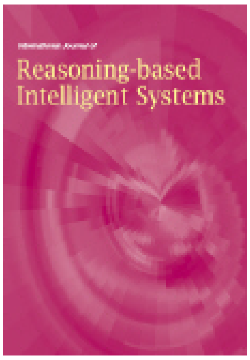

International Journal of Reasoning-based Intelligent Systems

ISSN online: 1755-0564 - ISSN print: 1755-0556
https://www.inderscience.com/ijris

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DOI: 10.1504/IJRIS.2023.10053464

Article History:

Received:	12 July 2022
Accepted:	22 November 2022
Published online:	19 March 2024

Complex background image segmentation based on multi-scale features

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Abstract: Aiming at the problems of large feature extraction error and poor segmentation effect in complex background image segmentation, a complex background image segmentation algorithm based on multi-scale features is designed. Firstly, the kernel function of multi-scale extraction method is used to initially determine the image feature density, and the Gaussian kernel function is introduced to determine the distance between the feature distribution points and the centre point to complete the image global feature extraction; then, set the grey level constraint of the local feature image to complete the local feature extraction; finally, determine the image edge threshold, divide the complex pixel feature area, determine the image feature membership and fuzzy rate, transform the segmentation problem into a nonlinear problem, and complete the segmentation. The experimental results show that the proposed algorithm can reduce the feature extraction error, have a maximum error of less than 1%, and optimise the image segmentation results.

Keywords: multi-scale feature; complex background image; kernel function; LBF model; optimal curve; image segmentation.

Reference to this paper should be made as follows: Cao, Y. (2024) ‘Complex background image segmentation based on multi-scale features’, *Int. J. Reasoning-based Intelligent Systems*, Vol. 16, No. 1, pp.43–49.

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1 Introduction

In recent years, multimedia electronic technology has developed rapidly on the basis of Internet technology. As an important technology in this field, image has changed people’s lifestyle. In people’s daily life, it has become a common phenomenon to obtain images through a variety of digital products (Zhang et al., 2022a). In this context, hundreds of millions of images have appeared. These images contain a lot of key information, which has become the basis of the development of image processing technology and promoted the rapid development of image processing technology. So far, image processing technology has developed rapidly in many fields (Zhang et al., 2020). Among them, image segmentation technology is the key processing technology in this technology. Image segmentation technology is a key technology to analyse images. As the basis of image expression, it plays a key role in the response to image features. Image segmentation will analyse the characteristics, targets, parameters, etc. of the image, and transform the image into a more compact form (Fan et al., 2021), so that complex images can be segmented into simpler images, and promote the progress of image technology. However, with the complexity of image form and background, the effect of image segmentation is affected, and the image expression cannot be fully explained (Zhang et al., 2022b). Therefore, researchers in the field of image technology have done a lot of research on the segmentation of complex background images.

Liang et al. (2020) designed an improved kernel likelihood c-means clustering image segmentation method. This method aims at the deficiency of image local information processing during segmentation. In the process of segmentation, the local information of the image is obtained through the median filter method, and the corresponding objective function is set. The objective function is solved with the help of kernel space to determine the membership degree of pixels in the process of image segmentation. The region with serious noise after segmentation is processed to complete the predetermined image segmentation, which effectively improves the effect of local image segmentation, but there are certain limitations because the influence of background is not considered too much in the segmentation. Wang et al. (2020) proposed a method of image segmentation using kernel function and Mahalanobis distance. In the research of this method, the image pixels to be studied are nonlinear mapped by kernel function, the image information is transformed into high-dimensional space, and the distance between pixels in this space is calculated with the help of Mahalanobis distance to determine the specific key points of image segmentation. Combining the results of kernel function and Mahalanobis distance calculation, the effective image segmentation is completed. After segmentation, the image noise is low, but there are still many noise points in the complex background in the segmentation. It is necessary to improve the noise point suppression method to improve the effect of image segmentation. Ding et al. (2021) designed a deep interactive image segmentation method integrating multi-scale marker information. By analysing the problems existing in the existing interactive image segmentation, aiming at the influence range of each image click point, the image segmentation technology is improved. Set different Gaussian radii of interactive images, generate different mapping results, classify and remove different mapping results, design image non-local feature attention module, fuse Gaussian mapping, improve the probability information of image segmentation, determine the loss rate of image segmentation, segment nearby targets, and study the implementation method. This method can maintain the integrity of the image after segmentation, but the segmentation process is complex and affected by many factors, so it is difficult to achieve the desired segmentation effect.

In view of the problems in the above methods, a new complex background image segmentation method based on multi-scale features is proposed. The key technical route of this paper is as follows:

1 The kernel function in the multi-scale extraction method is used to initially determine the image feature density, and the Gaussian kernel function is introduced to determine the distance between the feature distribution points and the centre point to complete the image global feature extraction. By determining multi-scale features of complex background images, and effective preprocessing for different features, combined with multi-scale features of complex background images, local feature extraction is completed.

2 Set the limited area of the local optimal curve of the complex background image, introduce the LBF model to determine the image energy of the local area, increase the level set penalty item to constrain the local feature optimal curve, and set the grey level constraint of the local feature image to complete the local feature extraction.

3 Determine the image edge threshold, divide the feature area of complex pixel points, build a multi-scale feature difference set through European space, determine the image feature membership and fuzzy rate, transform the segmentation problem into a nonlinear problem, and complete the design of complex background image segmentation algorithm.

4 Experimental analysis, taking the feature extraction error and image segmentation effect as experimental comparison indicators, the method in this paper is compared with traditional methods.

2 Multi-scale feature extraction of complex background images

In order to achieve accurate segmentation of complex background images, it is necessary to research by extracting the features of complex background images. In this feature extraction of complex background image, multi-scale feature extraction method (Guo et al., 2021) is used to extract complete image features. Multi-scale feature extraction method is the process of transforming image features of different scales after processing the resolution of the image to be segmented. Therefore, in this feature extraction of complex background image, multi-scale extraction of image local features and global features is used to achieve feature extraction, which lays a foundation for subsequent complex background image segmentation.

In the multi-scale feature extraction of complex background image, the global feature of background image is related to the accuracy of image segmentation. Therefore, firstly, the global features of complex background images are extracted by kernel function in multi-scale extraction method. Kernel function is an effective global feature extraction method in multi-scale feature extraction. This method is essentially a density estimation function (Khadangi et al., 2021), which realises the extraction of target features through the estimation of image kernel density.

Set the global feature of the complex background image in the n dimensional Euclidean space, and there are any pixels as $a \in A^n$, where A represents the real region of the global feature of the complex background image, and the definition of a essence is:

$$\| a \|^2 = a^T a, k(a) : [0, +\infty] \to A \tag{1}$$

where $k(a)$: $[0, +\infty]$ represents the global contour function of the complex background image, which is greater than 0. It is a non-increasing function. In its global contour, integrable calculation can be carried out continuously in segments, and the complex background image can be divided globally in more detail, that is:

$$k(a) = \int_n^\infty k(a) dr < +\infty \tag{2}$$

After the complex background image is globally segmented, the kernel density of the complex background image is calculated. Set the kernel function to meet the following constraints, namely:

$$k(a) : A^n \to A' \left[k \| a \|^2 \right] l \tag{3}$$

where l represents the window width value of the kernel function.

Set any set of independently distributed sample pixels in the complex background image as:

$$B = \{b_1, \ldots, b_n\} \tag{4}$$

Among them, $\{b_1, \ldots, b_n\}$ represents any pixel in the global feature of the complex background image.

Calculate the kernel density estimation value of any pixel in the complex background image to obtain the kernel density of the global feature of the image. Through calculation, we can get:

$$f(a) = \frac{1}{nl^2} \sum_{i=1}^{n} k\left(\frac{a - a_i}{l}\right) \tag{5}$$

where $f(a)$ represents the kernel density result of the global feature of the image.

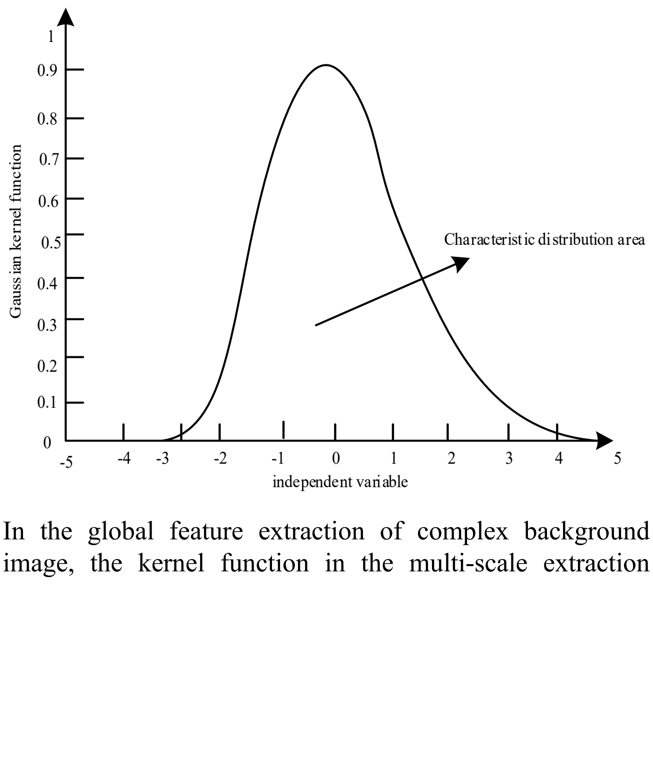
In the above calculation of global feature kernel density of complex background image, because there are many pixels in complex background image, it is difficult to determine them one by one in global segmentation, which will affect the effect of image segmentation. Therefore, Gaussian kernel function is introduced into global feature extraction to further extract the global features of complex background images. The global feature extraction formula is:

$$k_i(a) = \frac{1}{(2\pi)^{\frac{2}{n}} s^n} \exp \frac{|x|^2}{2s^n} \tag{6}$$

where s^n represents the density estimation result of global pixels extracted by Gaussian kernel function.

In the global feature extraction of complex background images using Gaussian kernel function, the distance between the distribution point of Gaussian kernel function (Ahmad et al., 2022) and the centre point increases or decreases monotonically, and the extracted feature points are concentrated in the whole region, as shown in Figure 1.

Figure 1 Schematic diagram of centralised distribution area of global feature points



In the global feature extraction of complex background image, the kernel function in the multi-scale extraction method is used to preliminarily determine the image feature density, and the Gaussian kernel function is introduced to determine the distance between the feature distribution point and the centre point, so as to complete the global feature extraction of the image.

After extracting the global features of the complex background image, in order to improve the effect of image segmentation, the local features of the complex background image are extracted according to the multi-scale features of the complex background image. In the local feature extraction, the local contour curve of the complex background image is found, and the local feature extraction research is completed by fitting the curve. In the search for the optimal local curve of the image, set the limited area of the local optimal curve of the complex background image (Liu et al., 2021) as:

$$C : c \in D^d \tag{7}$$

where d represents the dimension of the complex background image, and c represents the corresponding vector of image pixels.

According to the determined area of the optimal contour curve, calculate the energy of the image in this area, and introduce LBF model to calculate in this calculation process, and get:

$$\begin{aligned} &E(C, f_1, f_2) = \\ &\tau_i \int_u^n V_i(x-y)\left|C(y) - f_1(y)\right| + V_i\left|C(y) - f_2(y)\right| \end{aligned} \tag{8}$$

Among them, V_i represents the weight coefficient, f_1 and f_2 represent the grey values of complex background images in different regions, and τ_i represents local regions.

When the local feature area of the complex background image becomes smaller, the grey value of the image is also constantly changing. When the local area is reduced to the minimum, the grey value can be set to 0. At this time, the local area features are corresponding through the horizontal set of the model, and the corresponding feature function is set as:

$$\begin{aligned} &w^{LBF}(C, f_1, f_2) = \\ &\varphi_i \int_u^n V_i(x-y)\left|C(y) - f_1(y)\right| + V_i\left|1 - \left(C(y) - f_2(y)\right)\right| \end{aligned} \tag{9}$$

where $w^{LBF}(C, f_1, f_2)$ represents the corresponding feature function, and φ_i represents the smoothness of the optimal curve in the local feature.

In order to ensure that the optimal curve in the local feature set maintains a certain degree of smoothness for a period of time, at this time, a penalty item is added to the horizontal set of the model to constrain the local feature optimal curve, that is:

$$\begin{aligned} &w^{LBF}(C, f_1, f_2) = \\ &\mu \sum \varphi_i \int_u^n V_i(x-y)\left|C(y) - f_1(y)\right| + V_i\left|1 - \left(C(y) - f_2(y)\right)\right| \end{aligned} \tag{10}$$

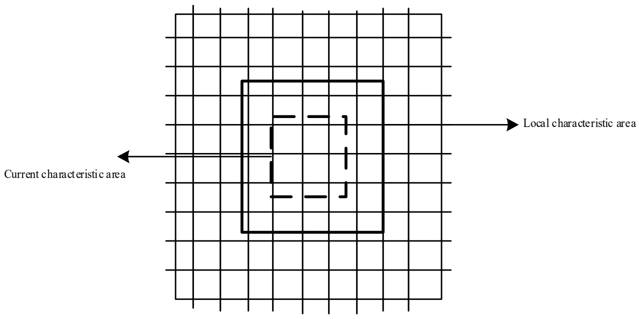
where μ represents the penalty constraint term. At this time, the energy function value in the local features of the complex background image is the smallest, which means that the degree of the optimal curve extracted at this time is the best.

In local feature extraction, the processing ability of complex background image to its grey level is not good, which easily leads to the instability of the extracted local features. Therefore, it is also necessary to constrain the grey level of the extracted local feature image (Ostdiek et al., 2022). Set the local feature grey-scale image of the complex background image as $P(x, y)$, and the mathematical expression model of its constraint is:

$$P(x, y) = g(x, y)U(x, y) + M(x, y) \tag{11}$$

Among them, $U(x, y)$ represents the complex background image with uniform grey level, $g(x, y)$ represents the local characteristic grey uneven field, and $M(x, y)$ represents the local characteristic curve noise value, which is usually small and generally negligible. The schematic diagram of features extracted after grey constraint of local feature image is shown in Figure 2.

Figure 2 Schematic diagram of feature extraction after grey constraint of local feature image



In the multi-scale extraction of local features of complex background images, the limited region of the local optimal curve of complex background images is set, the LBF model is introduced to determine the image energy of the local region, the level set penalty item is added to constrain the local optimal curve, and the grey constraint of the local feature image is set to complete the local feature extraction.

3 Design and research of image segmentation algorithm for complex background

Based on the above multi-scale feature extraction of complex background image, a complex background image segmentation algorithm is designed. Due to the fuzziness of the edge and region of the complex background image, there are some obstacles in image segmentation. Therefore, in this complex background image segmentation, the edge region of the complex image is segmented according to the multi-scale characteristics of the complex image. By determining the edge threshold of the complex background image, the characteristic areas of the pixels of the complex background image are divided, and these pixels are separated from the pixels of the complex background (Deng et al., 2021). Set the pixel space of the complex background image as R, and place the space in the grey space F, and the mapped space is Q. Then, divide it appropriately according to the grey level of the image pixels, and get:

$$\prod RF = \{F_1, F_2, \dots, F_K\}, F_k = \left\{\frac{f}{Q}\right\} \tag{12}$$

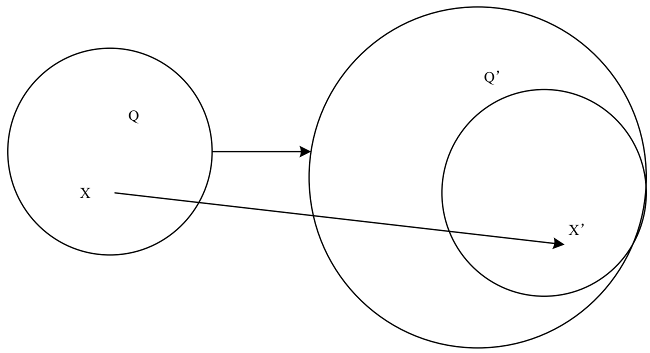
where $\prod RF$ represents the moderate division result of grey level.

According to the grey value of the divided image pixels, the multi-scale feature of a complex background image is selected to express the difference between different image feature points. At this time, the difference set of multi-scale features of all complex background images is composed of a set of European spaces as follows:

$$X = \{x_1, x_2, \dots, x_{mn}\} \tag{13}$$

where x_1, x_2 represent the pixel value in the multi-scale feature space, and x_{mn} represents the mapped multi-scale feature set value. The multi-scale feature diagram of the complex background image after European space mapping is shown in Figure 3.

Figure 3 Schematic diagram of multi-scale feature mapping of complex background image



On this basis, a multi-scale feature matrix of complex background image is constructed, which is taken as the target object of image segmentation. The constructed matrix is:

$$X = \begin{bmatrix} x_{11}, x_{12}, \dots, x_{1n} \\ x_{12}, x_{22}, \dots, x_{2n} \\ \cdots \\ x_{n1}, x_{n2}, \dots, x_{nn} \end{bmatrix} \tag{14}$$

The background multi-scale feature pixels of all images in this matrix are mapped points, and each pixel corresponds to a corresponding feature point. When it is segmented, the attributes of pixels will change, and the number of spatial samples of corresponding pixels will be extremely large, which will affect the speed of image segmentation. Therefore, it is necessary to set the segmentation rules for these pixels to be segmented to limit the infinite expansion of the pixel set. The membership function values corresponding to the pixel points of each multi-scale feature are relatively consistent. At this time, it is necessary to reduce the background pixels of the segmented image. In this process, it is necessary to determine the feature membership of the complex background image (Yang et al., 2021), that is:

$$W_i = \sum_{i=1}^{n} \sum_{j=1}^{m} r_{ik} d_{ik} \tag{15}$$

where W_i represents the membership of the complex background image, r_{ik} represents the fuzzy subset of image pixels, and d_{ik} represents the positive definite matrix.

After determining the membership degree of the image, the effective segmentation of the complex background image is implemented. Set the segmentation algorithm as a clustering problem and transform it into a nonlinear optimisation problem (Ali et al., 2021), that is:

$$\begin{cases} \min W_i = v\sum_{i=1}^{n} \sum_{j=1}^{m} r_{ik} d_{ik} \\ \quad \text{s.t. } W_i \in H_k \end{cases} \tag{16}$$

where v represents the segmentation coefficient, min W_i represents the objective function, and H_k represents the image noise value.

Determine the blur rate of the complex background image, and get:

$$Z(x) = \frac{2}{n} \sum_{x=1}^{n} \delta(i)\omega(i) \tag{17}$$

where $Z(x)$ represents the size of blurred pixels, $\delta(i)$ represents the grey level of pixels, and $\omega(i)$ represents the window width of membership function.

On this basis, the complex background pixels of the complex background image are further determined, namely:

$$\vartheta(x, y) = \begin{cases} 1 & \beta_i(x, y) \geq T \\ 0 & \beta_i(x, y) < T \end{cases} \tag{18}$$

where T represents the background threshold.

Thus, the complex background image is segmented, and the segmentation formula is set as:

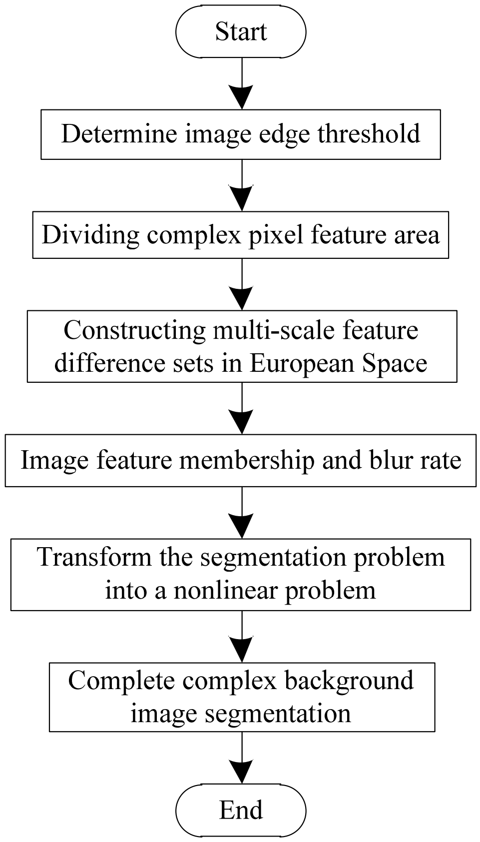
$$G_x = \frac{1}{n\beta_i} {}^\circ F \sum_{x=1}^{n} \delta(i)\omega(i) \sum v(i, j) \tag{19}$$

where G_x represents the segmentation result, n represents the image pixels, v represents the window width after segmentation, and $°F$ represents the background grey value after segmentation.

The specific process of complex background image segmentation is shown in Figure 4.

In the design of complex background image segmentation algorithm, determine the image edge threshold, divide the complex pixel feature area, construct a multi-scale feature difference set through European space, and determine the image feature membership and fuzzy rate, so as to transform the segmentation problem into a nonlinear problem, and complete the design of complex background image segmentation algorithm.

Figure 4 Complex background image segmentation process



4 Experimental analysis

4.1 Experimental scheme

In this experiment, we choose the complex background image in the MATLAB 7.0 library as the research object and segment it. The image size is 1,024 * 1,024, and the image clarity is high, meeting the experimental requirements. According to the needs of the experiment, the image is processed by grey level, which is easy to segment in the experiment. The background of the complex background image is calibrated by the binary method. The black part is set to 0, and the white part is 245. The segmentation interval is set to 1.5 s, and the noise in the image is set to be between [–2, 2] dB. The specific experimental image is shown in Figure 5.

4.2 Experimental indicators

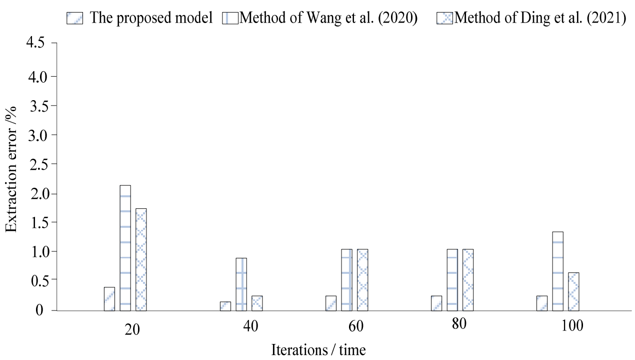
According to the set experimental scheme, this experiment is tested by comparing the error of multi-scale feature extraction and the segmentation effect of the sample image as the experimental indicators. Among them, the more the multi-scale feature extraction error is, the better the performance of the method is. The closer the segmentation effect is to the actual effect, the stronger the segmentation performance of the method is. In the experiment, the method in this paper, the method in Wang et al. (2020) and the method in Ding et al. (2021) are compared. The sample image is first extracted with multi-scale features, and then effectively segmented according to the extracted multi-scale features.

Figure 5 Schematic diagram of sample segmentation image

4.3 Experimental result

In the experiment, by comparing the method in this paper, Wang et al. (2020) method and Ding et al. (2021) method to analyse the extraction error of multi-scale features for the sample image, the results are shown in Figure 6.

Figure 6 Error analysis of multi-scale feature extraction of sample image



Analysing the experimental results in Figure 6, it can be seen that among the extraction errors of the method in this paper, the method in Wang et al. (2020) and the method in Ding et al. (2021) for multi-scale features of sample images, the extraction error of the method in this paper is the lowest, and is always less than 1%. The extraction error of the method in Wang et al. (2020) and the method in Ding et al. (2021) for multi-scale features of sample images is higher than the method in this paper, and there are some fluctuations, it can be seen that this method has certain advantages in multi-scale feature extraction of complex background images. The reason why the method in this paper has low feature extraction error is that the method in this paper extracts the special scale features of the image under the grey constraint, thus avoiding the interference caused by noise and reducing the feature extraction error.

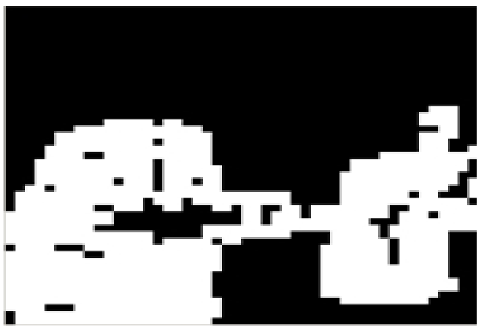
Based on the above multi-scale feature extraction, this method, Wang et al. (2020) method and Ding et al. (2021) method are used to segment the sample image, and the segmentation effect is shown in Figure 7.

Figure 7 Segmentation effect of complex background image with different methods, (a) actual segmentation result (b) paper method (c) Wang et al. (2020) method (d) Ding et al. (2021) method

(a)

(b)

(c)



(d)

Analysing the segmentation results in Figure 7, it can be seen that there is a certain difference between the effect of sample image segmentation and the actual segmentation effect through the method in this paper, the method in Wang et al. (2020) and the method in Ding et al. (2021). Among them, the effect of sample image segmentation using this method can maintain a good degree of integrity, and the effect of Wang et al. (2020) method and Ding et al. (2021) method on sample image segmentation is worse than this method, which shows that this method can effectively achieve the effective segmentation of complex background images. This is because the method in this paper divides the feature extraction of complex pixel points through image edge threshold after accurate multi-scale feature extraction of images. Combining the membership degree and fuzzy rate of image features, the nonlinear transformation of segmentation problem is carried out, thus improving the image segmentation effect.

5 Concluding remarks

In order to solve the problems of complex background image segmentation, a complex background image segmentation method based on multi-scale features is designed. The performance of the method is verified from both theoretical and experimental aspects. This method has lower feature extraction error and better segmentation effect in complex background image segmentation. Specifically, compared with the segmentation method based on kernel function and Mahalanobis distance, the feature extraction error of this method is significantly reduced, up to no more than 1%; compared with the segmentation method based on multi-scale marker information, the segmentation effect of this method is better, and the edge of the target segmentation region is clear. Therefore, the proposed segmentation method based on multi-scale features can better meet the requirements of complex background image segmentation.

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