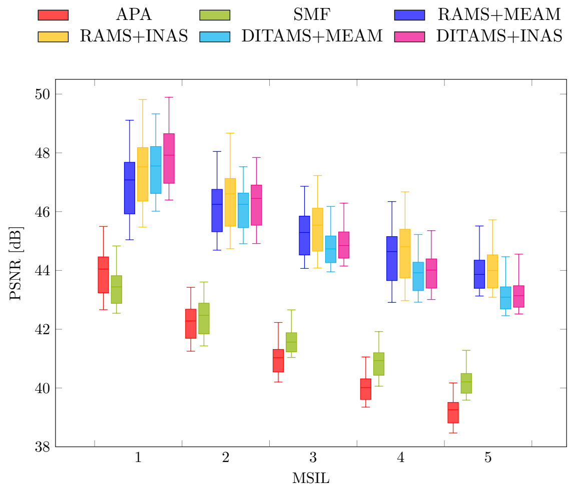


Figure 9: Efficiency of MS removal evaluated using PSNR quality measure for increasing marine snow intensity levels.

works almost perfectly.

Figure 9 depicts the efficiency of the MS detection and removal through the application of MEAMS and INAS inpainting methods in terms of PSNR measure. As can be observed the proposed RAMS and DITAMS methods yield comparable results, which are much better than those offered by the APA and SMF. Additionally, the plots show that the fast MEAM inpainting algorithm provides results similar to those achieved using the INAS interpolation, which make the proposed algorithms very attractive, especially in the case of real-time applications.

Figure 10 exhibits results of marine snow removal using the APA and SMF methods compared with those obtained with the combination of RAMS and DITAMS detection methods and MEAM and INAS inpainting techniques. As can be observed the marine snow particles are removed and the image is well restored using the novel, proposed techniques. As both the MS detection techniques and inpainting methods are computationally efficient, the new enhancement frameworks can be applied for real time imaging tasks.

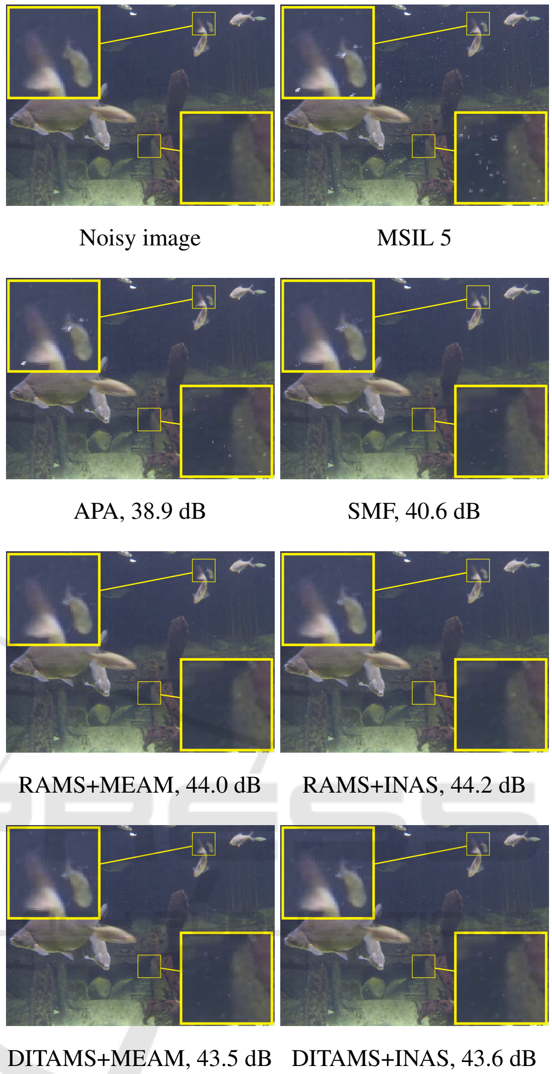


Figure 10: Result of marine snow removal expressed with PSNR obtained for exemplary MSIL 5 image.

5 CONCLUSIONS

In this paper two novel methods of marine snow detection and their removal with the use of fast inpainting methods have been proposed. The first one is based on the ROAD measure of pixel impulsiveness and the second is determining the cost of a connection between the central pixel and the boundary of the filtering window. The quality of inpainting techniques, which were applied to restore the underwater images with detected clusters of pixels forming the marine snow particles, was evaluated using the objective PSNR quality measure and the results were also assessed visually. Extensive experiments confirmed that the developed marine snow techniques coupled with the fast MEAM and INAS inpainting methods offer better image restoration results than the algorithms already known from the literature. The developed techniques are computationally inexpensive and can be applied in real time applications. Although the elaborated algorithms are intended for marine snow removal, they can be applied in various applications in which the detection and inpainting of small clusters of pixels is required.

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