Multi-Objective Differential Evolution Algorithm for Underwater Image Restoration

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***Abstract*—Underwater image processing area has been considered an important topic within the last decades with important achievements. This kind of images are essentially characterized by their poor visibility because light is exponentially attenuated as it travels in the water and the scenes result poorly contrasted and hazy. On the other hand, image restoration takes into account the influence of the environment on the image in order to achieve an image with an improved quality. This technique consist of inverting the physical model of image formation. That model contains parameters which represent variables such as coefficients of absorption, scattering, among others. In this case, the quality of the restored image depends on the correct estimation of these parameters. In this work, an approach based on evolutionary optimization algorithms is proposed, for restoring underwater images by estimating the model parameters, and using two metrics for quality assessment. The degradation in the images has been simulated by using an image formation model. Results show that image restoration based on a Multi-Objective Differential Evolution (MODE) algorithm achieves images with good contrast and sharpness, being even better than the original image.**

I. Introduction

After image acquisition, storage and transmission processes the received image often appears as a degraded version of the original image due to imperfections in the imaging system, weather conditions, intensity of light among others non-ideal conditions [1], [2], [3]. These distortions make the image analysis, which is necessary for several applications, very difficult. The challenge of image restoration consist of removing blur from a noisy image [4]. Image restoration has been a longstanding problem in the image processing area and several methods for image restoration have been developed. One of the most classic methods is the inverse filtering by Wiener filter [1], [3].

The medium on which the scene is contained plays an important role in the image features. Often, in imaging process is assumed that the medium is not relevant. However, this assumption cannot be applied to environments with mist, pollution, and above all to underwater environments. In these conditions, the medium has a strong influence on light propagation, and consequently on the quality of the acquired image [5]. In particular, the physical properties of underwater environments cause additional degradation effects. Underwater images are characterized by the poor visibility, due to light attenuation as long as light propagates in the water, and also by the blur and low contrast.

Attenuation of light limits the visible distance to about 20 meters on clean water and less than 5 meters in turbid water [6]. The attenuation effect is generated, mainly, by two processes: (1) absorption and (2) scattering. In the absorption process, the luminous energy is transformed in other kind of energy along the path traveled by light, due to interactions with matter. This process generates a significant loss in the brightness of the object. On the other hand, scattering refers to any deflection with respect to the straight-line propagation path, which is caused by the collision of photons with the particles in suspension in the medium. In this case, there are two types of scattering: (1) *Back-scattering*, where light from a light source is reflecting back from particles in the lenss field of view causing specks of light to appear in the image

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and low contrast, and (2) *Forward-scattering* where the light is randomly deviated on its way from an object to the camera, causing blurring [6].

Underwater image restoration is based on the inversion of physical models, which represents the interactions between the light and the environment. These models are represented by the quantities mentioned above (i.e. attenuation coefficient, scattering coefficient, etc.). The restoration process can be divided into two types: (1) non-blind restoration, where the values of the physical parameters are known; and (2) blind restoration, where there is not information about the medium's properties and, therefore, these parameters have to be estimated. In most practical situations, a blind restoration process is the only option, given that the medium's features are unknown. Therefore, the quality of the restored image strongly depends on the estimation of the parameters of the physical model that represents the interaction between the light and the medium. In general, the estimation of these parameters can be performed by an optimization process [7].

In the last two decades research on optimization algorithms has been very active [8], [9]. In the literature, there are several algorithms that are able to restore degraded images with reasonable quality. These algorithms can be divided into two classes: deterministic and stochastic approaches. Among the stochastic approaches, population-based, evolutionary algorithms and swarm intelligence methods [10], [11] offer a number of advantages that make them very attractive. Some of the advantages are the easy implementation, implicit parallelism, robust and reliable performance, global search capability, no need for specific information about the problem, robustness to noise, and no requirement for a differentiable or continuous objective function [12]. In recent years, the development of new artificial intelligence algorithms, such as genetic algorithms and particle swarm optimization, has also yielded good results in restoration area [7].

A very important aspect on optimization algorithms is the objective function or cost function. In image restoration task this function corresponds to an objective related to a measure of the image quality. In this context, an image quality metric aims to estimate the quality of an image, taking into account not only its difference with regard to an ideal (or original image) but also how these differences are perceived by the human visual system. In this case, there are three types of objective approaches: (1) Full Reference Metrics (FR), (2) Reduced-reference (RR), and (3) No-Reference Metrics (NR). In Full-Reference (FR), a degraded image is compared with an ideal version (or reference) in order to estimate its quality [13]. The most popular full-reference image quality metrics are the peak Signal-to-Noise Ratio (PSNR) and the Mean Squared Error (MSE) [14]. In Reduced-reference (RR) image quality measures try to predict the visual quality of distorted images by using only partial information about the reference images.

Otherwise, there are applications in which the reference image does not exist (i.e. underwater environments). In these cases, a NR image quality metric is needed for achieving a *blind restoration*. In order to use this quality metric the restoration process need to achieve three goals [13]: (1) to estimate faithfully the quality of an image without *a priory* knowledge of the parameters of the different environments (i.e. different water optical properties); (2) to be independent of the content; (3) to be immune or less sensitive to noise, specially those caused by multiple scattering in turbid underwater environments. Such metric is a critical component in the automated image restoration process, where the optimization algorithm needs to know the stop ping criteria and determine if it has found the best result [13].

Since an underwater image is submitted to different kinds of distortions (i.e. blurring, low contrast, etc.), more than one metric for image quality assessment must be used. This makes the Multi-Objective optimization processes ideal for this kind of applications.

In this paper we present an algorithm for restoration of simulated underwater environments. The approach consist of using a Multi-Objective Differential Evolution (MODE) algorithm for the optimization process, and two NR metrics. In order to achieve the multi-objective approach two metrics has been used as objective functions which detect jointly the classical problems involved in restoration tasks as well the contrast problem, which is also related in degradation process related to underwater case. The optimization problem consists specifically on obtain the parameter of the Trucco model (see section II) and testing the results of the image quality. The first metric is the Naturalness Image Quality Evaluator (NIQE) [15], while the second one is based on the distribution of contrast [16].

The main contribution of this work consist of the novel use of the MODE algorithm in image restoration problem applied for underwater case, and the use of adequate metrics as objective function. Results show that, using these metrics, the optimization process is able to estimate the model parameters correctly. In our case, the estimated parameters are used to invert the image degradation model and producing a restored image.

This work is organized as follows. In section II, the theoretical background on underwater degradation models and MODE optimization algorithm is presented. In Section III, some related works on underwater image restoration are presented. Section IV presents the implementations and results achieved by the restoration system. And finally, Section V presents the conclusions.

II. Theoretical Background

A. Underwater Image Acquisition

To understand underwater image processing, we have to analyze the basic physics of light propagation in the water medium. Light interacts with water through two processes, namely: (1) absorption and (2) scattering. Absorption is the loss of power that occurs when light travels in the medium, which depends on the index medium refraction. Scattering refers to any deflection from a straight-line propagation path [6], [17]. The scattering process can be divided into two classes: (1) back-scattering and (2) forward-scattering.

Back-scattering refers to a process in which a fraction of light is reflected by particles in water. This reflected light is captured by the camera before it reaches the object in the scene, limiting the contrast of the images. Forward-scattering corresponds to the light that is randomly deviated on its way from the object to the camera. Generally this leads to blurring of the image [6]. The most complete and popular model was proposed by Jaffe-McGlamery [18], [19]. According to this model, the underwater image can be represented as the linear superposition of three components, as shown in Fig. 1: (1) direct component, (2) forward-scattered component, and (3) backscatter component. These three components are linearly summed, representing the total irradiance captured by the camera sensor, being expressed by equation 1.

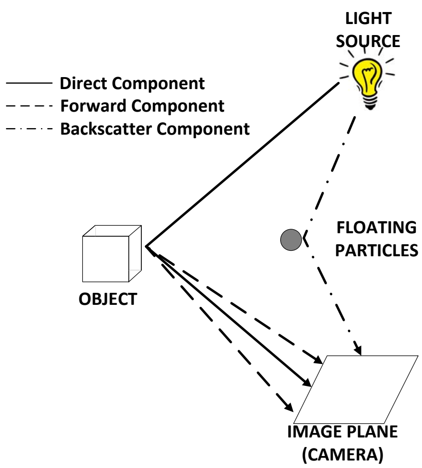

Fig. 1. Components of Jaffe-McGlamery Model [17].

$$E_t = E_d + E_f + E_b, \tag{1}$$

where E_t is the total irradiance, E_d the direct component, E_f the forward-scattered component, and E_b the backscatter.

Another assumption used by the Jaffe-McGlamery model is that the intensity of the light traveling in the water decreases exponentially. This loss can be described by the following equation [20]:

$$E_i(d) = E_{0,i} \exp(-c_i d), \tag{2}$$

where i is the light wavelength , d is the distance traveled, $E_i(d)$ is the light intensity of wavelength i, $E_{0,i}$ is the light intensity of wavelength i at the light source, and c_i is the attenuation coefficient at wavelength i. Note that the attenuation coefficient depends on the light wavelength or, in others words, of the color of light [21].

Based on the two assumptions described above (Eqs. (summarized in 1) and (2)), the complete JaffeMcGlamery underwater image model has been derived in[19]. Due to the complexity of Jaffe-McGlamery's model, researchers have made simplifications in order to reduce the amount of calculations needed. One of most common simplifications is presented in a model proposed by Trucco and Olmos in [22]. This model reduces generality but still accounts for a sufficiently wide class of practical situations [22]. In this case, the authors consider an uniform illumination, which is a reasonable assumption for shallow waters, where illumination is provided by direct sunlight. Also, they assume that the forward-scattering process is the main cause of degradation, and that the backscatter effect can be ignored. The final is given by the equation 3.

$$E_f = E_d * g(x, y, d, G, c, B). \tag{3}$$

This model is based on the development of the PSF (Point-Spread-Function), $g(x, y, d, G, c, B)$. With some further simplifications, the presented model is reduced to the construction of an inverse filter in frequency domain [22], represented by equation 4.

$$G(f, d, c, K) = K \exp(-cd\omega). \tag{4}$$

B. Multi-Objective Differential Evolution Algorithm

The Differential Evolution (DE) algorithm has been widely applied to multi-objective problems with relative success. For a review on the DE algorithm and also its multi-objective versions see [53]. Among them, a simplified version was proposed by [54] called DEMO/parent, adopting the Pareto-based ranking and crowding distance metric as in the Non-dominated Sorting Genetic Algorithm version II (NSGA-II) [55]. Another approach was the Pareto Differential Evolution Algorithm (PDEA), proposed by [56].

The DEMO/parent algorithm adapts the original DE algorithm in order to cope with multi-objective problems as follows. The greedy selection at the end of each iteration of the DE algorithm is replaced by a strategy, which considers for the child solution the dominance regarding its parent, namely: if the child solution is dominated by its parent, discard it; else if the child solution dominates the parent, substitute the parent by its child solution; else, keep both of them in the population. After this checking is done (for all child solutions) the population is truncated according to the dominance and crowding distance criterion such as in NSGA-II. The PDEA is slightly different than DEMO/parent. It concatenates both parent and child populations and truncate them according to the same criteria (dominance and crowding distance). We show the description of the DEMO/parent and PDEA algorithms below, marking whenever those algorithms differ.

- Step 1 (Initialization): Randomly initialize the parent solutions P_i inside the given search space and evaluate the solutions.
- Step 2 (Create candidate solution): For each P_i, create a child solution C_i according to DE update equations;
- Step 3 (Evaluate child solutions): Calculate the objective functions for each child solution C_i;
- Step 4 - DEMO/parent (Keep solutions): Update the parent solutions for the next generation: if C_i is dominated by P_i, discard it, else if C_i dominates P_i, replace P_i by C_i, else keep both C_i and P_i;
- Step 4 - PDEA (Keep solutions): Keep both child and parent populations for the next step;
- Step 5 (Truncate parent solutions): At this point, the number of parent solutions for the next iteration range from N to $2N$ in DEMO/parent and is equal to $2N$ in PDEA, where N is the size of the population. Then

we set the parent population for the next iteration as the truncation of the parent and child solutions as in the NSGA-II, according to the nondominance criterion and the crowding distance metric;

- Step 6 (Iteration counter increase): $g = g + 1$;
- Step 7 (Termination criterion check): If the total number of iterations has been reached, terminate, otherwise, go to Step 2.

III. Related Works

In image restoration process is considered that the environment does not change the image features. However, for images taken in underwater environments, the interactions between the light and the environment generate a degradation in the acquired image, which cannot be ignored.

Bio-inspired algorithms are a good alternative to arrive at optimal solutions in real problems of high complexity. Considering that underwater image restoration is a very complex problem, bio-inspired algorithms may present a good solution for this application. In this section, the more relevant works on underwater image restoration and their optimization using bio-inspired algorithms, are discussed.

A. Underwater Image Restoration

Schettini and Corchs [6] present a wide review on underwater image restoration techniques. One of most cited works in this area is the technique proposed by Trucco and Olmos-Antillon [22] in 2006. The main contribution of Trucco and Olmos is the simplified image formation model. This model ignores the effect of back-scattering component for scenes in which the distance between the object and the camera is short. Based on this model, the authors presents a self-tunable filter for underwater image restoration that assumes that the environment illumination is uniform.

A different simplification of the original model was proposed by Schechner and Karpel in 2004 [26] and 2005 [27]. These new models consider the back-scatter effect and ignore the forward-scattering for wide scenes, considering distances between 20 and 30 meters between the camera and the scene. The authors propose a technique to recover the visibility in underwater scenes using light polarization. In 2009, Treibitz and Schechner [28] presented a different approach based on polarization. Although this method provides good results in real life situations, it requires the use of external optical elements, such as polarizers and artificial light sources.

Another important contribution was presented by Lui *et. al.* in 2001 [29]. In this work, the authors propose a methodology for measuring the PSF. The measurements was done in controlled environments with images taken in a tank, with distances ranging 3 meters. The authors implement a Wiener filter for restoring the images with the measured PSF. Hou *et. al.* [30], [31] presented a different methodology for PSF measurement and image restoration. In more recent work, Y. Chen *et. al.* [32] presented a review about several empiric PSF models in underwater environments, testing these models using blind restoration algorithms to validate their solution.

E. Nascimento *et. al.* (2009) [33] presented an automatic methodology for restoration based on the propagation of light in underwater environments. This technique uses pairs of images acquired from different points under the same conditions (a stereo vision system is used). Considering that scattering an absorption processes are function of the distance, the intensity captured by each camera tends to be different for each point. Assuming that properties of water are the same for both images and knowing the distance between the scene and the image plane, the model parameters are estimated and used for restoration.

Also in 2009, Y. Tian *et. al.* [34] presented a model based on the wave equation in order to estimate the shape of water surface. In this case, the camera is placed out of the water and the model is used to recover the image of the underwater scene. The presented approach does not need calibration patterns or a priori information to achieve the objective.

In 2010, F. Fan *et. al.* [35] presented a blind restoration algorithm based on Lucy-Rchardson algorithm. In order of estimate the PSF, it used a small angle approximation proposed by Wells in 1973 [36] that considers scattering angles from 0 to 10 degrees. In the same year, W. Ferreira de Barros [5] presented a simplification for the Jaffe-McGlamery model that performs an inversion to restore the degraded image. The model parameters are estimated using a non-linear multi-objective optimization function available in the Matlab Optimization Toolbox [37].

Boffety and Galland [38] presented a model for simulation of "*marine snow*" based on the Jaffe-McGlamery model in 2011. The authors present an interesting study of the impact of marine snow in the restoration performance. In 2012, D. Lee *et. al.* [39] proposed a system for restoration of visibility for an underwater robot. The restoration method is based on the inversion of the Jaffe-McGlamery model, considering only the direct component. Due to the attenuation coefficient depends on the wavelength of light, this coefficient is different for each color channel. The coefficients used by the authors correspond to the values determined experimentally for shallow waters by Yamashita *et. al.* [40].

In 2012, M. Yang *et. al.* [41], [42] presented a strategy for image restoration based on the atmospheric turbulence model by Hufnagel e Stanley [43] in 1964. In this case, the PSF depends on a value called *turbulence coefficient* and a coarse-to-fine strategy is used in the search for the optimal value. Once the parameter has been estimated, the restoration process performed using a Wiener filter.

B. Image Restoration Using Bio-inspired Optimization

Zhang *et. al.* [44], in 2008, presented a strategy for image restoration using neural networks. The PSO algorithm is used to optimize the neural network, taking an error measure as a fitness function.

In 2009, Dash *et. al.* [45] presented an algorithm for image restoration based on regularization. The optimal regularization parameter (λ) is estimated using the PSO algorithm. In this case, the objective function is the MSE.

T. Sun *et. al.* [46] discussed a restoration algorithm based on a fusion between genetic algorithms (GA) and neural network in 2010. The approach uses the advantages of genetic algorithms for parameter estimation and of the neural network for training the restoration system.

J. Papa *et. al.* [47] presented a technique for restoration called *Projections onto Convex Sets*. This technique consists of projecting solutions into hyperspaces until they achieve a convergence criteria. The number of convex sets and their combination allow to project several algorithms for image restoration [47]. This technique uses a relaxation parameter (λ) that strongly depends on the features of the image to be restored. Thus, wrong values of λ can lead to poor restoration results. The PSO algorithm is used to find the optimal relaxation parameter. The authors compare the achieved results with more traditional algorithms, like Wiener filter and Lucy-Richardson algorithm.

In 2011, Li et al. [3] introduced the selection process of genetic algorithms into a basic PSO to solve the premature convergence problem. The proposed algorithm uses a Least Squares Estimation (LSE) model for restoration [3], assuming that every image is a particle. In other words, every image is a solution for the optimization problem.

Also in 2011, Qinquing et al. [48] presented an strategy for image enhancement based on a parameterized transformation function. To solve the problem of premature convergence of the PSO, the parameters of this function are estimated using the PSO algorithm mixed with a Simulated Annealing (SA) mechanism. In this strategy, the objective function gives information about the entropy and the edges in the image.

Sun et al. [7] proposed a restoration algorithm based on regularization methods. The optimal value of the regularization parameter is estimated using a modified PSO algorithm.

In 2012, Toumi et al. [49] used a PSO algorithm for blind restoration, estimating the optimal parameters for PSF. The authors proposed a new Search Efficiency Function as a cost function.

F. Latifoglu et al. [50], in 2013, presented an approach based on 2D FIR filters for noise elimination. In this work, the coefficients for the filter are estimated using an ABC (*Artificial Bee Colony*) algorithm. The objective function used is the MSE (Mean Squared Error).

Related to underwater restoration issues as well as the use of bio-inspired techniques it can be observed the tendency to obtain restoration techniques (for underwater case) based on more acquired models. In this case, the problem is related to the complexity of the models, which can contain several parameters, representing an inversion problem in which optimization techniques can be applied in order to obtain more accurate parameters. In this case, the Trucco model is the more used based on the simplicity a potential to represent the physics effects involved in underwater images. Most of the related works involving bio-inspired optimization algorithms are based on PSO in which were not applied multi-objective techniques. Otherwise, the use of specific metrics for restoring underwater image is a challenge due to the close relation involved among different physics variables and the problem of contrast which was detected in experimental researches developed by the authors of this approach. In this case, the proposal of more than one cost functions has not been discussed in the related works, such as has been developed in this work.

IV. Implementations and Results

In this work, the degradation process was simulated using an image degradation model. Since this is a blind-restoration problem and no-reference image quality metrics were used in the optimization process. In this section, the obtained results for image degradation, optimization and image restoration are presented.

A. Image Degradation

In this work, we use the image model proposed by Trucco for simulation of underwater degradation (see Section IIA). Taking the model described in Eq. (3) in the frequency domain, we obtain the following equation 5.

$$E(u,v) = E_d(u,v)Ke^{(-cd\omega)}. \tag{5}$$

In Eq. (5), the term $Ke^{(-cd\omega)}$ corresponds to the Point Spread Function (PSF). This function can be presented as a low-pass filter, where K is the gain of the filter and ω is the frequency. E_d is the direct component and can be presented by equation 6.

$$E_d(u,v) = \Im\left\{E_0(i,j)e^{-cd}\right\}, \tag{6}$$

where $E_0(i,j)$ corresponds to the reference (without degradations) image in the space domain and $\Im$ represents the Fourier Transform. This model is used to simulate images captured in an underwater environment. The results of the implementation of this model are shown in Figure 2.

Fig. 2. Degraded image using the Trucco's model. (a) Original image. (b) Degraded image. Parameters used for degradation: $c = 0.3m^{-1}$, $K = 0.7$, $d = 3m$. (Image taken from LIVE database [51])

B. Image Restoration

In order to restore the degraded image, the model used for degradation has to be inverted to find an approximation of the original image $\hat{E}_0$. The inverted model is presented by equation 7.

$$\hat{E}_0(i,j) = \Im^{-1}\left\{\frac{\Im\{E(i,j)\}}{Ke^{-cd\omega}}\right\}e^{cd}, \tag{7}$$

where $E(i,j)$ corresponds to the degraded image in the spatial domain, c the attenuation coefficient, K the gain of the PSF function and d the distance between the camera and the scene.

TABLE I. RESULTS FOR SPACING METRIC OF PDEA AND DEMO/PARENT ALGORITHMS (10 RUNS)

	PDEA	DEMO/Parent
Mean	0.0638	0.0653
S. deviation	0.0220	0.0314
Min.	0.0378	0.0312
Max.	0.0940	0.1152

In underwater imaging, degradations could change the quality of the image in different ways. For this reason, more than one metric for image quality assessment has to be used, leading to a multi-objective approach. In order to estimate the parameters of the model, a MODE algorithm was used. In this work, the parameters c and K are considered as the decision variables for optimization process. It is important to notice that, physically, parameters c and K not depends on the distance d. Also, d can be estimated in others ways (i.e. using a stereo vision system [33], [52]).

The metric NIQE [15] and the distribution of contrast [16] are used as cost functions. NIQE is based on the construction of a "quality aware" collection of statistical features based on a simple and successful space domain natural scene statistic (NSS) model [15]. Low values of NIQE mean better quality of the image. On the other hand, in the case of the distribution of contrast [16], only the range of the distribution is used. Larger values for the range of distribution means a better quality.

In this work, the parameters used for degradation are the same described in Figure 2. Better results are achieved with a population size of 30 and 250 iterations for the MODE. Also, it is defined values of 0.5 for the scaling factor and 0.9 for the crossover probability. Two different approaches for MODE algorithm were implemented, the PDEA and DEMO/Parent. Each algorithm was performed 10 times. Figure 3 show the non-dominated solutions after the 10 runs for both algorithms. These figure also shows the values chosen (the black square) for restoration. The image is restored using the parameters c and K estimated by the optimization algorithms (typical values for c and K are between 0.1 and 0.9).

Results for image restoration processes using the MODE algorithm are shown in Figure 4, which was chosen only for validating our approach. Also, two metrics to measure the quality of the obtained Pareto's fronts were used, namely the spacing and hypervolume were measured through 10 runs with different initial conditions. Table I shows the spacing metric for both algorithms. There we can see that both approaches performed equally well according to the diversity of the solutions. Table II shows, on the other hand, that the PDEA approach showed itself superior with a higher mean, minimum and maximum values for this metric. It shows that the PDEA approach was able to provide Pareto fronts which covered a larger area in the space of objectives when compared to DEMO/parent algorithm.

As mentioned above, the parameters used for degradation process were $c = 0.3m^{-1}$ and $K = 0.7$, for a fixed distance of $d = 3m$. After optimization and restoration processes, the estimated parameters are $c = 0.3899m^{-1}$ and $K = 0.7521$. The cost function values obtained are $NIQE = 3.779$ and $Range = 1.912$. On the other hand, the cost function values for original image are $NIQE = 3.3998$ and $Range = 1.1723$,

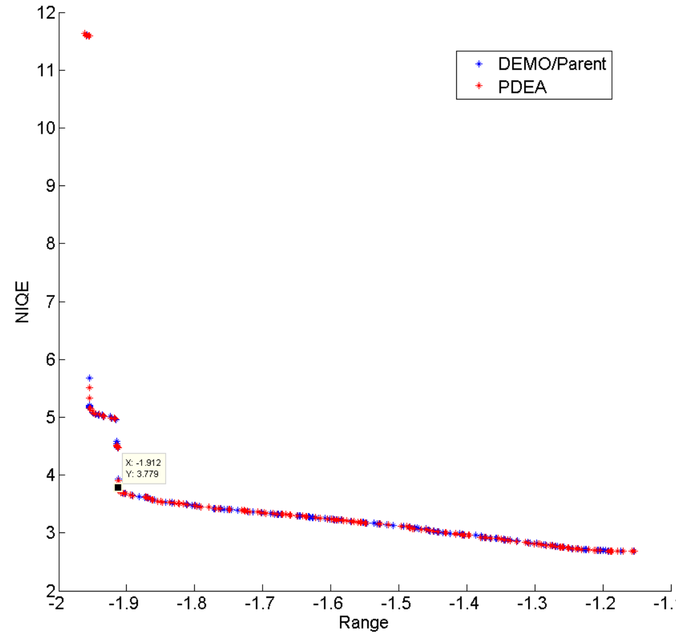

Fig. 3. Filtered Pareto's frontier obtained by DEMO/Parent and PDEA algorithms after 10 runs.

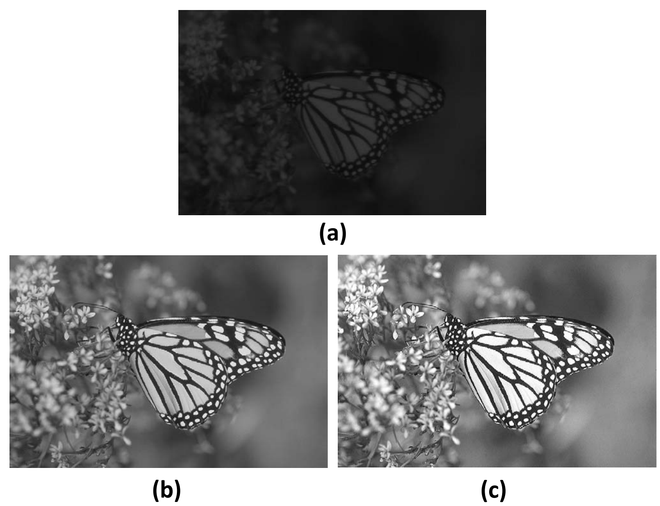

Fig. 4. Results of image Restoration. (a) Degraded image ($c = 0.3m^{-1}$, $K = 0.7$, $d = 3m$). (b) Original image. (c) Restored image using MODE algorithm $c = 0.3899m^{-1}$, $K = 0.7521$, $d = 3m$.

TABLE II. RESULTS FOR HYPERVOLUME METRIC OF PDEA AND DEMO/PARENT ALGORITHMS (10 RUNS)

	PDEA	DEMO/Parent
Mean	0.8820	0.8289
S. deviation	0.0700	0.0683
Min.	0.7749	0.7668
Max.	0.9269	0.9259

and for distorted image are $NIQE = 9.0044$ and $Range = 0.3842$. Results show that estimated values for c and K are really close to the real values used for degradation process.

On the other hand, values of cost functions for original and restored images are also similar. However, by doing a subjective analysis of Figure 2, it is possible to conclude that the restored image has slightly better quality than original image. The images used in this work are part of LIVE Image database [51]. These images were taken in natural environments and it can present some distortions, that is because it is not strange to obtain a restored image with better quality than original image. It means that the restoration process is also restoring some of these degradations.

Figure 5 shows more results using different images with different values for c and K. In column (a) are the original (no degradation) images, in column (b) are the degraded images and the column (c) belongs to restored images.

Fig. 5. Results of image Restoration. (a) Original. (b) Degraded image. (c) Restored image using MODE algorithm

V. Conclusions and Future Works

In this work, the implementation of a restoration system based on MODE optimization was presented. The optimization algorithm estimated values for degradation parameters really similar to the real parameters used for the degradation process. By doing a subjective analysis of image results, it can be seen that restored image has even better sharpness and contrast than original image. However, in this work, simulated degradation were used by implementing the Trucco's degradation model and it is needed a more real approach. This restoration process would by implemented for real underwater images in order to test the system in real conditions. In a real underwater environment, the distance between the camera and the scene could be measured using distance measurement technique such as the stereo vision.

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