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Multi-Objective Image Enhancement Using Particle Swarm Optimization

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Abstract

Images sometimes become unusable due to adverse environment conditions. Image enhancement methods solve the problem. There are miscellaneous methods for image enhancement operations such as gray scale modification, histogram equalization and contrast stretching techniques. In addition, metaheuristic optimization techniques are used for image enhancement. Particle Swarm Optimization (PSO) is one of the metaheuristic algorithms. In this study, firstly a transformation function was determined for image enhancement from the literature. PSO was developed with Pareto Optimal approach as a multi-objective. The improved PSO was used to determine optimal values of parameters in the function. The parameters are pretty influential on transformation of images. Entropy and Contrast Improvement Index (CII) of obtained images were calculated for evaluation process. Finally, the experimental outputs were compared with the results of another study.

Keywords: Image Processing, Metaheuristic Algorithm, Pareto Optimal Approach, PSO

INTRODUCTION

Along with the invention of imaging devices, images have started to be used in many areas. There is a variety of imaging devices as the purpose of imaging changes. For instance, an X-ray image is used to diagnose a health problem while objective of a satellite image is mapping. “The intelligibility” criterion of images will change accordingly in order to comply with the specific requirement.

Images could be unusable due to several reasons or they may not contain appropriate information for purpose of use. Image enhancement is defined as the improvement process of low quality images [1].

Histogram equalization and contrast stretching methods are classical methods that are frequently used in image enhancement processes. Metaheuristic methods are used as an alternative approach to the classical methods. For example, Gorai and Ghosh [2] utilized Particle Swarm Optimization technique to improve gray level images. Draa and Bouaziz [3] performed image enhancement using Artificial Bee Colony algorithm and obtained efficient results. Image enhancement operations are mostly performed on gray level images, but they are also used for colored images.

The optimization is defined as a transaction of how a problem can be solved better. There are many optimization methods like metaheuristic approaches in the literature. Particle Swarm Optimization (PSO) is one of those methods.

In this study, PSO was used as a multi-objective with Pareto Optimal approach. The proposed method was applied over the sample gray level images. The outputs were compared with the results of another study in the literature.

Literature Review

Metaheuristic methods can give good results in image enhancement applications. But sometimes the desired output cannot be obtained accurately. In recent years, multi-objective approaches are used together with metaheuristic methods in order to increase the quality of solutions. Ngai M. Kwok et al. [4] developed a Particle Swarm Optimization method with multi-objective approach to improve gray level images in their work. In the study, they identified two objectives to achieve the desired result. One of objectives was preserving image density and the second one was obtaining maximum information from image. They optimized a scaler gamma factor to achieve two contradictory objectives, and applied a gamma correction to preserve intensity. They used the highest entropy value to maximize information in the image. Each particle in PSO algorithm was used to provide an average intensity with the gamma factor and a fitness value.

Shanmugavadivu and Balasubramanian [5] proposed multi-objective histogram equalization for image enhancement in their work. The method consisted of three phases:

Phase I: Separating histogram of input image by "Otsu" threshold value according to information in the image.
Phase II: Improvement of constraint weights according to the threshold value.
Phase III: Optimization of constraint weights with PSO.

In the study, there are various criteria such as discrete entropy and contrast improvement index to determine the success of enhanced image. They minimized the difference between the entropy and average values for input and output image.

Kaushal et al. [6] proposed a modified histogram equalization method to preserve color and brightness while enhancing contrast of the image. Firstly, they converted image / video into YCbCr color model, and removed brightness (Y) component in order to reducing the computational complexity. They segmented input image using Otsu threshold value. They used Otsu method to determine the foreground and background in the image. They used q, r, s, t parameters for histogram equalization in equations. They optimized these parameters by Water Cycle algorithm. The algorithm is inspired by the solutions of rivers and flood flows in the nature.

Singh et al. [7] used a multi-objective particle swarm optimization based on dynamic stochastic resonance in their work. They performed image enhancement using diffusion weighted magnetic resonance. According to the study, diffusion-weighted magnetic resonance image maps the diffusion process of water in living tissues. The study states these images are useful for examining tissue microstructure. Low Signal-to-Noise Ratio (PSNR) and low contrast causes a loss on the benefit of images. Singh et al. solved the problem using multi-objective Particle Swarm Optimization. They maximized contrast enhancement factor and average image score using PSO.

MATERIAL AND METHOD

Particle Swarm Optimization

For the first time, Kennedy and Eberhart (1995) demonstrated PSO approach, based on food finding behavior of fishes and birds in the nature. At the beginning, they studied for graphical modeling of the choreography of these animals. As time progressed, they saw that model could be used to solve problems [8].

According to the study, the swarms in PSO are come into existence birds in real life. The approach is based on collaboration. Each bird is represented by candidate solution for the problem in the digital world and called as particle. In a standard PSO each particle should have the ability to remember its position, velocity, previous position, ability to share its information, ability to use information to reach a decision. The basic philosophy of the particle swarms is Adaptive Culture Model. Basis of cultural adaptation is consist of three principles these named "evaluate", "compare" and "imitate" [9].

In PSO approach, birds spread randomly to looking for food in the solution space. Each bird moves in different directions at the same time [10]. At the beginning, birds do not know where the food source is located. Nevertheless, they try to find out how they are away from food source. For attain this knowledge, each particle follows to the bird that is closest to the source of food. When the particle moves, distance to the food is calculated. This value is called as fitness value. The particle updates the its velocity and position in each iteration (in other words, each generation) with using neighbors' and own best coordinates [8].

In each iteration, particles update themselves with the following two "best" values: The first “best” is the particle obtained best solution so far. The value is named as *pbest* (particle best). The second "best" is any one of the particles in all generations best solution ever reach. The value is named as *gbest* (global best). The velocity and position information of the particle are updated using two values which mentioned above with the following Equation 1 and 2 [2].

$$v_i^{t+1} = W^t v_i^t + c_1 r_1 (pbest_i^t - X_i^t) + c_2 r_2 (gbest^t - X_i^t) \quad (1)$$

$$X_i^{t+1} = X_i^t + v_i^{t+1} \quad (2)$$

In equations, v_i^t is the velocity and X_i^t is the position for the i^{th} particle at time t. The inertia weight at the t^{th} time is W^t. The positive acceleration factors are c_1 and c_2. The random values in the range [0-1] are r_1 and r_2. $pbest_i$ is the best solution on the flight path of the i^{th} individual particle, and $gbest^t$ is the best particle within that all of generations [2].

Multi-objective Methods

Multi-objective methods are aimed to solve problems that have in generally contradictory and more than one objective. For instance, a multi-objective method can have used to design a complex hardware that targets the highest performance and lowest cost. In such a problem, some of the objectives are treated as the constraints. For example, while a system is optimized with the lowest cost and the highest performance, the certain size of system may have a different criterion [11].

In some situation, providing all of conflicting objectives at the same time, cannot be possible for some optimization problems. Pareto-Optimal Solution approach is one of the methods that used in such situations. The approach provides reasonably alternative solutions for each objective. Decision makers make a choice from these solutions. Each of solutions is called Pareto-Optimal Solution and the cluster of solutions is known as Pareto-Optimal Solution Set. A Pareto-Optimal solution is defined as better than the others for at least one objective and not worst for any objective. Results of multiple objective functions are compared with each other for the evaluation process. They are evaluated according to the Pareto predominance [12].

PSO and Multi-Objective Image Enhancement Transformation Function

The main purpose of this study is improving quality of images. In this context, equation 3 shows the image enhancement process on the intended positional area.

$$g(i,j) = T\,[f(i,j)] \quad (3)$$

Where $f(i,j)$ represents the gray value of pixel $(i,j)^{th}$ of input image, and $g(i,j)$ represents the gray value of pixel $(i,j)^{th}$ of enhanced image. T is corresponded to transformation function. Equation 4 shows the transformation function in this study [2].

$$g(i,j) = K(i,j)[f(i,j) - c \times m(i,j)] + m(i,j)^a \quad (4)$$

In equation, a and c are constant parameters, the local average of pixel $(i,j)^{th}$ in input image taken by a window n x n is $m(i,j)$. $K(i,j)$ is an enhancement function that includes both local and global information. Equation 5 shows a mathematical expression for local average and enhancement function.

$$m(i,j) = \frac{1}{n \times n} \sum_{x=0}^{n-1} \sum_{y=0}^{n-1} f(x,y) \quad (5)$$

Equation 6 shows the enhancement function that is expressed by *K(i,j).*

$$K(i,j) = \frac{k.D}{\sigma(i,j)+b} \quad (6)$$

For Equation 6, k and b are two parameters, D is global average. $\sigma(i,j)$ indicates local standard deviation value for pixel $(i,j)^t$ of input image on a *n x n* sized window. Equation 7 and 8 shows D and $\sigma(i,j)$.

$$D = \frac{1}{M \text{x} N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} f(i,j) \quad (7)$$

$$\sigma(i,j) = \sqrt{\frac{1}{nxn} \sum_{x=0}^{n} \sum_{y=0}^{n} (f(x,y) - m(i,j))^2} \quad (8)$$

Consequently, Equation 9 shows the last state of the transformation function that is given in Equation 3.

$$g(i,j) = \frac{k.D}{\sigma(i,j)+b} [f(i,j) - c.m(i,j)] + m(i,j)^a \quad (9)$$

Evaluation Criteria

Every evaluation made by human eye for enhanced image are subjective. On the other hand, an objective evaluation needs to numerical criteria. In this study, Contrast Improvement Index (CII) and Entropy are used to evaluate the result objectively.

Entropy

Probability of existence for any color tone in an image is defined as the ratio of pixel count of the color to the total number of pixels. This calculation gives a probability distribution for color tones in the image. The distribution provides the entropy value [13]. Equation 10 shows a mathematical statement for the entropy.

$$E = -\sum_{i=0}^{G} p(i)\, log_2(p(i)) \quad (10)$$

Where *p(i)* is pixel density histogram in gray scale, and *G* is number of gray levels [14].

Contrast Improvement Index

Contrast Improvement Index (CII) is a quantitative ration for image contrast enhancement, and it is defined with Equation 11.

$$CII = \frac{C_p}{C_o} \quad (11)$$

Where C_o is contrast value of the original image, and C_p is contrast value of the processed image. Contrast value of any image is defined with Equation 12.

$$C = \frac{(mfg - mbg)}{(mfg + mbg)} \quad (12)$$

In equation, mfg and mbg is defined as grayscale foreground and background averages of the image [5].

Proposed Method

Incrementing the number of edge pixels in image brings higher edge intensity. One of the improvement indicators in the image is higher edge intensity but only this indicator is not adequate. The entropy gives information about content of the image. If the intensity distribution is uniform, the histogram tends to get equalized. In this respect, the entropy value should be higher for an enhanced image. Accordingly the first objective function is defined with Equation 13 [12].

$$F(I_e) = \log(\log(E(I_s))) \text{ x } \frac{n_{edgels} - (I_s)}{M \text{ x } N} \text{ x } H(I_e) \quad (13)$$

Where I_e represents the enhanced image that is obtained from the equation 3. Edges or borders in an image can be detected using many effective edge detection algorithms, such as Sobel, Laplacian and Canny. In this study, Sobel was used to determine the edges. I_s is an edge image that is obtained from I_e by using the Sobel edge detection operator [2].

In the study, preserving of brightness was defined as the second objective. In order to achieve this second objective, the average intensity difference between the input and output images was minimized.

In PSO algorithm, the particles use the *gbest* and *pbest* values in each loop to achieve their objectives. Each particle updates its own state according to these values. However, in situations where there is more than one objective, processing according with *gbest* value is not possible. Thus, MOPSO (Multi-objective PSO in the study) uses the concept of *lbest* (local best) or "leader" instead of *gbest* in the multi-objective PSO [15]. Accordingly, Equation 14 shows the process of updating velocities of these particles.

$$v_i^{t+1} = W^t v_i^t + c_1 r_1 (pbest_i^t - X_i^t) + c_2 r_2 (pLeader^t - X_i^t) \quad (14)$$

In the PSO studies where Pareto-Optimal approach using, each particle on the Pareto surface has the potential to become the leader. The tests in the study demonstrated that random selection of the leaders among the solution space could lead to undesired results. Even if the solutions in the Pareto surface don't dominate each other, this situation does not imply that every solution can be an ideal solution candidate. This is because there can exists some solution in the extreme-point. If such a particle become the leader by a random selection, the particle swarm can move in the extreme-point direction. In this study, each particle in the solution set was ranked according to the PSNR (Peak-Signal to Noise Ratio) values in order to solve the problem. The particle with the highest PSNR value was chosen as the leader. The particles update their values with referring to the value that the leader particle has. A pseudo-code the algorithm of the method is described below:

Start
Create P number of particles.
<u>*Start a loop from i = 1 to P for each particle:*</u>
    Assign random values to a, b, c and k parameters of particle according to their value ranges and set the corresponding velocity and position value
<u>*End particle loop.*</u>
<u>*Set a particle with the highest PSNR value as the leader.*</u>

<u>Start a loop that continues till finishing condition for each generation:</u>

<u>Start a loop from i = 1 to P for each particle:</u>

Create an enhanced image according to Equation 9.

Calculate first objective value according to Equation 13.

Calculate density difference between input and output image for second objective.

If $F((I_e)_i) > F(pbest_i)$ *than*

$pbest_i = P_i$

End if;

Calculate PSNRi value for I_e

If PSNRi > PSNR_leader than

PSNR_leader = PSNRi

leader = P_i

End if;

<u>End particle loop.</u>

<u>Start a loop from i = 1 to P for each particle:</u>

Update velocity of particle according to Equation 14.

Update position of particle according to Equation 2.

Apply NSGA-II [16] algorithm for each particle.

<u>End particle loop.</u>

<u>End generation loop.</u>

In last case, apply image enhancement according to Equation 9 using values of the current leader particle.

Finish.

RESULTS AND DISCUSSION

The proposed method was tested using a wide variety of images such as satellite, X-ray film and standard images. In addition, four of commonly used images in the literature (Cameraman, F16, Truck, Pirate) were selected to objectively evaluate success of this study. The proposed method was applied 15 times to these images. Entropy, CII, PSNR values were recorded each time.

When results are considered in terms of CII values, MOHE method is higher for Cameraman, F16 and Truck images with a value of 1.0. However, MOPSO method gives a very close result to MOHE method with a value of 0.99. MOPSO method is higher with 0.9995 for Pirate image. At the same time, MOHE gives closest value with 0.9846. When results are evaluated in terms of entropy values, MPSO method gives higher result for Cameraman and F16 images. However, outputs of MOPSO give the closest result to MPSO. MOPSO method offers higher result for Truck and Pirate images. The resulting numerical data and images were shared at the end of this study.

In this study, there are parameters in the transformation function determined for image enhancement process. Ideal values for these parameters were determined using Pareto Optimal approach with Multi-Objective Particle Swarm Optimization. CII and entropy values were calculated for outputs of MOPSO. Results of this study were compared with GHE (Global Histogram Equalization), BBHE (Brightness Preserving Bi-Histogram Equalization), DSIHE (Dualistic Sub-Image Histogram Equalization), HS (Histogram Specification), RMSHE (Recursive Sub-Image Histogram Equalization), MPSO (multi-objective PSO), MOHE (Multi-objective histogram equalization). Results of these methods were taken from the similar study [5]. Pirate and F16 images are appeared in Fig. 1 and Fig 2. Entropy and CII values are shared in Table 1 and Table 2.

Table 1 Comparison of CII Values

	GHE	**BBHE**	**DSIHE**	**HS**	**RMSHE**	**MPSO**	**MOHE**	**MOPSO**	**MOPSO (avg.)**
Cameraman	0.8133	0.8478	0.8448	0.8780	0.8968	0.9234	**1.0000**	0.9996	0.9986
F16	0.8323	0.8470	0.8465	0.8693	1.0000	0.9125	**1.0000**	0.9993	0.9971
Truck	0.9217	0.9488	0.9253	0.9627	0.9726	0.9145	**1.0000**	0.9984	0.9958
Pirate	0.6710	0.6813	0.6813	0.7001	0.9078	0.9068	0.9846	**0.9995**	0.9973

Table 2 Comparison of Entropy Values

	Original	**GHE**	**BBHE**	**DSIHE**	**HS**	**RMSHE**	**MPSO**	**MOHE**	**MOPSO**	**MOPSO (avg.)**
Cameraman	7.0097	5.0000	6.8081	6.7792	6.7614	6.9259	**7.4211**	6.9787	7.4076	7.2566
F16	6.6744	5.7103	6.5877	6.5601	6.4533	6.4677	**7.9254**	6.6269	7.1172	6.8173
Truck	6.5461	5.8041	6.4384	6.4204	6.4693	5.8881	6.7852	6.5461	**7.0052**	6.8578
Pirate	7.3118	5.9842	7.2232	7.2223	7.2473	7.1627	7.6233	7.0167	**7.6335**	7.4962

CONCLUSION

This study was utilized PSO method as multi-objective in order to enhancing images. Pareto Optimal approach was used for obtaining multiple objectives as independent each other. Ideal solution was selected with PSNR among solutions in the Pareto Optimal surface.

MOPSO method produced very good outputs both in terms of CII and entropy. It also improved the quality and intelligibility of images noticeably while preserving the brightness of images.

The contribution of this study is using multiple objective as independent each other while obtaining images with PSO. Previous studies do not take objectives separately. Instead, objectives are used together as a single value. Some studies give weighting coefficients for objectives while the others use sum of objectives without any weight. This study, by utilizing Pareto approach, handles values for the two objectives separately. The particle with best PSNR among candidate solutions in the Pareto Optimal surface was selected as the leader for all particles. In this way, this method produced output image that is better than original image.

Especially, if details are significant, and preservation of brightness is necessary, MOPSO method can be preferred. The proposed approach could be developed for the different objectives apart from the two objectives in this study.

Fig. 1 Pirate Image. (a) Original, (b) HE, (c) BBHE, (d) HS, (e) RMSHE (r=2), (f) MPSO, (g) MOHE and (h) MOPSO

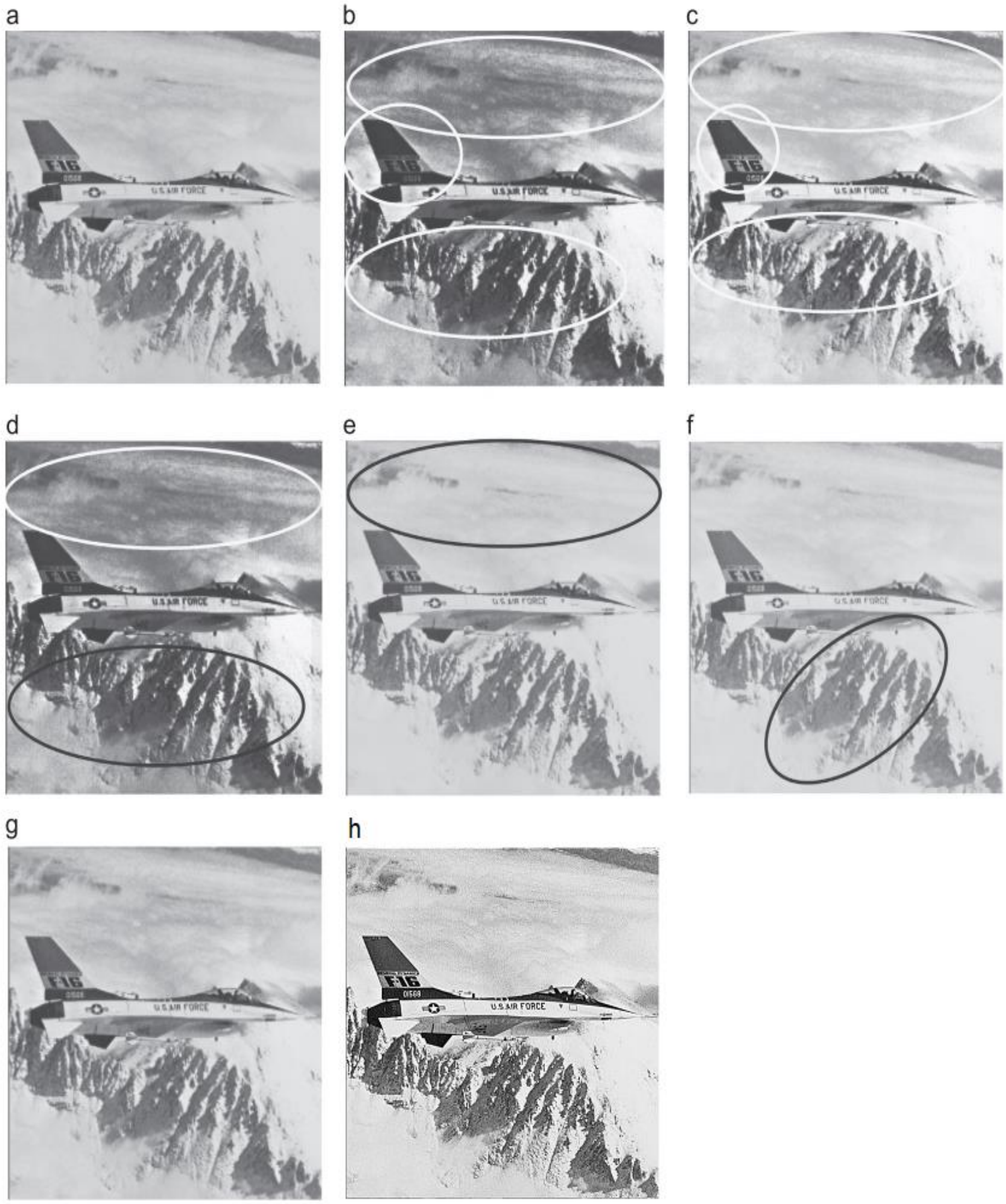

Fig. 2 F16 Image. (a) Original, (b) HE, (c) BBHE, (d) HS, (e) RMSHE (r=2), (f) MPSO, (g) MOHE and (h) MOPSO

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