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IMAGE ENHANCEMENT BY PARTICLE SWARM OPTIMIZATION (PSO) TECHNIQUE

Ashish Verma[1], Neena Jaggi[2]

Department of Physics, NIT Kurukshetra, Haryana

ABSTRACT

Image enhancement is considered as an optimization problem and PSO is used to solve it. Image enhancement is mainly done by maximizing the information content of the enhanced image with intensity transformation function. The process is as follows. Image enhancement is considered as an optimization problem and Particle Swarm Optimization (PSO) is used to solve it. The quality of the intensity image is improved by a parameterized transformation function, in which parameters are optimized by PSO based on an objective function. Since there is always a trade-off between the requirements for the enhancement of contrast and preservation of intensity, an improved multi objective particle swarm optimization procedure is proposed to resolve this contradiction, making use of its flexible algorithmic structure. The effectiveness of the proposed approach is illustrated by a number of images including the bench-marks and an image sequence captured from a mobile robot in an indoor environment.

Keywords: Histogram equalization, Image enhancement, Particle swarm optimization.

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, spatial operation, transformation, and pseudocoloring. The work done in this paper is based on spatial operation. Histogram transformation is considered as one of the fun-damental processes for contrast enhancement of gray level im-ages [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. Pseudocoloring 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 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 functions with different parameters are used to produce the enhanced image by GA in

IJARSE
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[5]. In this paper we have performed gray-level image contrast enhancement by PSO. In comparison to GA, PSO does not require selection, crossover and mutation operations (for de-tails of PSO refer to [8]). 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 discussion are put, and finally in Section V, conclusion of the work are made.

A. 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.

TRANSFORMATION FUNCTION

Image enhancement done on spatial domain uses a trans-form function which generates a new intensity value for each pixel of the $M \times N$ 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

$$g(i, j)=T[f(i,g)] \qquad (1)$$

T is the transformation function. Local enhancement method apply transformation on a pixel considering intensity distribution among its neighboring pixels [14]. Adaptive histogram equalization (AHE) is one such local enhancement method which gives good result on medical images [16]. However AHE is quite expensive. The method used in this paper is less time consuming and is similar to statistical scaling presented in [16]. The function used here is designed in such a way that takes both global as well as local information to produce the enhanced image.

B. Evaluation Criterion

To evaluate the quality of an enhanced image without human intervention, we need an objective function which will say all about the image quality. Many objective functions are presented in literature [6] [7] [9]. In this study the objective function is formed by combining three performance measures, namely entropy value, sum of edge intensities and number of edgels (edge pixels). It is observed that compared to the original image good contrast enhanced image has more number of edgels [16] and enhanced version should have a higher intensity of the edges [4]. But these two are not sufficient to test an enhanced image and that is why one more measure has been taken i.e. entropy value of the image. Entropy value reveals the information content in the image. If the distribution of the intensities are uniform, then we can say that histogram is equalized and the entropy of the image will be more.

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THEORY OF PSO

PSO is an optimization algorithm proposed by J. Kennedy and R. C. Eberhart in 1995 [13]. This optimization algorithm is a multiagent based search strategy [18] [19] modeled on the social behavior of organisms such as bird flocking and fish schooling. PSO as an optimization tool, provides a population based search procedure in which individuals called particles change their position with time. In a PSO system, particles fly around in a multidimensional search space. During flight, each PSO as an optimization tool, provides a population based based search procedure in which individuals called particles. Particle adjusts its position according to its own experience, and the experience of its neighboring particles, making use of the best position encountered by itself and its neighbors. Thus, as in modern GAs and memetic algorithms, a PSO system combines local search with global search, attempting to balance exploration and exploitation.

A. Pso Algorithm

PSO algorithm is a population-based search algorithm based on the simulation of the social behavior of birds within a flock. In PSO, each single solution is a "particle". All of the particles have fitness values which are evaluated by the objective function to be optimized, and have velocities which direct the flying of the particles. The particles fly through the problem space by following the personal and global best particles.

The swarm is initialized with a group of random particles and it then searches for optima by updating through iterations. In every iteration, each particle is updated by following two "best" values. The first one is the best solution of each particle achieved so far. This value is known as $pbest$ solution. Another one is that, best solution tracked by any particle among all generations of the swarm. This best value is known as $gbest$ solution. These two best values are responsible to drive the particles to move to new better position.

After finding the two best values, a particle updates its velocity and position with the help of the following equations:

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

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

where X_t and v_t denotes the position and velocity of i_{th} particle at time instance t, W_t is inertia weight at t_{th} instant of time, c_1 and c_2 are positive acceleration constants, and r_1 and r_2 are random values generated in the range [0,1], sampled from a uniform distribution. $Pbest_i$ is the best solution of i_{th} individual particle over its flight path, $gbest$ is the best particle obtained over all generations so far.

B. Proposed Methodology

To produce an enhanced image a transformation function defined in eq. (7) is used, which incorporates both global and local information of the input image. The function also contains four parameters namely, a, b, c, and 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 mentioned in the parameter setting section. 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 parameters 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 components a, b, c, and k. Now using these parameter value, each particle generates an enhanced image. Quality of the enhanced image is calculated by an objective function defined

IJARSE
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in eq. (8) which is termed as fitness of the particle. Fitness value of all the enhanced images generated by all the particles are calculated. From these fitness values $Pbest$ and $gbest$ are found. In PSO the most attractive property is that $Pbest$ and $gbest$ are highly responsible to drive each particle (solution) to the direction of best location as it is reflected in the eq. (11) and eq. (12). In each step (iteration) a swarm of P number of new particles are generated. From every generation $Pbest$ and $gbest$ 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 $gbest$ particle, as it provides the maximum fitness value and the image is displayed as the final result.

Algorithm 1 PSO based image enhancement

Create P number of d dimensional particles. for Each Particle $i=1$ to P do

Initialize parameters a, b, c, k (randomly within their range) and corresponding random velocities.

end for

while (Termination condition $\neq$ true) do for each Particle $i=1$ to P do

Generate enhanced image using eq. (7). Calculate objective functional value using eq. (8). //Set $Pbest$ as the personal best solution of i_{th}

// particle achieved so far.

if $F((I_\epsilon)_i) > F(Pbest_i)$ then

$pbest_i = P_i$

// P_i is the i^{th} particle

end if

//Set $gbest$ as the global best solution achieved

// so far among all generation.

if $F((I_\epsilon)_i) > F(gbest)$ then

$gbest = P_i$

for Each Particle $i=1$ to P do Update the velocity using eq.(11). Update the position using eq.(12).

end for end while

II. RESULT

TABLE 1

gBest availability	8.656652862666801e+07
Entropy of original image	7.510809197565425
Entropy of modified image	5.258579426977620
Mean Optimized	1.942334782176612e+02

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Var optimzed	68.394242487814225
PSNR	24.730063790429856

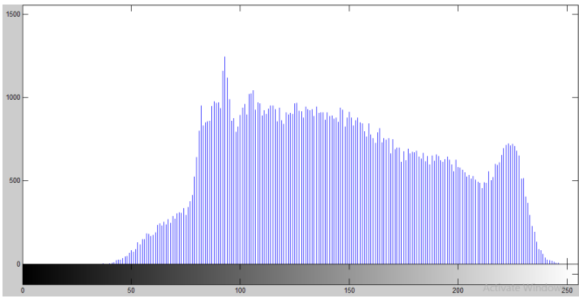
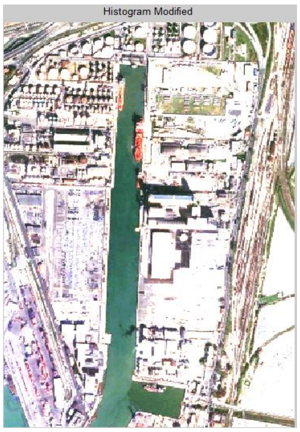


Figure 1: Orginal Image   Figure 2: Histogram Of Original Image



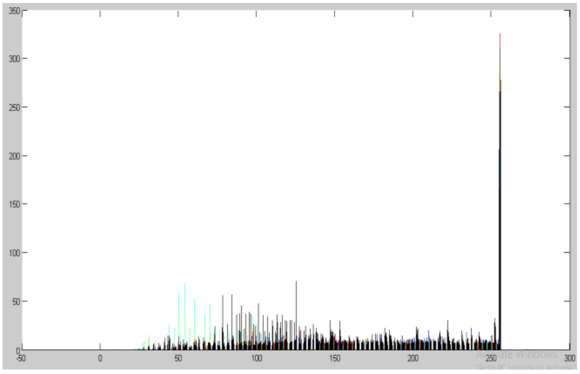


Figure 3: Pso Modified Image   Figure 4: Histogram Of Pso Modified Image

III. CONCLUSION

In this paper, we have proposed a PSO based automatic color image enhancement technique. Results of the proposed technique are compared with two other recent image enhancement techniques. For all the three images shown in this paper, it is observed that the proposed technique produces better results compared to other methods. In HPCIE technique pixels may get transformed to CMY color space without having gamut problem also. This technique is not adaptive with image type without human intervention. The proposed technique takes care of these points. In PSO, the most important property is that it can produce better results with fine tuning of parameters. At present there are many variants of PSO, we can try our proposed algorithm using these variants to improve the results further. We can also try with multi objective particle swarm optimization to improve the enhancement quality of color images considering other relevant objective function.

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