Application of Particle Swarm Optimization in Ceramic Image Segmentation

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Abstract

Clustering has become an important method for researching neighborhoods such as image processing, computer vision and pattern recognition. In this paper, according to the complexity of different ceramic image segmentation, a method of ceramic image segmentation based on particle swarm optimization algorithm is proposed which is combined with the k-clustering thought of pattern recognition theory. This method obtains the optimal threshold of the image to be segmented based on the search of global optimal solution by particle swarm optimization algorithm. Experimental results show that compared with other test algorithms, the proposed method can achieve better segmentation results and shorter thresholds for both single-threshold and dual-threshold image segmentation.

Keywords: Particle Swarm Optimization, Ceramic Image Segmentation.

1. INTRODUCTION

Image segmentation, as the key technology in computer vision and digital image processing, is an important first step in image recognition and image understanding. To some extent, the quality of image segmentation directly determines the advantages and disadvantages of its subsequent image processing steps (Tang et al., 2017). The image segmentation method is to divide or divide the image into regions with similar features (such as grayscale, color, texture, density). The main methods are threshold method, edge detection method, region tracking method and texture method. Recently, swarm intelligence optimization has been applied to more and more fields of economics, scientific theory and industrial production (Wen et al., 2017). In addition, applied research was a kind of emerging technology that can solve different types of optimization problems. However, from the available literature both at home and abroad, the research results of applying the improved PSO method to the image processing of ceramic artifacts are rare (Bilal et al., 2016). At present, the domestic and foreign methods for the edge detection of damaged areas such as cracks before the restoration of ceramic cultural relics are still dominated by the traditional artificial visual inspection. The statistical results of the manual inspection show that the reliability of the test is only 80%. The experience and sense of responsibility depend more on it. In addition to manual testing methods, nondestructive testing methods are often used both at home and abroad. Non-destructive testing methods can effectively prevent the wear of ceramic materials caused by other external force contact. Domestic and foreign ceramic crack nondestructive testing techniques can be summed up (Velmurugan et al., 2016).

The advantage of non-destructive testing is that it evaluates material integrity and continuity without changing the usability of the test object, and detects inherent defects and their shape, location and size. However, various methods have their own advantages and disadvantages and need to be further improved by the ancient ceramic materials themselves and subjective factors (Chakraborty et al., 2016). As the ceramic artifacts of the crack detection and digital image segmentation techniques exist in principle common, that is based on the image surface known information to identify the edge of the object, which carried out in-depth ceramic treatment, such as ceramic artifacts image reconstruction, restoration of ceramic artifacts. Therefore, the crack detection process of ceramic artifacts can be preliminarily realized on the computer in advance so as to provide reference value for the manual repair of the subsequent ceramic artifacts, and to improve the credibility and accuracy of the restoration of ceramic artifacts (Ko et al., 2016).

This paper draws on the classical K-clustering algorithm in pattern recognition and applies PSO and clustering to target extraction of ceramic images. A method of image segmentation based on particle swarm clustering is proposed. The experimental data show that the new method proposed in this paper cannot only extract the
character and the background accurately from internationally accepted standard images, but also obtain the optimal threshold with less cost. The clustering effect of the algorithm is more effective.

2. PARTICLE SWARM OPTIMIZATION

The PSO method originally originated from a simulation of foraging behavior of bird flocks and was inspired from the process and applied to the solution of different kinds of optimization problems (Chen et al., 2017). The basic principle of PSO is described as follows: According to the feasible region of the problem to be solved, the range of the region searching for potential solutions by the particle swarm in the search space is determined. The fitness of each particle in the search space is determined by a predetermined evaluation function. In addition, the neighbors of the particles can be pre-set as particles in the neighborhood of the population. In this case, the global extremum originates from the local extrema in all the neighborhoods of the particles. Particles in the search space flight process, each particle and particle groups have a certain exchange of information and share their potential solution to the region where the collection of information (Singh et al., 2016).

\begin{equation}
    v_{k+1} = \omega v_k + c_1 r_1 (p_{best_k} - x_k) + c_2 r_2 (p_{best_k} - x_k)
\end{equation}

\begin{equation}
    x_{k+1} = x_k + v_{k+1}
\end{equation}

Where k is the number of iterations, $v_k$ is the velocity vector of a single particle in the search space, $x_k$ is the particle's current flight position in the search space, $p_{best_k}$ is the velocity of a single particle after k flights in the search space. Find the optimal flight position, which is solved as a single particle to obtain the provisional optimal solution, $p_{best_k}$ represents the optimal flight position of the particle swarm found after k flight, which corresponds to the current flight time when the particle swarm The optimal solution. $v_{k+1}$ is the vector sum of $v_k$. Here, in order to prevent particles from being too fast or too slow during particle flight, the velocity per particle of the particle is usually limited within a reasonable range $[v_{min}, v_{max}]$. If the velocity of a certain flight is not within the defined Velocity, the velocity will be reset as follows.

\begin{equation}
    v_k = \begin{cases} 
    v_{max}, & v_k > v_{max} \\
    v_{min}, & v_k < v_{min} \\
    v_k, & otherwise 
\end{cases}
\end{equation}

In addition, the parameters involved in the execution of the PSO method include the inertia weight $\omega$. Two accelerating constants are called learning factors $c_1$, $c_2$.

3. OPTIMAL THRESHOLD IMAGE SEGMENTATION BASED ON PARTICLE SWARM OPTIMIZATION ALGORITHM

3.1 Optimal Threshold Selection in Clustering

The idea of k-clustering in pattern recognition is applied to image segmentation based on the goal of maintaining the maximum similarity among the in-class pattern samples while keeping the maximum distance among the classes. Optimal threshold for image segmentation is achieved by using the iterative method (Ramadhani et al., 2017). The steps are:

1. In the case of a single threshold, given a threshold $t_1$, which is randomly divided into two categories of target $c_1$ and background $c_2$, and the probability of the two categories are:

\begin{equation}
    p_1 = \frac{n_{c1}}{N_{image}}, \quad p_2 = \frac{n_{c2}}{N_{image}}
\end{equation}
Where \( n_{i1} \) is the number of ci-type pixels and \( N_{image} \) is the total number of pixels in the image. Two types of center gray mean \( u_{i} \) and variance \( \sigma_{i}^{2} \) are expressed as follows,

\[
u_{i} = \frac{1}{n_{c_{i}}} \sum_{x,y} f(x,y)
\]

\[
\sigma_{i}^{2} = \sum_{x,y} (f(x,y) - u_{i})^2
\]

\[
h(t_{1}) = p_{1}\sigma_{1}^{2} + p_{2}\sigma_{2}^{2}
\]

The image of each pixel classification processing. The way is as follows,

\[
(x, y) = \begin{cases} \ c_{1}, \text{if } |f(x,y) - u_{1}| \leq |f(x,y) - u_{2}| \\ \ c_{2}, \text{else} \end{cases}
\]

After the classification process, all the pixels in the target and the background need to recalculate the center gray mean value.

\[
h(t_{2}) = \sum p_{i}^{new} \sigma_{i}^{2(new)}
\]

The threshold should be determined as follows: If \( h(t_{2}) < h(t_{1}) \), the pixels are classified again. Otherwise, \( t_{1} \) is the determined threshold. From the above analysis, we can see that the optimal clustering threshold should be determined to meet the following equation.

\[
t^{*} = \arg \min h(t)
\]

Similarly, after each classification is completed, the following thresholds are determined if the following formula is satisfied; otherwise, pixel allocation is performed again and compared as follows.

\[
h(t^{old}) = p_{1}^{old} \sigma_{1}^{2(old)} + p_{2}^{old} \sigma_{2}^{2(old)} + p_{3}^{old} \sigma_{3}^{2(old)}
\]

\[
h(t^{new}) = p_{1}^{new} \sigma_{1}^{2(new)} + p_{2}^{new} \sigma_{2}^{2(new)} + p_{3}^{new} \sigma_{3}^{2(new)}
\]

\[
h(t^{new}) > h(t^{old})
\]

3.2 Particle swarm optimization algorithm for image segmentation
Using the ability of particle swarm optimization, the image segmentation problem can be considered as the PSO problem in the process of PSO implementation. When different particles are constantly learning from each other and the information is exchanged continuously, the majority of particles can find the best location or its vicinity for determining the best threshold for image segmentation (Godinho et al., 2016). Since the gray level of the pixels in the image processing is 256, the initial position and velocity of the particles in the experimental test in each iteration are limited to [0,255]. Figure 1 depicts Particle swarm clustering algorithm implementation process, the corresponding particle swarm clustering algorithm described below.

1. Initialize Particle Swarm: Set the particle number to np, set the particle's initial position and velocity randomly, and set the initial position of each particle pbest, pgstst the best among pbest, The maximum number of iterations for nmax, up to the counter nc = 0;

2. Calculate fitness value of each particle according to the particle's current position, and calculate the single threshold value using equation (7). Then we can calculate the double threshold value using formula (11) to find the global maximum position;

3. According to equation (1) update the speed of particle j, and determine whether the speed of cross-border. If the cross-border is based on equation (3) to adjust the speed.

4. According to equation (2) update the position of particle j.

5. According to the current particle position, each sample can be obtained according to the principle of minimum distance classification.

6. According to the individual extremum of each particle, we can find the global extreme position and the global fitness value.

7. Output global fitness value and global extreme position.

**Figure 1.** Flow chart of PSO clustering algorithm
4. EXPERIMENT ANALYSIS

Experimental operating environment: Intel Pentium 4, CPU 2.26 GHZ, Windows XP, Matlab 7.0. In the experiment, we propose the particle swarm optimization algorithm as ISPO for short, and apply the proposed PSO algorithm to the edge segmentation of two ceramic images to identify the fine crack detail in the ceramic image. And the proposed algorithm is compared with OTSU, which is the most common universal inter-class variance method. The size of the test image bowl and tile are respectively 243 × 300 and 512 × 512, and the corresponding histogram is shown in Figure 2.

![Figure 2. Effect after the image segmentation by OTSU and ISPO](image)

Experimental test, the particle number is set to np = 20, and inertia factor w linearly decreasing mode, which is from 0.9 to 0.3. Diego up to the number of nmax = 200. Acceleration constant c1 = 1.5, c2 = 1.6. Particle swarm clustering algorithm is repeated with respectively 10 independent experiments. Figure 2 is the effect of using the OTSU method to segment the image.

In this paper, the optimal threshold for OTSU segmentation of bowl and tile images is 175.0065 and 196.9875, respectively. For the ISPO proposed in this paper, we run the method 10 times and get the optimal threshold of the bowl and tile images respectively 178.5 and 204.2. In addition, the time of obtaining the threshold ten times is relatively close as shown in Table 1. And the time to obtain the optimal threshold is also within the acceptable range. The comparison between the two methods shows that the ISPO method proposed in this paper can effectively extract the crack details and effectively separate the cracked area from the surrounding background.

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5. CONCLUSIONS
Based on the idea of k-clustering algorithm in pattern recognition, this paper proposes an improved particle swarm optimization method and applies it to the segmentation of ceramic images. From the experimental results, the improved PSO method can compare the good implementation of segmentation and extraction of people and target regions in the image. The determination of the segmentation time further indicated that the improved PSO method has some practical results. The successor work of this paper will continue to study in depth the influence mechanism of different parameters of improving PSO method on the image segmentation effect and quantitatively analyze its influence degree. In addition, it is also a part of the follow-up work to integrate the mechanism of better solving the optimization problem in other intelligent optimization methods into the improved PSO method in this paper.

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REFERENCES