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Infrared Image Segmentation using Adaptive FCM Algorithm Based on Potential Function

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Abstract

Traditional Fuzzy C-means segmentation algorithm requires to set clustering number in advance, and to calculate image clustering center by the iterative arithmetic. So the traditional algorithm is sensitive to the initial value and the computation complexity is high. In order to improve the traditional Fuzzy C-means algorithm, this paper presents an infrared image segmentation method using adaptive Fuzzy C-means algorithm based on potential function. The presented algorithm can directly determine the optimal clustering number and clustering center for infrared image to be segmented by the potential function. After calculating the membership matrix of pixels in the infrared image by the fuzzy theory, the final segmented image is obtained through the fuzzy clustering. The experiments show that the presented algorithm in the paper could determine the optimal clustering number of the infrared image adaptively, and ensure the accuracy of segmentation, while significantly reducing the computation speed and complexity of the algorithm.

Keywords: *infrared image segmentation, potential function, optimal clustering number, FCM algorithm*

1. Introduction

As the basis of the infrared target recognition and tracking, infrared image segmentation technique is one of the key technologies to improve the infrared warning system and the infrared guidance system performance [1]. In view of the infrared images with low contrast, low SNR and edge blur characteristics, traditional infrared image segmentation methods mainly include the edge method, threshold method, region growing method and feature clustering algorithm, etc.

The FCM segmentation algorithm [2-4] as an unsupervised clustering algorithm, is one of the most perfect in theory and the most widely used clustering algorithms based on the objective function. Its greatest contribution lies in that the fuzzy theory is introduced into the membership degree of image pixels. But the algorithm requires to set the clustering number in advance, and to calculate image clustering center by the iterative arithmetic, so the algorithm is sensitive to the initial value and the computation complexity is high.

In general, the traditional FCM clustering algorithm has slower convergence speed, and bigger sensitivity to initial value [5], researchers have proposed a number of improved FCM algorithm. Literature [6] uses the statistical histogram of the image instead of the image pixel in calculating the clustering center. It also cited the potential function neighborhood information as weights to determine the value of the fuzzy membership of the current pixel for image segmentation. Though this algorithm improves the image segmentation quality, it still requires to set the clustering number in advance, and is still sensitive to the initial value. Besides, Literature [7] and Literature [8] have improved the FCM algorithm according to their own areas of application f and achieved certain results.

This paper presents a method to adaptively determine the maximum potential residual height and directly determine the optimal clustering number and clustering center for infrared image segmentation by the potential function clustering method, and then through the fuzzy clustering to obtain the segmented infrared image. Experimental results show that the presented algorithm in the paper can realize infrared image segmentation adaptively, and ensure the accuracy of segmentation, while significantly reducing the computation speed and complexity of the algorithm. It is conducive to achieve real-time processing of infrared images.

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2. The Adaptive FCM Algorithm Based on Potential Function
2.1. Potential Function Clustering Algorithm [9]

Define the histogram probability function of the image I :

$$H_p(k) = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \delta_{ij}(k) \tag{1}$$

Where, $I = I\ (i, j)$ is a digital image, the size of the image to be segmented is $M \times N$, and:

$$\delta_{ij}(k) = \begin{cases} 1 \ \ if \ \ I(i, j) = k \\ 0 \ \ else \end{cases}, \quad k = 0,1,\cdots,255 \tag{2}$$

The probability of the appearance of pixel gray value k in the image I is represented by $H_P(k)$ approximately. The normalized histogram probability function of the image I is:

$$H_N(k) = H_P(k) / \max_g (H_P(g)) \tag{3}$$

The basis function of potential function generally adopts the form of $C(x) = 1/(1+\alpha x^2)$. When the normalized histogram probability function $H_N(k)$ interpolates over the basis function $C(x)$, the histogram potential function of the image I can be got:

$$P(k) = \sum_{i=0}^{255} \frac{H_N(i)}{1+\alpha(i-k)^2}, \quad k = 0,1,2,\cdots,255 \tag{4}$$

Using an appropriate control factor α can make the peak valley characteristics of the histogram potential function be very close to the ones of the normalized histogram probability function.

Define the normalized histogram potential function of the image I :

$$P_N(k) = P(k) / \max_g (P(g)), \ k = 0,1,\cdots,255 \ , g = 0,1,\cdots,255 \tag{5}$$

Let $P_0(k) = P_N(k)$, which is the normalized histogram potential function of the image I , and define C order histogram remaining potential function as follows:

$$P_c(k) = P_{c-1}(k) - P_c^* \frac{1}{1 + r_d (k - x_c)^4}, \quad c = 1,2,\cdots,C, \quad k = 0,1,\cdots,255 \tag{6}$$

Where,

$$P_c^* = \max\{ P_{c-1}(k), k = 0,1,\cdots,255 \}, \ x_c = \{k \mid P_{c-1}(k) = P_c^*\} \tag{7}$$

r_d is the factor to control the radius of attenuation, and C is the number of crests in the histogram. Experience has shown that if the pixel gray level range of the infrared image to be segmented is bigger, the radius of attenuation should be larger, and the corresponding value of the factor r_d should be smaller; if the crests of the infrared image to be segmented are more, the radius of attenuation should be smaller, and the corresponding value of the factor r_d should be larger. Define the factor r_d as follows:

$$r_d = \frac{\beta (C - 1)}{5 D_H^2} \tag{8}$$

Where, β is a constant in the experiment, and D_H means the gray depth of image I, whose value is the difference between the maximum and minimum values of image I.

Based on histogram remaining potential function define function groups divided by potential as follows:

$$F_c(k) = P_c^*(k) \frac{1}{1 + r_d \| k - x_c \|^4}, c = 1,2,\cdots,C, k = 0,1,\cdots,255 \tag{9}$$

As can be seen from the expression, function groups divided by potential is actually a quartic basis function whose center is x_c and whose height is $P_c^*(k)$. So when the value of C is known, dividing histogram potential function is a process where the quartic basis function is the best fitting of the given histogram potential function, and the fitting functions are F_1, F_2,..., F_C in Equation (9).

According to the above algorithm, use the function groups divided by potential to divide the histogram potential function, and the clustering center is obtained. However, due to the influence of the radius of attenuation parameter, some potential which should not be divided into is likely to appear in the process of division, and the potential should be eliminated is named as pseudo-potential [10]. Ideally, each crest in the histogram function divided by potential is in uniform distribution, and the interval between the two crests should be D_H/C. Though in reality this condition is generally not met, according to the ideal interval we can define an adaptive fuzzy pseudo-potential factor f_p as follows:

$$f_p = \frac{2 \gamma D_H}{3 C} \tag{10}$$

Where, C is the number of categories, D_H means the gray depth of image I, and γ is a constant in the experiment. Set x_i and x_j are two abscissas of the adjacent peak points in the function groups divided by potential, their value can be calculated by the type (7), if:

$$| x_i - x_j | < f_p \tag{11}$$

Then either must be a pseudo-potential. Extract the two extremum values of the both histogram function divided by potential respectively, and compare these two extremum values to obtain the maximum. Then add the two curves of the both histogram function divided by potential together, and give the sum function a fitting according to the following equation, and then the histogram function divided by potential, $F'(k)$,after merging pseudo-potentials is obtained:

$$F'(k) = \frac{y}{1 + r_d (k - x)^4} \tag{12}$$

Where, y represents the maximum of the two histogram function divided by potential above, and x means extremum value point of the sum function.

2.2. The Adaptive Determine of the Maximum Remaining Height of Potential

The algorithm described above still requires to be set the number of category C artificially, which makes the algorithm reduces its versatility, so a threshold value to make the iteration stop should be set in the algorithm. The threshold value R_h is called the maximum remaining height of potential, and its range is $0 < R_h < 1$. If the value of R_h could be determined adaptively, the value of C can also be obtained adaptively.

In the curve of potential function, the grayscale every abscissa of the peak point represents has the possibility to be a clustering center. This is because:

(1) In a neighborhood interval, the corresponding grayscale k to the crest has the highest probability;

(2) The grayscales around the grayscale k has the least variance with the grayscale k , which accords with the clustering thought.

Since the maximum remaining height of potential R_h is a value greater than 0 and less than 1, if the least crest value of the normalized histogram potential function of the image I is as the reference standard, the value of R_h could be set in the three situations:

(1) The value is greater than the least crest value and less than 1;
(2) The value is equal to the least crest value;
(3) The value is less than the least crest value and greater than zero.

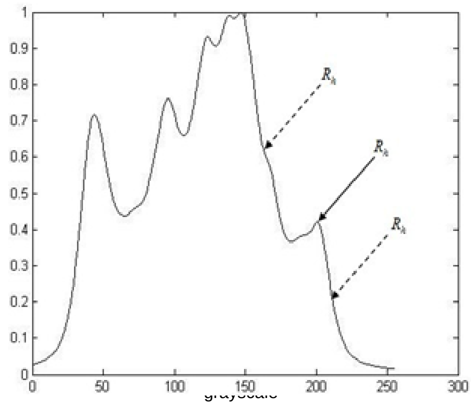


Figure 1. The Relationship of R_h and the Normalized Histogram Potential Function

As shown in Figure 1, if the value of R_h is set a value greater than the least crest value and less than 1, the potential information of the smallest crest will be lost in the process of computing. Meanwhile, in the curve of potential function, the grayscale every abscissa of the peak point represents has the possibility to be a clustering center, which means that if the value of R_h is set during the interval, a clustering center could be lost; Assume that the value of R_h is set a value less than the least crest value and greater than zero. As during the descending range from the least crest value to the value of R_h , there is no crest in the curve of normalized histogram potential function, that is to say, the possibility to exist a category in the corresponding grayscale during the interval is very small. So it is not meaningful to set the value of R_h in the interval.

In summary, the value of R_h should be set as the second case, in which the crest value in the curve of the normalized histogram potential function is the most reasonable. Define the R_h as follows:

$$R_h = \min\{P_1, P_2, ..., P_n\} \tag{13}$$

Where, $P_1, P_2, \cdots, P_n$ represent the crest values in the curve of the normalized histogram potential function, and n is the number of the crests in the curve of the histogram potential function.

2.3. The Principle of the Adaptive FCM Algorithm Based on Potential Function

The traditional FCM algorithm [11] is a method which uses the gray value of image and the distance information between the pixels to calculate image clustering center and the membership matrix of pixels by the iterative arithmetic, and then image segmentation is achieved. However, the complexity of the iterative arithmetic is higher, and it is not conducive to achieve real-time segmentation of infrared images. The potential function clustering algorithm can calculate the potential information of every grayscale during the image gray range, and through merging the pseudo-potential determine the optimal clustering number and the clustering center for the infrared image to be segmented adaptively.

This paper introduces the potential function clustering algorithm into the traditional FCM segmentation algorithm, and presents an infrared image segmentation method using adaptive FCM algorithm based on potential function. The presented algorithm can directly determine the optimal clustering number and clustering center for infrared image segmentation by the potential function, instead of the traditional FCM segmentation algorithm setting the clustering number in advance and calculating image clustering center by the iterative arithmetic. And then obtain the final segmented image by the fuzzy clustering. The steps are as follows:

1) Calculate the histogram potential function for infrared image I by the formula (4), k is the gray series, and obtain the crest values $P_1, P_2, \cdots, P_n$ of the normalized histogram potential function. Then calculate the maximum remaining height of potential R_h by the formula (13).

2) Let the initial number of categories $C = 2$, and the number of pseudo-potential $K = 0$.

3) Calculate the factor r_d by the formula (8), the fuzzy pseudo-potential factor f_p by the formula (10), the c order histogram remaining potential function $P_c(k)$ by the formula (6), where $c = 1,2,..., C + K$, and the corresponding x_c. K is the number of pseudo-potential.

4) Calculate the crest value of $P_c(k)$, and obtain the value of P^*_{c+1}. If $P^*_{c+1} < R_h$, then go to step 5; Otherwise, repeat step 3.

5) Calculate the function groups divided by potential $F_1, F_2, \cdots F_{C+K}$ by the formula (9), and order x_c in the order of ascending. Then the corresponding sorting result of $F_1, F_2, \cdots F_{C+K}$ is $F_1^{'}, F_2^{'}, \cdots F_{C+K}^{'}$.

6) If $K > 0$, the pseudo-potential exists. Calculate the fitting function by the formula (12), and then obtain the final function groups divided by potential F_1^s $, F_2^s, ..., F_C^s$, in which the value of x_c is the clustering center, and the final value of C is the clustering number.

7) Calculate the Euclidean distance between each pixel and the clustering center in the infrared image, $D(i, j, c)$.

$$D(i, j, c) = | I(i, j) - Center \quad (c) | \tag{14}$$

8) Define the membership of each pixel belonging to the clustering center as follows:

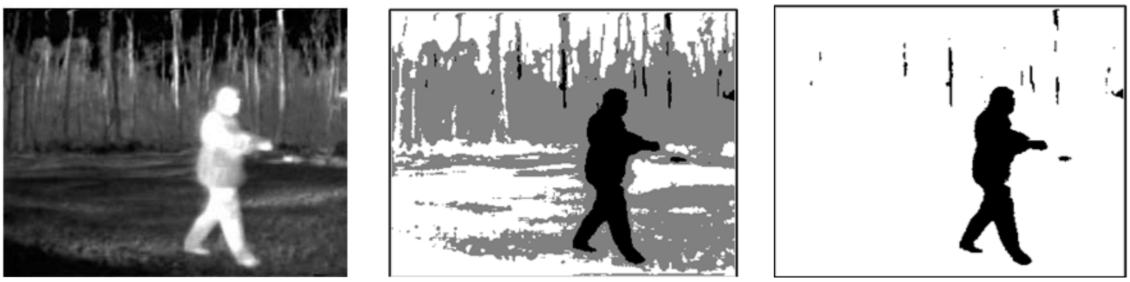
$$U(i, j, c) = \frac{1}{\sum_{c^{'}=1}^{C} \left(\frac{D(i, j, c)}{D(i, j, c^{'})}\right)^{\frac{2}{m-1}}} \tag{15}$$

9) Classify the pixels, and compare the memberships of each pixel (i, j) in the infrared image, $U(i, j, c)$ $c = 1,..., C$. The pixel (i, j) belongs to the class whose membership is the largest, and the final image segmented is gotten by clustering.

3. Results and Discuss

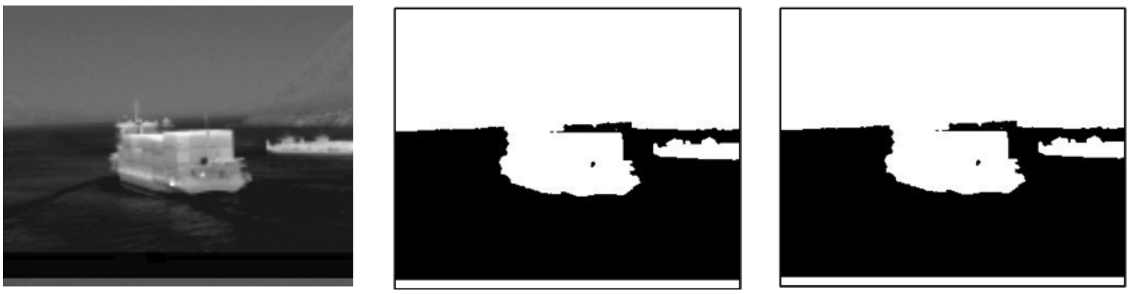
To validate the algorithm this paper presents, the clustering number set in the traditional FCM segmentation algorithm was equal with the optimal clustering number obtained adaptively by the algorithm in this paper. Compare the segmentation results and efficiency of the two algorithms in this circumstance.

Four infrared images were adopted in the experiment, of which the single-man infrared image shown in Figure 2 is from the infrared data made by laboratory, with 240×320 pixels. The ship infrared image shown in Figure 3 is from a domestic research institutes, with 240×320 pixels. The double pedestrians infrared image shown in Figure 4 is from an infrared database in the Internet, with 240×320 pixels.



(a) the original image (b) the result of FCM (C=3) (c) the result of the improved algorithm (C=3)

Figure 2. The Single-man Infrared Image



(a) the original image (b) the result of FCM (C=2) (c) the result of the improved algorithm (C=2)

Figure 3. The Ship Infrared Image

(a) the original image (b) the result of FCM (C=4) (c) the result of the improved algorithm (C=4)

Figure 4. The Double Pedestrians Infrared Image

From Figure 2 to Figure 4, the Figure (a) is the original infrared image to be segmented, the Figure (b) is the segmentation result of the infrared image by the traditional FCM segmentation algorithm, and the Figure (c) is the segmentation result of the infrared image by the improved algorithm proposed in this paper. As can be seen from the figures, the proposed algorithm can achieve the same results as the traditional FCM segmentation algorithm even better. Table 1 shows the comparison of the two methods in computation time.

Table 1. The Comparison of the Two Methods in Computation Time

Simulation image	The clustering number C	The time of FCM(s)	The time of the improve method(s)
the single-man	3	12.4641	1.5772
the tank	3	20.1532	1.6524
the double pedestrians	4	18.7104	1.9106

We can see that when their clustering number is set equally, the efficiency of the algorithm proposed in this paper is superior to one of the traditional FCM segmentation algorithm.

In addition, the traditional FCM algorithm is sensitive to the initial value. So after setting the clustering number, though each clustering result is the same, there is a visual difference in the image, which is not conducive to people's subjective evaluation. The improved algorithm in this paper adaptively determines the clustering number and the clustering center, so there is no influence of initial value on the segmentation result, and the result is unique. Figure 5 are the segmentation results of the single-man infrared image through the traditional FCM segmentation algorithm simulating several times. Let clustering number $C = 3$.

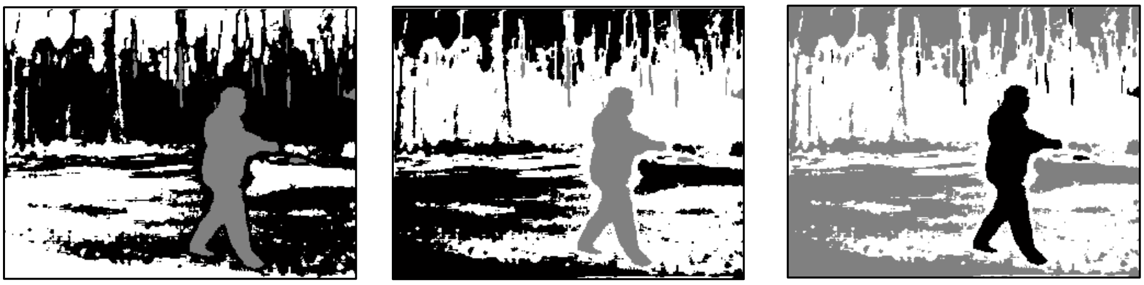


Figure 5. The Segmentation Results of the Single-man by FCM

As can be seen from the figure above, the Figure 6 are the simulating results of the same infrared image by the same method and the clustering number was set equally. Although the final clustering results are three categories, the results displayed in the image are different in vision. After many times simulation to the same single-man infrared image by the algorithm in this paper, the result is unique and is the same as Figure 2(c). We can conclude that the improved algorithm in this paper overcomes the defect of traditional FCM algorithm sensitive to the initial value.

4. Conclusion

Traditional FCM segmentation algorithm requires to set clustering number in advance, and to calculate image clustering center by the iterative arithmetic. So the traditional algorithm is sensitive to the initial value and the computation complexity is high, and it is not conducive to achieve real-time segmentation of infrared images. The proposed algorithm in this paper can adaptively determine the optimal clustering number and clustering center by the potential function clustering algorithm, calculate the membership matrix of pixels using the fuzzy theory, and then obtain the final segmented result by the fuzzy clustering. The experiments show that the proposed algorithm can ensure the accuracy of segmentation, while significantly reducing the computation speed and complexity of the algorithm. In addition, it overcomes the defect of traditional FCM algorithm sensitive to the initial value.

However, image noise has a great influence on the infrared image segmentation. The proposed algorithm does not perform well in the noise suppression processing, so the reduction noise part will be one of the future research in this algorithm.

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