An Adaptive Fuzzy Clustering Algorithm Based on Multi-threshold for Infrared Image Segmentation

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Abstract. To obtain the satisfied performance of infrared image segmentation in complex environments, an adaptive fuzzy clustering algorithm based on multi-threshold (AFC_MT) is proposed. The methodology uses a coarse-fine concept to reduce the computational burden required for the fuzzy clustering and to improve the accuracy of segmentation that a single fuzzy clustering cannot reach. The coarse segmentation attempts to segment coarsely using the multi-thresholding technique. Firstly, the pseudo peaks in a multi-threshold algorithm are removed by introducing a control factor of peak areas and a control factor of peak widths to segment an image coarsely, then in order to find a finer segmentation result, the coarse segmentation result is clustered by an improved fuzzy clustering algorithm that introduces an adaptive function to get the most reasonable cluster number and that defines a logarithmic function as a measurement of distance. Experimental results show that AFC_MT behaves well in segmenting infrared images in complex environments.

Keywords: Adaptive fuzzy clustering · Infrared image segmentation · Multi-threshold segmentation · Pseudo-peak removal

1 Introduction

As the low-level processing technology of computer vision and image understanding and the key technology in automatic target recognition technology, image segmentation plays an important role in image analysis and pattern recognition. For example, an essential requirement of the recognition, tracking and accurate positioning of military targets is the precision and real-time segmentation of infrared images. Deciding how to separate an infrared target and complex background in an efficient and effective way has always been difficult in the field of the recognition, tracking and accurate positioning of military targets [1, 2]. Many efforts have been made on image segmentation, and accordingly a variety of segmentation algorithms are developed, such as a fast and robust level set method for image segmentation using fuzzy clustering and Lattice Boltzmann method [3], a nonlinear adaptive level set for image segmentation [4], and mean shift based FCM image segmentation algorithm [5]. However, these algorithms are specific for natural images, and there are fewer algorithms that can be applied to segmenting infrared images because of the less available information and lower

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grayscale contrast of infrared images. Therefore it is still of the vital significance to study more general and effective infrared image segmentation algorithms.

A multi-threshold segmentation algorithm [6] becomes the most basic and widely used segmentation technique for its simple implementation, low computational cost, strong adaptability, stable performance and no requirement for prior knowledge. However, this method requires the gray histogram of an image for obvious peaks and valleys. When the grayscale difference between the objective and background of an image is small, there would be serious pseudo-peak interference. The study in [7] introduced a peak area, a peak width and a peak-to-valley ratio of a separate peak to remove a certain amount of pseudo peaks, which could achieve a good effect. But the three values are obtained by prior knowledge and experiment validation and cannot be adaptive, which is not conducive to real-time processing. As an unsupervised clustering segmentation algorithm, fuzzy c-means (FCM) algorithm is theoretically elegant and the most widely used based on the objective function [8]. However, it needs to set the number of clusters before clustering, which does not facilitate real-time processing. Moreover, the case that some object regions with low gray level are omitted or the background regions with similar grayscale as the objective regions are misclassified may occur for a separate use of an FCM algorithm. What's more, a good partition should satisfy two requirements: (a) divergence, i.e., the inter-cluster distances should be as big as possible; and (b) compactness, i.e., the intra-cluster distances should be as small as possible [11]. As a result, the value of the ratio of the compactness and the divergence can be the criterion of the clustering validity. According to this guideline, Xie and Beni [9, 10] take account of the inter-cluster distances and intra-cluster distances and define a validity function (XB index). By fully considering the relationship between inter-cluster distances and intra-cluster distances, Li and Yu [12] proposed a validity function that can adaptively select the best and the most reasonable number of clusters and have an ideal clustering effect, while the result is not ideal for infrared images in complex environments.

Inspired by these studies and the characteristics of infrared images, an adaptive fuzzy clustering algorithm based on multi-threshold (AFC_MT) is proposed. The idea of the proposed algorithm is stated as follows. First, a control factor of peak areas and a control factor of peak widths are introduced to remove the pseudo peaks that exist in a multi-threshold algorithm and the corresponding accurate valley positions act as the multiple thresholds to segment the image coarsely. Then an adaptive function is introduced in fuzzy clustering to adaptively determine the best cluster number and a logarithmic function is defined as the measurement of distance. Areas of small gray value difference are adaptively merged by the improved fuzzy clustering algorithm to achieve a fine segmentation.

2 Adaptive Fuzzy Clustering Algorithm Based on Multi-threshold for Infrared Image Segmentation

2.1 Multi-threshold Pseudo-Peak Removal

The multi-threshold segmentation method is based on the peak and valley characteristics of the grayscale histogram curve of an image to determine optimal thresholds to

segment the image. This idea can be summarised as follows. The number of regions is determined by finding the main peak number in the grayscale histogram curve of an image, and the corresponding thresholds to divide each region are determined by the valleys between the major peaks. However, there is a serious pseudo-peak interference when it applies to infrared image segmentation in complex environments.

Motivated by the work in [7], we introduce a control factor of peak areas and a control factor of peak widths that calculate the minimum peak area and the minimum peak width, respectively, to remove a certain pseudo-peak interference and obtain more rational thresholds

$$MA = \Psi * IS \tag{1}$$

$$MW = \mu * IG \tag{2}$$

where MA and MW denote the minimum peak area and the minimum peak width, respectively, ψ and μ the control factor of peak areas and control factor of peak widths (set as empirical values 0.001 and 0.15 in the experiments), respectively, and IS and IG the image size and the image grayscale, respectively. Valleys satisfying Eqs. (1) and (2) are the thresholds to coarsely segment the image. Since pixels of low-grayscale and high-grayscale that are few in number have a small effect on the segmentation result, but those of mid-grayscale have a great influence on the segmentation result, it is significant to remove the valleys in intermediate grayscale. The calculation for a peak width and a peak area is for two adjacent valleys, and therefore, the latter valley is determined by the previous one.

Different from the work in [7], where the peak area, the peak width and the peak-to-valley ratio of a separate peak are determined by priori knowledge and experimental verification, and the three values should be reset once the size or the grayscale of the image changed, which means the three values cannot be self-adapting when the image changes, our method can only set the two control factors even if the image changes. Moreover, the three values in [7] are set according to each image. However, our two control factors are set according to a majority of images.

2.2 Adaptive Fuzzy Clustering

Studies have shown that visual sensitivity to brightness difference varies with the background brightness nonlinearly [13]. A distance measurement based on the exponential function was proven to be more robust to noise and meet the vector distance criteria [14]. Moreover, the frequently-used visual model is the lowpass-logarithmic-highpass model of the visual system that can be used to explain most of the visual phenomenon [15]. Therefore, in order to simulate the visual perception characteristics better, an improved distance expression based on logarithmic function is applied to a fuzzy clustering algorithm. The similarity measure is defined as

$$d(g_i, v_j) = In(1 + \beta \| g_i - v_j \|) \tag{3}$$

where β denotes a degree of freedom parameter for adjusting the curvature of a curve, v_j the center of the *j*th cluster, and g_i the pixel grayscale of the *i*th pixel.

A fuzzy clustering algorithm is an effective clustering analysis method, but it requires the number of clusters be set in advance, which makes the rationality of clustering result be validated. Thus, it is necessary for the number of clusters to be computed adaptively. As we already know that the geometric meaning of clustering is to classify the data and make the inter-difference as great as possible and the intra-difference as small as possible, and according to the point of view in information theory that entropy is the characterization of average information, consequently we introduce an adaptive function

$$L(c) = \frac{\sum_{j=1}^{c}(-\sum_{i=1}^{f} u_{ij}\mathrm{In}(u_{ij}))d^2(v_j, X) \Big/ (c-1)}{-\sum_{j=1}^{c}\sum_{i=1}^{f} u_{ij}\mathrm{In}(u_{ij})d^2(g_i, v_j) \Big/ (f-c)} \tag{4}$$

where $X = \sum_{j=1}^{c}\sum_{i=1}^{f} u_{ij}^m g_i \Big/ f$ presents the center vector of all the pixels, f and c the pixel grayscale and cluster number of an image, respectively, and u_{ij} the membership degree of *i*th pixel belonging to the *j*th cluster. The numerator of adaptive function $L(c)$ denotes the sum of the entropy between classes and the denominator of $L(c)$ denotes the sum of the intra-entropy of all the clusters. As a result, the bigger $L(c)$ is, the more reliable the clustering result is. Hence, the clustering number c is the best when $L(c)$ reaches its maximum value. We just need to compare two values of $L(c)$ in some local area since the solution point is the local minimum of the objective function in fuzzy clustering. As a consequence, the best number of clusters can be found by finding a point satisfies $L(c-1) > L(c-2)$ and $L(c-1) > L(c)$.

2.3 Algorithm

Now, we outline the AFC_MT algorithm based on the newly defined measurement of distance that can better simulate the human eye to perceive changes in brightness and the introduction of an adaptive function $L(c)$ that can adaptively compute the best number of clusters and a control factor of peak areas and a control factor of peak widths to calculate the minimum peak area and the minimum peak width, respectively, that can remove a certain pseudo peaks effectively.

The steps of implementation in our universal AFC_MT algorithm are stated as follows.

1. Calculate the possible thresholds using the traditional multi-threshold algorithm [6];
2. Remove the pseudo peaks based on the adaptively obtained minimum peak area and the minimum peak width shown in Eqs. (1) and (2) to obtain the accurate positions of valleys, and divide the image into M regions according to the positions;

3. Morphological smooth the image obtained above;

4. Set the termination condition $\varepsilon > 0$, cluster number $c = 2$, the adaptive function $L(1) = 0$, the number of iterations $l = 0$, and the cluster center matrix $V^{(0)}$;

5. Calculate the partition matrix $U^{(l)}$ and the cluster center matrix $V^{(l+1)}$, i.e.,

$$u_{ij}^{(l)} = 1 \Big/ \sum_{j=1}^{c} \left(\frac{d(g_j, v_i)}{d(g_j, v_j)}\right)^{2/(m-1)} \tag{5}$$

$$v_i^{(l+1)} = \sum_{j=1}^{f} (u_{ij})^m g_j \Big/ \sum_{j=1}^{f} (u_{ij})^m \tag{6}$$

6. Calculate the variation of partition matrix

$$\| V^{(l+1)} - V^{(l)} \| \tag{7}$$

If $\| V^{(l+1)} - V^{(l)} \| \le \varepsilon$, then go to step 7. Else let $l = l + 1$ and go to step 5.

7. Calculate $L(c)$. If $L(c-1) > L(c-2)$ and $L(c-1) > L(c)$ under the condition $c > 2$ and $c < M$, then stop the iteration to take the result when $c = c - 1$. Else go to step 5 with $c = c + 1$. If $c > M$, then take the result when $c = Arg\left\{\max_{2 \le c \le M}(L(c))\right\}$.

3 Experimental Results and Analysis

To validate the effectiveness of the proposed adaptive fuzzy clustering algorithm based on multi-threshold for infrared image segmentation, four comparative experiments on the method in [7] (MT), the FCM algorithm, the self-adapting FCM [12] (SFCM) and the AFC_MT algorithm are conducted to validate the effectiveness of the proposed method. Our experimental infrared images of size 320×240 are derived from the OTCBVS Benchmark Dataset [16]. For all experiments, the proposed method sets the degrees of freedom parameter β to 0.1, and stopping threshold ε for iteration to 0.00001. To compare FCM and AFC_MT better, we set the cluster number of FCM the same with that of AFC_MT which can be obtained adaptively. All the experiments are conducted on MATLAB R2012b installed in a computer with a 3.40GHz Intel Core i3 CPU and 4GB of RAM.

In infrared data 1, the background and objective are relatively simple, while the grayscale of objective area is close to that of the background, as shown in Fig. 1(a). Therefore, the FCM algorithm and the MT algorithm can separate the objective from background well with producing some misclassification and leakage points, as shown in Fig. 1(c) and (d). However, the SFCM algorithm cannot segment the objective well because of the low grayscale contrast, as shown in Fig. 1(e). The proposed algorithm filters out a certain pseudo peaks in the process of multi-threshold computation, and then adaptively selects the most reasonable number of clusters to obtain a more complete objective and a single background, as shown in Fig. 1(f).

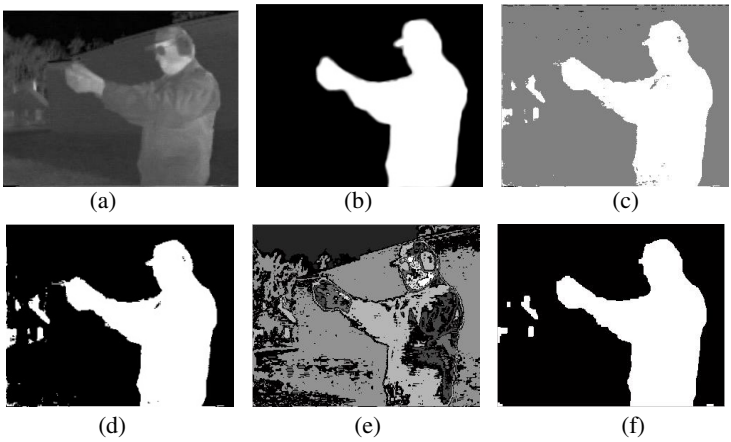


Fig. 1. Segmentation results on infrared data 1: (a) original image, (b) benchmark image, (c) MT segmentation with a peak area set to 100, a peak width to 50, and a peak-to-valley ratio to 10, (d) FCM segmentation with c set to 2, (e) SFCM segmentation with adapting c to 8, and (f) AFC_MT segmentation with adapting c to 2.

In infrared data 2, the background is relatively complex, and its pixel grayscales are widely distributed. However, pixel grayscales of objective are not unique, and pixel grayscales of background overlap that of objective, as shown in Fig. 2(a). The objective of the segmentation result from the MT algorithm and the FCM algorithm is relatively integrated, but the pixel grayscales of background that are close to that of objective are misclassified, as shown in Fig. 2(c) and (d). However, the SFCM algorithm cannot segment the objective well, as shown in Fig. 2(e). The proposed algorithm can adaptively find the most reasonable cluster number and the segmentation result of AFC_MT is of more complete objective and single background, as shown in Fig. 2(f).

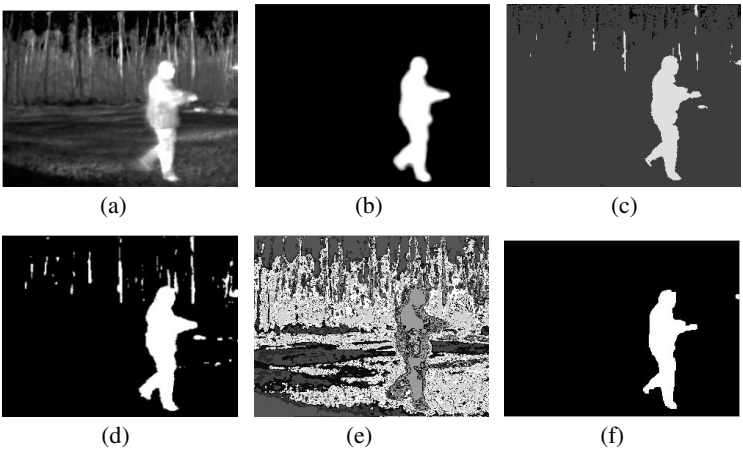
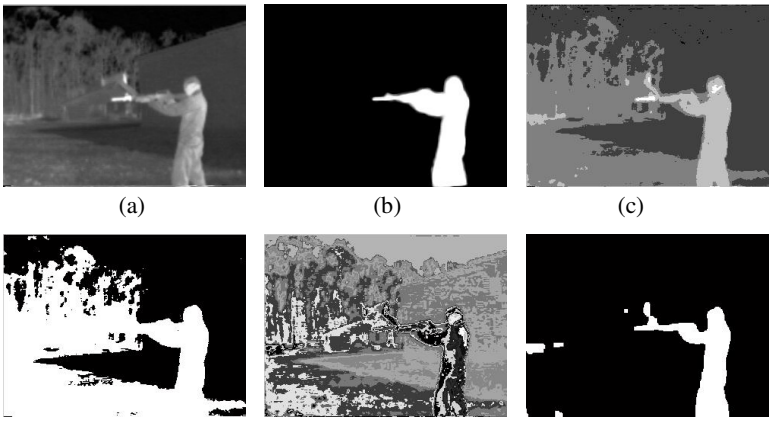


Fig. 2. Segmentation results on infrared data 1: (a) original image, (b) benchmark image, (c) MT segmentation with a peak area set to 100, a peak width to 50, and a peak-to-valley ratio to 1, (d) FCM segmentation with c set to 2, (e) SFCM segmentation with adapting c to 19, and (f) AFC_MT segmentation with adapting c to 2.

In infrared data 3, the objective and background are relatively complex, and some pixels in background are similar to that in objective in grayscale, as shown in Fig. 3(a). The objective can be roughly segmented by the MT algorithm, but the parts that are of similar pixel grayscale cannot be distinguished from background, as shown in Fig. 3(c), and the objective in Fig. 3(d) segmented by the FCM algorithm is complete while the background is also classified as the objective. The objective cannot be separated from the background by the SFCM algorithm and the objective in Fig. 3(e) is separated into several parts. The segmentation result by the proposed algorithm consists of a more complete target and a single background, as shown in Fig. 3(f).



(a) (b) (c)

(d) (e) (f)

Fig. 3. Segmentation results on infrared data 1: (a) original image, (b) benchmark image, (c) MT segmentation with a peak area set to 300, a peak width to 40, and a peak-to-valley ratio to 1, (d) FCM segmentation with c set to 2, (e) SFCM segmentation with adapting c to 18, and (f) AFC_MT segmentation with adapting c to 2.

In infrared data 4, the background is complex, and there is obvious interference, as shown in Fig. 4(a). It is difficult either for the MT algorithm or for the FCM algorithm to separate the objective from the background since the interference is obvious, as shown in Fig. 4(c) and (d). Moreover, the result of the SFCM is terrible misclassified, as shown in Fig. 4(e). The segmentation result by the proposed algorithm, as shown in Fig. 4(f), are of single background and more complete objective, which suffer no influence from the background that interferes a lot.

Two measures [3] [17], F-Measure (FM) and Localization error (LE), are utilized to compare the four methods. A higher score on FM means that a method is more accurate. Meanwhile, a small score on LE means that the localization error is small and the segmentation result is better. Scores in Tables 1 and 2 quantitatively show that the proposed method obtains competitive performance by comparing with the other three algorithms. In addition, comparisons in terms of running time of the four algorithms, represented by the average of running 100 times, are shown in Table 3. The running time of the proposed algorithm is reduced compared with the time-consuming FCM or the SFCM algorithm and meanwhile weighs against the MT algorithm, which

means the coarse-fine concept reduces the computational burden required for the fuzzy clustering. All the experiments show that the proposed algorithm is a real-time and effective segmentation algorithm.

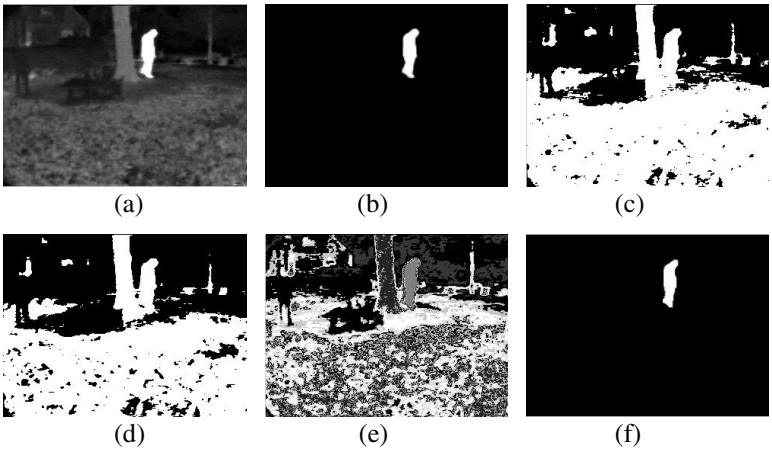


Fig. 4. Segmentation results on infrared data 1: (a) original image, (b) benchmark image, (c) MT segmentation with a peak area set to 100, a peak width to 50, and a peak-to-valley ratio to 5, (d) FCM segmentation with c set to 2, (e) SFCM segmentation with adapting c to15, and (f) AFC_MT segmentation with adapting c to 2.

Table 1. FM scores of four algorithms

Infrared data	MT	FCM	SFCM	AFC_MT
1	0.9232	0.9493	0.3141	0.9554
2	0.8585	0.8029	0.1737	0.9034
3	0.3021	0.2887	0.0878	0.8475
4	0.0401	0.0443	0.0422	0.9520

Table 2. LE scores of four algorithms

Infrared data	MT	FCM	SFCM	AFC_MT
1	0.0352	0.0308	0.5727	0.0266
2	0.0202	0.0336	0.4506	0.0131
3	0.3925	0.4123	0.5378	0.0262
4	0.5834	0.5268	0.4855	0.0011

Table 3. Running time of four algorithms (Seconds)

Infrared data	MT	FCM	SFCM	AFC_MT
1	0.3562	0.5722	3.5472	0.2929
2	0.2995	0.6549	4.6334	0.3427
3	0.2937	0.6531	4.4177	0.3049
4	0.3053	0.6416	3.6259	0.3386

4 Conclusions

In this article, an adaptive fuzzy clustering algorithm based on multi-threshold (AFC_MT) for infrared image segmentation is proposed. It retains the characteristics of the multi-threshold algorithm in simple realization and fast speed, and can effectively remove pseudo-peak interference by introducing a control factor of peak areas and a control factor of peak widths in multi-threshold selection. In addition, the proposed algorithm can take full advantage of the fuzzy clustering algorithm in automatic classification without human intervention. The experimental results show that AFC_MT outperforms both of the MT, the FCM algorithm and the SFCM algorithm, and that it can achieve the desired effect on infrared image segmentation in a complex environment.

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