Color Image Enhancement Using Particle Swarm Optimization (PSO)

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ABSTRACT

Image enhancement is aimed to improve image quality by maximizing the information content in the input image. In this article a PSO based hue preserving color image enhancement technique is proposed. 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. The intensity transformation function uses local and global information of the input image and the objective function considers the entropy and edge information to measure the image quality. The enhanced color image is then obtained by scaling, which sometimes leads to gamut problem for few pixels. Rescaling is done to the saturation component to remove the gamut problem. The algorithm is tested on several color images and results are compared with two other popular color image enhancement techniques like hue-preserving color image enhancement without gamut problem (HPCIE) and a genetic algorithm based approach to color image enhancement (GACIE). Visual analysis, detail and background variance of the resultant images are reported. It has been found that the proposed method produces better results compared to other two methods.

I. INTRODUCTION

Optimization is a mathematical discipline that concerns the finding of minima and maxima of functions, subject to so called constraints. Optimization originated in the 1940s, when George Dantzig used mathematical techniques for generating "programs" (training timetables and schedules) for military application. Since then, his "linear programming" techniques and their descendents were applied to a wide variety of problems, from the scheduling of production facilities, to yield management in airlines. Today, optimization comprises a wide variety of techniques from operations research, artificial intelligence and computer science, and is used to improve business processes in practically all industries.

Discrete optimization problems arise, when the variables occurring in the optimization function can take only a finite number of discrete values. For example, the staff scheduler of a hospital unit has a finite set of staff members available, and thus staff scheduling consists of taking discrete decisions, one for each slot of the resulting schedule. Discrete optimization aims at taking these decisions such that a given function is maximized (for example revenue) or minimized (for example cost), subject to constraints, which express regulations or rules, such as required numbers of rest days for the staff in a schedule.

II. PSO METHODOLOGY

PSO: Particle Swarm Optimization

Particle Swarm Optimization was firstly introduced by Dr. Russell C. Eberhart and Dr. James Kennedy in 1995. As described by Eberhart and Kennedy [22], PSO algorithm is a population based search algorithm based on the simulation of the social behaviour 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. From this initial objective, the concept evolved into a simple and efficient optimization algorithm. In PSO, individuals, referred to as particles, are "flown" through hyper dimensional search space. Changes to the position of particles within the search space are based on the social psychological tendency of individuals to emulate the success of other Individuals. The changes to a particle within the swarm are therefore influenced by the experience, or 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). The consequence of modelling this social behaviour is that the search process is such that particles stochastically return toward previously successful regions in the search space.

Particle Swarm has two primary operators:

- Velocity update
- Position update

Global Best PSO

For the global best PSO, or *gbest* PSO, the neighbourhood for each particle is the entire swarm. The social network employed by the *gbest* PSO 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

$$v_{ij}(t+1) = w.v_{ij}(t) + c_1.r_{1j}(t)[y_{ij}(t) - x_{ij}(t)] + c_2.r_{2j}(t)[\hat{y}_j(t) - x_{ij}(t)] \quad (3.1)$$

Where, w is weight inertia.

$v_{ij}(t)$ is the velocity of particle *i* in dimension $j = 1, \ldots, n_x$ 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

$$y_i(t+1) = f(x) = \begin{cases} y_i(t), & f\big(x_i(t+1)\big) \geq f(y_i(t)) \\ x_i(t+1), & f\big(x_i(t+1)\big) < f(y_i(t)) \end{cases} \quad (3.2)$$

Where, f(.) is fitness function. The gbest $\hat{y}_j(t)$ at any time step is equal to min $\{f(y_0(t)), \ldots, f(y_{ns}(t))\}$ and ns is number of particle in a swarm. The gbest PSO is summarized figure 3.2

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.

Create and initialize an n_x – dimensional swarm;

repeat
  for each particle $i = 1.....n_s$ **do**
    // set the personal best position
    if $f(X_i) < f(Y_i)$ **then**
      $Y_i = X_i$;
    end
    // set the global best position if $f(Y_i) < f(\hat{Y})$ then
      $\hat{Y} = Y_i$;
    end
  end
  for *each particle* $i = 1,....,n_s$ **do**
    update the velocity
    update the position
  end
until *stopping condition is true*;

III. SIMULATION RESULTS

Original Image

Enhanced Image

IV. 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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