Research on Adaptive Segmentation Algorithm of Image Weak Target Based on Pattern Recognition

Tao Lei[1] and Xiao-gang Zhu[2](✉)

[1] South China Normal University, Guangzhou 510006, China
hcy211727@163.com
[2] Nanchang University School of Software, Nanchang 330047, China
csy22215@163.com

Abstract. Based on the comprehensive research of image segmentation technology, an adaptive segmentation algorithm based on pattern recognition for image weak targets is proposed. By systematically designing the image segmentation algorithm by analyzing the algorithm requirements and principles, the modules such as image preprocessing, weak target detection, image feature extraction and adaptive threshold selection are designed and implemented according to the algorithm implementation flow. In order to verify the experimental performance of the algorithm, experimental analysis shows that the adaptive image segmentation algorithm can be used to preserve image details, improve the quality of the segmented image, and shorten the image segmentation time.

Keywords: Pattern recognition · Image adaptation · Segmentation algorithm

1 Introduction

The transmission of pictures and the processing of images are one of the important symbols of new media [1]. Some special operations on images, such as recognition, restoration, compression and segmentation, can be realized by using new media technologies. Image segmentation is the technique and process of dividing an image into specific regions of unique nature and proposing objects of interest. It is a key step from image processing to image analysis. The process of image segmentation is a marking process, image segmentation is a critical preprocessing for image recognition and computer vision. Without proper segmentation, it is impossible to have a correct identification. However, the only basis for segmentation is the brightness and color of the pixels in the image. When the computer automatically processes the segmentation, various difficulties will be encountered. Therefore, image segmentation is a technology that needs further research. Especially for some weak image targets in pattern recognition, it is necessary to design an adaptive segmentation algorithm to achieve image segmentation. Pattern recognition is the use of computer mathematical methods to study the automatic processing and interpretation of patterns. An important form of the information processing process is the identification of the environment and the object by the living body. This recognition method is applied to image segmentation to obtain higher quality segmentation results. Nowadays, there are many image segmentation

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algorithms. There is no uniform solution to the image segmentation problem. This technology is usually combined with the knowledge of related fields, so that the image segmentation problem in this field can be more effectively solved.

2 Principle of Image Segmentation

The principle of image segmentation-based image weak target adaptive segmentation algorithm is to divide the image into regions with specific characteristics and extract the target of interest. The characteristics include grayscale, color, texture, etc., and the selection of the target may be a corresponding single area, or may correspond to multiple areas. Image segmentation is a key step from image processing to image analysis and a basic computer vision technology. With the concept of collection, image segmentation can be given the following more formal definitions: Let the set R represent the entire image area, and the segmentation of R can be regarded as dividing R into a number of non-empty subsets R_1, R_2, …, R_n satisfying the following conditions: The sum (set) of all sub-regions obtained by segmentation should be able to include all pixels in the image, or segmentation should divide each pixel in the image into a sub-region. Each sub-region does not overlap with each other, or one pixel cannot belong to two regions at the same time; pixels belonging to different regions obtained after segmentation should have such different characteristics. Pixels within the same sub-area should be connected. The segmentation of the image is always based on the criteria of a segmentation [2]. There are many types of segmentation algorithms, among which the main application is the combination of the threshold segmentation algorithm and the region segmentation algorithm. The principle of the threshold segmentation algorithm is: Assuming that the object and the background are at different gray levels, the image is polluted by zero-mean noise. The gray distribution curve of the image approximately represents two normal distribution probability density functions representing the objective function and the background histogram respectively. Using the composite curve of these two functions to fit the histogram of the overall image, the histogram of the image will have two separate peaks. Then, according to the minimum error theory, the threshold value of the segmentation is obtained for the gray value corresponding to the valley between the two peaks of the histogram. After determining the appropriate threshold, the threshold is compared with the gray value of the pixel one by one, and pixel segmentation can be performed for each pixel in parallel, and the result of the segmentation is directly given to the image area.

3 Weak Target Adaptive Segmentation Algorithm

3.1 Image Preprocessing

Image preprocessing for pattern recognition includes image filtering, contrast enhancement and histogram enhancement, and effective preprocessing for infrared image features. Image filtering includes neighborhood averaging and median filtering. The neighborhood averaging method takes the average gray value of all the pixels in the neighborhood of the pixel on the input image as the output value of the pixel, so that the noise of the original image can be reduced. After smoothing the image with this filtering method, it can be reflected from the visual effect that the image has become softer than the original image, the noise is reduced, and the gray level changes more smoothly. However, this method does not carefully consider the actual difference between edge jump and noise, so the filtering effect is general. The median filtering method is a nonlinear image enhancement technique that has a good suppression effect on the interference pulse and the point noise, and can better maintain the edge of the image. Its working steps include roaming the template in the image and aligning the center of the template with a pixel location in the image; the gray value of each corresponding pixel in the template is read; the gray values are arranged in a row from small to large; one of the values is found in the middle; and the intermediate value is assigned to the pixel corresponding to the center position of the template. Different shapes of windows produce different filtering effects [3], which must be selected according to the content of the image and different requirements. One way is to use a small-scale window first, then gradually increase the window size until the median filter has more disadvantages than the benefit. Another method is to use a one-dimensional filter and a two-dimensional filter alternately. There is also an iterative operation that performs the same median filtering of the input image until the output no longer changes. Contrast enhancement can be performed after the image filtering process is completed. Contrast enhancement is a relatively simple but important method in image enhancement technology. The method is to modify the gray level of each pixel of the input image according to certain rules, thereby changing the dynamic range of the image gray level. It can expand the gray dynamic range, or compress it, or segment the grayscale, and compress it in a certain interval according to the characteristics and requirements of the image to expand in another interval. In practice, due to insufficient exposure or nonlinearity of the imaging system, the contrast of the image is not high, and the contrast enhancement can effectively improve the image quality. Contrast enhancement can take either a grayscale linear transformation or a grayscale nonlinear adjustment. Such as logarithmic transformation, exponential transformation. Logarithmic transformations are commonly used to extend low gray values and compress high gray values, which makes low grayscale image details easier to see. In addition to contrast enhancement, the enhancement method also has histogram enhancement. The histogram enhancement is based on probability theory, and the gray point operation is used to realize the transformation of the histogram. Histogram equalization is the transformation of an image of a known gray probability distribution into a new image with a uniform gray probability distribution. Since the new grayscale has a uniform probability distribution, the image looks very clear. Histogram equalization is a form of transformation, which is a transformation algorithm that makes the output image histogram become approximately uniform distribution. The calculation process is: List the original image gray level f_j, $j = 0,1,\ldots, k,\ldots, L-1$, where L is the number of gray levels; then count the number of pixels n_j of each gray level; Calculate the original image histogram and cumulative distribution function using Eq. 1;

$$\begin{aligned} P_f(f_f) &= \frac{n_j}{n},\ j = 0, 1, \ldots k, \ldots L-1 \\ c(f) &= \sum_{j=0}^{k} P_f(f),\ j = 0, 1, \ldots k, \ldots L-1 \end{aligned} \tag{1}$$

The calculated result transfer function is used to calculate the gray level g_j of the output after the mapping, and the calculated value of g j is rounded. The number of pixels of each gray level after the mapping is counted and the output image histogram is calculated. The mapping relationship between f_j and g_j is used to modify the gray level of the original image to obtain an output image with a nearly uniform distribution of the histogram. Histogram equalization belongs to a gray-scale nonlinear transformation. In the equalization process, the gray level corresponding to the pixel transformation depends on the gray probability distribution of the entire image and its own occurrence probability. This is different from the grayscale contrast broadening. In the gray-scale contrast broadening, after determining the parameters, the gray-scale after pixel transformation usually only depends on its own gray-scale level, and has nothing to do with the entire gray-scale distribution. The histogram equalization causes the gray level interval with fewer pixels to narrow in the gray level interval corresponding to the transformed result image. Due to the proper quantization, the gray layer with lower probability of occurrence is integrated into other gray layers after the transformation. Therefore, the histogram can be balanced to overcome the problem that the smaller pixels existing in the linear stretching process occupy a large gray interval.

3.2 Weak Target Detection

The weak targets in the image mainly include noise and clutter [11–13]. The noise source comes from the structural noise generated by the imaging system during the photoelectric conversion process. In the imaging work, it will be affected by many factors, such as external environmental conditions during image shooting, such as temperature, humidity, etc., as well as the performance of the sensor itself will decrease with the increase of use time. At the same time, when the signal is digitally extracted after the image is taken, noise is introduced due to the error. There are two methods for detecting weak targets in the image: normality test and whiteness test. The normal test is to subtract the original infrared image from the estimated background image after background estimation of the infrared image. In the ideal case, the suspicious target point and the residual Gaussian white noise in the image can be obtained from the image. But we hope to have a more intuitive way to test the normality of residual noise. Since we can't simply plot the probability density function from the gray histogram of the image, we can reflect the distribution of gray values at different frequencies. After the noise is detected, the clutter is detected and suppressed. The detection and suppression of image background clutter is the premise of target tracking and detection. The main methods of background clutter suppression are divided into linear and nonlinear methods [4]. Linear methods such as low-pass filtering and adaptive enthalpy methods have the characteristics of simple structure, high computational efficiency, and high target-target signal clutter ratio gain output. The disadvantage is that the filtering performance of the non-stationary image background is poor. The nonlinear method can effectively deal with the non-stationary image background. Since this paper assumes that each image sub-block is short-term stationary, a linear filtering method is used to perform background suppression of image clutter. The linear background clutter suppression method is a spatial filtering method based on nonparametric regression estimation, that is, a spatial domain adaptive filtering method.

3.3 Feature Extraction

In the segmentation image, the feature needs to be extracted to facilitate the delineation of the boundary. The feature extraction includes color feature extraction, texture feature extraction, boundary feature detection and region feature tracking. Color is the most important feature of color image. Firstly, the image is converted from RGB color space to X*Y*Z* space, and the average color of X, Y and Z channels is extracted as the 3-dimensional color feature of each region; The shape feature is the most powerful tool for describing the contour of the region, the 1-dimensional density ratio of the extraction region, the 2-dimensional centroid, the 4-dimensional rectangular box, and the 7-dimensional invariant moment as the 14-dimensional shape feature; the texture feature describes the texture characteristics of the image, calculates the co-occurrence matrix of the region, and extracts four statistical properties of energy, inertia, enthalpy and uniformity as 16-dimensional texture features. Thus each segmentation region is represented by a 33D feature vector. The texture features are described by means of a co-occurrence matrix. The co-occurrence matrix is calculated by the spatial dependence of the pixels of the gray image. The statistical methods are used to calculate 14 second-order statistics, and these second-order statistics are used as texture features. However, among the 14 texture features, 4 features are generally used to extract the texture features of the image, namely energy, inertia, enthalpy, and uniformity [5–7]. Energy is the sum of the squares of the values of the symbiotic matrix elements, reflecting the degree of uniformity of the gray distribution of the image and the degree of texture thickness. The energy of the fine texture is relatively small, and the energy of the coarse texture is relatively large; Inertia can reflect the complexity of image grayscale, the inertia of a simple grayscale image is small, and the inertia of a complex image is large; Di is a measure of the amount of information contained in an image [8–10]. The image with a fine texture is larger, and the value of the image with less texture is smaller. When the image does not contain any texture, the value of Di is close to zero. The uniformity reflects the local homogeneity of the image. When the symbiotic matrix is concentrated along the diagonal, the uniformity value is relatively large. After extracting the color and texture features in the image, the edge of the image needs to be detected. The edge of the image is the most basic feature of the image. The so-called "edge" refers to a collection of those pixels whose pixel gray level has a step change or a roof change, and the specific form is as shown in Fig. 1.

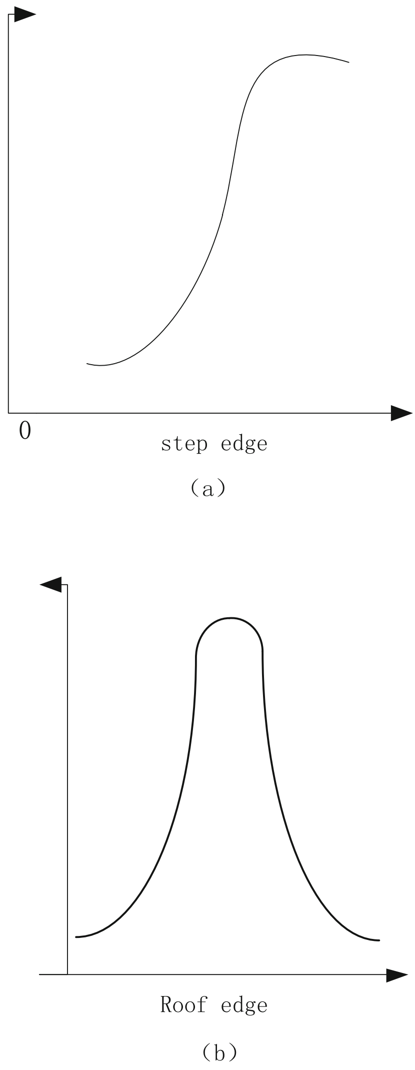


Fig. 1. Step edge and roof edge

The edge is widely present between the object and the background, between the object and the object. Therefore, it is an important feature that image segmentation relies on. The edge detection segmentation method detects the edge points in the image first, and then joins the contours according to a certain strategy to form a segmentation region. Edges are the result of discontinuities in gray values, which can often be easily detected using first and second derivatives. In fact, the derivative in the digital image is performed by differential approximation, so the detection of the edge is often done by convolution by means of the spatial differential operator. The edge detection operator examines the neighborhood of each pixel and quantifies the grayscale rate of change, which typically also includes the determination of the direction. In the operator operation, a similar convolution method is adopted, and the template is moved on the image and the gradient value of the corresponding central pixel is calculated at each position. Its gradient magnitude is given by:

$$G\mathrm{rad} = \sqrt{[f(x,y) - f(x+1,\ y+1)]^2 + [f(x+1,\ y) - y(x,\ y+1)]^2} \tag{2}$$

In Eq. 2, Grad is the edge gradient of the image, f() is the gray level of the pixel, and x and y are the positions of the pixel. The formula method not only detects edge points but also suppresses the effects of noise.

3.4 Adaptive Threshold for Image Segmentation

The image is segmented by adaptive threshold, and the selection of the threshold is based on the optimal group pitch iteration strategy. The implementation steps are as follows:

(1). Obtaining all equal weekly rates of the original image by improving the equal-peripheral rate method;
(2). The equal-period ratios are arranged from small to large, and the gray level t corresponding to the minimum value is set as the candidate threshold value;
(3). The equal-peripheral ratio corresponding to the gray level in the range of [t–k * bwt + k * bw] is set to be, where k is a positive integer and bw is the optimal histogram interval width, which is defined by the following formula:

$$bw = 3.49\,\alpha N^{-\frac{1}{3}} \tag{3}$$

Where N and α are the number of pixels and the standard deviation of the original image, respectively, and the calculation is repeated until all the equal-period rates are ∞. For the full gray level of the image, this paper firstly uses the above iterative strategy for preliminary screening, and obtains some candidate threshold values. Then, the method of dynamically determining the number of node clusters is introduced to automatically determine the number of thresholds D. Finally, the previous D candidate thresholds perform multi-level segmentation on the image. In order to realize the adaptive selection function of the threshold, the automatic determination of the threshold and the number of thresholds is set. Dynamically determining the number of enthalpy values has always been a difficult problem in the multi-level enthalpy segmentation algorithm. It is solved by introducing the criterion Q for determining the number of node clusters. The definition criterion Q is as follows:

$$Q(P_k) = \sum_{c=1}^{K} \left[\frac{A(V_c, V_c)}{A(V, V)} - \left(\frac{A(V_c, V)}{A(V, V)} \right)^2 \right] \tag{4}$$

Where: P_K is the K division of the image G, $\frac{A(V_c, V_c)}{A(V,V)}$ and $\frac{A(V_c, V)}{A(V,V)}$ respectively indicate the experimental probability p of the two end nodes of any one of the graphs G in the class C and the experimental probability p of the at least one end node in the cth class. Then the criterion Q can be regarded as the degree of deviation of p. In the formula, A(V, V) is a constant, and the number D of thresholds can be determined. The function of adaptive threshold determination can be realized by algorithm formula, and the threshold is optimally selected in order to improve the effect of segmentation image. Draw a Euler curve formed by a Euler number and a corresponding closed value, and define the Euler angle point on the Euler curve to the point on the straight line passing through the start point and the end point. The threshold corresponding to the point is the corresponding threshold, that is, the optimal threshold. After the threshold segmentation process is completed, the foreground and background regions of the image are basically separated. Since some isolated heterogeneous regions may appear inside the foreground or background region during processing, which will directly affect the subsequent image feature point extraction, these isolated regions should be post-processed. Using the morphological method, the noise region is eliminated by the open operation and the closed operation to obtain a more connected cluster cluster. Generally, the open operation can remove the false region in the foreground, and the closed operation can remove the error region in the background. It is considered that in the background of the image, some noise similar to the image texture sometimes appears, such as a straight line, a curve, etc., and a circle having a radius r is used as a structural element for the opening and closing operation. The use of circular structural elements to treat strip noise is good, while smoothing the edges of the fingerprint. To get a finer edge, you can use the Gaussian template to smooth out the final result. Because the running process is more complicated, the hardware implementation uses time-sharing operation, that is, the real-time processing part can be divided into odd field and even field to process, so that the time for processing one frame can be doubled. The peripheral circuits for the memory and DSP processor sections can be implemented with an FPGA to save area and achieve non-uniformity correction of the image from the detector in the FPGA.

In summary, the specific process of the image weak target adaptive segmentation algorithm based on pattern recognition is shown below (Fig. 2).

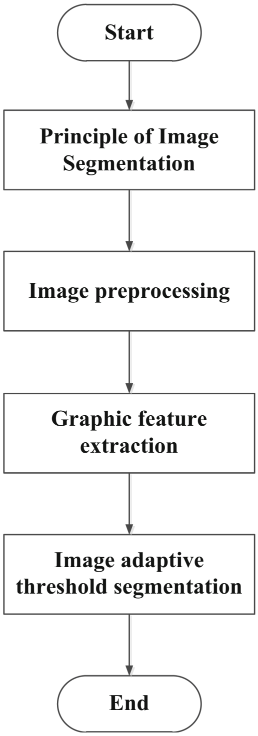
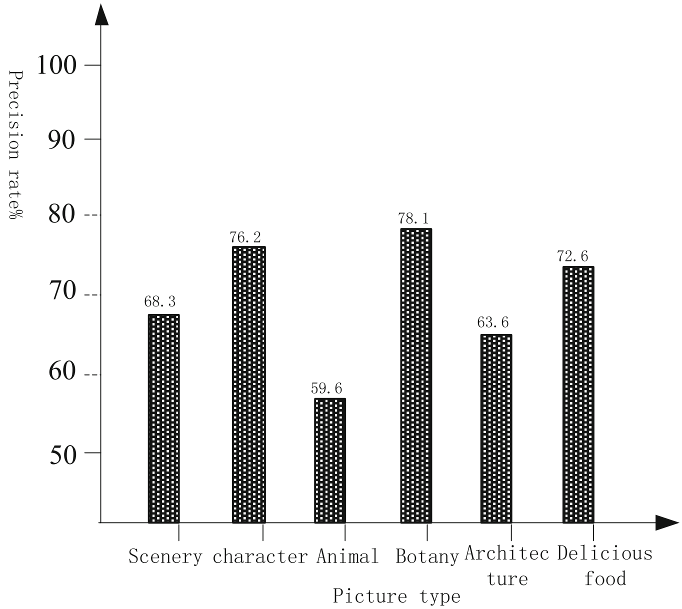


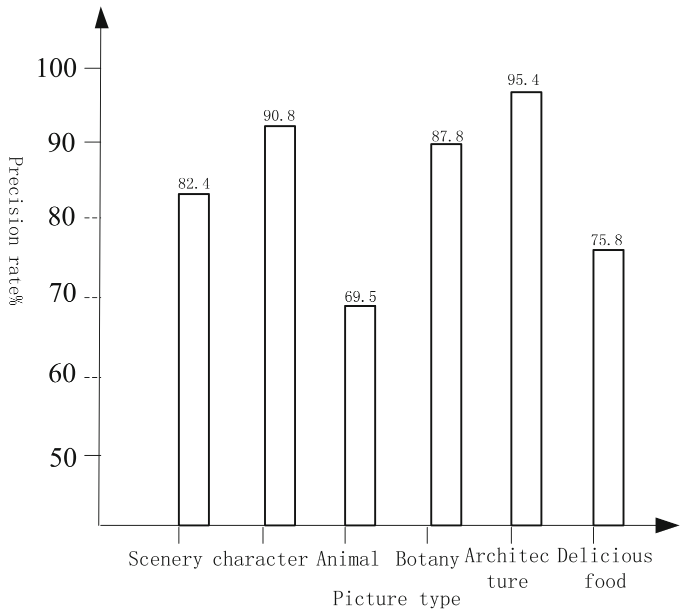
Fig. 2. Specific flow chart

4 Simulation Experiment

In order to ensure the validity and feasibility of the image segmentation-based image weak target adaptive segmentation algorithm proposed in this paper, experimental demonstration is carried out. The experimental demonstration uses all the image resources in the same image database, and has the same resolution and image file parameters for image segmentation experiments. In order to ensure the rigor of the experiment, the traditional image segmentation method is used as the experimental argumentation comparison, and the precision and the quality of the segmented image are counted. The precision is calculated as: precision = e/(e + s), where e is the number of similar images retrieved, s is the number of dissimilar images retrieved, and the value of the precision is expressed as a percentage. The average of all image precisions in the image library is defined as the average precision. Based on image pixel statistics, peak signal-to-noise ratio and mean square error are two common quality evaluation methods. They measure the quality of the image to be evaluated from a statistical point of view by calculating the difference between the gray value of the pixel corresponding to the image to be evaluated and the reference image. The experimental demonstration result curve is shown in Fig. 3 Fig. 4.

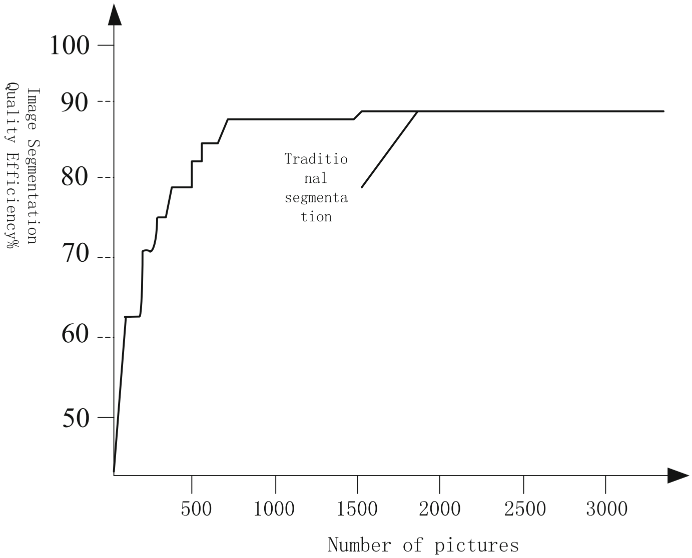


(a) Segmentation accuracy of traditional methods

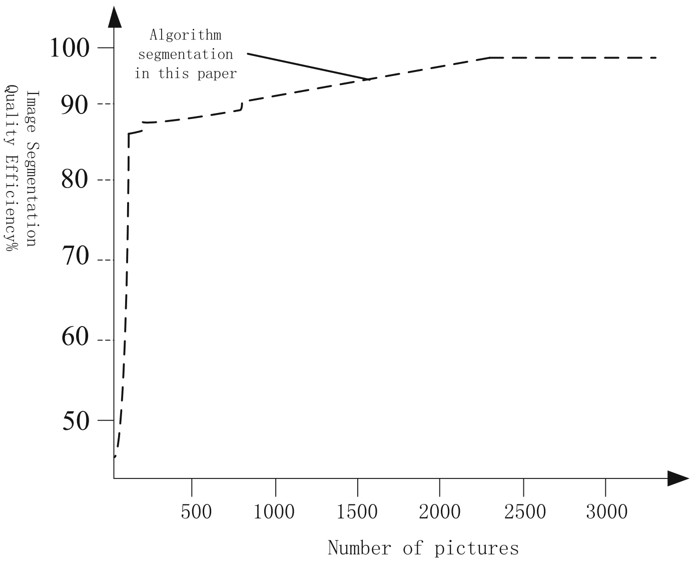


(b) The segmentation accuracy of this method

Fig. 3. segmentation accuracy of the two methods



(a) Image segmentation quality efficiency of traditional methods



(b) Image segmentation quality efficiency of the method in this paper

Fig. 4. Image segmentation quality efficiency of two methods

It can be seen from the experimental results that compared with the traditional image segmentation method, the proposed image segmentation of the image weak target adaptive segmentation algorithm has a relatively high precision in segmenting any type of image. It can be seen from Fig. 3 that it is particularly evident in the pictures of buildings; In terms of image segmentation quality, after calculation and comparison analysis, as the number of segments increases, the segmentation quality will gradually increase, and the algorithm segmentation method will always rise. According to the curve (b) in Fig. 4, it can be concluded that the image quality of the algorithm segmentation is always higher than that of the traditional method segmentation. It fully reflects the feasibility and use value of the algorithm, and provides a more comprehensive segmentation processing method for China's image processing business.

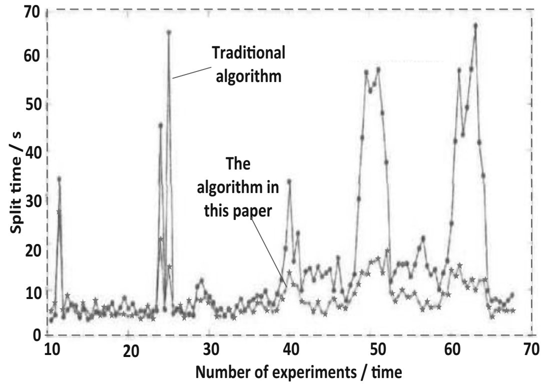


Fig. 5. Comparison of segmentation time between two algorithms

In order to verify the effectiveness of the algorithm in this paper, the adaptive segmentation time of the weak target image of the algorithm in this paper and the traditional algorithm is compared and analyzed. The comparison result is shown in Fig. 5.

According to Fig. 5, the image weak target adaptive segmentation time of the algorithm in this paper is within 20 s, while the image weak target adaptive segmentation time of the traditional algorithm is within 68 s, which shows that the image weak target adaptive segmentation time of this algorithm is longer than the image weak target of this algorithm. The adaptive segmentation time is short.

5 Conclusion

Image segmentation processing is an important processing link in image processing. However, in the process of image acquisition and imaging, there are inevitable degradation and degradation processes such as blur, motion deformation and noise, which not only affect people's visual perception of images, but also greatly reduce the use of effective information in images. The image segmentation based image weak target adaptive segmentation algorithm is used to segment the degraded image to improve the segmentation accuracy and improve the image quality.

References

1. Qin, L., Xiong, Y., Ke, L., et al.: Similarity calculation method of scene image based on adaptive weighting of similarity matrix. Pattern Recogn. Artif. Intell. **30**(11), 1003–1011 (2017)
2. Wang, J., Hong, Z.: Target tracking algorithm with saliency target indication and background adaptive constraints. Pattern Recogn. Artif. Intell. **30**(10), 875–884 (2017)
3. Quanhua, Z., Hongyun, Z., Xuemei, Z., et al.: Fuzzy Clustering Image Segmentation Based on Neighborhood Constrained Gauss Mixture Model. Pattern Recogn. Artif. Intell. **30**(3), 214–224 (2017)
4. Genggeng, L., Zhisheng, C., Wenzhong, G., et al.: Steiner minimum tree algorithm with X structure based on adaptive PSO and hybrid transformation strategy. Pattern Recogn. Artif. Intell. **31**(5), 398–408 (2018)
5. Lu, M., Liu, S.: Nucleosome positioning based on generalized relative entropy. Soft. Comput. **23**(19), 9175–9188 (2018). https://doi.org/10.1007/s00500-018-3602-2
6. Liu, S., Pan, Z., Cheng, X.: A Novel Fast Fractal Image Compression Method based on Distance Clustering in High Dimensional Sphere Surface. Fractals **25**(4), 1740004 (2017)
7. Moreno, R., Graña, M., Ramik, D. M., et al.: Image segmentation on the spherical coordinate representation of the RGB color space. Iet Image Process. **6**(9), 1275–1283 (2018)
8. Huang, Q., Luo, Y., Zhang, Q.: Breast ultrasound image segmentation: a survey. Int. J. Comput. Assist. Radiol. Surg. **12**(3), 493–507 (2017)
9. Khan, A.U.M., Torelli, A., Wolf, I., et al. AutoCellSeg: robust automatic colony forming unit (CFU)/cell analysis using adaptive image segmentation and easy-to-use post-editing techniques. Sci. Rep. **8**(1), 7302–7310 (2018)
10. Liu, S., Glowatz, M., Zappatore, M., Gao, H., Gao, B., Bucciero, A.: E-Learning, E-Education, and Online Training, pp. 1–374, Springer, Bethesda
11. Mariano, R., Oscar, D., Washington, M., et al.: Spatial sampling for image segmentation. Comput. J. **3**, 313–324 (2018)
12. Chen, L.C., Papandreou, G., Kokkinos, I., et al.: Deeplab: semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFs. IEEE Trans. Pattern Anal. Mach. Intell. **40**(4), 834–848 (2018)
13. Costa, H., Foody, G.M., Boyd, D.S.: Supervised methods of image segmentation accuracy assessment in land cover mapping. Remote Sens. Environ. **205**, 338–351 (2018)