# Niche Particle Swarm Optimization Combined with Chaotic Mutation Application in Image Enhancement

Yu DONG, Lin-Lin ZHAO
Department of Automation and Electrical Engineering
Lanzhou Jiao Tong University
Lanzhou, Gansu, 730070
P.R.CHINA
Zhaolllzjtu@163.com

*Abstract:* **-** A niche chaotic mutation particle swarm optimization (NCPSO) algorithm is proposed to overcome the problem of loss details of images, the contrast is not obvious and poor adaptability in traditional image enhancement methods. In this algorithm, niching methods and elimination strategy are introduced to improve the global optimization ability. Mutative scale chaos mutation algorithm has refined local traversal search performance, which makes the algorithm has higher searching precision. The results indicate that image enhancement based on the algorithm has such advantage as image detail clearly, strong contrast and excellent versatility.

*Key-Words:* **-** Image enhancement; Niche particle swarm; Chaotic mutation; Particle swarm optimization

## 1 Introduction

In the image acquisition, transmission, and the process of sending and receiving, every step will suffer various limitations and multiple disturbance, which makes image become out of clarity, lower quality and other negative impacts, as a result, the image enhancement is an efficient method to solve problems above[1].

Image enhancement is an image analysis, identification and pre-processing method according to different applications, it is for the purpose of meeting requirements for specific application, highlighting interest areas in the image information, and suppressing or removing the other information. The goal of the method is to transform the original image information into a series of methods which are more suitable for the man-machine identification[2]. Therefore how to improvement the effect of the image enhancement is becoming an important topic in the area of image-processing .

According to different processing domain, the image enhancement method is generally divided into two major categories, they are spatial domain and frequency domain method. Frequency domain method is an indirect method based on modifying the Fourier transform of the image. It has disadvantages of large amount of calculation, and more artificial intervention during selects transform parameters. While spatial domain is a direct method based on image pixel processing, where, the nonlinear gray transformation becomes a commonly used method[3,4] because of its strong image contrast, broad dynamic range and other advantages. Tubbs put forward an incomplete Beta function aiming at gray image enhancement algorithm in spatial domain, which can completely cover image enhancement function type, but the parameters determination of Beta function is still a complex problem.

Based on particle swarm optimization (PSO)[5] algorithm and the chaos theory, a niche chaotic mutation particle swarm optimization (NCPSO) algorithm is proposed to determine the best parameters of nonlinear transformation. The algorithm combines chaos theory, niche technology and PSO algorithm, which can speed up the algorithm convergence, improves the population diversity, and eventually converges to the global optimal solution. Results show that the algorithm can adjust the transform parameters adaptively according to the nature of image gray scale, and enhanced image has a wide dynamic range, strong contrast and rich in detail.

## 2 Basic Particle Group Algorithms

PSO algorithm is an iterative optimization method. System is initialized to a group of random solutions, particles search in the solution space to follow the optimal particles. In the process of each iteration, the algorithm updates particles by tracking two extreme values: one is the optimal solution found by particles themselves, namely a local optimal solution; the other is the optimal solution found by entire population, which is called global optimal solution. The mathematical description and iterative formula is as follows: assumes that a function optimization problem is as follows

$$\min f(X), X=[x_1, x_2, \cdots, x_n]$$
$$\text{s.t.} x_i \in [a_i, b_i], i=1,2,\cdots,n \quad (1)$$

Where, $f(X)$ is objective function, $n$ is the dimensions of the independent variables $x_i$, $[a_i,b_i]$ is searching region of $x_i$.

PSO algorithm is iterative evolution technique based on swarm intelligence; each particle $x_i$. in the group represents a possible solution of objective function $f(X)$. Particle iterative computation formula is as follows[6]:

$$V_i[t+1]=\omega V_i[t]+c_1 rand(\cdot)(P_i - X_i) + c_2 rand(\cdot)(P_g - X_i) \quad (2)$$

$$X_i[t+1]=X_i[t]+V_i[t+1] \quad (3)$$

Where, $V_i=[V_{i1},V_{i2},\ldots,V_{in}]$ is the speed of particle $i$ it represents the distance between present position and the next target position of the particle $i$, $X_i=[X_{i1},X_{i2},\ldots,X_{in}]$ is the current position of the particles $i$; $P_i$ is the optimal solution of particles $i$ has been searched for so far; $P_g$ is the optimal solution of the entire group; $c_1$ and $c_2$ are acceleration factors, to control the speed of particles tracking to extreme value, usually the value is 2; $\omega$ is the inertial factor, it is used to control the influence of last step speed on the next step; *rand* is the random number between [0, 1], the particle swarm iterates according to the above type, stops and outputs the results until to search for a satisfactory solution or to a certain search algebra.

# 3 Niche Particle Swarm Algorithm Based on Chaotic Mutation

## 3.1 The RCS Niche Evolution Strategy

Niche strategy can effectively solve multimodal function optimization problems, so it is widely used in evolutionary algorithm. In the existing algorithm, niche technology is mainly using exclusion method and sharing method. The two methods all need more individuals to participate in the competition for sharing resource, which causes the waste of time to a large extend. The RCS[7] strategy is proposed as the basis of niche construction in this paper, which can be realized by several individuals. Through control the exclusion and competition between species, the algorithm makes each population form their own independent search space dynamically during the evolution, thereby to realize synchronous search on multiple local minima and to avoid the premature convergence of the algorithm.

In PSO algorithm, each particle is chasing for the best individual in population, in other word; it is the best individual in the population that controlled the searching direction of the whole population. For this reason, RSC strategy only controlled the best individual in the population so that it can decrease the step of the iteration and increase the speed of the calculation.

The implementation of RCS niche algorithm is as follows: assume that population of PSO algorithm is consisted of N subpopulations, the best individual of each species is $P_{nbest}$.

Step1: For $i$=1 to $N$=1, For $j$=$i$+1 to $N$;

Step2: When $d_{ij}$ (the distance between the two optimal individual $P_{ibest}$ and $P_{jbest}$ ) < $R_{niche}$ (niche radius), compare the fitness of the best two niche individuals, then set the smaller to zero and the bigger remain the same;

Step3: The best individual which set to zero should be reinitialized, and reselect the best individual in its own niche range, return to step1, until each niche has the best individual.

In the algorithm, the niche radius $R_{niche}$ defines the independent searching space of each species, once a niche optimal individual enter into the searching space of other niche, then reset the individual, and reselect the best individual in its own niche. So that each child population niche naturally forms different independent searching space, chases different local optimal solution, and effectively solves the defects of standard PSO algorithm that it easily traps into local optimum.

## 3.2 Mutative Scale Chaos Variation

Chaos is a kind of nonlinear phenomenon widely exists in nature, which have the merits of randomness, ergodicity, and sensitivity to initial conditions and so on, and it is widely applied in the fields of random optimization, local optimization, etc. The chaotic mapping logistic iterative equation used in this paper is as follows

$$\beta_j^{k+1}=\upsilon\beta_j^k(1-\beta_j^k), k=1,2,\cdots \quad (4)$$

$$\beta_j \in (0,1), \beta_j \neq 0.25, 0.5, 0.75 \quad (5)$$

Where, $\beta_j$ is the $j$th chaotic variable of particle $X_i$. When $\upsilon$=4, Logistic equation fully enters into a state of chaos.

During the optimization, the chaotic iteration variations are carried out for optimal individual of each child population and the variation spaces of them narrowing with the increase of the number of iterations. The chaotic iteration mutation is operated for the best individual $P_{ibest}=[X_1,X_2,\ldots,X_n]$ of the $j$th child population, the steps are as follows:

Step1: Assume $\beta_j^k$ , $k$=1;

Step2: Get $\beta_j^k$ through Logistic iterative equation;

Step3: Variation scales are obtained by the following formula

$$P_c = x_{jmin} + \beta_j^{k+1}(x_{jmax} - x_{jmin}) \tag{6}$$

Step4: Get new location of variable $x_i$ by following formula

$$x_j^{k+1} = (1-\lambda_g)x_j^k + \lambda_g P_c \tag{7}$$

Step5: Recalculate the fitness value of $P_{ibest}$ , if the new fitness value is more than original fitness value or a certain number which chaos iteration reaches, then stop chaos search, otherwise turn to step2.

$\lambda_g$ is the contraction factor, it determines the mutation space of variable $x_j$, it is obtained by follow formula

$$\lambda_g = 1-((g-1)/g)^m \tag{8}$$

Where, g is evolution algebra of particle swarm, $m$ is used to control the shrinkage rate.

From the formula(8), we can see the searching space of the optimal particle variable $P_{ibest}$ narrowing around the niche pole with the increase of algebra. In this way, the scale is large in early evolutionary stage, it is beneficial for the algorithm to search the global optimal solution in the broad space, while in the late evolutionary stage, mutation scale is small, the algorithm fine searches in small space closely around local extreme value, it is in favor of improving the precision and accelerating the speed of search.

### 3.3 Niche Particle Swarm Algorithm Based on Chaotic Mutation

Combining advantages of global optimization of niche strategy and fine search of mutative scale chaos variation, this paper proposes a new particle swarm optimization algorithm with population selection strategy; it is combined with sub-population competition strategy of niche well. In the operation, at first, the RCS competition strategy is used to make each niche to form independent searching space, and to chase different extreme values, then in every certain algebra, randomly initialize the worst sub-population fall into local optimum. This can not only make the population evolve forward in constant competition and update, but also can avoid the problems of algorithm to premature convergence, get into local optimal, etc, so that the algorithm can guarantee the convergence to the global optimal and make the niche population without update will continue to evolve, ensure the continuous improve of searching precision.

In PSO algorithm, the inertia factor $\omega$ has a great influence on the performance of the algorithm, a larger $\omega$ is beneficial to a wide searching range, and will make the population jump out of local extreme points, but it also will lengthen the searching time; while a small $\omega$ will have an advantageous of rapid convergence speed, but is easy to trap into local optimum. This article adopts the adaptive adjustment strategy[8], along with the iteration, dynamically diminishing the value of $\omega$ according by the following formula:

$$\omega = \omega_{\max} - g\frac{\omega_{\max} - \omega_{\min}}{T_{\max}} \tag{9}$$

Where, $\omega_{\max}$ and $\omega_{\min}$ are the maximum and the minimum value of $\omega$, $g$ is the current algebra, and $T_{\max}$ is the iteration stop algebra.

The implementation of NCPSO algorithm is as follows:

Step1: Initialize the niche particle population;

Step2: Calculate the particle fitness, and find out the optimal particle in each species niche;

Step3: Carry out RCS niche to eliminate choice evolutionary strategy; determine the best individual in independent searching space of each niche;

Step4: If the number of iterations reaches a certain algebraic, to update and reinitialize the worst niche child population;

Step5: Do mutative scale chaos variation for all optimal individual, to further improve the search precision;

Step6: Optimize every niche populations independently with PSO;

Step7: If satisfy the end condition, stop iteration, and output the optimal solution, otherwise, turn to step2.

## 4 Image Enhancement Process

If the non-linear image noise is processed according to the linear, the enhancement effect will unfit for human visual effect, only according to the nonlinear processing method can achieve good effect. The nonlinear transformation form of image pixel gray is

$I'(x,y)=F[I(x,y)]$, where $I'(x,y)\in[0,255]$ is the gray value of output enhanced image pixel dot $(x,y)$, $I(x,y)$ is grey value of fuzzy image pixel dot $(x,y)$, $F(\ )$ is a nonlinear transformation function, which can able to completely cover bright, dark and middle area of image which need to be enhanced[9]. $F(u)$ can be transformed and enhanced as

$$F(u)=B^{-1}(\alpha,\beta)\times\int_0^u t^{\alpha-1}(1-t)^{\beta-1}\mathrm{d}t \tag{10}$$

Where, $0<\alpha$, $\beta<10$, $B(\alpha,\beta)$ is a non-complete Beta function

$$B(\alpha,\beta)=\int_0^1 t^{\alpha-1}(1-t)^{\beta-1}\mathrm{d}t \tag{11}$$

Different values of $\alpha$ and $\beta$ can get different transformation curves, de-noising and enhancing the different gray scale region of image. When $\alpha<\beta$, de-noising and enhancing the dark area of fuzzy image, when $\alpha=\beta$, de-noising and enhancing the intermediate region, and when $\alpha>\beta$, de-noising and enhancing the bright area.

The enhancement process of fuzzy image $I(x,y)$ is as follows, at first, normalizing the image grey value

$$g(x,y)=\frac{f(x,y)-L_{\min}}{L_{\max}-L_{\min}} \tag{12}$$

Where, $L_{\max}$ and $L_{\min}$ are the maximum and the minimum value of the image grey.

Transpose the $g(x,y)$

$$g^{'}(x,y)=F[\mathrm{g}(x,y)] \tag{13}$$

Different values of $\alpha$ and $\beta$. will get different enhancement effect, only when the $\alpha$ and $\beta$ is the best group, will get the best enhancement effect of fuzzy image, through niche chaotic mutation particle swarm algorithm to optimize and achieve the best value of $\alpha$ and $\beta$ in fuzzy image enhancement, the optimal value got after optimization corresponding to the distribution uniformity of image gray. Enhanced image function after the optimization is

$$I^{'}(x,y)=(L_{\max}-L_{\min})g^{'}(x,y)+L_{\min} \tag{14}$$

The image grayscale range after enhancement is

$$[L_{\min}(1-\left|\frac{\alpha-\beta}{\alpha+\beta}\right|),L_{\max}(1+\left|\frac{\alpha-\beta}{\alpha+\beta}\right|)] \tag{15}$$

Where, $\alpha\leq\beta$ which expand the gray area of the image.

Take fitness function $f(n)$ as evaluation standard of image quality

$$f(n)=\sum\sum f^2(x,y)-\sum\sum f^{'2}(x,y) \tag{16}$$

Where, $n$ is the number of particles. The greater the fitness function $f(n)$ is, the more uniform the grayscale distribution is, and the contrast ratio and image quality become higher after fuzzy image enhancement.

The algorithm process is as follows:

Step1: Input image and normalize gray scale;

Step2: Search for optimal value of $\alpha$ and $\beta$ according to the niche chaotic mutation particle swarm optimization algorithm;

Step3: Update the iteration, when meet the conditions of fitness function, determine the optimal $\alpha$ and $\beta$, terminate the iteration and turn to step4, otherwise turn to step2;

Step4: Renormalize and output the image.

Step3 is the key of algorithm process, the initial particle solution is given as random value $\alpha$ and $\beta$, calculate the fitness of particles corresponding to $\alpha$ and $\beta$, repeats the local search, until meet the fitness function of the image quality, and ultimately determine the optimal value of $\alpha$ and $\beta$.

# 5 Experiment Simulations

To test effect of image enhancement based on niche chaotic mutation particle swarm optimization, image processing is implemented in MATLAB R2009b simulation environment from two aspects of subjective visual effect comparison and objective quality evaluation to examine the algorithm.

## 5.1 Subjective visual contrast

The "tree" and "girl" image in standard image library are enhanced using unsharp masking method, histogram equalization method and algorithm proposed[10,11] in this paper, respectively. the enhancement effect is shown in figure 1 and figure 2.

Figure 1 original visual effects are dim and blurred edges, and image by the sharp masking process is so dim that contrast is not strong. Image histogram equalization treatment is evenly distributed, but the dark is not obvious. The image processed by the algorithm in this paper has high contrast and is rich in detail. Figure 2 original visual effects are bright side, but the use of post-processing algorithm, the image gray is so wider in dynamic ranges that the dark details is performing significantly and improving the image contrast to reaching better image enhancement effect.

Niche chaotic mutation particle swarm optimization proposed in this paper is adopted to calculate the optimal solution of parameters $\alpha$, $\beta$ of the incomplete Beta function, and the optimal transformation parameters are shown in table 1[12].

The optimum gradation transformation curve of figure trees and girl are shown in Figure 3 which is adopted from table 1. The abscissa is the original image pixel gray value and the vertical axis is a gradation transformed image pixel gray values , which coordinate units are 1.

(a) The original image (b) unsharp masking method

(c) histogram equalization (d) proposed method

Fig.1 Enhancement effect comparison of trees

(a) The original image (b) unsharp masking method

(c) histogram equalization (d) proposed method

Fig.2 Enhancement effect comparison of girl

Tab.1 The best transforms parameters in the proposed algorithm

| Name | Size | $\alpha$ | $\beta$ |
|---|---|---|---|
| trees | 292*29 | 3.82 | 7.04 |
| girl | 471*47 | 9.11 | 4.27 |

It can be seen from figure 3, when $\alpha$=3.24 and $\beta$=7.51, a small number of lower grey values are below the function $y=x$, while, most of the higher grey values are above the function $y=x$, it illustrates that the original image is darker, It is necessary to stretch the darker areas of the original image, make the image gray scale range distribution more uniform; When $\alpha$=4.81 and $\beta$=7.24, most of lower grey values are below the function $y=x$, while, a small number of the higher grey values are above the function $y=x$, which indicates that the original image is brighter, therefore, in order to improve the visual effect, it needs to stretch the brighter areas of the original image.

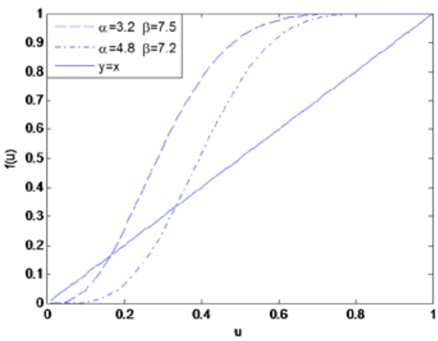


Fig.3 The gray level transformation curves of trees and girl

## 5.2 Objective Quality Evaluation

In this paper, the average evolutionary generation, the average running time and no global optimal solution rate are selected as the index, to reflect the speed of the algorithm convergence and the ability to converge to the global optimal solution[13,14].

Tab.2 The evaluation standard of trees

| Evaluation index | Original image | Unsharp masking | Histogram equalization | NCPSO |
|---|---|---|---|---|
| mean | 44.805 | 68.445 | 91.652 | 80.189 |

| | | | | |
|---|---|---|---|---|
| Standard deviation | 38.165 | 57.739 | 59.186 | 74.316 |
| Entropy | 6.697 | 7.322 | 7.682 | 7.472 |

Tab.3 The valuation standard of girl

| Evaluation index | Original image | Unsharp masking | Histogram equalization | NCPSO |
|---|---|---|---|---|
| mean | 48.904 | 64.772 | 81.612 | 83.858 |
| Standard deviation | 70.252 | 68.659 | 61.872 | 85.581 |
| Entropy | 5.664 | 7.160 | 7.393 | 6.840 |

As can be seen from the data in table 2, the mean value and standard deviation of original image are smaller, it shows that the picture visual effects is partial darkness and low contrast. After the sharp image masking process, the mean value and standard deviation changed little, which illustrates that the enhancement effect is generally very poor; while the mean value and standard deviation of the image are increase significantly after histogram equalization method process, showing that the visual effect of images are carried bright and the contrast is enhanced; the standard deviation of the image is the biggest after processed by algorithm in this paper, however it lowers the mean value. As seen in table 3, original image has higher average value and smaller standard deviation, showing that the picture visual effects is partial bright and contrast is not strong, the analysis of the mean value and standard deviation are similar to table 2.

The information entropy index of the algorithm in this paper is inferior to other two algorithms. Due to the information entropy can not only reflect the amount of image information, but also can measure ordering degree of the system, the more orderly a system is, the less the information entropy is. From this perspective, the image is more orderly processed by the algorithm.

## 6 Conclusions

This paper uses niche strategy to control particle swarm global searching direction, which is widely used in multi-objective optimization problems, and its competition strategy makes the child population automatically search for different extreme value point and form different search space; while, elimination strategy makes the population update constantly. The combination of the two strategies manages to avoid the premature convergence of the algorithm and improves the ability of global optimization; The introduction of mutative scale chaos mutation improves the precision of the algorithm. Experimental results show that compared with the traditional PSO algorithm, the algorithm in this paper has better optimization ability, high precision and good stability.

Appling the algorithm to image enhancement, it can realize adaptive adjustment of image enhancement effect, broaden the gray dynamic range, highlight the dark details, and improve the image contrast, all these can make the image enhancement effect more obvious, so as to meet the needs of subsequent processing.

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