

## Research On Steel Strip Image Segmentation Algorithm Based On Particle Swarm Optimization

Zhiyong Zhang<sup>a</sup>, Xiaoyang He<sup>a\*</sup>, Xiaohua Sun<sup>b</sup>, Junhao Wang<sup>c</sup>, Fushun Wang<sup>c</sup>

<sup>a</sup> College of Information Science and Technology, Agricultural University of Hebei, Baoding, China

<sup>b</sup> Department of Digital Media, Hebei Software Institute, Baoding, China

<sup>c</sup> College of Information Science and Technology, Agricultural University of Hebei, Baoding, China

hexiaoyang0667@163.com

A method based on particle swarm optimization (PSO) for steel strip image segmentation was presented. Considered the traditional markov method is hard to get good effect in global optimization solution, the particle swarm optimization is used to enhance search capacity in the multi-dimensional space and determine the parameters of markov random field to optimize the objective function which comes from the random field. The method is compared with the classical simulated annealing algorithm. The segmentation effect is quantitative assessed by pixel dispersion, coincidence degree and area of detesting. Results show that the proposed algorithm performs better than the traditional algorithm in the three aspects. It can rapidly get the better segmentation result with satisfactory noise rejection and edge preserving. The robustness to noise and the smoothness are remarkably improved.

### 1. Introduction

Steel strip is one of the main products of large iron and steel enterprise. Its production process is rolling method. The defects of the steel strip products mainly includes shell shaped bulge, peeling, scaly skin, bruises, pressed dirt and pressed iron scale which was confirmed (S. W. Lee, et al. (2001); Mohammad Reza Yazdchi, et al. (2008); Keesug Choi, et al. (2006)). The quality detection for steel strip surface based on image processing technology has become the research focus of non-destructive testing now. Image segmentation is critical in image processing and its results affect the post-algorithms directly. Steel strip images usually present low contrast and blurry edges because of the complexity of imaging environment which was confirmed (Ge-Wen Kang, et al. (2005); Sugimoto, et al. (1998); Wu Xiu-yong, et al. (2008)). The markov model is one of the most popular algorithms in use of image segmentation; however, it needs a lot of computation time which limits its application. Particle swarm optimization has strong search capacity in the multi-dimensional space which was confirmed (Tim McInerney, et al. (1996); H.D. Cheng, et al. (2000); Yazhong Lin, et al. (2004); P. Andrey, et al. (1998); Carlos F Gorges, et al. (1999); N. Giordan, et al. (1997)). This study uses the optimization to determine the parameters of markov random field to optimize the objective function which comes from the random field. It can rapidly get the better segmentation result with satisfactory noise rejection and edge preserving. The method is compared with the classical simulated annealing algorithm and the results are analyzed.

### 2. Particle swarm optimization algorithm

In traditional markov model, image segmentation is converted to be calculating the maximum a posteriori of the label field which was confirmed (Nithin Nagara, et al. (2013); Eleftherios Kofidis, et al. (2014)). The process can be considered as calculating the minimum value of likelihood energy function. It is a problem about objective optimization. However, the traditional markov model has the weakness in multidimensional parametric searching which was confirmed (Nithin Nagara, et al. (2013)). PSO is a new type of group intelligence algorithm to effectively find out the global optimization solution. Starting from a set of random solutions, it searches for the optimal solution by iterative procedure. For the optimization in a d-dimensional

space, the data of velocity and position of the  $t$ -generation can be calculated by the formula below, in which the inertia weight  $w$  is used to enhance the algorithm. The velocity update rules are:

$$v_{id} = w * v_{id} + c1 * r(p_{id} - x_{id}) + c2 * R(p_{gd} - x_{id})$$

$$x_{id} = x_{id} + v_{id}$$

In this formula,  $i = 1, 2, 3, \dots, M$  and  $d = 1, 2, 3, \dots, N$ . The accelerated factors  $c1$  and  $c2$  can be regarded as the weight factor, which is more than zero. The rational accelerated factors  $c1$  and  $c2$  can quicken the convergence speed and reduce the calculation burden efficiently. The usual form is that  $c1 = c2 = 2$ .  $R$  and  $r$  are random numbers between 0 and 1.  $v_i$  represents the speed of particle  $i$  in the  $d$  dimension in iteration.  $x_{id}$  represents the current position of particle  $i$  in the  $d$  dimension.  $p_{id}$  represents the position of particle  $i$  in the local extreme point.  $p_{gd}$  represents the position of particle  $i$  in the global extreme point. For preventing that the particle is kept far from the searching space, the speed of each dimension is limited within  $[-Vd \max, +Vd \max]$ . Usually  $Vd \max = kX_{d \max}$ ,  $k \in [0.1, 1.0]$ . The same method is used to the other dimensions. The decline formula of inertia weight  $w$  is list below.

$$w = w_{\max} - \text{iter} \frac{w_{\max} - w_{\min}}{\text{iter}_{\max}}$$

The maximum and minimum values of  $w$  are expressed as  $W_{\max}$  and  $W_{\min}$  respectively. The current recursive step is expressed as  $\text{iter}$  and the largest recursive step is expressed as  $\text{iter}_{\max}$ . The weight  $w$  is used to control the effects of the last speed to the current speed. So it can escape from the local minimum by adjusting the weight  $w$  to improve the local search ability.

In the method for image segmentation based on particle swarm optimization algorithms, fitness function determining is the key point. On each step of iteration, the probability values before and after can reflect the standard in search process. The calculation steps are:

Step 1: Initialization. Initialize particle and calculate the fitness value of each particle. Initialize particle's velocity and best point.

Step 2: Calculate the fitness value of each particle and list them from large to small. Find the best particle among the neighbor particle.

Step 3: Update the individual best value and group optimal value. Update the velocity and position using particle swarm optimization.

Step 4: Update the individual best position and the global best position.

Step 5: Judge the termination condition. Stop iterative if it satisfies the condition, otherwise go to Step 2.

For the sake of comparison, simulated annealing algorithm is used to design the elements. The simulated annealing algorithm is a global optimal method and independent on the selection of the initial points. It is a global optimal method and independent on the selection of the initial points. Its transition probability  $pt$  can be expressed as below.

$$Pt(i \Rightarrow j) = \begin{cases} 1, & f(j) \leq f(i) \\ \exp\left(\frac{f(i) - f(j)}{t}\right), & \text{others} \end{cases}$$

$pt$ . can determine whether to accept the transfer from  $i$  to  $j$ . The parameter of temperature control is expressed as  $t$ . At the beginning, let  $t$  select the value of the higher. Reduce value of  $t$  slowly when the steps go on. This process can be repeated until it can satisfy the stopping condition.

### 3. The testing results

Simulation result is also given in the mat lab environment. The number of particles is 20 and the iterative time is 200. Numerous experiments are made. The convergence curves of fitness values are as shown in fig. 1.

At the same time, simulated annealing algorithm (SA) is presented for the image segmentation and the iterative times are compared within the table below.

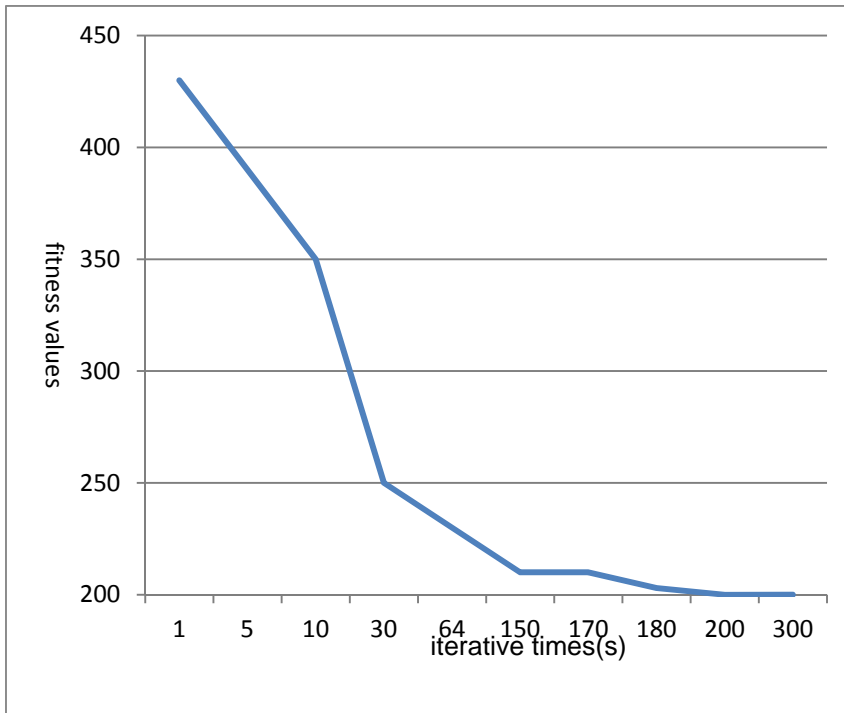
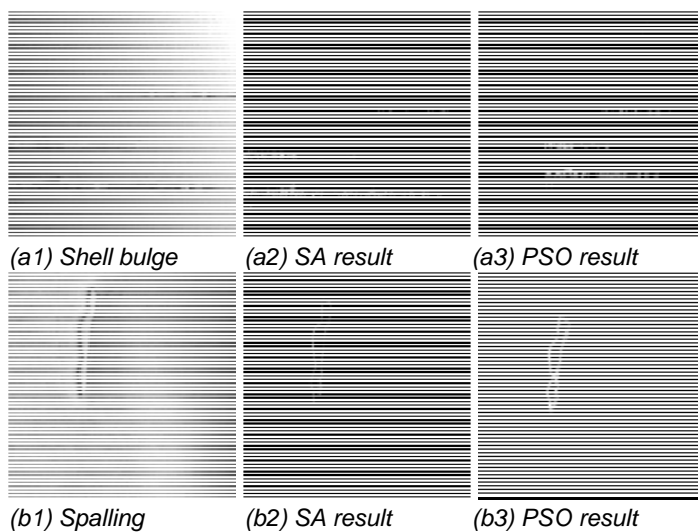


Figure 2: The Convergence curves of fitness values

Table 1: Iterative times between simulated annealing and PSO

algorithm / times	1	2	3	4	5	6	7	8	9	10
SA	185	195	200	199	198	190	201	180	182	210
PSO	120	91	15	110	89	85	120	130	95	115

A set of images are segmented with the two proposed methods respectively, as shown in fig. 1.



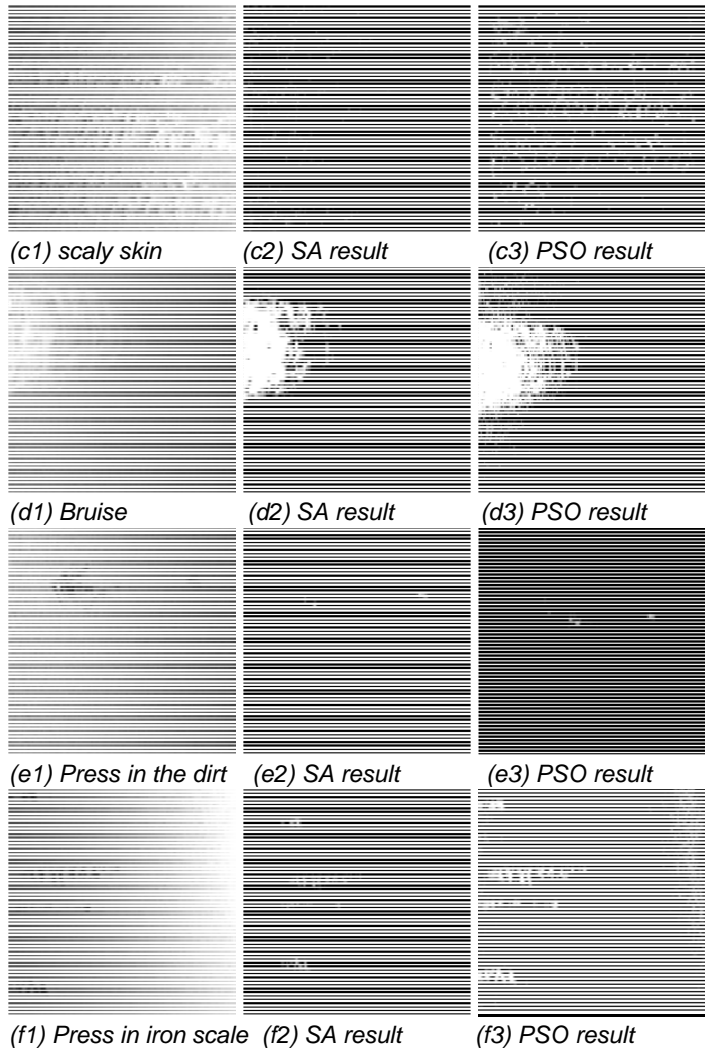


Figure 3: The segmentation results with the two proposed methods

The results show that the robustness to noise and the smoothness are remarkably improved. The segmentation effect is quantitative assessed by three criterions. One is pixel dispersion, which can be expressed as the mean distances between each pixel and the center of mass. It is formulated as below.

$$Dc = \left[ \sum_{i,j=1}^n Dis(mc_i, mc_j) \right] / n / (mn)$$

$$mc_i(x_i, y_i) = \left( \frac{\sum ip_x}{Num}, \frac{\sum jp_y}{Num} \right)$$

The second is coincidence degree, which represents the similarity measure between defect area and segmentation results of images. It is formulated as below.

$$Coi = Dis(mc_m, mc_a)$$

The third is area of detecting, which represents the amount of pixels.

The Pixel dispersion comparison results of the two algorithms are shown in the table below.

*Table 2: The Pixel dispersion comparison results*

	shell bulge	peeling	scaly skin	bruises	dirt	iron scale
SA	0.1419	0.3209	0.4097	0.5691	0.6217	0.1813
PSO	0.1560	0.3912	0.5126	0.1329	0.1168	0.1202

The results show that the dispersion of raised, peeling and scales is little difference but there is large difference in bruises, pressed into dirt, pressed into iron scale between the two algorithms. The pixel dispersion based on the particle swarm optimization is significantly lower than that based on the traditional algorithm. The coincidence degree comparison results of the two algorithms are shown in the table below.

*Table 3: The coincidence degree comparison results*

	shell bulge	peeling	scaly skin	bruises	dirt	iron scale
SA	36.5515	66.8995	79.2417	18.0099	12.2276	6.6138
PSO	42.4009	39.2166	59.8045	10.2458	8.5266	1.0749

The results show that the coincidence degree based on the particle swarm optimization is significantly lower than that based on the traditional algorithm besides shell shaped bulge.

The measure of area comparison results of the two algorithms is shown in the table below.

*Table 4: The measure of area comparison results*

	shell bulge	peeling	scaly skin	bruises	dirt	iron scale
SA	2870	1726	10767	12029	1215	3199
PSO	5210	2535	15543	15328	722	1930
Actual area	5083	2129	18014	14448	799	2071

The results show that the measure of area based on the particle swarm optimization is significantly more accurate than that based on the traditional algorithm besides shell shaped bulge. The merit of the new algorithm comes from the properties of the space of markov. The proposed method focuses more on the correlation between neighboring pixels. The neighboring pixels are regarded as the same type. In the strip defect image, there are so far almost no other properties pixels. So the proposed method is very fit for strip defect image segmentation.

The optimization algorithm combining the particle swarm optimization and markov model uses not only the local probabilistic features of random field but also the maximum a posterior probability estimation to enhance the effect of image segmentation.

#### 4. Conclusions

A new image segmentation method about strip defect image is proposed in this paper. In order to rapidly and correctly determine the random field parameters, particle swarm optimization is used for image segmentation. Experiments show that the algorithm is feasible and effective. It can greatly reduce the iterations and it has faster calculation speed and better global convergence ability. The method is worth being widely adopted.

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