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Parameter Optimization In Image Enhancement Using PSO

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Abstract: In this paper parameters of the transformation function is considered as an optimization problem and Particle Swarm Optimization (PSO) is used to solve it.(PSO) algorithms is a new approach for optimization. With intensity transformation function image enhancement is done by maximizing the information content of the enhanced image. In this work a parameterized transformation function is used, which uses local and global information of the image. Here an objective criterion for measuring image enhancement is used which considers entropy and edge information of the image. We tried to achieve the best enhanced image according to the objective criterion by optimizing the parameters used in the transformation function with the help of PSO. Results are compared with other enhancement techniques, viz. Histogram equalization, contrast stretching based image enhancement.

Keywords: *Particle swarm optimization, image enhancement and histogram equalization.*

I. INTRODUCTION

Image enhancement, one of the important image processing techniques, can be treated as transforming one image to another to improve the interpretability or perception of information for human viewers, or to provide better input for other automated image processing techniques. According to [16], image enhancement techniques can be divided into four main categories: point operation transformation, spatial operation, and pseudo coloring. The work done in this paper is based on spatial operation. Histogram transformation is considered as one of the fundamental processes for contrast enhancement of gray-level images [15], which facilitates subsequent higher level operations such as detection and identification. Linear contrast stretching employs a linear transformation that maps the gray-levels in a given image to fill the full range of values. Pseudo coloring is an enhancement technique that artificially ”color” the gray- scale image based on a color mapping, with the extensive interactive trials required to determine an acceptable mapping [16]. Color images can be enhanced by separating the image into the chromaticity and intensity components [17]. Majority of the image enhancement work usually manipulates the image histogram by some transformation function to obtain the required contrast enhancement. Consequently, this operation also delivers the maximum information contained in the image. Evolutionary algorithms have been previously used to perform image enhancement [1] - [5]. In [1], the authors applied a global contrast enhancement technique using genetic programming (GP) [11] to adapt the color map in the image so as to fit the demands of the human interpreter. In [2] a real coded GA is used with a subjective evaluation criterion to globally adapt the gray-level intensity transformation in the image. Combination of different transformation n functions with different parameters is used to produce the enhanced image by GA in [5].In this paper we have performed gray-level image contrast enhancement by PSO. In comparison to Linear Contrast Stretching (LCS) and Histogram Equalization (HE), PSO does not require selection, crossover and mutation operations. At the same time PSO takes less time to converge to a better optima. The resulted gray-level enhanced images by PSO are found to be better compared with other automatic image contrast enhancement techniques. Both objective and subjective evaluations are performed on the resulted image which says about the goodness of PSO.

The rest of the paper is organized as follows: In Section II, functions used for the proposed work (transformation and evaluation function) are described. In Section III, theory of PSO (basic PSO, proposed methodology, parameter setting) is discussed. In Section IV, results and discussions are put, and finally in Section V, conclusion of the work is made.

II. FUNCTIONS USED

For image enhancement task, a transformation function is required which will take the intensity value of each pixel from the input image and generate a new intensity value for the corresponding pixel to produce the enhanced image.

To evaluate the quality of the enhanced image automatically, an evaluation function is needed which will tell us about the quality of the enhanced image. In this section we describe the function used for the proposed work.

A. Transformation function

Image enhancement done on spatial domain uses a trans- form function which generates a new intensity value for each pixel of the MxN original image to generate the enhanced image, where M denotes the number of columns and N denotes the number of rows. The enhancement process can be denoted by :

$$g(x,y) = T\big(f(x,y)\big) \quad (1)$$

Where f(x, y) is the input image, g(x, y) is the output (processed) image, and *T* is an operator on *f* defined over a specified neighborhood about point (x, y). In addition, *T* can operate on a set of images, such as performing the addition of *K* images for noise reduction.

The principal approach for defining spatial neighborhoods about a point (x, y) is to use a square or rectangular region centeredat (x, y). The center of the region is moved from pixel to pixel starting, say, at the top, left corner, and, as it moves, it encompasses different neighborhoods. Operator *T* is applied at each location (x, y) to yield the output, *g*, at that location. Only the pixels in the neighborhood centered at (x, y) are used in computing the value of *g* at (x, y).

$$g(x,y) = K(x,y)[f(x,y) - c.m(x,y)] + m(x,y)^a \quad (2)$$

Where,*a* and*c* are the parameters whose value is to be optimized.
m(x, y) is local mean over a window of *n x n*.
$K(x,y)$Is enhancement function which takes both local and global information into account.
Expression for local mean and enhancement function are defined as:

$$m(x,y) = \frac{1}{nxn}\sum_{i=0}^{n-1}\sum_{j=0}^{n-1} f(i,j) \quad (3)$$

$$D = \frac{1}{M \times N}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)$$

The enhancement function $K(x,y)$ can be defined as:

$$K(x,y) = \frac{k.D}{\sigma(x,y)+b} \quad (4)$$

Where,*b* and *k*are the parameters to optimize.
D is the Global mean of the input image.
$\sigma(x,y)$is local Standard Deviation over a window of n x n

$\sigma(x,y)$is defined as :-

$$\sigma(x,y) = \sqrt{\frac{1}{M\times N}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\big(f(i,j) - m(x,y)\big)^2} \quad (5)$$

Hence, the complete transformation function is defined as follows:-

$$g(x,y) = \frac{k.D}{\sigma(x,y)+b}[f(x,y) - c.m(x,y)] + m(x,y)^a \quad (6)$$

With the transformation stated in eq. (6) contrast of the image can be stretched considering local mean as the centre of stretch. The last term $m(x,y)^a$ has brightening & smoothing effect thus smooths the output image and the four parameters introduced in the transformation function i.e. a, b, c & k are the parameters of the enhancement function and the small variation in their value produces a large variation in the processed output image and thus the value of these parameters should be precisely set. The approximate range of these parameters is defined as: a [0, 1.5]; b [0, (D/2)]; c [0, 1]; K [.5, 1.5].

A. Evaluation Criterion

In order to evaluate the performance of the proposed algorithm and the quality of an enhanced image without human intervention, we need an objective function which tells us about thequality of the output image. Many objective functions are presented in literature [45]-[47]. It is observed that compared to the original image good contrast enhanced image has more number of edgels i.e. number of edge pixels and enhanced version should have a higher intensity of the edges. But these two measures are not sufficient to test an enhanced image and that why one more performance measure is taken into account i.e. entropy value of the image. Entropy value reveals the information content in the image. If the distribution of the intensities is uniform, then we can say that histogram is equalized and the entropy of the image will be more. Thus, the objective function considered here uses three performance measures i.e. entropy value, sum of edge intensities value and number of edgels (edge pixels) and is defined as:-

$$F(I_{enh}) = log(log(E(I_c))) \times \frac{n(I_c)}{M \times N} \times H(I_{enh}) \qquad (7)$$

In the above mentioned equation I_{enh} is the enhanced image resulted from the transformation function defined above. In eq. 4.8 the edges or edgels can be detected by many efficient edge detector algorithms such as Sobel [1], Laplacian [1], Canny [5] etc. In this study Canny is used as an automatic threshold detector [15]. Canny's edge detection algorithm is computationally more expensive compared to Sobel, Prewitt and Robert's operator. However, the Canny's edge detection algorithm performs better than all these operators under almost all scenarios and thus in this work after using Canny edge operator we produce an edge image I_C.
$E(I_c)$is the sum of M x N pixels intensities of canny edge images. *n*is the number of pixels, whose intensity value is greater than a threshold in canny edge image. Entropy of the enhanced image I_{enh} is given by:-

$$H(I_{enh}) = -\sum_{i=0}^{1} e_i \qquad (8)$$

Where,

$$e_i = \begin{cases} h_i \, log_2(h_i), & h_i \neq 0 \\ 0, & otherwise \end{cases} \qquad (9)$$

III. THEORY OF PSO

PSO algorithm is a population based search algorithm based on the simulation of the social behavior of birds within a flock. The initial intent of the particle swarm concept was to graphically simulate the graceful and unpredictable choreography of a bird flock, with the aim of discovering patterns that govern the ability of birds to fly synchronously, and to suddenly change direction with a regrouping in an optimal formation.

B. PSO Algorithm

In PSO, individuals are referred to as particles, which are "flown" through hyper dimensional search space [49]. Change in the position of each particle within the search space is based on the social psychological tendency of particle to emulate the success of other particle. The change to a particle's position within the swarm is therefore influenced by the past experience, or by the knowledge of its neighbours. The search behaviour of a particle is thus affected by that of other particles within the swarm (PSO is therefore a kind of symbiotic cooperative algorithm). Particle Swarm optimization technique has mainly two primary operators:

- Velocity update
- Position update During each generation each particle is accelerated toward the particle's previous best position (pbest) and the global best (gbest) position and new velocity value for each particle is calculated based on:

✶ Its current velocity.
✶ The distance from its previous best position.
✶ The distance from the global best position.

The new velocity value is then used to calculate the next new position of the particle in the search space. In PSO, initially each potential solution is assigned a randomized velocity and is "flown" through the problem space. Each particle adjusts its flying according to its own flying experience and its companion flying experience.

$$v_i^{t+1} = w.v_i^t + c_1.r_1^t * [pbest_i^t - X_i^t] + c_2.r_2^t[gbest - X_i^t] \quad (10)$$

$$X_i^{t+1} = X_i^t + v_i^{t+1}$$

Where;
v_i^t is velocity of i^{th} particle at iteration t,
*w*is weight inertia.

c_1, c_2 is Acceleration Constants.
r_1, r_2 is random number between 0 and 1.
x_i^t is current position of i^{th} particle at iteration t,
pbest$_i$ is personal best of i^{th} particle,
gbest is global best value of the group.

C. Proposed Methodology

In the proposed method an enhanced image produced from a transformation function which incorporates both global and local information of the input image defined in eq. 4.7 is used. The function also contains four parameters namely a, b, c, k which are used to produce diverse result and help to find the optimal one according to the objective function. These four parameters have their defined range which is described above. Now our aim is to find the best set of values for these four parameters which can produce the optimal result and to perform this work PSO is used. P number of particles are initialized, each with four parameter a, b, c and k by the random values within their range and corresponding random velocities. It means position vector of each particle X has four component a, b, c and k. Now using these parameter values, each particle generates an enhanced image. Quality of the enhanced image is calculated by an objective function defined in eq. 4.8 which is termed as fitness of the particle. Fitness value of all the enhanced images generated by all the particles is calculated. From these fitness values pbest&gbest are found. In PSO the most attractive property is that pbest&gbest are found according to their fitness values. With the help of these best values, component wise new velocity of each particle is calculated to get the new solution. In this way new positions of particles are created for generations. When the process is completed the enhanced image is created by the global best (gbest) particle, as it provides the maximum fitness value and the image is displayed as the final result.
Main steps for PSO algorithm is as follows:

- Initialize number of particles with random position and velocity.
- Evaluate the fitness value for each particle.
- Evaluate gbest.
- Evaluate pbest.
- Update velocity & position.
- Evaluate the fitness value for new position
- If condition is fulfilled gbest is the solution else repeat above steps

The pseudocode for the proposed methodology :
Repeat
for i = 1 to number of particles **do**
if $G(X_i) > G(pbest_i)$ then G() evaluates goodness
for d = 1 to dimensions **do**
$pbest_i = X_i$ // $pbest_i$ is the best state found so far
end for
end if
gbest = i// arbitrary
for j = indexes of neighbours **do**
if $G(pbest_j) > G(gbest)$ then
gbest = j // gbest is the index of the best performer in the neighbourhood
end if
end for
for d = 1 to number of dimensions **do**
$V_i^t = f(X_i^{(t-1)}, V_i^{(t-1)}, pbest_i, gbest)$ //Update velocity
$V_i = (-V_{max}, +V_{max})$
$X_i^t = f(V_i^t, X_i^{t-1})$ //Update position
end for
end for
until stopping criteria
end procedure

D. Parameter setting

The result of PSO algorithm for image enhancement is very much parameter dependent and fine tuning of these defined parameters is required in order to get the better result than other optimization algorithms. Parameter *w* used in eq. 10 plays an important role in balancing the global & local search and is known as inertia weight. Maximum and minimum value for this is set to two and zero respectively, which is same for all particles. It may have fixed value throughout the procedure but in our case we start with maximum inertia value i.e. 2 and gradually reduce it to minimum. Therefore, initially inertia component is large and explore larger area in the solution space, but gradually inertia component becomes small and exploit better solutions in the solution space. Inertia value w is calculated as follows:

$$w_t = (w_{max} - w_{min}) \times \frac{t}{t_{max}} \quad (11)$$

Where, t is the i^{th}iteration and t_{max} is the total number of iteration. Parameters c_1&c_2 are positive acceleration constants, given a random number between 0 & 2. These parameters are fixed for each particle throughout its life. c_1 is also known as cognitive coefficient and it controls the pull to the personal best position while c_2 is known as social-rate coefficient and it control the pull to the global best position. $r_1$called cognition random factor & r_2 called social learning random factor. These are random numbers in [0, 1] and varies for each component of the particles in every generation. These have important effect on balancing the global & local search.

The experiment proves that the four parameter to be optimized i.e. a, b, c & k give better results if there values are selected in the following range $a \in [0, 1.5]$; $b \in [0, (D/2)]$; $c \in [0, 1]$; $K \in [.5, 1.5]$Where D is the global mean of the original image.

IV. RESULT AND DISCUSSION

The experimentation is done for the four images shown below. Results of the proposed method is compared with two other methods, namely (i)linear contrast stretching (LCS),(ii) histogram equalization (HE)

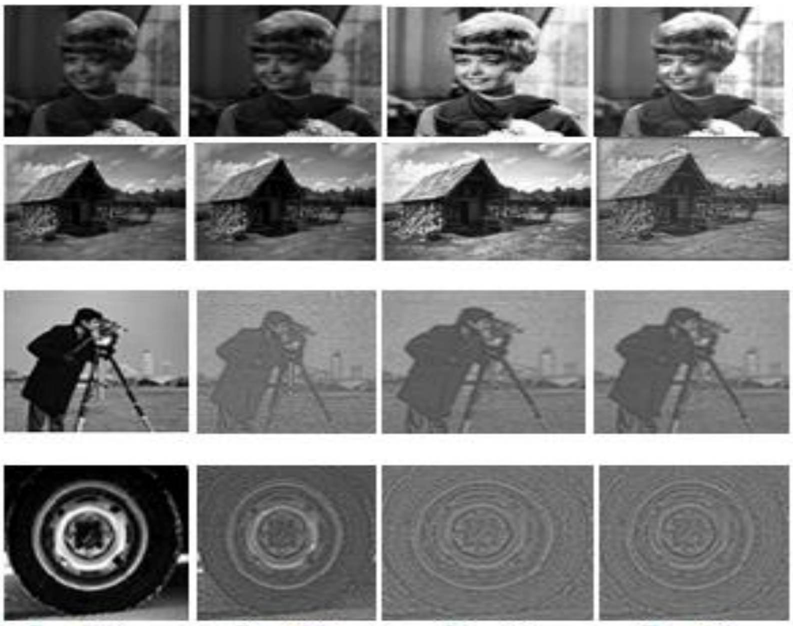

Figure (a): Original imageFigure (b): Image obtained by LCS Figure (c): Image obtained by HEFigure (d): Image obtained by PSO

DETAILSABOUTTHEORIGINALIMAGES
TABLE.1

IMAGE	SIZE	P/I/W	FITNESS		
			LCS	HE	PSO
Cameraman	256×256	30/20/5	0.51088	1.12475	1.9363
Hut	280×272	30/20/3	1.25004	1.90515	2.03482
Tire	205×232	30/20/7	0.42902	1.61869	2.38565
Angle	291×240	40/20/7	0.85795	1.70078	1.89644

P/I/W thirdcolumnofTable-1signify the number of particles maximum number of generation sand window size taken to extract the local information correspondingly.

V. CONCLUSION

Results of the proposed technique are compared with some other image enhancement techniques, like linear contrast stretching, histogram equalization based image enhancement. Most of the times it is observed that our technique is giving better result compared to other techniques mentioned above. In PSO, the most important property is that, it can produce better result with proper tuning of parameters. But in case of contrast stretching and histogram equalization, they always produce only one enhanced image for a particular. In this paper we have propose a PSO based automatic image enhancement technique for gray level images. In this paper we have propose a PSO based automatic image enhancement technique for gray level images VI .Acknowledgment

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