SPATIAL INFORMATION BASED FCM FOR INFRARED SHIP TARGET SEGMENTATION

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ABSTRACT

Segmentation of infrared (IR) ship images is always a challenging task, because of the intensity inhomogeneity and noise. The Fuzzy C-Means (FCM) clustering is a classical method widely used in IR ship image segmentation. However, it has some shortcomings, like not considering the spatial information or being sensitive to noise. In this paper, an improved FCM algorithm based on the spatial information is proposed. The improvements include two parts: (1) adding the non-local spatial information based on the ship target; (2) using the spatial shape information of the contour of the ship target to refine the local spatial constraint by Markov Random Field (MRF). A pre-processing procedure and a target selection method are also used to further improve the performance of the segmentation result. Experimental results show that our method is very effective and performs better than the conventional FCM methods in segmentation of the infrared ship images.

Index Terms— Image segmentation, FCM, MRF, Spatial information, IR ship image

1. INTRODUCTION

In recent years, IR imaging systems are widely used in maritime surveillance, including the IR ship target detection [1, 2], segmentation [3], tracking [4], enhancement [5, 6], etc. In this paper, we focus on the segmentation of the IR images. However, the IR ship images usually have some properties, such as low target-to-background contrast, low signal-to-noise ratio, the lack of details, and intensity inhomogeneity, which make it difficult to segment the ship targets in infrared images [1, 2]. Many methods were proposed to deal with the segmentation of the infrared ship images. Otsu's method [7] is a well-known thresholding segmentation method. However, this method would not perform well when the histogram of the IR ship image is unimodal or close to unimodal [8]. The minimum error thresholding algorithm [9] is another frequently used thresholding method. However, in this method, both classes are assumed to have a Gaussian distribution, which no longer holds for the real IR ship images [10]. Mean shift (MS) [11] is a nonparametric clustering method, which has been used to segment the IR ship image. However, it would not have a good performance if the original distance metric fails to capture the underlying cluster structure [12]. Active contour based methods are also widely applied in the segmentation of the IR ship images. Chan-Vese model (C-V) [13] is a commonly used contour based method and it performs well for the infrared image segmentation. However, it could only be used for the segmentation of the images with simple homogeneous intensities [14]. An improved method based on C-V is active contour model driven by local image fitting energy (AC-LFE) [15], but it is sensitive to the initialization of the contour [16]. FCM [17] is a classical clustering method, which has been utilized in the segmentation of the IR ship images. However, it does not consider any information about spatial context [18]. Thus, it is highly sensitive to noise [18]. Several algorithms [18-20] have incorporated the spatial information to the objection function of FCM to improve the performance of FCM. However, these extensions of FCM still have some shortcomings, for example, they only consider the local spatial information of the IR ship images and there are at least one parameter to control the tradeoff between the original image feature and spatial constraint [21].

In this paper, to segment the IR ship targets in infrared image with low-contrast and uneven distribution of intensity, a method based on FCM and Markov theory is proposed. Here, we utilize both the non-local spatial information and spatial shape information to improve the performance of FCM. Moreover, the proposed method is compared with nine existing segmentation methods, in both the qualitative and quantitative ways. Experimental results show that the proposed method is very effective and performs very well for the segmentation of the IR ship images.

2. PROPOSED METHOD

2.1. The standard FCM method [17]

FCM aims to minimize the sum of the errors between the intensity of each pixel and the centroid of each class, with respect to the membership μ_{jk} and the centroid υ_k [19].

$$J_{FCM} = \sum_{j\in\Omega} \sum_{k=1}^{c} \mu_{jk}^{m} d_{jk}^{2}, \tag{1}$$

where d_{jk} is the Euclidean distance between the pixel z_j and the centroid υ_k ; Ω is the set of pixel locations in the image;

c is the number of classes [19]. Here, c is equal to 3, because the IR image are consisted of sky, sea and ship targets; m is the fuzzifier value (1 for hard clustering, and increasing for fuzzy clustering) and is usually set as 2 [22].

The membership functions should satisfy [19]:

$$\mu_{jk} \in [0,1], \quad \sum_{k=1}^{c} \mu_{jk} = 1. \tag{2}$$

Considering the constraints above, we calculate the first derivatives of J_{FCM} with respect to μ_{jk} and υ_k and set them to zero, resulting in the following two conditions for minimizing J_{FCM} [19]:

$$\mu_{jk} = 1 \Big/ \sum_{l=1}^{c} \left(d_{jk} / d_{jl} \right)^{2/(m-1)}, \tag{3}$$

$$\upsilon_k = \sum_{j \in \Omega} \mu_{jk}^{m} z_j \Big/ \sum_{j \in \Omega} \mu_{jk}^{m}. \tag{4}$$

The FCM optimizes J_{FCM} with respect to μ_{jk} and υ_k by iterative method to complete the segmentation.

The main drawback of the standard FCM method is that the objection function does not take any information about spatial context into consideration [18]. Therefore, it is sensitive to noises.

2.2. The proposed FCM

2.2.1. Improvement of FCM based on non-local spatial information

In order to overcome the drawback of FCM, we add a term on the objection function based on the ship target to make use of the non-local spatial information. As it is known, if a pixel is closer to the centroid of the ship target, then it should have bigger degree of membership to the ship target. Therefore, if the centroid of the ship target and the possible area of the ship target are known, a weight could be constructed to improve the performance of FCM. In fact, the centroid of the ship target and the possible area of the ship target could be obtained from the pre-processing procedure which will be discussed in detail in Step 2 of 2.2.4.

Then, we can rewrite the objection function with the weighted term as follows.

$$J_{FCM} = \sum_{j \in \Omega} \sum_{k=1}^{c} \left(\mu_{jk} \partial_{jk} \right)^{m} d_{jk}^{2}, \tag{5}$$

where ∂_{jk} is the weighted term and it can be mathematically expressed as:

$$\partial_{jk} = \left(diag \Big/ \sqrt{\left(y_j - y_0\right)^2 + \left(x_j - x_0\right)^2} \right)^{1/k}, \tag{6}$$

where $diag$ is the length of the diagonal line of the possible area of the IR ship target, (x_0, y_0) is the coordinate of the centroid of the IR ship target. Here, we assume that the larger the k is, the larger the class it represents.

2.2.2. Improvement of FCM based on spatial shape information

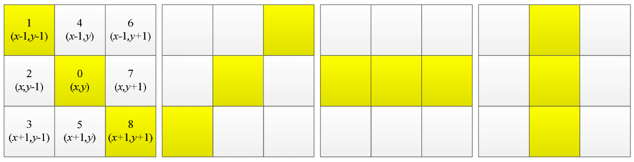

Fig. 1. The straight lines of the ship target

In 2.2.1, we utilize the non-local spatial information and add a weight on the objection function of the standard FCM to suppress the effect of noise. Chen al. [19] proposed a Gibbs Fuzzy C-means (GFCM) method, in which they combined the FCM with MRF, and introduced the prior probability $P_s(k)$ of MRF to indicate the local spatial constraint. The refusable level $1 - P_s(k)$ is defined as the resistance of the neighbors N_s to assign the pixel s to the label k [19]. This method actually adds a weighted term $1 - P_s(k)$ on the objection function of FCM. However, they do not consider the situation that the neighborhood pixels of different distributions have different effects on the pixels in the boundary of the ship target, so that the contour of the ship target could not be accurately segmented. In this paper, we make use of the shape spatial information to overcome this problem. Fig. 1 shows some situations.

In Fig. 1, the pixels with yellow color are assumed on the contour of the ship target. If most of the pixels labeled by 2, 3, 4, 5, 6 and 7 (the pixels with white color) have small degrees of membership to the ship target, then the pixel (i, j) is easy to be wrongly clustered by the GFCM method. To overcome this problem, we introduce a weight to revise the refusable level.

Based on the analysis above, we could replace the refusable level $1 - P_s(k)$ with the following formula:

$$\xi_s(k) = \sqrt{\left(1 - p_s(k)\right)\left(1 - q_s(k)\right)}, \tag{7}$$

where $\left(1 - p_s(k)\right)$ keeps unchanged, $\left(1 - q_s(k)\right)$ is the weight we add. According to the Hamersley-Clifford theory [19] and special Multiple Level Logic (MLL) model [19], it could be calculated as follows:

$$q_s(k) = \exp\left(-L_s(k)/\beta^2\right) \Big/ Z, \tag{8}$$

where β is a constant called temperature, which is assumed to be 1 [22]; L_s and Z can be calculated as the following equations.

$$\begin{aligned} L_s(k) = &\left(1 - \mu_k(x-1, y-1)\right)\left(1 - \mu_k(x+1, y+1)\right) \\ &+ \left(1 - \mu_k(x-1, y)\right)\left(1 - \mu_k(x+1, y)\right) \\ &+ \left(1 - \mu_k(x, y-1)\right)\left(1 - \mu_k(x, y+1)\right) \\ &+ \left(1 - \mu_k(x-1, y+1)\right)\left(1 - \mu_k(x+1, y-1)\right) \end{aligned}, \tag{9}$$

where $\mu_k(x, y)$ is the degree of membership of the pixel (x, y) belonging to the k class.

$$Z = \sum_{k=1}^{c} \exp\left(-L_s\left(k\right)/\beta^2\right). \tag{10}$$

2.2.3. The proposed FCM

In this paper, we utilize both the non-local spatial information and the spatial shape information to improve the performance of FCM. The objection function of the proposed FCM is expressed as follows:

$$J_{FCM} = \sum_{j\in\Omega}\sum_{k=1}^{c}\left(\mu_{jk}\partial_{jk}\right)^m \xi_j\left(k\right) d_{jk}^2. \tag{11}$$

The objection function J_{FCM} could be minimized in a similar way to the standard FCM [17]. Then, we have:

$$\mu_{jk} = \left(d_{jk}^{-2}\xi_j^{-2}\left(k\right) \Big/ \sum_{k=1}^{c} d_{jk}^{-2}\xi_j^{-2}\left(k\right)\right) \Big/ \partial_{jk}^2, \tag{12}$$

$$\upsilon_k = \sum_{j\in\Omega}\left(\left(\mu_{jk}\partial_{jk}\right)^2 \xi_j\left(k\right) z_j\right) \Big/ \sum_{j\in\Omega}\left(\left(\mu_{jk}\partial_{jk}\right)^2 \xi_j\left(k\right)\right). \tag{13}$$

Iteratively, the segmentation of the IR ship images could be achieved.

2.2.4. The whole procedure of our method

Before the segmentation of the IR ship targets, a pre-processing procedure is developed to suppress the background and noise.

Step 1: The source images are smoothed by a Gaussian filter to suppress the effect of noise. The size of the filter is 3 and the standard deviation used is 0.5.

Step 2: The variance matrix of the image is calculated to roughly locate the ship target. In this process, the Chebyshev's inequality [23] is used to select the appropriate threshold.

$$P\left\{\upsilon - E_\upsilon \geq k\sigma_\upsilon\right\} \leq 1\big/\left(1+k^2\right), \tag{14}$$

where E_υ is the expectation of the variance matrix and σ_υ is the standard deviation of the variance matrix. k is a constant.

For simplicity, the variance matrix could be normalized as follows [23].

$$D_n\left(x,y\right) = \begin{cases} D\left(x,y\right), & D\left(x,y\right) < 1 \\ 1, & D\left(x,y\right) > 1 \end{cases}, \tag{15}$$

$$D\left(x,y\right) = \left(\upsilon\left(x,y\right) - Min_\upsilon\right)\big/\left(Max_\upsilon - Min_\upsilon\right), \tag{16}$$

where Min_υ and Max_υ are the minimum and the maximum of the variance set, respectively.

According to the Chebyshev's inequality, the threshold could be $\mu + k \bullet \sigma$ [23], where μ and σ are the expectation and the standard deviation of D_n, respectively. k is assumed to be 10, to suppress the influence of the noise pixels. If the value of D_n is larger than the threshold, it is reasonable that the corresponding pixel belongs to the IR ship target. Then, the centroid and the possible area of the IR ship target could be roughly obtained.

Step 3: Here, we make use of the top-hat [5] filtering with a disk structuring element to suppress the extensive continuous background. Considering that the location and the size of the IR ship target have been roughly estimated, the radius R of the disk-shaped structuring element could be adaptively calculated as follows.

$$R = \sqrt{2\times\left(\min\left(w,h\right)\right)^2}\Big/2, \tag{17}$$

where w and h are the width and the height of the possible area of the IR ship target, respectively.

Step 4: Then the K-Means [24] method is used to initialize the degree of membership and the original centroid of the improved FCM.

Step 5: The proposed FCM in this paper is used to segment the ship target in IR images. In 2.2.3, the proposed FCM has been described in detail.

Step 6: An IR ship target selection method based on the characteristics of the IR ship target is used to extract the ship targets from the segmentation results in this step. According to prior knowledge, the ratio of the length and width of the IR ship target should be less than 6. Also, the ratio of upper 1/3 area and lower 2/3 area of the ship target should be less than 1. For example, in the segmentation result, if the ratio of the length and width of a region is less than 6, and also the ratio of the upper 1/3 area and lower 2/3 area of this region is less than 1, then this region is selected as the ship target. Otherwise, this region should be regarded as the background.

The flow chart of our method is shown in Fig. 2.

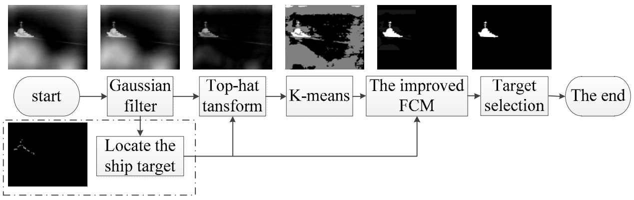

Fig. 2. The flow chart of our method

3. EXPERIMENTAL RESULTS

We tested our method on 200 IR images, which include different ship targets and backgrounds. The size of the images ranges from 320×256 to 720×576. The IR ship image dataset is supplied by the co-researchers [25].

3.1. Qualitative evaluation

Our method is compared with nine existed methods, and these comparison methods could be roughly divided into thresholding based methods, clustering based methods, contour based methods and others. The thresholding based methods include the minimum error thresholding algorithm [9], the maximum entropy based method [26] and the 2D entropy based method [27]. The clustering based methods include FCM [17], the spatial fuzzy c-means method [20],

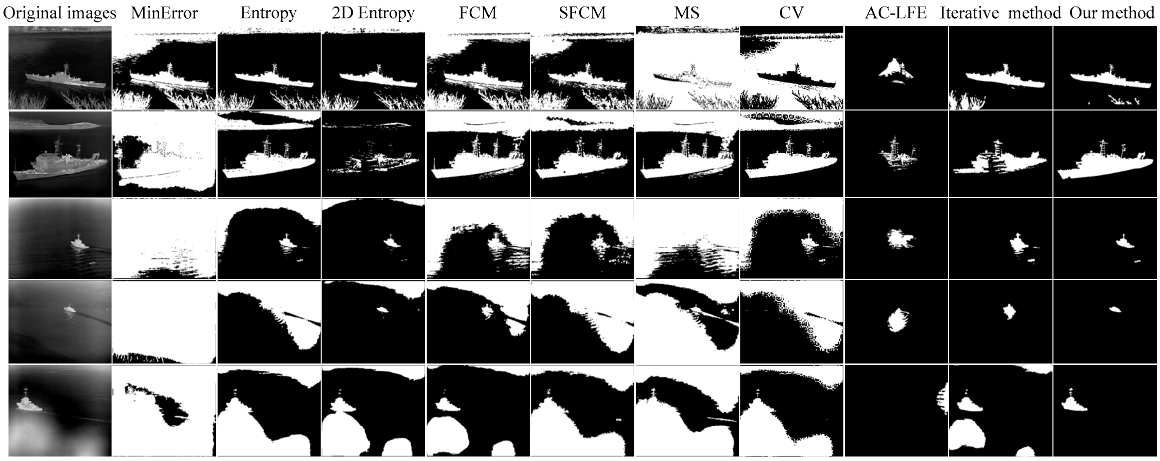

Fig. 3. Comparison results

and mean-shift [11]. And, the active contour based methods include C-V [13], and AC-LFE [15]. Also, another effective method called iterative method [25] is used. Some comparison examples are shown in Fig. 3.

In Fig. 3, we can see that the segmentation results of the thresholding based methods are not satisfying. For the images with high contrast, the segmentation results are acceptable (e.g., the images of the first row). However, the background would be wrongly classified into the ship target, if the IR images have low contrast (e.g., the images of the fifth row). The clustering based methods may merge the sea clutters into the ship target, if the sea clutters in images are near the ship target (e.g., the images of the third row). The C-V method could only segment the images with homogeneous intensities in each region [14], and the AC-LFE method overly depends on the initialization of the contour, thereby, they do not work for the segmentation of the IR ship images (e.g., the images of the fourth and fifth rows). The iterative method is effective, but it suffers the noise around the ship target and the uneven intensity (e.g., the images of the second and third rows). Obviously, it can be seen from the comparison results that the proposed method could accurately extract the ship targets (e.g., the images of the third and fifth rows), and the performance of the proposed method is evidently superior to other methods.

3.2. Quantitative evaluation

To further verify the validity of our method, quantitative evaluations, including misclassification error (ME) [28] and relative foreground area error (RAE) [29] are used. The ME is the percentage of the pixels which are wrongly classified. RAE represents the segmentation accuracy between the segmented image and the reference image. A smaller RAE reflects a better segmentation, so is ME. And, the comparison results are listed in Table 1.

From Table 1, we can see that the proposed method has smaller values of ME and RAE in average than other methods, which implies that our method is effective and robust. And, our method performs better than the other nine methods for the segmentation of the IR ship images.

Table 1. Quantitative comparison results

Methods	ME			RAE		
	Max	Min	Aver-age	Max	Min	Aver-age
MinError	0.9296	0.0009	0.5028	0.9989	0.0090	0.8040
Entropy	0.9726	0.0002	0.2645	0.9988	0.0015	0.7598
2D Entropy	0.9940	0.0001	0.3954	0.9997	0.0009	0.7742
FCM	0.8067	0.0042	0.4790	0.9989	0.0035	0.9060
SFCM	0.7841	0.0178	0.3826	0.9987	0.0008	0.8951
MS	0.9710	0.0005	0.4954	0.9985	0.0381	0.8623
C-V	0.9468	0.0083	0.3829	0.9986	0.1177	0.8689
AC-LFE	0.6104	0.0004	0.0713	0.9709	0.0066	0.5737
Iterative Method	0.9637	0.0002	0.0259	0.9894	0.0034	0.3594
Our Method	0.1375	0	**0.0151**	0.9956	0	**0.2642**

4. CONCLUSION

This paper presents an effective segmentation method for ship target in IR images. To enable the robust segmentation and overcome the disadvantages of the FCM based methods, both the non-local spatial information and spatial shape information are used to improve the performance of FCM. From the quantitative and qualitative comparisons, it can be seen that the proposed method is very effective for segmentation of the IR ship images and it outperforms the existed algorithms.

5. REFERENCES

[1] X. Bai, and F. Zhou, “Analysis of new top-hat transformation and the application for infrared dim small target detection,” Pattern Recognition, Vol. 43, pp. 2145–2156, 2010.

[2] X. Wang, G. Lv, and L. Xu, “Infrared dim target detection based on visual attention,” Infrared Physics & Technology, Vol. 55, pp. 513-521, 2012.

[3] A. Wang, *et al.*, “Adaptive segmentation algorithm for ship target under complex background,” Proc. of IEEE International Conference on Advanced Computer Theory and Engineering (ICACTE), vol. 2, pp. 219-223, 2010.

[4] S. Kima, and J. Lee, “Scale invariant small target detection by optimizing signal-to-clutter ratio in heterogeneous background for infrared search and track,” Pattern Recognition, Vol. 45, pp. 393–406, 2012.

[5] X. Bai, F. Zhou, and B. Xue, “Image enhancement using multi scale image features extracted by top-hat transform,” Optics & Laser Technology, Vol. 44, pp. 328–336, 2012.

[6] X. Bai, F. Zhou, and B. Xue, “Infrared image enhancement through contrast enhancement by using multi scale new top-hat transform,” Infrared Physics & Technology, Vol. 54, pp. 61–69, 2011.

[7] N. Otsu, “A threshold selection method from gray-level histograms,” IEEE Transactions on Systems, Man and Cybernetics, Vol. 9, No. 1, pp. 62-66, 1979.

[8] J. Fan, and B. Lei, “A modified valley-emphasis method for automatic thresholding,” Pattern Recognition Letters, Vol. 33, pp. 703–708, 2012.

[9] J. Kittler, and J. Illingworth, “Minimum error thresholding,” Pattern Recognition, Vol. 19, No. 1, pp. 41-47, 1986.

[10] Y. Ban, “Multitemporal Spaceborne SAR Data for Urban Change Detection in China,” IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, Vol. 5, No. 4, 2012.

[11] D. Comaniciu, and P. Meer, “Mean shift: a robust approach toward feature space analysis,” IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 24, pp. 603-619, 2002.

[12] S. Anand, and S. Mittal, “Semi-Supervised Kernel Mean Shift Clustering,” IEEE Transactions on pattern analysis and machine intelligence (Accepted).

[13] T.F. Chan, and L.A. Vese, “Active contours without edges,” IEEE Transactions on Image Processing, Vol. 10, No. 2, pp. 266-277, 2001.

[14] Y. Peng, F. Liu, and S. Liu, “Active contours driven by normalized local image fitting energy,” Concurrency and Computation: Practice and Experience, 2013.

[15] K. Zhang, H. Song, and L. Zhang, “Active contours driven by local image fitting energy,” Pattern Recognition, Vol. 43, pp. 1199-1206, 2010.

[16] X. Yu, *et al.*, “Implicit Active Contours Driven by Local and Global Image Fitting Energy for Image Segmentation and Target Localization,” Journal of Sensors, Vol. 2013, 2013.

[17] H. Nomura, and N. Wakami, “Segmentation of thermal images using the fuzzy c-means algorithm,” Proc. of IEEE International Conference on Fuzzy Systems, Vol. 2, pp. 719-724, 1993.

[18] I. Despotovic, *et al.*, “An improved fuzzy clustering approach for image segmentation”, Proc. of IEEE International Conference on Image Processing, pp. 249-252, 2010.

[19] Y. Feng, and W. Chen, “Brain MR Image Segmentation Using Fuzzy Clustering with Spatial Constraints Based on Markov Random Field Theory,” Medical Imaging and Augmented Reality, Lecture Notes in Computer Science, Vol. 3150, pp. 188-195, 2004.

[20] K.S. Chuang, *et al.*, “Fuzzy c-means clustering with spatial information for image segmentation,” Computerized Medical Imaging and Graphics, Vol. 30, pp. 9-15, 2006.

[21] J. Wang, *et al.*, “A modified FCM algorithm for MRI brain image segmentation using both local and non-local spatial constraints,” Computerized Medical Imaging and Graphics, Vol. 32, pp. 685–698, 2008.

[22] S. Ramathilagam, *et al.*, “Modified fuzzy c-means algorithm for segmentation of T1–T2-weighted brain MRI,” Journal of Computational and Applied Mathematics , Vol. 235, pp. 1578–1586, 2011.

[23] P. Zhang, and D. Cui, “Infrared image segmentation algorithm based on visual cognition,” Journal of Applied Optics, Vol. 34, No. 1, 2013.

[24] A.K. Jain, “Data clustering: 50 years beyond K-means,” Pattern Recognition Letters, Vol. 31, Is. 8, pp. 651-666, June 2010

[25] Z. Liu, *et al.*, “Iterative infrared ship targets segmentation based on multiple features,” Pattern Recognition, Vol. 47, pp. 2839-2852, 2014 .

[26] J.N. Kapur, P.K. Sahoo, and A.K.C. Wong, “A new method for gray-level picture thresholding using the entropy of the histogram,” Computer Vision, Graphics and Image Processing, Vol. 29, No. 3, pp. 273-285, 1985.

[27] F. Du, *et al.*, “Infrared image segmentation with 2-D maximum entropy method based on particle swarm optimization (PSO),” Pattern Recognition Letters, Vol. 26, No. 5, pp. 597-603, 2005.

[28] W.A. Yasnoff, J.K. Mui, and J.W. Bacus, “Error measures for scene segmentation,” Pattern Recognition, Vol. 9, No. 4, pp. 217-231, 1977.

[29] Z. Fan, C. Wang, and X. Ma, “Double-threshold image segmentation method based on gray gradient,” Proc. of SPIE International Conference on Optical Instruments and Technology, Vol. 7506, 2009.