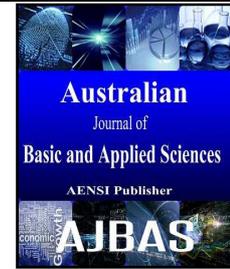




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An Efficient Method for Image Enhancement by Channel Division Method using Discrete Shearlet Transform and PSO Algorithm

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ABSTRACT

Image enhancement plays a vital role in image processing technique. This paper presents a Novel method for image enhancement by channel division method using discrete shearlet transform and particle swarm optimization algorithm. In this proposed algorithm, the RGB image converted into HSI (Hue, Saturation and Intensity) model, where as Intensity and Hue colour considered for Image enhancement after conversion. The Hue component decomposed into directional co-efficient by discrete shearlet transform. The higher directional coefficients are eliminated as it causes artifact and unnatural efforts in a image and the intensity components of image is contrast enhanced by using PSO Algorithm. The performance of the proposed image enhancement method is compared with existing histogram equalization and discrete shearlet transform based image enhancement. The result of the proposed method achieves satisfactory performance in visualization.

INTRODUCTION

Contrast enhancement, a process applied on image to increase their dynamic range. This can be done using several contrast image enhancement techniques. An effective and simple algorithm for this purpose is histogram equalization (Gonzalez, R.C., 2006). An improved version of histogram is adaptive histogram equalization techniques has been proposed (Laine, A., W. Hudu, 2000), which brings a limited improved, because fixed contextual regions cannot adapt to features of different size. To overcome this limitations another, more advanced enhancement algorithms Automatic weighting mean separated histogram equalization and is only suitable for gray scale image. Consequently, more complex method is the multi scale retinex (MSR) algorithm (Jobson, D.J., 1997). The fast version of the MSR (Jobson, D.J., 1997) is defined by

$$I_e = \sum_{n=1}^N (\log(I) - \log(LPF_n(I))) \quad (1)$$

Where LPFn(.) is the nth low pass spatial filtering function. I is the image to be enhanced, I_e is the enhanced image. Several methods are proposed (Orsini, G., 2003; Watanabe, T., 2005) to improve image enhancement by using MSR nevertheless, method based on the MSR have high computational complexity. Another widely used method is image enhancement by using Directional Wavelet Transform (Heric, D., B. Potocnik, 2006), which has two disadvantages of shift invariance and poor directional selectivity for diagonal features. Another efficient method is enhancement using Discrete Shearlet Transform (Premkumar, S., K.A. Parthasarathi, 2014) and is only enhanced the contrast colour of an image.

Different Genetic approaches have been applied for image contrast enhancement (Munteanu, C., A. Rosa, 2000; Gao Qinqing.). The proposed method in is based on a local enhancement technique. In this method transformation function is adapted using a genetic algorithm. In another genetic approach, the relations between

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input and output gray levels are represented by a lookup table (LUT) (Saitoh, F., 1999). These relations between gray levels are determined based on a curve by a Genetic Algorithm.

An novel particle swarm optimization approach is based on a Simulated Annealing PSO Algorithm, is used to find the best gray level to enhance the original image. In this paper we proposed an efficient method for contrast image enhancement method based on Discrete Shearlet Transform and PSO Algorithm.

This paper is organized as follows section II describes the channel division method, section III explains the PSO approaches for proposed method. Section IV gives an introduction to DST, Section V gives details of proposed approach is presented. Section VI presents results that illustrate the effectiveness of the method and compared with previous methods. Finally we conclude this paper in section VII.

Channel Division Method:

Channel division method is the process of merging the Local Contrast Indicator (LCI) i.e. grouping contrast pairs in to channels. To do this first the original image is split into regions of hue (H), saturation (S), intensity (I) using ad hoc transformation which is based on information from contrast of textured and boundary regions. Proposed algorithm is only applied to the Hue and Intensity (I) region and at the same time Saturation is maintained constant until merging. Contrast is coded by contrast pairs because of its inspiration so that it spreads over the dynamic range of intensities. Intensity channels are building blocks of region channel that can be used to control the interference and overlap of contrast pairs. In region channels, channels are grouped to simulate the human visual characteristics with a set of transformation functions which enhances the each image particular characteristics and merge the process results to reduce artifacts. To adjust final transformation for enhancing the image this method uses channel division and mixture process. Contrast pairs are used to model the intensity difference between two pixels.

Simulated Annealing PSO Algorithm:

A. Classical PSO algorithm:

PSO is an evolutionary computation algorithm - proposed by Kennedy and Eberhart in 1995 - which simulates birds' behavior of foraging. Similar to genetic algorithm, PSO is an optimization algorithm based on iteration. Compared with the genetic algorithm, PSO has the advantage of simple and easy to implement and there is no need to adjust many parameters. Now it is widely applied to optimization function, neural network training, fuzzy system control and other applications of genetic algorithms.

As an evolutionary computing, PSO algorithm can be calculated based on individual fitness of particles. In it, each optimization problem can be seen as the "particle" in the search space, and each "particle" has two properties: on the one hand, it has self-nature, which means that it can judge the speed and position of the flight according to self-experience; on the other hand, it has sociality - they can adjust their flight speeds and positions according to the flight of the surrounding particles. Therefore, "particles" look for the balance between personality and sociality in flight (Zhang Lili, 2007). Each particle has a adaptive value decided by optimized function and a speed which determines its flight direction and distance. After that, particles will be in iterative search for the optimal value following the current best particle in the n-dimensional space.

PSO initializes a group of random particles (random solutions), and then find the optimal solution through iteration. In each iteration, each particle updates itself by tracking the two "extreme ": the first is the optimal solution found by the particle itself (individual extreme pBest), the other is the best current solution sought out by the whole population (global extreme gBest). When finding these two optimal values, the particles update their own speeds and new locations according to the following formula.

Let $X_i = (x_{i1}, x_{i2}, \dots, x_{in})$ be the current position and $V_i = (v_{i1}, v_{i2}, \dots, v_{in})$ be the current speed for the particle i . In the process of evolutionary, the current best position is recorded as $P_i = (p_{i1}, p_{i2}, \dots, p_{in})$ among the history of the particle i , and the global best position of all particles is recorded as $P_g = (p_{g1}, p_{g2}, \dots, p_{gn})$. To improve the convergence, Y Shi and RC Eberhart firstly introduced inertia weight in rate evolution equation in 1998, so the PSO algorithm equation can be described as:

$$v_i(t+1) = \omega v_i(t) + c_1 r_1 (p_i(t) - x_i(t)) + c_2 r_2 (g(t) - x_i(t)). \quad (2)$$

$$x_i(t+1) = x_i(t) + v_i(t+1). \quad (3)$$

Where, ω is called inertia weight, used to achieve the balance between global search and local capacity of development. r_1, r_2 are random numbers and c_1, c_2 are learning factors.

In (9), the first part is the inertia velocity of the particle; the second part displays particle's judgments made by its own experience; the third part is the group's experience - sociality. The weight determines spatial search capabilities of particles.

B. Simulated Annealing:

SA, originally proposed by the Kirpatrick *et al*, can be used to solve combinatorial optimization problems, or NP complete problem. Taking random into account, this method makes the system "jump" out of local minimum, and it continues to search for global minimum search during searching for global minimum. If they may not "jump" local minimum, the local minimum will be the final results by the iterative search method (Fredric, M.).

During the optimization, simulated annealing firstly determines the initial temperature, and randomly selected an initial state and inspected the objective function value of the state. Secondly, a small perturbation is added on the current state and the objective function value of the new state is calculated. We will accept the good point with probability 1 and a lower point with probability P , as the current point until the system cooling. Simulated annealing may achieve the global optimum value with probability 1 when the initial temperature is high enough and the temperature dropped slowly enough. This method has the ability to jump out of local optimal solution because of acceptance its poor points at some probability.

C. Simulated annealing PSO algorithm:

Similar to other global optimization algorithms (e.g. genetic algorithm), PSO also exists the phenomenon of premature convergence, especially in the more complex multi-peak searching problems. Currently, it is the main method to solve this problem to increase the size of particle swarm. Although this is a certain improvement on algorithm performance, drawbacks remain equally. First, it can't overcome the fundamental problem of premature convergence; secondly it will roll up algorithm complexity.

Simulated annealing PSO algorithm takes particle swarm optimization algorithm as the main body and introduces simulated annealing mechanism. These better the ability of particle swarm optimization algorithm to get over the local minimum points and also improve the convergence speed and accuracy. The primary process, firstly, generates the initial population randomly, then updates the individual and global extreme of each particle, and then updates the position and velocity of each particle by equation of PSO algorithm. Finally, we will carry simulated annealing separately on the individual and make the results as the individual in the next generation groups (Gao Ying Xie Shengli, 2004).

D. Parameters and settings:

- c_1, c_2 are learning factors, usually setting $c_1 = c_2 = 2$.
 - Yet in rest literatures, there are other values, and generally, c_1 is equal to c_2 and both are between 0 and 4. c_1 reflects that the best location in particle's memory affects the flight velocity of the particle in flight, known as "cognitive factor"; c_2 reflects that the best position which the entire population of particles can remember in the flight affect flight velocity of particles, called "social learning factor".
- ω is called inertia weight, used to achieve the balance between global search and local development capacity. And Y Shi and RC Eberhart showed that it can get better results through experiments when ω decreases linearly with the increase of generation. Let ω_{\max} be the largest weighting coefficient, ω_{\min} be the minimum weighted coefficient, run be the current iteration and run_{\max} be the total number of iterations for the algorithm. There are:

$$\omega = \omega_{\max} - run (\omega_{\max} - \omega_{\min}) / run_{\max} \quad (4)$$

- Number of particles: generally 20 - 40. In fact, 10 particles have been enough to good results for most of the problems. But for the more difficult problems or specific categories of problems, the number of particles can take up to 100 or 200.
- Maximum speed V_{\max} : determine the largest distance particle can walk in a circular movement.
- Termination condition: the maximum number of cycles and the minimum error.
- The length of particles: determined by the optimization problem. That is the length of solutions. This is a, b, c and k.
- Range of particles: determined by the optimization problems, and each dimension can be set different ranges. Refer to (Zhang Lili, 2007),

$$a [0,1.5], b [0, 0.5], c [0,1], k [0.5,1.5].$$

Cooling temperature coefficient C : it is more probable to converge to the global optimal value at the probability 1 when C becomes smaller in the case that initial temperature T is high enough.

Discrete Shearlet Transform:

The proposed contrast image enhancement is based on new multi-scale directional representations called the shearlet transform introduced in. An $N * N$ image consists of a finite sequence of values, $\{x[n_1, n_2]_{n_1, n_2=0}^{N-1, N-1}\}$

where $N \in \mathbb{N}$. Identifying the domain with the finite group \mathbb{Z}_N^2 , the inner product of image $x, y : \mathbb{Z}_N^2 \rightarrow \mathbb{C}$ is defined as

$$(x, y) = \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} x(u, v) \overline{y(u, v)} \quad (5)$$

Thus the discrete analog of $L^2(\mathbb{R}^2)$ is $l^2 \mathbb{Z}_N^2$. Given an image $f \in l^2(\mathbb{Z}_N^2)$, let $\hat{f}[k_1, k_2]$ denote its 2D Discrete Fourier Transform (DFT):

$$\hat{f}[k_1, k_2] = \frac{1}{N} \sum_{n_1, n_2=0}^{N-1} f[n_1, n_2] e^{-2\pi i (\frac{n_1}{N} k_1 + \frac{n_2}{N} k_2)} \quad (6)$$

The brackets in the equations $[\cdot, \cdot]$ denote arrays of indices, and parentheses (\cdot, \cdot) denote function evaluations. Then the interpretation of the numbers $\hat{f}[k_1, k_2]$ as samples $\hat{f}[k_1, k_2] = \hat{f}(k_1, k_2)$ is given by the following equation from the trigonometric polynomial.

$$\hat{f}(\xi_1, \xi_2) = \sum_{n_1, n_2=0}^{N-1} f[n_1, n_2] e^{-2\pi i (\frac{n_1}{N} \xi_1 + \frac{n_2}{N} \xi_2)} \quad (7)$$

First, to compute

$$\hat{f}(\xi_1, \xi_2) V(2^{-2j} \xi_1, 2^{-2j} \xi_2) \quad (8)$$

In the discrete domain, at the resolution level j , the Laplacian pyramid algorithm is implemented in the time domain. This will accomplish the multi scale partition by decomposing $f_d^{j-1}[n_1, n_2], 0 \leq n_1, n_2 < N_j - 1$, into a low pass filtered image $f_d^j[n_1, n_2]$, a quarter of the size of $f_d^{j-1}[n_1, n_2]$, and a high pass filtered image $f_d^{j-1}[n_1, n_2]$. Observe that the matrix $f_d^{j-1}[n_1, n_2]$ has size $N_j * N_j$, where $N_j = 2^{-2j} N$ and $f_d^0[n_1, n_2] = f[n_1, n_2]$ has size $N * N$. In particular,

$$\hat{f}_d^j(\xi_1, \xi_2) = \hat{f}(\xi_1, \xi_2) V(2^{-2j} \xi_1, 2^{-2j} \xi_2) \quad (9)$$

Thus, $f_d^j[n_1, n_2]$ are the discrete samples of a function $f_d^j[x_1, x_2]$, whose Fourier transform is $\hat{f}_d^j(\xi_1, \xi_2)$. In order to obtain the directional localization the DFT on the pseudo-polar grid is computed, and then one-dimensional band-pass filter is applied to the components of the signal with respect to this grid. More precisely, the definition of the pseudo-polar coordinates $(u, v) \in \mathbb{R}^2$ as follows:

$$(u, v) = (\xi_1, \frac{\xi_2}{\xi_1}), \text{ if } (\xi_1, \xi_2) \in D_0 \quad (10)$$

$$(u, v) = (\xi_1, \frac{\xi_1}{\xi_2}), \text{ if } (\xi_1, \xi_2) \in D_1 \quad (11)$$

After performing this change of coordinates, $g_j(u, v) = \hat{f}_d^j(\xi_1, \xi_2)$ is obtained and for $l=1-2^j, \dots, 2^j-1$:

$$\begin{aligned} \hat{f}_d^j(\xi_1, \xi_2) &= V(2^{-2j} \xi_1, 2^{-2j} \xi_2) W_{jl}^{(d)}(\xi_1, \xi_2) \\ &= g_j(u, v) W(2^j v - l) \end{aligned} \quad (12)$$

This expression shows that the different directional components are obtained by simply translating the window function W . The discrete samples $g_j[n_1, n_2] = g_j(n_1, n_2)$ are the values of the DFT of $f_d^j[n_1, n_2]$ on a pseudo-polar grid. That is, the samples in the frequency domain are taken not on a Cartesian grid, but along lines across the origin at various slopes. This has been recently referred to as the pseudo-polar grid. One may obtain the discrete Frequency values of f_d^j on the pseudo-polar grid by direct extraction using the Fast Fourier Transform (FFT) with complexity $ON^2 \log N$ or by using the Pseudo-polar DFT (PDFT).

Proposed Method:

The proposed contrast image enhancement approach using DST and PSO is shown in Fig 1. It includes

- RGB to HSI Conversion
- DST Decomposition
- Intensity values are modified by Simulated annealing PSO Algorithm.
- DST Reconstruction
- HSI to RGB conversion

Fig 1. shows the DST and PSO based proposed image enhancement approach.

The input RGB image is initially, converted into HSI model. Further hue and intensity components are used as the inputs for the proposed resolution enhancement process. Hue is decomposed by DST at 2 levels with 2 directions, which produces five shearlet bands, includes four higher sub-bands and one lower sub-band. The decomposed lower frequency is alone taken into the account for inverse shearlet transforms. Then intensity values are transformed by using Simulated annealing PSO Algorithm. Finally, the HSI model (modified Hue by DST and modified Intensity values by PSO and preserved Saturation) which are converted into RGB model to obtain enhanced image.

Experimental Results:

In this section, to demonstrate the performance of the proposed algorithm, the proposed method is compared with other image enhancement techniques in terms of ability in contrast and detail enhancement, the proposed method to produce natural looking images. Histogram equalization, are contrast enhancement methods which are used for comparison. In this study, the proposed method was simulated on $512 * 512$ images and comparison of various enhancement is shown in Fig 2. Fig 2(a) Input Image, Fig. 2(b) Histogram equalization image result, Fig. 2(c) Discrete Shearlet transform result, (d) Proposed Technique result.

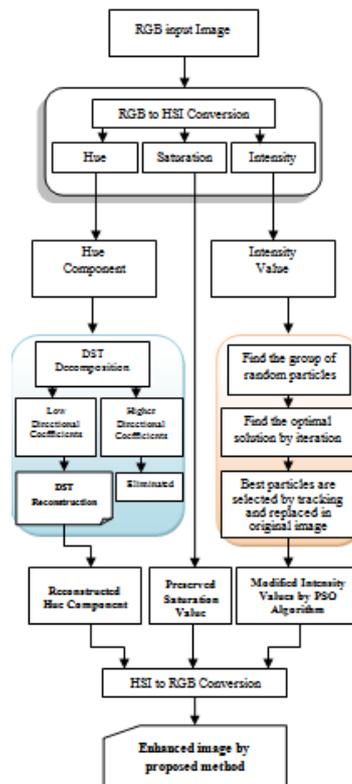


Fig. 1: Block diagram of the proposed image enhancement system using DST and PSO.

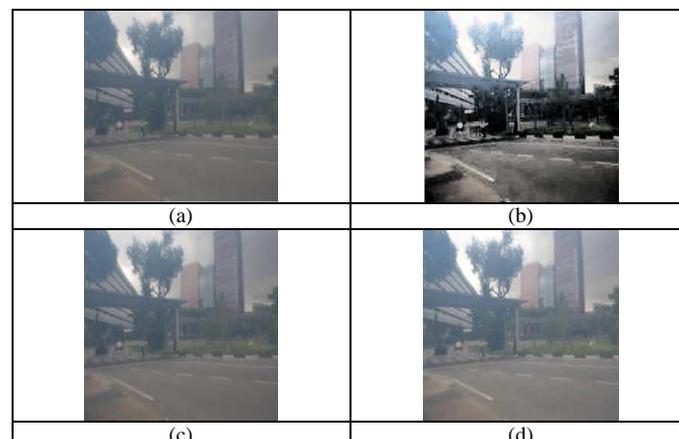




Fig. 2: Comparison of proposed technique with Histogram equalization method and DST (a) Input Image (b) Histogram equalization image (c) Discrete Shearlet transform (d) Proposed Technique

Conclusion:

A novel approach for image enhancement has been proposed in this paper based on discrete shearlet transform and Genetic Algorithm. Initially, the color image converted into HSI model. In order to improve the contrast of the image, the hue colour and intensity channels only considered. The shearlet decomposition produces low and high directional sub bands on the hue channel. The lower directional sub band is used for inverse shearlet transform to reconstruct the Hue channel. Intensity value is transformed by Genetic Algorithm and saturation is preserved. Then, the enhanced image is obtained by converting HSI to RGB model. The satisfactory result is achieved from the proposed DST and GA based image enhancement approach.

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