TV image enhancement technology based on particle swarm optimization

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Received 1 May 2014, www.cmnt.lv

Abstract

Television images can be blurred and indistinct by noises in the acquisition and transmission process. Traditionally, control parameters of fuzzy enhancement algorithm are manually controlled, which leads to poor enhancement effect and efficiency. In this work, particle swarm optimization (PSO), due to its fewer parameters and global optimization capability, is combined with fuzzy enhancement algorithm for the optimization of fuzzy enhancement parameters. Simulation results show that PSO can make television images clearer and highlight in certain features, thus improving the visual effect of television images.

Keywords: particle swarm optimization, fuzzy enhancement, image processing, fitness function

1 Introduction

Television image can be blurred and indistinct by noises in the acquisition and transmission process. Television image enhancement can improve the quality of television image and highlight certain features, thus making images clearer. There are three categories of image enhancement methods, namely fuzzy processing, frequency domain method and spatial domain method [1-3]. For these methods, transit point and saturation point are manually determined, which limits their application.

2 Image fuzzy processing

In 1981, S.K. Pal, et al [4-6] proposed a new membership function and fuzzy enhancement operator to enhance image contrast, and the algorithm steps are as follows.

Step 1: Due to different purposes of image enhancement, parameters F_e, F_d, $g_{\max}$ in the membership function are adjusted according to Equation (2). The set of μ_{mn} is the fuzzy characteristic plane; g_{mn} the maximum pixel value; F_e exponential fuzzy factor; F_d reciprocal fuzzy factor. These parameters determine the size of fuzziness.

Thus, appropriate fuzzy parameters F_e and F_d can effectively enhance the quality of images. When μ_{mn} = $G(g_c)$ = 0.5, the point calls transit point. Selection of parameters has close relationship with transit point g_c as below [7].

$$G_{mn} = \begin{cases} < 0.5 & g_{mn} < g_c \\ = 0.5 & g_{mn} = g_c \\ > 0.5 & g_{mn} > g_c \end{cases}, \tag{1}$$

F_d can be calculated through Equation (2) when transit point g_c and parameter F_e are determined.

Step 2: The image can be transformed from spatial domain to fuzzy domain by G-transformation.

$$\mu_{mn} = G(g_{mn}) = \left[1 + \frac{g_{\max} - g_{\min}}{F_d}\right]^{-Fe}, \tag{2}$$

$\mu_{mn} \to \mu'_{mn}$, the recursive correction membership of fuzzy enhancement operator, is calculated through Equation (3).

$$T(\mu_{mn}) = \begin{cases} 2 \cdot [\mu_{mn}]^2 & 0 \le \mu_{mn} \le 0.5 \\ 1 - 2 \cdot [1 - \mu_{mn}]^2 & 0.5 \le \mu_{mn} \le 1 \end{cases}. \tag{3}$$

The key of fuzzy enhancement is that operators increase the membership values μ_{mn} greater than 0.5, and decrease those less than 0.5, thereby reducing the fuzziness. Then fuzzy enhancement operator will create another fuzzy set based on fuzzy set G.

Step 3: Inverse transform G^{-1} generates new gray level g'_{mn} and transforms the image from fuzzy domain to spatial domain [9-10].

$$g'_{mn} = G^{-1}(\mu'_{mn}) = g_{mn} - F_d \left[(\mu'_{mn})^{\frac{-1}{F_e}} - 1 \right]. \tag{4}$$

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Original image

a) Original image

Enhance image

b) Fe=1,Fd=32

Enhance image

c) Fe=1,Fd=64

Enhance image

d) Fe=1,Fd=128

Enhance image

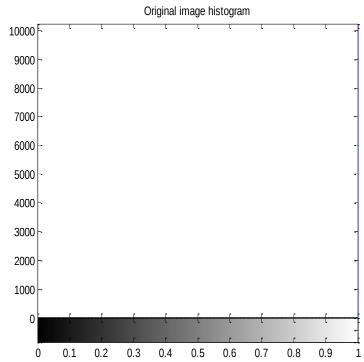
e) Fe=3,Fd=64

Enhance image

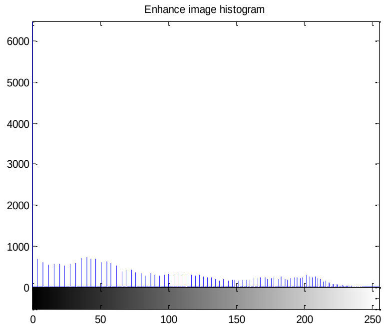
f) Fe=5,Fd=64

Enhance image

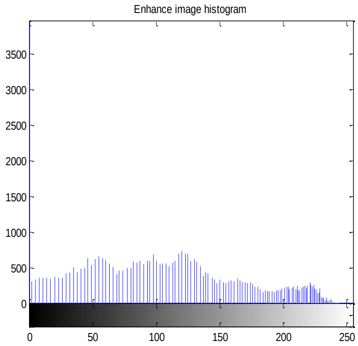
g) Fe=7,Fd=64



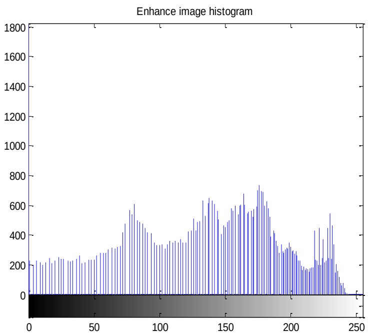
a’) Original image



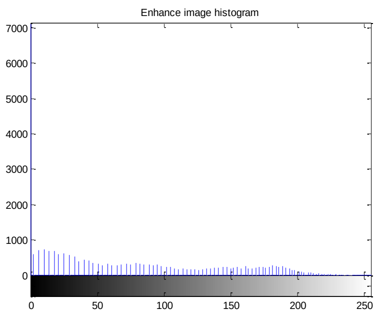
b') Fe=1,Fd=32



c') Fe=1,Fd=64



d') Fe=1,Fd=128



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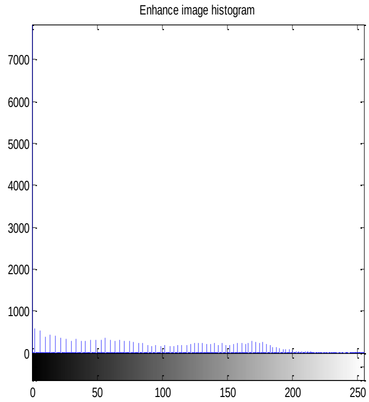
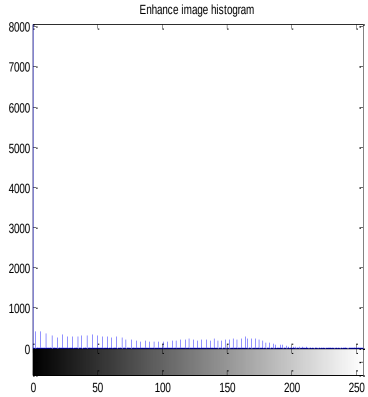


f')Fe=5, Fd=64



g') Fe=7, Fd=64

FIGURE 1 Different enhancement effect and histogram for different Fe and Fd

3 Particle swarm optimization (PSO)

3.1 ALGORITHM PRINCIPLE

PSO algorithm was firstly proposed by Kennedy, et al. for simulating the foraging behaviors of birds and achieving optimal results through collaboration and competition between groups. In PSO algorithm, each alternative solution calls a "particle", so after generating initial population, each particle is regarded as a feasible solution. Then fitness is determined by the objective function [11]. Each particle moves in the solution space, and the speed determines the direction and distance of movement.

Typically, the particle will follow the optimal particle and find optimal solution by iteration search. In each process of iteration, the particle follows two extremes to find the optimal solution for itself and the whole population.

3.2 MATHEMATICAL MODEL

For global optimization problem, a set of feasible solutions for the problem (p) is called as a population, where a feasible solution as a particle, and population size as the number of particles.

$$(P)\min\{f(x): x\in\Omega\subseteq R^n\},\ f:\Omega\subseteq R^n \to R^l . \tag{5}$$

The n-dimensional vector $X_i=(x_{i1},x_{i2},...,x_{in})^T\in\Omega$ is the position of i-th particle, and vector $V_i=(v_{i1},v_{i2},...,v_{in})^T\in\Omega$ the speed of i-th particle. During particles' movement in the search space, its best position is $P_{pi}=(p_{pi1},p_{pi2,},....,p_{pin})^T$. The index number g indicates the best position of all the particles, namely P_g. Thus, the velocity of particles in each iteration and the position evaluation function can be transformed by Equations (6) and (7), respectively [12].

$$v_{id}(t+1)=v_{id}(t)+c_1 rand_1\left(p_{pid}-x_{id}(t)\right)+ c_2 rand_2\left(p_{gd}-x_{id}(t)\right), \tag{6}$$

$$x_{id}(t+1)=x_{id}(t)+v_{id}(t+1), \tag{7}$$

where, $i=1,2,...,m$, $d=1,2,...,n$; $rand_1$ and $rand_2$ are subject to the distribution of $U(0,1)$; learning factors c_1 and c_2 are non-negative constants; for $v_{id}=[-v_{\max},v_{\max}]$, $v_{\max}$ is the speed limit set by users. Iterative algorithm is as follows:

Initialize population: random X_i
Repeat:
  For each particle $i\in[1,S]$
    If $f(X_i)<f(P_i)$
    $P_i=X_i$
  End
  If $f(P_i)<f(P_g)$
    $P_g=P_i$
  End
  Update the position and velocity of particle using Equations (6) and (7)
End
Until termination criterion is satisfied.

4 PSO fuzzy enhancement

4.1 Measurement of fuzzy enhancement

Main purpose of image fuzzy enhancement is to decrease information entropy, namely measuring the effect by comparing the information entropy before and after image enhancement. Entropy is defined in Equation (8).

$$H=-\sum_{i=1}^{256} p_i\log(p_i), \tag{8}$$

where p_i is the normalized histogram. Fuzzy entropy is defined in Equation (9).

$$1+\frac{1}{MN\ln 2}\sum_{i=1}^{M}\sum_{j=1}^{N}\left[S_n(\mu_{ij})\right], \tag{9}$$

where MN is the image size; S_n is Shannon function:

$$S_n=-\mu_A(x_i)\ln(\mu_A(x_i))-(1-\mu_A(x_i))\ln(1-\mu_A(x_i)). \tag{10}$$

4.2 Fitness function

Fuzziness entropy is a parameter describing the effect of image enhancement. Only reflecting the brightness of images, it has low insensitivity to the contrast, so some improvements are needed. The fitness function of improvement is in Equation (11).

$$Fitness(\mu)=\frac{\max(\mu_{ij})-\min(\mu_{ij})}{1+\frac{1}{MN\ln 2}\sum_{i=1}^{M}\sum_{j=1}^{N}\left[S_n(\mu_{ij})\right]}, \tag{11}$$

where, $\max(\mu_{ij})-\min(\mu_{ij})$ is the fuzzy contrast; $\max(\mu_{ij})-\min(\mu_{ij})$ are the maximum and minimum values of fuzzy feature plane, respectively. Larger $\max(\mu_{ij})-\min(\mu_{ij})$ makes the image clearer, while smaller fuzzy entropy Equation (9) makes the image clearer. Therefore, larger fitness function $Fitness(\mu)$ is good for the enhancement effect and image quality.

4.3 PSO FUZZY ENHANCEMENT ALGORITHM

A certain number of populations randomly generate during initialization, and corresponding $Fitness(\mu)$ of each population is calculated to find the maximum $Fitness(\mu)$ in the population. Then the velocity and position of particles can be updated according to PSO algorithm rules. After calculating for a given times of iteration, TV image fuzzy enhancement is conducted on parameters F_e, F_d corresponding to the obtained maximum fitness. The algorithm is as follows.

Step 1: Initialize the particle position and parameters;

Step 2: Calculate the corresponding $Fitness(\mu)$ of each population and compare the historical optimal value of individual particle with that of the population; if current value is superior to historical optimal value, then this value is retained, and the historical optimal value of individual particle or the whole population will be updated; on the contrary, the historical optimal value is retained;

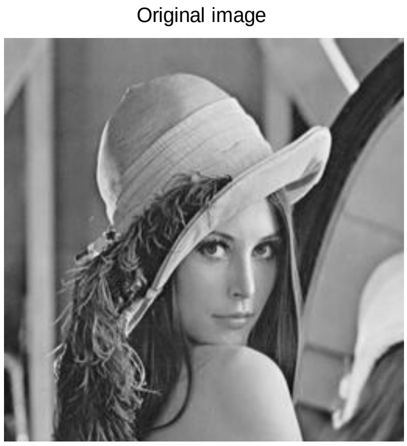
Step 3: Move particles to a new position according to the updation rules of particle position;

Step 4: If $Iteration < Maxgen$, then end the optimization; conversely, return to Step 2;

Step 5: TV image fuzzy enhancement is conducted with the fuzzy enhancement parameters F_e, F_d corresponding to the obtained maximum fitness $Fitness(\mu)$.

5 Simulation

In order to verify the proposed algorithm, the population size is set to 20, and $c_1 = c_2 = 2$, $v_{\max}$ =5. Three pieces of standard test images Lena.jpg, Cameraman.jpg and Baboon.jpg are the test objects for verifying the effect of PSO image enhancement. Results are shown in Figures 2-4.

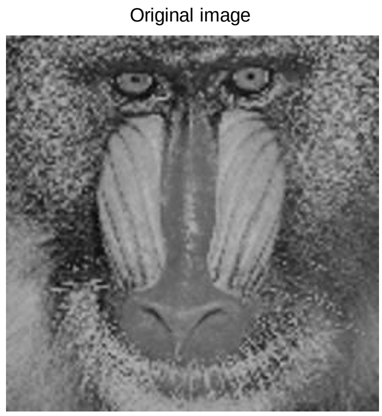


a) Lena.jpg

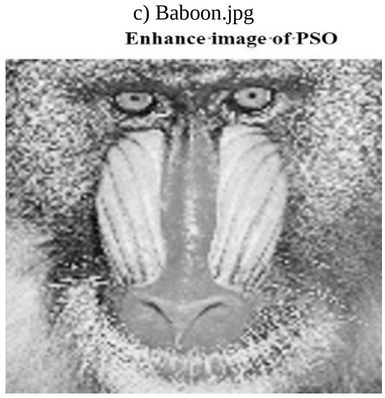
a’) Enhanced image

b) Cameraman.jpg

b’) Enhanced image

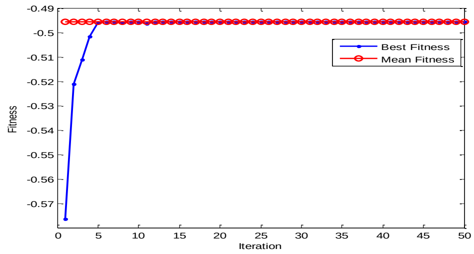


c) Baboon.jpg

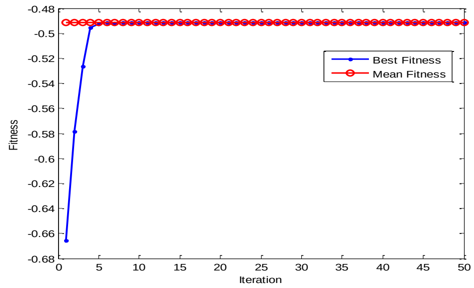


c’) Enhanced image

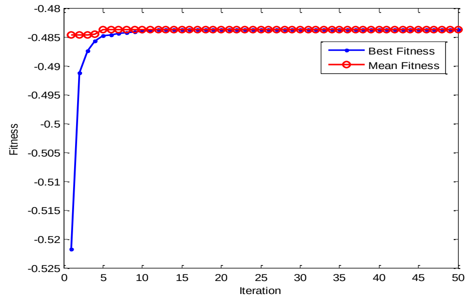
FIGURE 2 PSO fuzzy enhancement effect



a) Convergence curve of PSO fuzzy enhancement for Lena.jpg

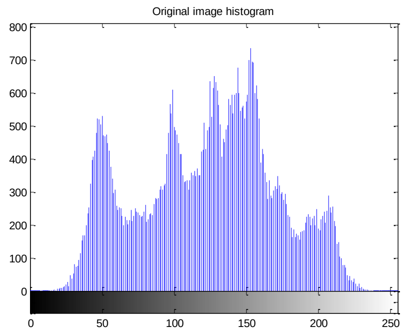


b) Convergence curve of PSO fuzzy enhancement for Cameraman.jpg

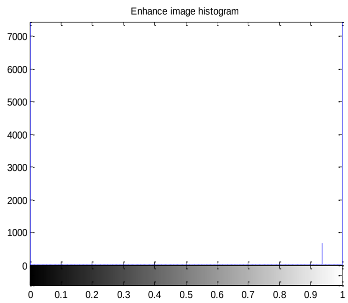


c) Convergence curve of PSO fuzzy enhancement for Baboon.jpg

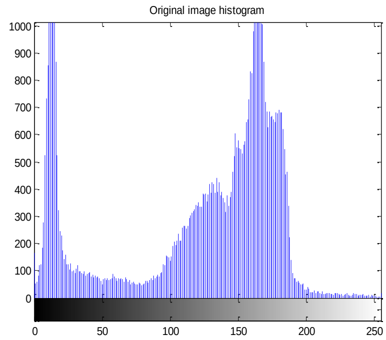
FIGURE 3 PSO Fuzzy Enhancement curve



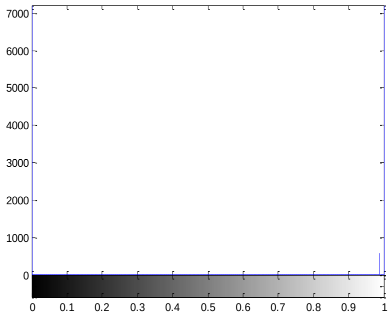
a) Initial histogram of Lena.jpg



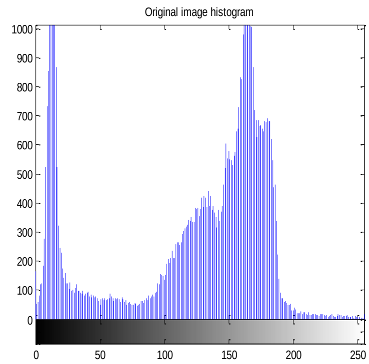
a') Histogram of enhanced Lena.jpg



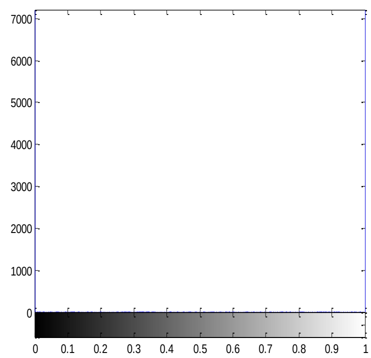
b) Initial histogram of Cameraman.jpg



b') Histogram of enhanced Cameraman.jpg



c) Initial histogram of Baboon.jpg



c') Histogram of enhanced Baboon.jpg

FIGURE 4 Comparison of the histogram before and after PSO fuzzy enhancement

Results of PSO fuzzy image enhancement prove that proposed algorithm can effectively highlight features of the image and improve visual effect. Besides, efficiency can be improved by avoiding manual adjustment of parameters, and the optimal fuzzy enhancement parameters are set after ensuring the best quality of images.

6 Conclusions

PSO algorithm, due to its excellent search performance, is combined with image enhancement algorithm for the optimization of fuzzy enhancement parameters F_e, F_d . And appropriate fitness function is built to achieve fuzzy enhancement of television image. Simulation results show that PSO has better effect in image enhancement than traditional methods, so it has certain practical value. Meanwhile, PSO algorithm can achieve self-adaption adjustment of fuzzy enhancement parameters, thus greatly improving the efficiency.

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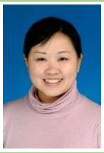

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