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Image Segmentation Prediction Model of Machine Learning and Improved Genetic Algorithm

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With the rapid development of science and technology, people's requirements for image technology have become more and more sophisticated. During segmentation, images are easily affected by external factors such as noise, offset, local effects and so on. As a result, it is difficult for the traditional segmentation algorithm to meet people's expectations; also, the computer load is large and the segmented images are prone to many problems. In this paper, by improving the image segmentation method of the genetic algorithm (GA), in order to ensure the consistency and integrity of image information, the segmentation region is determined, and the segmentation model is established. After applying the improved genetic algorithm, the segmented image is compared in terms of CPU utilization, segmentation effect and genetic times. The results show that the accuracy of the improved genetic algorithm is increased by 13.2%, and the genetic number is reduced by 45.2%. The improved segmentation algorithm ensures the consistency and information integrity of the segmentation area, and the segmented interface is relatively clear. It also shows that the image segmentation obtained by the improved genetic algorithm is better and more accurate than that produced by the traditional algorithm.

Keywords: image segmentation, improved genetic algorithm, machine learning, traditional algorithm

1. INTRODUCTION

Image segmentation is a process that distinguishes the background and objects in an image. It requires computer-vision ability. Image segmentation is an essential step in the processing of medical images, the positioning of satellite images, as and in daily face recognition, fingerprint unlocking, agricultural images, etc. Image segmentation is an intermediate step of computer processing and plays an important role in the subsequent image processing. However, due to the various forms of images, the segmentation process is problematic and needs to be improved.

The problems in the traditional algorithm need to be reduced or eliminated. The traditional genetic algorithm can easily be affected by individual differences, and the standard of image segmentation accuracy and algorithm speed is high. The image is also easy to be affected by offset effect and local effect, and the ability to deal with external noise is relatively weak. Hence, the traditional algorithm cannot meet people's requirements of image segmentation. The improved genetic algorithm is of great significance to the current image segmentation process.

In this paper, the experimental results indicate that the image segmentation achieved by the improved genetic algorithm is significantly better than that obtained by the traditional algorithm. The accuracy of the algorithm is improved by 13.2%, the CPU utilization is reduced, the computer speed is faster, and the genetic times are greatly reduced, which prevents unnecessary factors from influencing image segmentation and ensures the integrity of the segmented image.

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2. RELATED WORK

With technological progress, image segmentation has appeared in many problems and applications, and a large number of researchers have studied and explored this topic. Chen et al. (2018) used deep learning to achieve image semantic segmentation. Their work makes three important contributions, which experiments have proven to be significant. First, the atrous convolution can clearly control the resolution of the characteristic response in the deep convolution neural network. At the same time, the filtering range can be expanded effectively without increasing the number of parameters and the amount of calculation. Secondly, a multi-scale spatial cone pool model is proposed to realize the robust partition of objects. Thirdly, DCNN is combined with a probabilistic graphic model to improve the edge position of objects [1] Keegan et al. (2017) proposed a new framework for energy-based multiphase segmentation on multiple channels. The framework allows users to combine information from each channel when they think it appropriate, thus allowing users to determine the impact of information from each channel. The framework is an extension of the two-phase logical framework model. The logical operators of the logical framework are used to define the objective function of multiple stages and prevent conflicts between energy items [2]. The Markov method of early visual process needs a lot of computing power. These algorithms can usually be implemented on parallel computing architecture. Schwarzlmüller (2017) showed that the Markov marking method can be implemented in a parallel cellular network architecture, using simple functions and data representation. This makes it possible to implement the model in parallel imaging VLSI chips. This is a new image processing tool which contains thousands of units with simulation dynamics, local memory and processing units. The entire pseudo-random segmentation process can be introduced into the CNN architecture using eight memory / cells [3]. It is often difficult to accurately segment non-uniform images because most representative algorithms are region-based and depend on the intensity of uniformity of the object of interest. Zhang et al. (2017) proposed a new hierarchical set method which can effectively solve the problem of segmenting an image with non-uniformity. Non-uniform objects adopt Gaussian distribution models with different averages and variances, and use sliding windows to map the original image with other regions, so that the brightness distribution of each object maintains Gaussian distribution, so as to achieve better segmentation effect [4]. Although scholars have made valuable contributions to this field using various methods, they have not considered improving the genetic algorithm for image segmentation, although research on the genetic algorithm has been conducted.

The genetic algorithm has been used to address a variety of problems and find the best solution. When selecting the redundancy strategy for each subsystem, Tavakkoli-Moghaddam et al. (2017) proposed a genetic algorithm for the redundancy allocation problem of series and parallel systems. Most methods for solving general redundancy allocation problems assume that the redundancy strategy of each subsystem is predetermined and fixed. However, in practice, both active redundancy and standby redundancy can be used in specific system design, and the choice of redundancy strategy becomes an additional decision variable. Therefore, each subsystem selects the best redundancy strategy, components and redundancy level to maximize system reliability under system level constraints [5]. Dawid (2019) discussed the use of artificial adaptive agents in economic theory. The genetic algorithm (GA) is used to simulate the learning behavior of adaptive and bounded rational agents interacting within an economic system. In the two versions of the cobweb model, the behavior of GA is analyzed, simulations with different coding schemes are proposed, and the mathematical theory of GA with a state-dependent fitness function is used to explain the results of different settings. It is found that the results are quite surprising [6]. Job shop scheduling is a very difficult problem because it requires a very large combinatorial search space and there are some precedence constraints between machines. The data of real-world problems are imprecise, fuzzy or uncertain. In this case, Tsujimura (2017) studied the standard benchmark of a job shop scheduling problem by applying two different fuzzy subset sorting methods to prove its performance. Taking into consideration the uncertainty of the input data to estimate the input data, it can be represented by a fuzzy number to reduce the error. Because the job-shop is fuzzy, a new solution is proposed [7]. The genetic algorithm is used not only to solve redundancy problems, population adaptability problems, job shop scheduling problems; it is also used for image segmentation. This paper discusses two traditional algorithms and improved genetic algorithm for image segmentation.

3. METHODS AND ALGORITHMS FOR IMAGE SEGMENTATION

3.1 Methods of Image Segmentation

Image segmentation is the most basic technique in image processing and preprocessing, and is a key component of many image analyses and vision systems [8]. Image segmentation is conducted to divide an image into regions with specific features and detect them. In this way, the process of image analysis, recognition, compression, reconstruction, etc. has become the key to image segmentation. However, in the actual image segmentation, there is a certain error, and computer vision applications are required to minimize this error. For image segmentation, this paper proposes six methods based on threshold, edge, region, graph theory, and energy functional [9]. With the development of technology, other segmentation methods will become more and more advanced and have more advantages. Each method is explained below.

Edge-based segmentation is a new method of gray-based edge grayscale, which is displayed as a step-like or roof-like change. But this method has a big flaw, that is, it is very sensitive to noise, if its frequency is very low, then its first and second derivatives will become larger, which leads to its error. The more commonly-used operators are Robert, Prewitt, Sobel, Laplain, and Canny (Sonka, 2002) [10].

The thresholding method involves finding one or more grayscale thresholds based on the grayscale features of the image, comparing them with the thresholds, and finally classifying them. According to the corresponding discriminant function, the optimal grayscale threshold is obtained, which is a key method in such computing applications. In general, the threshold method is more suitable for the target grayscale evenly distributed outside the background. However, because it ignores the structure of the target, it cannot reasonably divide the target image with more complex background information. At present, the commonly-used algorithms include: large algorithm, minimum error, maximum entropy method, etc. [11].

With the regional division method, the image is divided into several regions according to the similarity, mainly including the regional growing method, the regional splitting and merging method, and the watershed method. Seed area growth is a program that merges pixels or sub-areas into a larger area according to a predetermined growth standard. Then, the newly-added pixel is used as a new seed pixel, and the synthesis continues until there are no new pixels. On this basis, a new seed pixel point is proposed, and a new growth criterion is determined. Unlike the growth of the seed area, the basic idea of the region splitting and merging method is to randomly divide the image into several independent regions, and then divide or merge them according to relevant standards to achieve the purpose of segmentation. Among them, the watershed method is a geometric morphological division method based on topology. Its basic concept is to regard the image as a topological terrain, and the gray value of each point represents the elevation of this point. The local minimum and its sphere of influence are called the ‘sump’, forming a watershed at its edge. This method can simulate the process of flooding, first submerging the lowest part in the image, and then gradually submerging the entire canyon by the water flow. When the water level rises above a certain level, the dam overflows and a dike is built over the flooded area, and so on, until all the water lines are submerged. The watershed algorithm has a good effect on the processing of weak boundaries; however, due to the noise in the image, the watershed algorithm is over-segmented [12].

In graph theory, graph segmentation is used to link the problem of minimum cropping of images with the problem of minimum truncation of blocks. First, the image is mapped into a weighted undirected graph. On this basis, we can use "similarity" to achieve "clipping" of the graph. And the best "clipping" method is to maximize the internal similarity of each subgraph and minimize the similarity of each subgraph. Since each pixel has a weight, this algorithm is not very sensitive to the contour of the object, and it also has a large computational cycle [13].

The partition method based on the energy functional involves using the motion contour model to make its own parameters include the boundary curve so as to convert the partition into the minimum energy functional. This can usually be solved by Euler equation, and the position of the curve with the minimum energy is the contour of the object. According to the curve representation in the model, it can be divided into two types: parametric motion contour mode and geometric motion contour mode. Of these, the parametric active contour model is based on the Lagrange framework to parameterize the curve into a curve, the most representative of which is the snake model proposed by Kassett (1987) [14]. However, its limitation is that it is affected by the setting value of the initial contour and the complex surface topology, and its energy function is determined only by the curve parameters, and does not take into account the geometric characteristics of the object, which restricts its application. Compared with the parametric active contour model, its curve motion process is based on the geometric measurement parameters of the curve, rather than the characterization of the curve, so it can deal with the change of topology well, and can also solve the problem of parametric active contour model well. The appearance of the horizontal set method has greatly encouraged the development of a geometric active contour model [15].

In addition to the methods described above, there are other methods.Due to the emergence of new theories in the fields of mathematical analysis, pattern recognition, artificial intelligence, computer technology and other disciplines, several multi-scale segmentation techniques based on wavelet analysis and transformation theory have been proposed, including multi-scale segmentation techniques based on wavelet theory, clustering-based segmentation techniques. Segmentation technology based on neural network, segmentation technology based on genetic algorithm, segmentation technology based on fuzzy theory and segmentation technology based on random field theory [16].

Usually, the threshold of the image contains Gaussian white noise and salt and pepper noise. The grayscale of the target image and the background in the image are very different. In order to obtain the desired target, firstly, the foreground must be extracted from the background, usually using a threshold, The image is divided into two regions and, in general, the selection of the threshold is usually based on empirical values.

3.2 Image Segmentation Model

Since traditional image segmentation methods are affected by external noise, displacement, local effects and other factors, a large amount of data aggregation occurs during segmentation, which has a great impact on image segmentation. When dividing an image, it is necessary to determine the divided quantity, and it is necessary to ensure that the data in the divided image are complete and that, after division, all areas have the same characteristics. In this regard, when performing image segmentation, it is also necessary to consider making the segmented image generally large. If the sizes of the segments are inconsistent, the value of the data and information expressed by the image may be reduced, and the running time of the algorithm system is too long. By unifying the image information after segmentation, a model of the number of segmentation areas is established. Assuming that the original image is I, and the image after segmentation is S, the relationship between them is expressed by entropy as:

$$H(I) = \sum_i F_I(i) \ln F_I(i) \tag{1}$$

$$H(S) = \sum_{S} F_S(s) \ln F_S(s) \tag{2}$$

$$H(I, S) = -\sum_{i,s} F_{I,S}(i, s) \ln F_{I,S}(i, s) \tag{3}$$

where $F_I(i)$, $F_S(s)$ are the probability distributions of I and S, and $F_{I,S}(i, s)$ is their joint probability distribution. The mathematical expression of image information consistency is:

$$MI(I, S) = H(I) + H(S) - H(I, S) \tag{4}$$

The entropy difference DMI for information consistency is:

$$DMI_K(I) = MI(I, S_K) - MI(I, S_{K-1}) \tag{5}$$

Both S_K and S_{K-1} belong to the original image, which are inconsistent images after segmentation of the original image. The number of their corresponding regions is K and K-1. In order to better compare the segmented images, the entropy difference of the information is unified. Unified processing, you can get:

$$KDMI_K(I) = \frac{MI(I, S_K) - MI(I, S_{K-1})}{MI(I, I)} N \tag{6}$$

Research has found that the entropy difference between the original image and the segmented image changes with the change of segmentation, showing a normal change, and the unified KDMI and S show a negative change [17].

3.3 Genetic Algorithms

As a random search algorithm with optimal solution, the genetic algorithm can well address the problem of optimal solution of images[18]. The genetic algorithm is a self-organizing, adaptive artificial intelligence algorithm that can simulate the evolution of organisms in nature [19]. When solving a specific problem, the method uses the information obtained during the evolution process to automatically and simultaneously search for and find the target point, which is a better method for solving complex nonlinear problems. Compared with other traditional genetic algorithms, the basic genetic algorithm has better search speed and search effect. However, it also has disadvantages in that the convergence is too fast, it is easy to fall into the local optimum, it is not stable, and the solution does not produce very accurate results. Therefore, the improvement of image segmentation is critical. Essentially, traditional image-segmentation methods involve finding one or more optimal solutions to maximize or minimize a specific objective function. The genetic algorithm is a randomization method modeled on the biological "survival of the fittest", and genetic variation occurs from generation to generation until the optimal gene required for survival is obtained. First, by encoding a set of initial individuals, an initial population for a solution space is formed. In this population, each individual can be regarded as a chromosome with information. As a carrier, it is generated with the evolution of generations. In each generation, each chromosome will use the objective function or fitness function to detect its adaptability to the environment, so as to select one as the next generation parent according to the size of fitness, eliminate individuals with poor fitness and performance, and retain individuals with good adaptability and high individual performance, forming the next generation of new groups [20]. This process makes the offspring of a species better and, like a naturally evolving species, the process is repeated until it reaches a predetermined goal. Finally, the optimal individual of the problem is solved, and the optimal approximation value of the problem is obtained. The genetic algorithm is a learning method based on the biological evolution theory. The prototype of the genetic algorithm can be abstracted with:

$$GA(F, F_t, p, r, m) \tag{7}$$

Here, F is the fitness function; F_t represents a critical point, which is used to determine the end of an iteration; p represents the assumed number included in a group; r represents that in each iteration, for the original members of the population, there is the possibility of cross substitution, that is, the probability of crossover; and m is the rate of change. The working principle of the genetic algorithm is shown in Figure 1.

In each iteration process, the genetic algorithm selects the most suitable individuals from the existing population according to a specific probability, and selects a new batch of individuals from these individuals. On this basis, based on a large number of experiments and the empirical model, the mutation probability of the model is [0.002, 0.04]. It can be seen that the fitness function of the model is one of the key factors to determine the performance of the genetic algorithm, and the correct fitness function is very important.While greatly improving the performance of the algorithm, an incorrect or inappropriate fitness function can also cause crowding problems, thereby greatly reducing the diversity of the population [21].

When the traditional genetic algorithm solves the optimization problem, the objective function is usually regarded as the fitness function, which not only satisfies the design characteristics of the fitness function, but also achieves the purpose [22]. However, when the traditional genetic algorithm produces pixel segmentation, it usually chooses to compare sequentially the image pixel threshold. When it exceeds the threshold, it is retained, and when it is less than the threshold, it is set to zero [23]. This is the traditional genetic algorithm compared in this paper. When the traditional genetic algorithm processes pixels, it usually enters the local optimal stage when looking for the final segmentation threshold. That is, if the threshold is too large or too small, in the future development process, these thresholds will become more and more difficult to replace, or the problem of over-segmentation will occur. To address this issue, an improved genetic algorithm is proposed in this paper.

3.4 Image Segmentation with Improved Genetic Algorithm

Compared with the traditional genetic algorithm, the improved genetic algorithm is different in two respects: first, linear extension is conducted before segmentation;

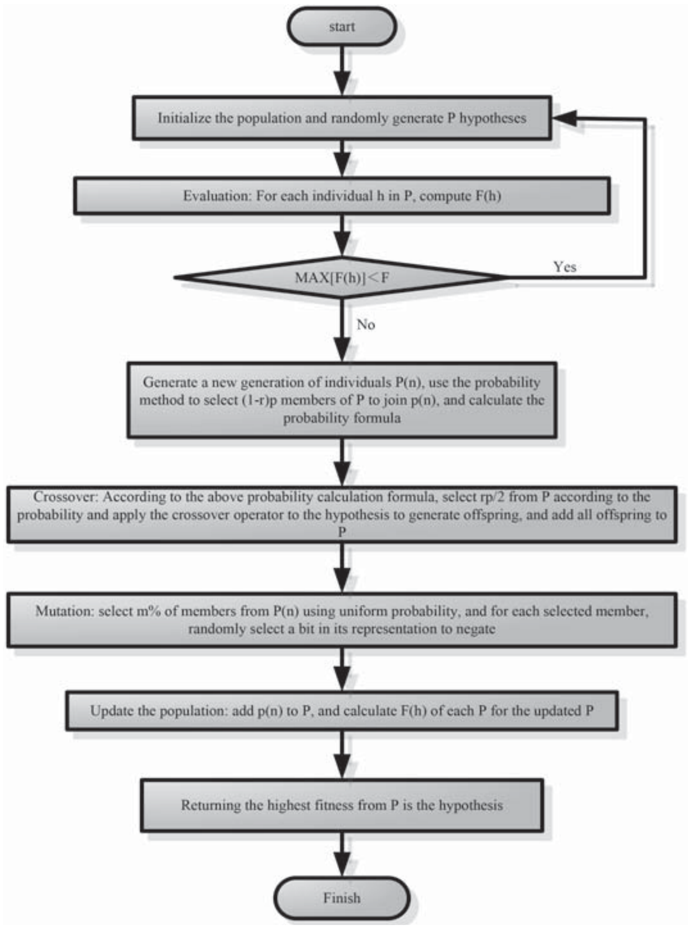

Figure 1 Flow chart of operation steps of the genetic algorithm.

second, depending on the fitness function, a normalization coefficient is added [24]. After each iteration, each group is counted, the number of pixels higher or lower than the set threshold is calculated, and two averages are obtained. The two averages are calculated using the normalization coefficient Correction, based on the revised average threshold.

The segmentation process, basic grayscale operation and genetic algorithm in Figure 2 will not be described in detail. Only the linear extension and the improvement of the genetic algorithm will be discussed below.

1) Improved Genetic Algorithm

Taking the pixel value of the image as the initialization group, the chromosome length, crossover probability, and 30 initialization groups are used. Then, the fitness function is optimized by means of the sorting method, and a normalization factor is added to ensure the non-negativity of the fitness function.

$$F(h) = L \times H \times (u_1 - u_2)^2 \tag{8}$$

In the formula, L represents the total number of pixels below the threshold, H represents the total number of pixels above the threshold, and $F(h)$ represents the pixels below the threshold and above the threshold. The fitness is arranged in the following order, and the optimal fitness and optimal threshold for each generation are counted to obtain the optimal segmentation threshold.

$$F = C_0 - \frac{\propto}{C_1} E \tag{9}$$

In the formula, $m = 255 \times 255 \times 16$, which is the initialization factor. The test results show that the value of 255 is the best, and the constant coefficient is [0,1]. The test results show that the value of 0.58 is the best [25]. For normalization coefficients, m and n represent the number of rows and columns, respectively, of the matrix stored in the program; E is the energy function of the Laplace operation, and $R(x, y)$ is the result of the calculation.

2) Improved linear stretch for dataset

Assuming that the minimum and maximum brightness of the input image are respectively I_l and I_h, and the minimum and maximum brightness of the enhanced image are respectively I_l and I_h, then, the method of straight-line extension is as follows:

$$O = \frac{I - I_l}{I_h - I_l}(O_h - O_l) + O_l \tag{10}$$

In the formula, I and O are the values of the pixels before and after the linear stretching of a pixel. If $I > O$, the high-brightness part of the pixel is enlarged, and the contrast of the brightness and darkness of the pixel is strengthened. Conversely, the brightness in the image is greater than Low areas will be reduce, and the light-dark contrast of objects will become weaker. Using the same linear stretch slope can make a big difference due to differences in the light-and-shadow structure of the image.

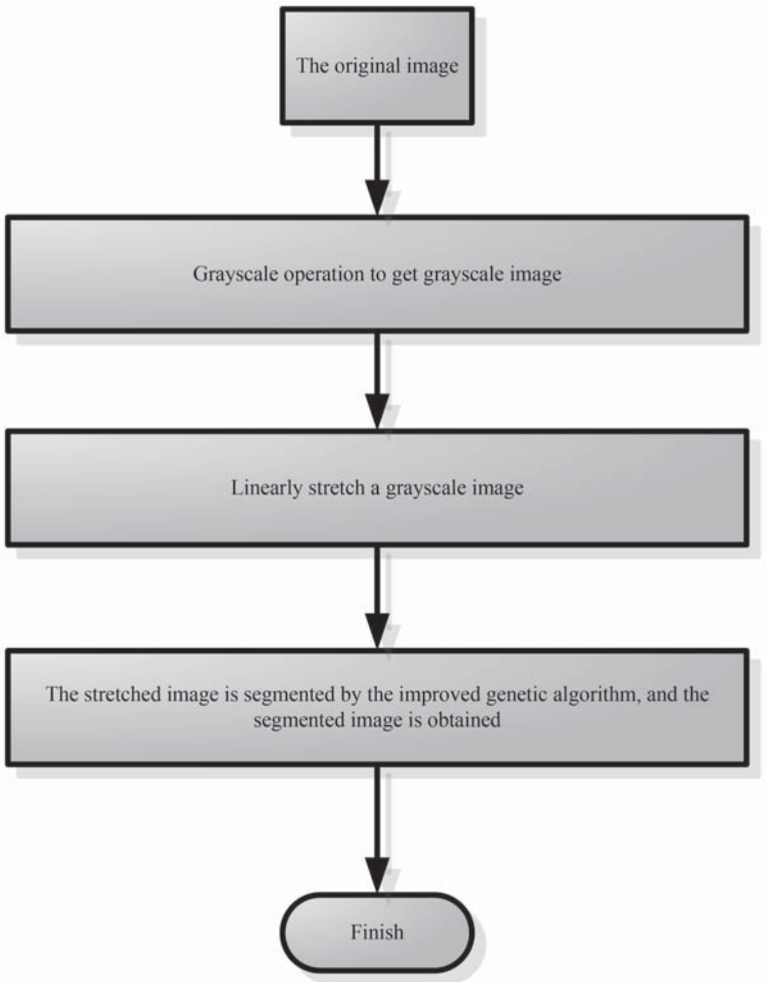

Figure 2 Image segmentation process based on improved genetic algorithm.

$$T(x, y) = \frac{(f(x, y) - f_{\min}) \times f_{\max}}{f_{\max} - f_{\min}} \quad (11)$$

In the formula, $f(x, y)$ represents the pixel value with (x, y) pixel in the image to be processed, $T(x, y)$ is the pixel value stretched by a straight line, $f_{\min}$ represents the image to be processed. Minimum pixel value, $f_{\max}$ represents the maximum pixel value of the image to be processed. Conversely, the weaker parts of the image can be made brighter [26].

4. EXPERIMENT AND RESULT ANALYSIS

In order to verify the effectiveness of the improved algorithm, a large number of graphs are selected, and the graphs with relatively obvious comparisons are used in the text. In this paper, three selected pictures are compared (Figure 3), showing the results obtained by the traditional threshold segmentation algorithm, the traditional genetic algorithm, and the improved genetic algorithm. Multiple data comparisons are made in terms of computer CPU usage, algorithm accuracy, and genetic times. They are represented by *, #, & respectively. This experiment uses a cluster database system, Intel I7 as the CPU, 2.4 G HZ main frequency and 8 GB memory, and is tested on the Windows 7.0 platform.

Different algorithms have different CPU usage rates. In this paper, four sets of experimental data are used to compare the CPU usage rates of three algorithms. For system algorithms, the smaller the CPU usage of the computer system, the better is the performance. The smoother and the higher the usage rate, the slower is the algorithm, the slower is the response, and the longer is the calculation time. Figure 4 shows a comparison of the three CPUs.

It can be seen from the picture that during operation, the CPU utilization rate of the traditional threshold segmentation algorithm fluctuates from around 40% to 53%. The traditional genetic algorithm is better than the threshold segmentation algorithm. Its floating area is between 30%–40%, and the maximum utilization rate reaches 51%. However, the floating area of the improved genetic algorithm is between 10%-20%, which greatly reduces the CPU utilization rate and streamlines the operation. It also shows that the system will run more smoothly and the algorithm speed will be faster when the improved genetic algorithm is used for image segmentation.

The image segmentation accuracy is evident in the segmentation effect. By comparing the same number of segmentation areas, the accuracy can be better explained. The higher the segmentation effect, the better the segmentation accuracy, and

Figure 3 Unsplit selection map.

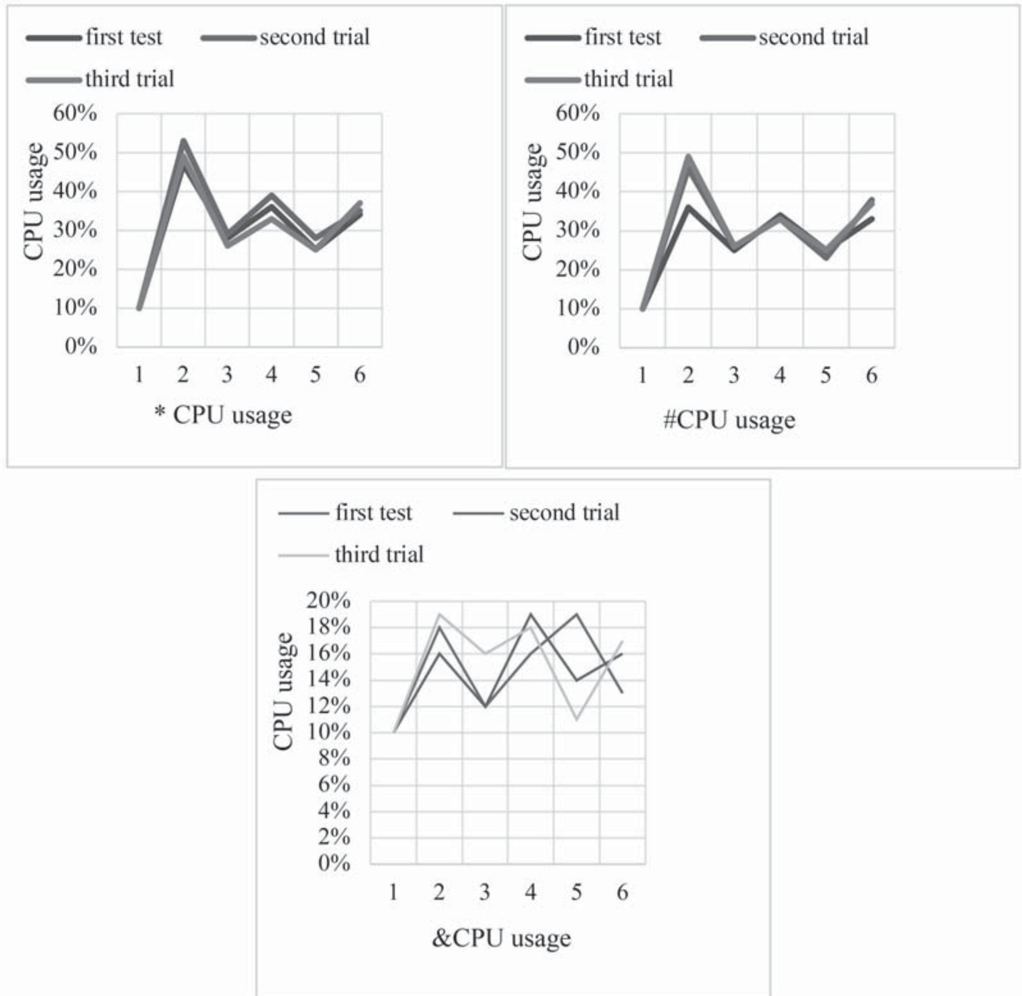

Figure 4 Comparison of three CPU usages.

the two show a positive correlation, as shown in Figure 5 which allows a comparison of the segmentation effects of these three algorithms under the same number of segmentation regions.

In this paper, we compare the segmentation effects in several groups of the same number of segmentation regions. According to the data in the figure, when the number of segmentation regions is 2, the segmentation effect of the traditional threshold segmentation algorithm is relatively low, and the subsequent rise is slow, and the segmentation effect is not significantly improved. The segmentation effect of

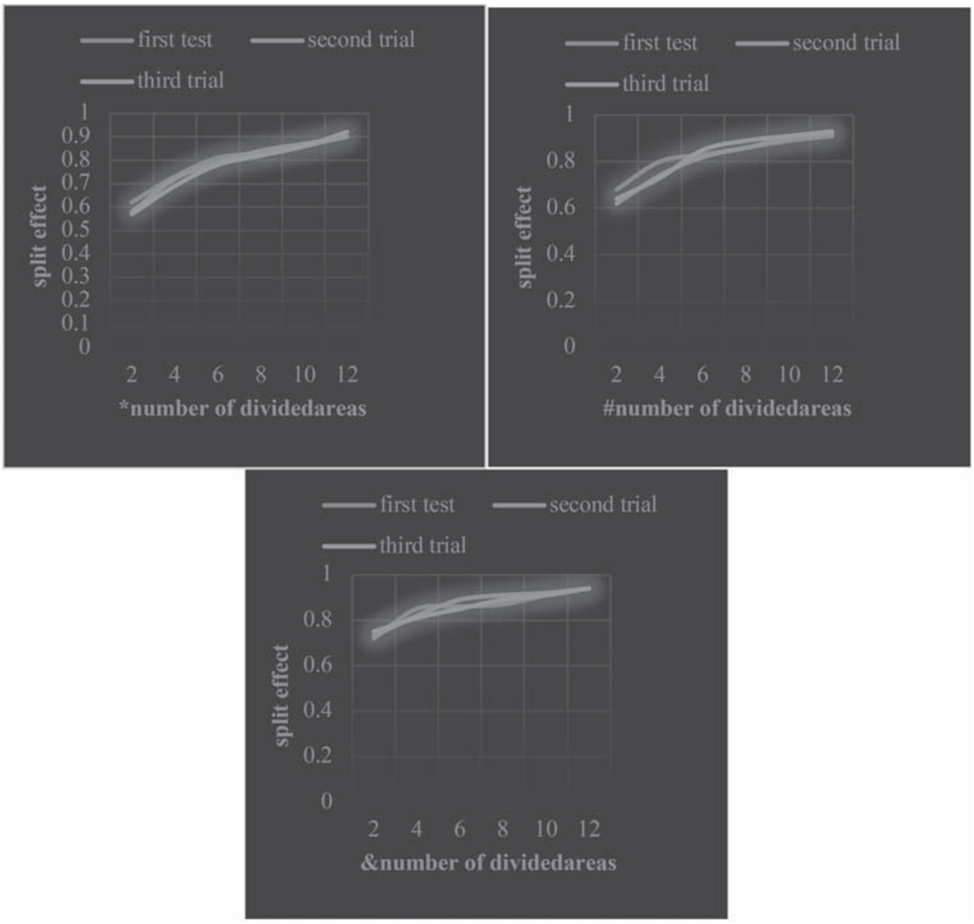

Figure 5 Comparison of segmentation effects.

the traditional threshold segmentation algorithm is the best at 0.9, and the segmentation effect of the traditional genetic algorithm is the best at 0.93, The best segmentation effect of the improved genetic algorithm is 0.94 and the initial segmentation effect is better. Compared with the threshold segmentation algorithm, the segmentation effect is improved by 13.2% and the accuracy is better.

The number of inheritance times of the algorithm determines the segmentation effect. The fewer the inheritance times, the higher the segmentation effect. The more times, the lower the segmentation effect. It is also related to the time of the system. For optimal segmentation, the simpler the method, the better. As shown in Figure 6, the of in three algorithms are compared in terms of the number of inheritances.

It can be seen from Figure 6 that the genetic number of the traditional threshold segmentation algorithm is higher than that of the traditional genetic algorithm and of the improved genetic algorithm, which also shows the complexity of the calculation. The number of times is reduced by about 45.2%, which greatly reduces the number of calculations.

It can be seen from Figures 4 to 6 that the improved genetic algorithm can better achieve image segmentation than the traditional segmentation method, and it is better than the traditional method in terms of CPU utilization, segmentation effect, and number of operations. The final image after segmentation is shown in Figure 7.

The segmentation results indicate that the proposed method is better than the two traditional methods. When comparing the original image with the image obtained by the traditional method, it can be seen that much of the information in the target object has been lost, and the segmentation results are also more prominent. The target area of the image area is well preserved, and the positioning performance is relatively complete.

5. CONCLUSION

Based on the incompleteness of the threshold algorithm and the traditional genetic algorithm, an improved genetic algorithm is introduced to improve the two segmentation methods and supplement the method of image segmentation. Under the condition of ensuring consistency, the segmentation area is determined, and the improved algorithm is used. The segmentation algorithm model is established. The experiment shows that in the case of the same texture scene, the improved genetic algorithm also greatly reduces the CPU usage. In terms of segmentation accuracy, the difference between the two traditional algorithms is not large, but the accuracy of the improved genetic algorithm is obtained. Improvement, in terms of the number of inheritances, there is little difference between the two traditional methods since both require multiple calculations, which increases the workload. Compared with the two traditional algorithms, the improved genetic algorithm greatly reduces the number of inheritances,

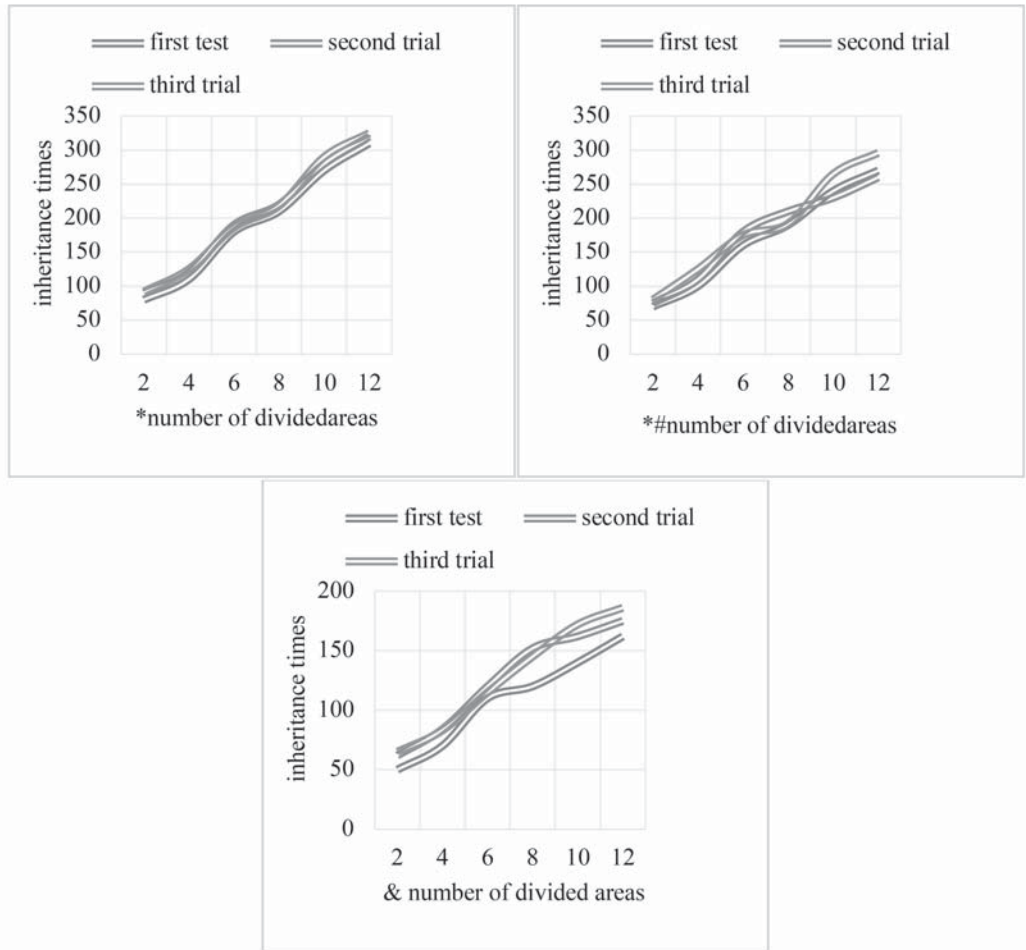

Figure 6 Comparison of inheritance times.

Figure 7 Comparison of results after segmentation.

which in turn greatly reduces the number of computers required. The improved segmentation algorithm ensures the consistency and information integrity of the segmentation area; the interface after segmentation is relatively clear; and there is no gray area. The shortcoming of this paper is the lack of a comprehensive comparison that considers various aspects of the three algorithms. It is acknowledged that, due to time constraints, this paper has several limitations which will be addressed in future work.

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DATA AVAILABILITY STATEMENT

No data were used to support this study.

CONFLICTS OF INTEREST

These are no potential competing interests in our paper. AA authors have seen the manuscript and approved its submission to your journal. We confirm that the content of the manuscript has not been published or submitted for publication elsewhere.

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