Particle Swarm Optimization-based Dark Channel Prior Parameters Selection for Single Underwater Image Dehazing

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Abstract. Underwater images are confronted with blurriness and poor color consistency due to the haze produced by the absorption and scattering effects of the turbid water. Dark Channel Prior (DCP) is the state-of-the-art and the algorithmic basis to solve underwater image restoration. However, the default parameters of DCP may not be applicable to underwater images with different levels of degradation. The selection of the appropriate DCP parameters for each underwater image is considered as an optimization problem and can be solved using Particle Swarm Optimization (PSO). The proposed PSO-based selection algorithm is defined by its operators: objective function, swarm size, inertial weights and acceleration coefficients. Obtaining appropriate combination of these operators are elaborated. The qualitative and quantitative evaluations observed acceptable visual improvements and measurements to underwater images applied with DCP at optimally selected parameters, in comparison to underwater images applied with DCP at default parameters. Hence, the proposed algorithm provides good adaptability and effectivity to the exhaustive search of appropriate DCP parameters.

Keywords: Dark Channel Prior, Image Restoration, Parameters Selection, Particle Swarm Optimization, Underwater Images

1. INTRODUCTION

The development of underwater-based image processing algorithms is an active research field, as visual data acquired from underwater setups contain significant amounts of information. Through computer vision technologies, a captured underwater visual scene can be automatically analyzed and interpreted for derivation of some knowledge related to advanced applications, such as saliency detection, object recognition, object detection and object tracking [1]. The analysis is necessary in the generation of predictive models and decision support systems towards fish production management and fish stock and quality monitoring [2], [3], [4]. However, underwater images and videos are confronted with low contrast, poor visibility, and degraded color representation, which makes underwater visual data analysis a challenging task. This poor quality is often manifested as haze or the whitish veil surrounding the concerned image [5].

Extensive amount of research is conducted to reduce the effects of haze to the quality of an underwater image. Dehazing methods rely on degradation models; some parameters of these models include combinations of illumination maps, color values, and contrast measurements [6]. The Dark Channel Prior (DCP) has translated its potential to solve dehazing in underwater images, as the properties of an atmosphere surrounding a terrestrial image is much similar to the whitish veil observed in an underwater image [7]. In fact, it is now considered the state-of-the-art in addressing underwater image dehazing. More so, other algorithms are inspired from DCP, due to its informative prior-based image formation model [8]. For instance, DCP is effectively utilized to estimate transmission maps [9], the light distribution throughout an underwater image that is not influenced by the scattering and absorption effects of the turbid medium. Another example is the modification of DCP image formation model to reduce the effects of highly attenuated red channel on images captured from shallow waters [10]. In another case, DCP is used with other dehazing methods to further improve the quality of a resulting image [11]. Besides, DCP and its variants has been utilized as a visual data preprocessing for subsequent tasks in computer vision-based applications, such as image classification [12], [13], and object/scene detection [14] .

However, the quality improvement of an underwater image restoration, such as DCP, varies with underwater images of different color intensities and illuminations [15], [16], which [17] argues its exclusion to visual data preprocessing tasks. To account for these differences, image degradation models usually introduces parameters as factors of the specific portions in the model [10], [18], [19]. Varying these parameters controls the influence of these portions in the underwater image restoration. In DCP's case, these parameters permits a small amount of haze to increase the naturalness of an image [20]. Improper selection of parameters or reliance to the default parameters limits the capacity of DCP to solve the underwater image restoration problem [18], [19]. Importantly, the proper selection of parameters for each underwater image ensures maximum quality [21]. The parameters selection problem for each underwater image is seen as an optimization problem and can be solved with metaheuristic optimization, an algorithm with well-defined rules or heuristics that governs the search for the best solution.

Metaheuristic optimizations are recognized to address search problems in any discipline [22]. For land-based image dehazing, Genetic Programming (GP) is utilized to develop a haze transmission function based on the search of appropriate operators which would produce the least Mean Absolute Error (MAE) [23]. For image dehazing parameters selection, Genetic Algorithm (GA) is used to select the appropriate parameters for each terrestrial image governed by acquired CNC Index, an image defogging metric [19].

Furthermore, Particle Swarm Optimization (PSO) is one of the states-of-the-art for image restoration parameters selection. Notable example include the optimal relaxation value estimation in Row-Action Projections convex set (RAP-2D) in satellite images based from Improvement Signal to Noise Ratios (ISNRs), Universal Image Quality Indexes (UIQIs), Mean Absolute Errors (MAEs) and Mean Squared Errors (MSEs) [24] and the search for optimal configurations of Fuzzy Logic-based Noise Detector in cDNA microarray images based from the acquired Error Rates [25]. For PSO towards image dehazing parameters selection, a notable application is the search of optimal DCP parameters for land-based images with criterion based on the relationship of the concerned parameters with CNC Index [18]. Another instance of PSO-based search is the selection of optimal parameters of Inverse of Barros' Underwater Image Degradation Model, facilitated by different objective functions from the relationship of the said parameters with different no-reference underwater image quality metrics, such as Underwater Color Image Quality Evaluation (UCIQE), Naturalness Image Quality Evaluator (NIQE), Blue Noise-Image Quality Assessment (BN-IQA) [21].

For the presented studies of metaheuristic optimization-based underwater image restoration parameters selection, an important factor is the design of objective function. In these cases, the objective function relates the parameters to a well-defined image quality metric. Such function governs the search towards the best parameters, which when correctly designed would extend the capability of an algorithm to address image dehazing. Currently, the lack of proper objective criteria that governs restoration on terrestrial or underwater images is acknowledged [18], [19], [21].

Particularly, PSO in DCP parameters selection towards restoration of underwater images is yet to be explored. In regards, this research aims to develop an algorithm that searches for the optimal parameters of DCP for an underwater image using PSO, and to evaluate the performance of the generated optimal parameters. This paper mainly contributes an adaptive method that generates appropriate DCP parameters for a single image based on PSO governed with an objective function that determines the appropriateness of such parameters.

2. DARK CHANNEL PRIOR

Dark Channel Prior, an underwater image dehazing introduced by [20], is considered as a state-of-the-art due to its simplicity and efficiency. This technique improves the contrast of an underwater image by removing the effects of haze, which is estimated using the dark channel, or the color channel that contains the minimum color values. The model that inspires the formation of an image with haze is the atmospheric scattering model,

$$I(x) = J(x)t(x) + A(1 - t(x)) \tag{1}$$

where $I(x)$ is the captured image, $J(x)$ is the scene radiance or the haze-free image, $t(x)$ is the transmission, the unaffected light throughout the captured image, and A, the background light. The first term is defined as the direct attenuation, the degradation of scene radiance by the medium and the second term is the airlight, the misrepresentation of the color resulting from the scattered light by the medium. The objective of this algorithm is the recovery of the scene radiance $J(x)$ and is represented as:

$$J(x)=\frac{I(x) - A}{\max(t(x),t_0)} + A \tag{2}$$

where t_0 is the minimum permissible amount of haze for some areas in an image heavily affected by the haze. The overview of the involved processes in this technique are as follows. First, the prior, or the moving patch, $\Omega(x)$, determines the dark channel, $J^{dark}(x)$, by containing the minimum color values throughout the three color channels. This operation is derived from an observation that the values within the dark channel of an image with lesser amount of haze approaches zero and is expressed as:

$$J^{dark}(x) = \min_{y \,\epsilon\, \Omega(x)}(\min_{c \,\epsilon\, r,g,b} J^c(y)) \tag{3}$$

where J^c is a color channel of scene radiance, J. Second, the atmospheric light, A^c, is estimated from the mean of 0.1% maximum values of a dark channel. Third, the transmission is derived from the image formation model (1) through the normalization with atmospheric light, minimization of terms, and addition of an adaptive parameter, ω, and is expressed as:

$$t(x) = 1 - \omega \min_{y \in \Omega(x)} \left(\min_{c \in \{r,g,b\}} \left(\frac{I^c(y)}{A^c} \right) \right) \quad (4)$$

The simplification of (1) through minimization accounts the aforementioned observation and the introduction of ω, the strength of transmission, another approach that allows a small amount of haze for the naturalness of the resulting image. Fourth, Guided Image Filtering is utilized to refine the transmission map [26]. This method, which counteracts the compromise between permissible haze and object edges, is defined by,

$$\tilde{t}(x) = \sum WI(x)_{gray}\, t(x) \quad (5)$$

where W is the filter kernel of a guided filter, a linear transform of the gray version of the underwater image, $I(x)_{gray}$. Finally, the scene radiance is recovered according to (2).

3. METHODOLOGY

The proposed algorithm for parameter selection of Dark Channel Prior (DCP) as applied to locally acquired underwater images was based on Particle Swarm Optimization (PSO). PSO is an algorithm that provides the best solution to a search problem by the iterative movements of units throughout the search space. The movements towards the best solution is inspired from the simulation of swarm behavior in nature, e.g. bird swarms and fish schools. Each unit, called a swarm particle, is identified with a position and velocity; the position represents a specific point and the velocity is the amount of movement in the solution space. In each iteration, all particles' positions are evaluated by some function that determines the viability of a particle to become the most optimal solution in the solution space. Based on the computed fitness, each particle on every iteration learns the best positions encountered by itself and by the whole swarm. This learning better directs the movements towards the optimal solution. The processes and its corresponding parameters and the assessment of outputs of the proposed framework are presented further.

3.1. Development

2.1.1. Objective Function Design

The objective function crucially defined the quality of the generated solution, as this function influences all movements produced by the iterations of PSO to converge into the best possible solution. In this application, its design was focused on the relationship between influential DCP parameters, ω and t_0 [19], and a no-reference measurement that defines the restored underwater image quality.

The metric used in this study is the Underwater Image Quality Measurement (UIQM). UIQM is the summation of improvements to the color, sharpness, and contrast of an underwater image, namely Underwater Image Colorfulness Measure (UICM), Underwater Image Sharpness Measure (UISM) and Underwater Image Contrast Measure (UIConM). This metric is developed to evaluate underwater images that considers the susceptibilities of a captured underwater image to absorption and scattering properties of water while incorporating inspirations from human visual perception properties, such as luminance and contrast masking, color perception, and relative contrast sensitivity. It is computed as:

$$\mathrm{UIQM} = c_1 \mathrm{UICM} + c_2 \mathrm{UISM} + c_3 \mathrm{UIConM} \quad (6)$$

where c_1=0.0282, c_2= 0.2953, c_3=3.5753 [27].

The development of objective functions for all test underwater images entailed the usage of multivariate polynomial regression at 5th degree with linear least

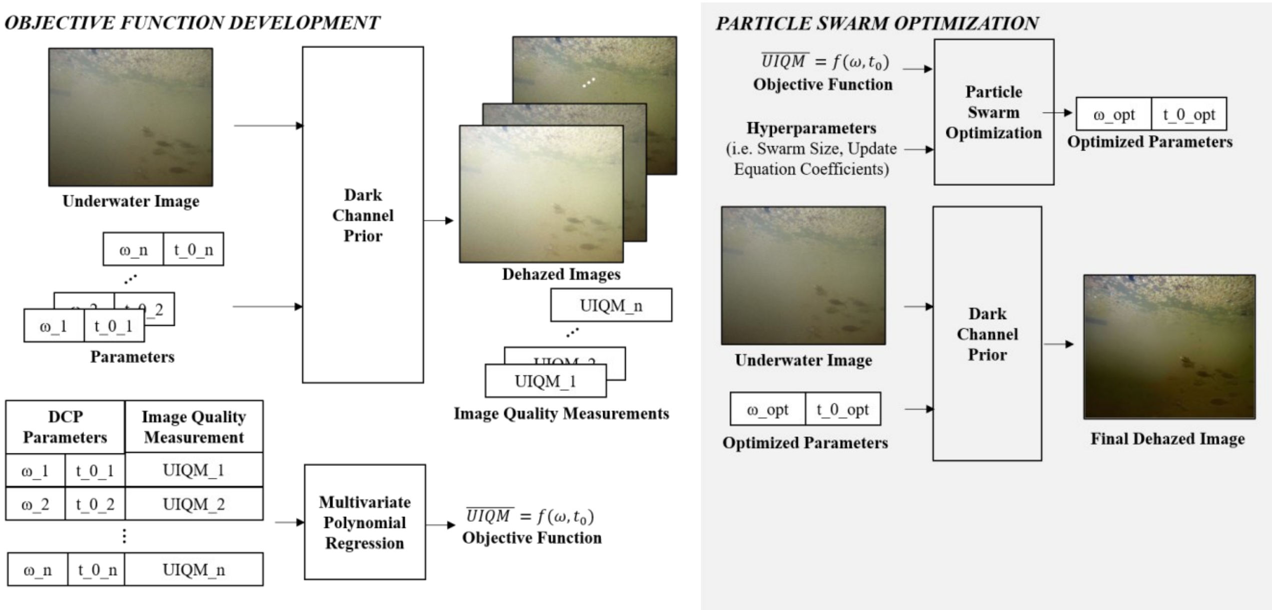

Fig. 1. PSO-based DCP Parameters Selection Algorithm Workflow

squares fitting. Such configurations generated objective functions with acceptable goodness-of-fit at 0.8637-0.9585 r-squared, 0.8556-0.9561 adjusted r-squared and 0.004257-0.006155 Root Mean Square Error (RMSE).

2.1.2. Swarm Initialization

A float vector of ω and t_0 values represented the position of a swarm particle. Usually, the swarm particles were initially assigned with positions and velocities at random values within the constraints. These constraints in the solution space were established to limit the search of this algorithm to valid and acceptable values of DCP parameters, which are $0 < \omega \leq 1$ and $0.1 \leq t\_0 \leq 0.95$ [18]–[20], [28]; this range of t_0 , with 0.1 as the most typical value, prevents extreme effects of transmission on the dehazing processes.

2.1.3. Fitness Evaluation

A fitness function was applied on each particle to determine the quality of the produced solution by the particle and by the whole swarm. The generated objective function was translated into a fitness function: the input of this function was a float vector that represents the position of a particle while the output was a fitness value, which is UIQM. In this case, for a particle in this swarm to be considered as an optimal solution, the result of the fitness evaluations must be of high value, as a high UIQM is expected from the application of DCP to an underwater image configured at optimally selected parameters.

2.1.4. Swarm Updating

Using the currently acquired fitness for all particles in an iteration, the particles' locally encountered best position p_{best} and the swarm's best position g_{best} were updated as follows:

- If the acquired fitness from the current position of a particle is greater than the fitness of p_{best}, the value of p_{best} is updated with the current position.
- If the acquired fitness from the current position of the particle is greater than the fitness of g_{best}, the value of g_{best} is updated with the current position of this particle, and this value is disseminated throughout all particles in the swarm.

After updating of the local and global best solutions, the position and velocity of each particle in the swarm was modified through the following update equations:

$$v(t+1) = wv(t) + \emptyset_p r_p (p_{best} - x(t)) + \emptyset_g r_g (g_{best} - x(t)) \quad (7)$$

$$x(t+1) = x(t) + v(t+1) \quad (8)$$

Equation (7), determines the velocity of a particle which defines the amount of movement of a particle from current to next position in the solution space. This equation accounts the effects of particle's current velocity, the particle's best position, and the swarm's best position in a generated solution. The first term of this equation includes w, the inertial weight, as a factor that controls the effect of the current velocity to the resulting velocity. The value of w determines the nature of the search: higher w ensures the greater influence of the current velocity in the resulting velocity, which leads in finding a solution that is farther from the current position, while lower w induces an opposite effect. The second term, cognitive component, focuses on the exploit of p_{best}. The difference between the current position and p_{best} is multiplied with two factors: r_p which represents a random number from 0 to 1, that avoids settling into a solution prematurely, and $\emptyset_p$, an acceleration coefficient, that represents the amount of influence of p_{best} in the generated solution. The third term, social component, focuses on the exploration on the search space via the interactions between the swarm particles, as manifested by g_{best}. Similar to the second term, the difference between the current position and g_{best} is multiplied with two factors: r_p and $\emptyset_g$, another acceleration coefficient that represents the amount of influence of g_{best} in the generated solution. The result of the velocity update equation is then added with the current position to determine the next position of each particle, as established in the position update equation, (8).

2.1.5. Termination

Criteria were established to terminate the PSO search process. Several terminating conditions can be used. For this application, the search for an optimal solution was terminated when the maximum number of iterations has been achieved or an acceptable solution has been met.

The operators, especially w, $\emptyset_p$ and $\emptyset_g$, were varied in their acceptable ranges for each application of PSO-based DCP parameters selection for restoration of a single underwater image. The variations were performed with determined initial positions, i.e. particles that are spaced evenly in the solution space, (instead of usual random initial positions) with random initial velocities. The best combination of the operators should produce a solution of highest fitness value and should converge into this solution at the fastest time. Such configurations, which are true for all algorithm applications to the test underwater images, are expressed below.

Table 1. Particle Swarm Optimization Operators

Hyperparameters	Values
Swarm Size	10
Inertial Weight, w	0.8 – 1.2
Cognitive Coefficient, $\emptyset_p$	2.0
Social Coefficient, $\emptyset_g$	1.5 – 2.0

3.2. Evaluation

Three (3) images of varying levels of illumination and color values, acquired locally from an inland aquaculture setup were sampled to form a test set. Then, this set were restored with DCP at default parameters ($\omega = 0.95$ and $t_0 = 0.1$ [20], [29]) and at optimized parameters, the output of proposed algorithm. The images restored with default DCP and the images restored with adaptive DCP were visually and numerically assessed.

2.2.1. Qualitative Assessment

The original images, the images restored by DCP at default parameters and the images optimally restored by the proposed algorithm were compared to each other. The color, contrast, and sharpness of an image, especially on the regions of interests (in this application, the fish pixels) were visually assessed to determine the presence of significant improvements and the naturalness of the image restoration. Also, the presence of unnecessary artefacts, speckles and/or noise to the restored images were noted.

2.2.2. Quantitative Assessment

The full reference-based metrics were used to measure the amount of restoration applied by the image restoration algorithms. The usage of full reference metrics was inspired by the human intuitive evaluation of two images: an image is referred to be high (or low) quality based on a reference image. These metrics, which utilizes both the image under assessment and the original image in the computation, were the Mean Square Error (MSE), Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM). These are well-known image quality metrics that estimates the noise content of a restored image. However, in this application, these metrics are used to quantify the difference between the restored images and the original images. MSE measures the sum of the average of the squares of the difference between the restored image and the original image and PSNR is ratio between the possible maximum power of an image intensity and the power which corresponds to the amount of differences of the restored image and the original image. Unlike former metrics that deals with summation of amounts of image pixel intensities, SSIM estimates any image degradation applied using the image restoration technique through the observed differences in luminance, contrast, and structure of the original and restored images. These metrics are calculated as:

$$\mathrm{MSE} = \frac{1}{\mathrm{i} \times \mathrm{j}} \sum_{\mathrm{i,j}} [\mathrm{I_o}(\mathrm{i,j}) - \mathrm{I_r}(\mathrm{i,j})]^2 \tag{9}$$

$$\mathrm{PSNR} = 20\ \log_2 \frac{1}{\sqrt{\mathrm{MSE}}} \tag{10}$$

$$\mathrm{SSIM} = \frac{\left(2\mu_{I_o}\mu_{I_r} + C_1\right) \times \left(2\sigma_{I_o}\sigma_{I_r} + C_2\right)}{\left(\mu_{I_o}{}^2 + \mu_{I_r}{}^2 + C_1\right) \times \left(\sigma_{I_o}{}^2 + \sigma_{I_r}{}^2 + C_2\right)} \tag{11}$$

where I_o and I_r are the original and restored grayscale images, μ_{I_o} and μ_{I_r}, σ_{I_o} and σ_{I_r}, and $\sigma_{I_o I_r}$ are the averages, standard deviations and cross-covariance of the original and restored images and C_1 and C_2 are constants that determine the comparisons between mean luminance values, contrast values and structure of the original and restored images.

Overall, these quantitative metrics verified the human observation on the degree of significant improvements to restored underwater images.

4. RESULTS AND DISCUSSIONS

The proposed algorithm and the corresponding processes were implemented in MATLAB 2019a. Such proposed algorithm in this implementation produced best solutions for each underwater image dehazing problem. The optimally selected DCP parameters by PSO are shown below.

Table 2. PSO-generated DCP Parameters

Sample Image	Optimized Parameters	
	ω	*t_0*
1 (Row 1, Fig. 2.)	1	0.5332
2 (Row 2, Fig. 2.)	0.9211	0.1689
3 (Row 3, Fig. 2.)	0.6007	0.95

These parameters were utilized in the underwater image restoration using DCP. The results of the restoration using default parameters and optimally selected parameters are shown in the figure on the next page.

4.1. Qualitative Assessment

The original images are characterized by blurriness and degraded colors due to the whitish haze that surrounds the images. DCP addresses the removal of such effects in the underwater images to some extent. Significant differences between the original images and restored images with DCP utilizing default parameters are observed. However, these restored images are characterized by oversaturation of colors, especially on areas with greater illuminations. Also, the edges of fish pixels in these restored images are characterized with pixels that are much lighter that the background, which gives a halo-like appearance from the fish. Apparently, patches of these lighter pixels are scattered throughout the images. The observations contribute to the unnaturalness and increased darkness of these restored images. Except at sample image 2, the restored images with DCP utilizing optimally selected parameters is more natural-looking than the restored images with DCP utilizing default parameters. Specifically, DCP utilizing optimally selected parameters had a much desirable effect on sample image 1, had a similar effect from the DCP utilizing default parameters on sample image 2, and had a fairly noticeable improvement on sample image 3. Furthermore, the restoration using optimally selected parameters on sample image 1 is the most prominent out of the sample images as the whitish haze near the water surface is removed, at the expense of darker-looking result, and the restored sample image 2 at optimized parameters is similar to that of the default parameters, because of the small difference between the optimized parameters and the default parameters.

4.2. Quantitative Assessment

The restored images were assessed using full-reference metrics that expresses the amount of improvement or the amount of similarity of the restored image in comparison to original images. These metrics which are shown on the next page supported the observations from the preceding visual observations. For example, the metrics in restored sample image 3 at optimized parameters achieves the lowest measurements in MSE and the highest measurements in PSNR and SSIM, in contrast to the other restored images. This is attributed to the profound similarity between the original image and this restored image; that the restoration by DCP utilizing optimally selected parameters is fairly noticeable on this image. Another example is the metrics in restored sample image 2 at optimized parameters is almost equal to the metrics in restored image at default parameters. This supports the observed similarity between the restored images utilizing different parameters. Lastly, the metrics of restored sample image 1 at optimally selected parameters shows the most desirable results out of all restored images at different parameters, as reflected by acceptably low MSE, high PSNR and SSIM. This certain image is restored well without compromising its naturalness and the balance between the noticeable structural similarity and significant improvement of visual characteristics from the original image.

The evaluations provided substantial basis that the utilization of PSO-generated DCP parameters provided restoration to locally-acquired underwater images with fair to good quality. Furthermore, PSO extends the capability of DCP to be adaptive to the differences in illumination and color representations between the underwater images. The generalization of the usage of default parameters to underwater images of different visual characteristics limits the capabilities of DCP to address underwater image restoration. The search of combination of parameters which would be effective on every underwater image would be an exhausting task and the proposed method provides an automated approach.

However, some limitations are observed in this study that motivates further research. The search is much dependent to the design of the objective function. The established relationship of UIQM to DCP parameters provides fair to good representation on the improvements for underwater images, as UIQM is compliant to human perceptions of color consistency, sharpness and contrast. According to [27], 10% increase of UIQM is necessary to obtain a significant amount of improvement to an underwater image. However, the gathered UIQM during the optimization only achieved 0.6-2.0% increase, which is far from established standards. This specific finding determines some difficulty of DCP in restoring the locally-acquired underwater images and supports the

1

2

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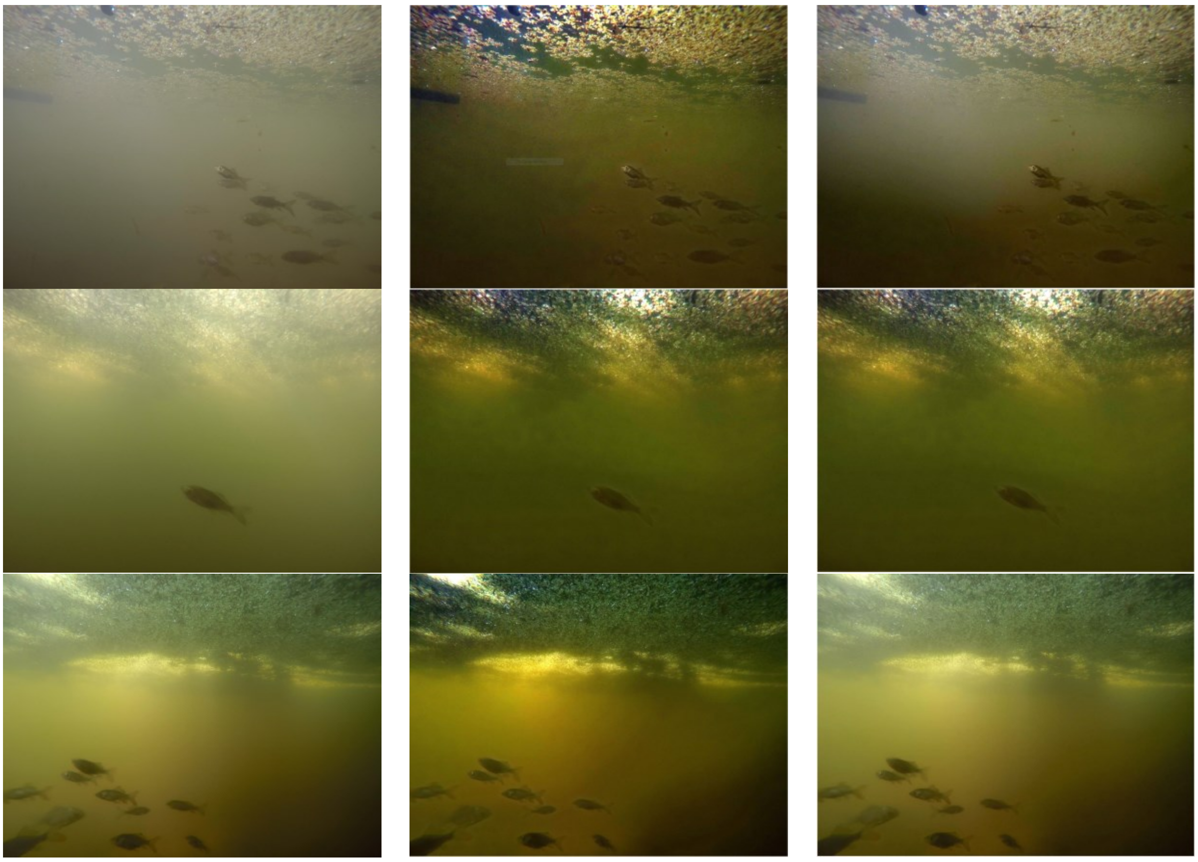

(a) (b) (c)

Fig. 2. (a) Original Images (b) Restored Images using Default DCP Parameters (c) Restored Images using optimally selected DCP Parameters

Table 3. Performance metrics Between Enhanced Images

Sample Image	**Restored using Default Parameters (Fig. 2 (b)) (ω = 0.95, t_0 = 0.1)**			**Restored using Optimized Parameters (Fig. 2 (c))**		
	Mean Square Error	***Peak Signal-to-Noise Ratio***	***Structural Similarity Index***	***Mean Square Error***	***Peak Signal-to-Noise Ratio***	***Structural Similarity Index***
1 (Row 1, Fig. 2)	0.046526	13.32308	14.19902	**0.021026**	**16.7724**	**17.41443**
2 (Row 2, Fig. 2)	0.05933	12.26722	12.49169	**0.051175**	**12.90946**	**13.10765**
3 (Row 3, Fig. 2)	0.024171	16.16709	17.3212	**0.000359**	**34.44739**	**34.61646**

statements of [18], [19], [21] in the persistent problem of objective function design in this application. Thus, a direction in extending this research is the utilization of other underwater image quality metrics in the design of objective functions that would generate parameters to significantly improve the underwater image.

Furthermore, DCP may be the algorithmic basis for other underwater image dehazing algorithms due to the simplicity of its image formation model, however, the existence of its variants addresses some shortcomings of the original algorithm. As DCP is a statistical method of deriving transmission maps to remove the haze, certain underwater images may evoke invalid computations [30]. This phenomenon was well observed in experimentations with sample images 2 and 3, the images with much complex illumination than that of sample image 1, where some color intensity values in the resulting enhanced images were negative; these negative values were then equated to zero to validly compute for UIQM and full-reference metrics. Hence, another direction in extending this research is the integration of PSO-based parameter selection with other DCP variants that are specifically generated for challenging underwater images.

5. CONCLUSIONS AND RECOMMENDATIONS

Selection of the appropriate Dark Channel Prior parameters for different underwater images can be adaptively facilitated by Particle Swarm Optimization. The search for optimal values of strength and the lower bound of transmission through specific ranges is effectively performed by this proposed framework. The restored images using these parameters improves the color, sharpness and contrast to an acceptable degree of naturalness and similarity from the original underwater images, in comparison to the restored image using the default parameters.

The proposed framework, however, is only prominent on some images, which supports the ongoing problem of varying effects of this image restoration algorithm towards underwater images with varying illuminations and other visual characteristics. Further investigations on robust designs of objective function and the integrations of such adaptive parameter selection method to other image restoration algorithms can be performed in the future.

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