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De-Noising of Color Image by Removing Random Impulse Noise Using MATLAB

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Abstract: Visual information, transmitted in the form of digital images, has become a major method of communication for the 2[st] century. Digital Color Image de-noising is attracting more and more researchers to satisfy the user's demand. It is emerging as one of the simple and most appealing area among all the digital image processing techniques and is defined as the process of manipulating an image so as to highlight certain feature of interest. The aim of image enhancement is to improve the interpretability or perception of information in images for human viewers, or to provide better input for other automated image processing techniques. During last few decades, a number of methods have been proposed by researchers for de-noising of digital color images. However, de-noising of image quality is still a major concern and daunting to meet the expectations of users. In this paper, we carry out survey on various methods proposed by researchers and propose a de-noising method of digital color images using Particle Swarm Optimization (PSO). Experimental results obtained in this research show that PSO is an improvised method for de-noising of color images.

Index Terms: De-noising, Image Enhancement, Particle Swarm Intelligence (PSO).

I. INTRODUCTION

Spatial Domain refers to image plane itself, and approaches in the category are based on direct manipulation of pixels in the image. The spatial domain processes are denoted by the expression

$$G(x, y) = T[(f(x, y)] \quad (1)$$

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 a sequence images for noise reduction. The

These values are related by the expression of the form s = T(r) where T is the transformation that maps a pixel value r into a pixel value s. There are three basic types of functions used frequently for image enhancement that are image negative transformation, log transformation and power law transformation.

(i) Image Negatives This is the most basic and simple operation in digital image processing is to compute the negative of an image. The negative transformation for images with gray levels in the range [0, L-1] is given by

$$s = L - 1 - r \quad (2)$$

Reversing the intensity levels of an image in this manner produces the equivalent of a photographic negative. This type of processing is particularly suited for enhancing white or gray detail embedded in dark regions of an image, especially when the black areas are dominant in size.

(ii) Logarithmic Transformation

Logarithmic and contrast-stretching transformations are basic tools for dynamic range manipulation. Logarithm transformations are implemented using the expression

$$g = c \times \log(1 + r) \quad (3)$$

Where c is a constant and r is floating point.

(iii) Power Law Transformation

- *Power law transformation has the basic form $s = cr^{\gamma}$*

  Where c and γ are positive constants

  - The transformation is entirely controlled by γ
  - The transformation is similar to the log transformation but it is easier to be tuned.

II. LITERATURE SURVEY

A number of research papers have been proposed for digital color image enhancement and are as appended below:
"Perceptually Motivated Automatic Color Contrast Enhancement", Choudhury et al. [1] in 2009 addresses the problem of contrast enhancement for color images. Their method to enhance images was inspired from the Retinex theory and tries to mimic human color perception. This method helps in achieving color constancy and also results in color contrast enhancement. They express the intensity as a product of illumination and reflectance and estimate these separately. Enhancement is then applied to the illuminant component only. Non-local means filter was used to estimate the illuminant and then the enhancement of the illumination is performed automatically without any manual intervention and multiplied back by the reflectance to obtain enhancement.
"a new enhancement function was proposed to enhance the edges by contour let transform.
"Image contrast enhancement based on intensity- pair distribution" Cheng et al. [3] in 2005 proposed a new approach for contrast enhancement based on the use of a so called intensity pair distribution. This distribution possesses both local information and global information of the image content. By analyzing the content of intensity-pair distribution, a set of expansion forces are generated for contrast enhancement while another set of anti-expansion forces are generated to suppress image noise. To avoid over enhancement and preserve the natural look of the processed images, a magnitude mapping function was also proposed. Experimental results show that the proposed algorithm does provide a flexible and reliable way for advantages of global approaches, such as HE, and local approaches, such as AHE. The implementation of this approach was simple and the performance of enhancement was quite promising.
"Human Visual System-Based Image Enhancement and Logarithmic Contrast Measure", Panetta et al. [4] in 2008 introduces two novel image enhancement algorithms: edge-preserving contrast enhancement, which is able to better preserve edge details while enhancing contrast in images with varying illumination, and a novel multi-histogram equalization method which utilizes the HVS to segment the image, allowing a fast and efficient correction of non-uniform illumination. They then extend this HVS-based multi-histogram equalization approach to create a general enhancement method that can utilize any combination of enhancement algorithms for an improved performance. Additionally, they propose new quantitative measures of image enhancement, called the logarithmic Michelson contrast measure (AME) and the logarithmic AME by entropy.
"A New Contrast Enhancement Technique by Adaptively Increasing the Value of Histogram", Lei et al. [5] in 2009 proposes a simple contrast enhancement scheme named AIVHE. It provides a convenient and effective mechanism to control the rate of contrast enhancement by means of an adaptive parameter, $\alpha(k)$, and a user defined value, β. AIVHE offers a gradually increment by the mean brightness of the image to modify the original PDF.
"Image interpolation using constrained adaptive contrast enhancement techniques" Philips et al. [6] in 2005 presented a method for interpolating images that also preserves sharp edge information. They concentrate on tackling blurred edges by mapping level curves of the image. Level curves are spatial curves with constant intensity. The mapping of these intensities can be seen as a local contrast enhancement problem; therefore, they use contrast enhancement techniques coupled with additional constraints for the interpolation problem. A great advantage of this approach was that the shape of the level set contours were preserved and no explicit edge detection was needed there.
"Particle Swarm Optimization for Gray-Scale Image Noise Cancellation",Te-Jen et al. [7] in (2008) presented a method
algorithm is used to search the optimal parameters for the best enhancement.

III. BASICS OF PARTICLE SWARM OPTIMIZATION

Individuals in a particle swarm follow a very simple behavior to emulate the success of neighboring individuals and their own successes. The collective behavior that emerges from this simple behavior is that of discovering optimal regions of a high dimensional search space. A PSO algorithm maintains a swarm of particles, where each particle represents a potential solution.
These two algorithms are 1. Gbest 2. lbest

III.1 ***Global Best PSO***

For the global best PSO, or gbestPSO, the neighborhood for each particle is the entire swarm. The social network employed by the gbestPSO reflects the star topology. In star neighbourhood topology, the social component of the

particle velocity update reflects information obtained from all the particles in the swarm. In this case, the social information is the best position found by the swarm, referred to as $\hat{y}(t)$.
For gbest PSO, the velocity of particle *i* is calculated as

$$v_{ij}(t+1) = w.v_{ij}(t) + c_1.r_{1j}(t)[y_{ij}(t) - x_{ij}(t)c_2.r_{2j}(t)\hat{y}_j(t) - x_{ij}(t) \qquad (4)$$

Where, w is weight inertia. $v_{ij}(t)$ is the velocity of particle i in dimension j = 1, .. . ,n_x at time step t.

$x_{ij}(t)$ is the position of particle i in dimension j at time step t.

c_1 & c_2 are positive acceleration constants used to scale the contribution of the cognitive and social components respectively.

$r_{1j}(t)$&$r_{2j}(t) \in$ U (0, 1) are random values in the range [0, 1], sampled from a uniform distribution.

These random values introduce a stochastic element to the algorithm. The personal best position, y_i, associated with particle *i* is the best position the particle has visited since the first time step.

Considering minimization problems, the personal best position at the next time step, t + 1, is calculated as

$$y_i(t+1) = f(x) = \begin{cases} y_i(t), & f(x_i(t+1)) \geq f(y_i(t)) \\ x_i(t+1), & f(x_i(t+1)) < f(y_i(t)) \end{cases}$$

Where, f(x) is fitness function. The gbest$\hat{y}_j(t)$at any time step is equal to min {f(y_0(t)), . . . , f(y_{ns}(t))} and ns is number of particle in a swarm.

III.2 ***Local Best PSO***

The local best PSO, or lbest PSO, uses a ring social network topology where smaller neighbourhoods are defined for each particle. The social component reflects information exchanged within the neighbourhood of the particle, reflecting local knowledge of the environment. With reference to the velocity equation, the social contribution to particle velocity is proportional to the distance between a particle and the best position found by the neighbourhood of particles.

IV. Spatial Transform

As indicated previously, the term spatial domain refers to the aggregate of pixels composing an image. Spatial domain methods are procedures that operate directly on these pixels. Spatial domain processes will be denoted by the expression:-

$$g(x,y) = T[f(x,y)]$$

Where, f(x, y) is the input image, g(x, y) is the processed image, and T is an operator on f defined over some neighborhood of (x, y). In addition, T can operate on a set of input images, such as performing the pixel by pixel sum of K images for noise reduction, as the principal approach in defining a neighborhood about a point (*x*, *y*) is to use a square or rectangular sub-image area centered at (*x*, *y*), as Fig.1 shows.

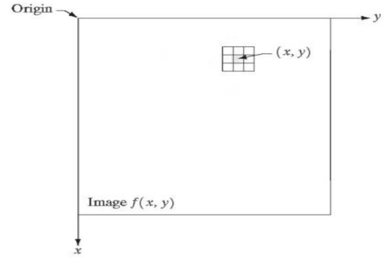

Fig.1: 3x3 neighborhood about a point (x, y) in an image

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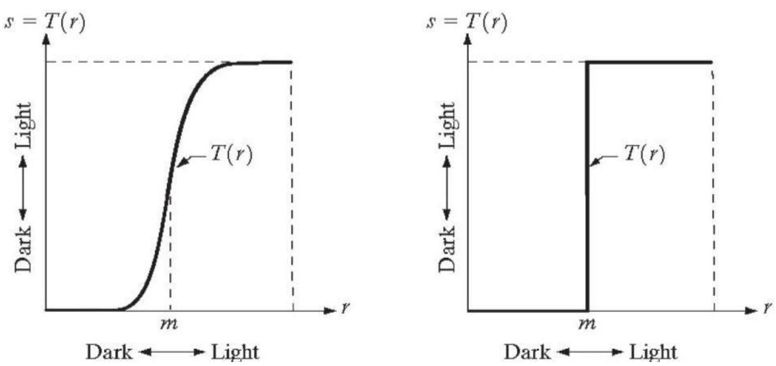
The centre of the sub-image is moved from pixel to pixel starting, say, at the top left corner. The operator T is applied at location (x, y) to yield the output „g" at that location. The process utilizes only the pixels in the area of the image spanned by the neighborhood. Although other neighborhood shapes, such as approximations to a circle, sometimes are used, square and rectangular arrays are by far the most predominant because of their ease of implementation.
The simplest form of T is when the neighborhood is of size l×l i.e. a single pixel. In this case, g depends only on the value of fat (x, y) and T becomes a gray level also called intensity or mapping transformation function of the form:

$$s = T(r)$$

Where, for simplicity in notation, r and s are variables denoting, respectively, the gray level of f(x, y) and g(x, y)at any point (*x*, *y*).



2(a) *2(b)* ***Fig. 2 (a) and (b) Gray level transformation functions for contrast enhancement***

For example, if T(r) has the form shown in fig. 2 (a), the effect of this transformation would be to produce an image of higher contrast than the original by darkening the levels below m and brightening the levels above m in the original image. In this technique, known as contrast stretching, the values of r below m are compressed by the transformation function into a narrow range of s, toward black. The opposite effect takes place for values of r above m. In the limiting case shown in fig.2 (b), T(r) produces a two level binary image. A mapping of this form is called a thresholding function. As enhancement at any point in an image depends only on the gray level at that point, techniques in this category often are referred to as point processing. Larger neighborhoods allow considerably more flexibility.
The general approach is to use a function of the values of f in a predefined neighborhood of (x, y) to determine the value of g at (x, y). One of the principal approaches in this formulation is based on the use of so called masks also referred to as filters, kernels, templates, or windows. Basically, a mask is a small say, 3×3 2-D array, such as the one shown in fig.1, in which the values of the mask coefficients determine the nature of the process, such as image sharpening. Enhancement techniques based on this type of approach often are referred to as mask processing or filtering.

V. Methodology

In PSO, individuals are referred to as particles, which are "flown" through hyper dimensional search space. 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 particles position within the swarm is therefore influenced by the past experience, or by the knowledge of its neighbours.
The complete transformation function is defined as follows:-

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

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. 10 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 as defined in eq. 10, which is termed as fitness of the particle. $F(I_{enh}) = \log(\log(E(I_c))) \times \frac{n(I_c)}{M \times N} \times H(I_{enh})$

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.

V.1 Algorithm of PSO based image denoising/enhancement.

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

V.II. **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. 8 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:

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

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 [0, 1.5]; b [0, (D/2)]; c [0, 1]; K [.5, 1.5].
This presents the simulation framework for the Gray Level image enhancement using PSO. The MATLAB simulation is carried for iterations = 200 certain specifications which is shown in Table.1:

Table.1: Fitness of Image

Image	Using PSO	Using HE
Cameraman	135.70	107.10
dad	250.56	240.32

A	B	C	KAPPA
1.21	0.65	0.44	0.73

VI. CONCLUSION

In this research paper, we have used Particle Swarm Optimization method for de-noising of digital color image. In our review, it is observed that various algorithms proposed by researchers are unique and also different types of filters are being used for de-noising. Our study found that PSO is one of the best emerging algorithms for de-noising of color image. The experimental results prove 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 [0, 1.5]; b [0, (D/2)]; c [0, 1]; K [.5, 1.5]. The MATLAB simulation is carried for iterations = 200 and optimized parameters are obtained. Results obtained show that PSO can be applied for de-nosing of digital color image and proves to be an emerging solution.
Further, the simulation framework for the image enhancement is done only using PSO. Other optimization methods on de-noising of color images will be compared in our future work.

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