International Journal of Signal Processing, Image Processing and Pattern Recognition
Vol.9, No.11, (2016), pp.93-98
http://dx.doi.org/10.14257/ijsip.2016.9.11.09

An Global Spatial Similarity based on Fuzzy C-means Clustering for Image Segmentation

Yufeng Yi[1,2] and Lei Wang[3*]

[1]*Academy of Opt-Electronics, China Electronic Technology Group Corporation, Tianjin, 300000, China*
[2]*Key Laboratory of Electronics Information Control and Security Technology, China Electronic Technology Group Corporation, Sanhe, 065201, China*
[3]*Department of Public Order, National Police University of China, Shenyang, 110854, China*
[3]*leonwang521@126.com*

Abstract

The segmentation results of the traditional FCM based image segmentation algorithms are only determined by the distribution of pixel intensity in the feature space, and they does not take the spatial distribution of pixels into consideration, which make the segmentation results discrete in the spatial distribution. To solve this problem, a global spatial similarity metric and a global intensity similarity metric are proposed, and introduced to a new distance metric which is used to calculate the difference between pixels and cluster centers. In addition, a maximal similarity based class merging mechanism is employed to achieve more accurate image segmentation. The experiments demonstrate that, comparison with the FCM and KFCM based image segmentation algorithms, the proposed method produces more accurate and applicable segmentation results.

Keywords*: FCM; Image segmentation; Similarity Metric; Distance Metric; KFCM*

1. Introduction

Image segmentation is a procedure to segment an image into homogeneous regions which are more meaningful and easier to analyze. It serves as a key role in computer vision and object recognition. Recently, various image segmentation methods have been an explosive growth [1-3], among them, the fuzzy c-means clustering (FCM) based image segmentation algorithm [4-5] has received much attention because it is highly effective for image segmentation. However, since the segmentation results of the conventional FCM based image segmentation algorithms are subject to quality depreciating factors such as intensity in homogeneity, spatial constraints are necessary to increase the robustness against outlier pixels.

In this Letter, we present a global spatial similarity based FCM for image segmentation, which enhances the continuity of the spatial distribution of the segmentation results. In addition, since the algorithm we proposed to some extent limits the spatial distribution of the segmentation results, we employ a maximal similarity based class merging method to achieve more accurate image segmentation.

2. FCM Based Image Segmentation

The FCM based image segmentation method casts the image segmentation problem

* Corresponding Author

ISSN: 2005-4254 IJSIP

into a minimization of the value of objective function:

$$J_{FCM} = \sum_{i=1}^{c}\sum_{k=1}^{n}\mu_{ik}^{m}\left\|x_k, v_i\right\|^2 \tag{1}$$

where $x_k \in X$, X is a set of pixels in the image; $v_i \in V$, V is a set of cluster centers, u_{ik} represents the membership that the pixel x_i belongs to the cluster center v_i, m is weighting exponent, and $m = 2$ in this paper, n is the number of the pixels in the image and c is the number of the cluster centers.

The value of objective function can be optimized by updating the cluster center and the fuzzy membership matrix using Equation (2) and Equation (3).

$$v_i = \frac{\sum_{k=1}^{n}\mu_{ik}^{m}x_k}{\sum_{k=1}^{n}\mu_{ik}^{m}} \tag{2}$$

$$\mu_{ik} = \left(\sum_{j=1}^{c}\left(\frac{\left\|v_i, x_k\right\|}{\left\|v_j, x_k\right\|}\right)^{2/(m-1)}\right)^{-1} \tag{3}$$

The value of objective function is minimized when the following condition is achieved:

$$\left|J_t - J_{t-1}\right| < \varepsilon \tag{4}$$

where J_t and J_{t-1} are the objective function values between two adjacent iterations; respectively. $\varepsilon > 0$ is a small value (the smaller the value of ε is, the greater is the degree of optimality achieved).

The value of the membership u_{ik} reflects the likelihood that pixel x_k belongs to the cluster center v_i, and each pixel is associated with a membership value after FCM clustering. By assigning each pixel to a label with the highest value of the membership, the results of image segmentation can be obtained. However, since the pixels in each class are discrete in spatial distribution when segmenting images using a conventional FCM clustering algorithm which can't meet the real needs with segmentation results. To overcome the intrinsic drawback of the FCM based image segmentation method, we introduce a global spatial constraint into the FCM model.

3. Proposed Method

In order to optimize the objective function value, one must utilize a distance metric that reflects the difference in nodes features. Several distance metrics are commonly used in the literature [6-8], such as the Euclidean distance metric, the Bhattacharyya distance metric and the Mahalanobis distance metric. Conventional FCM algorithms utilize Euclidean distance to calculate the distance between kth pixel and ith cluster center.

$$d_1^2(x_k, v_i) = \left\|x_k, v_i\right\|^2 \tag{5}$$

In this section, a novel distance metric is proposed to calculate the difference between kth pixel and ith cluster center, which is then used as discrimination function in FCM-based image segmentation algorithm.

$$d_2^2(x_k, v_i) = \left|1 - F_{ik} \cdot S_{ik}\right|^2 \tag{6}$$

where F_{ik} represents a global intensity (color) similarity metric between kth pixel and ith cluster center, S_{ik} represents a global spatial similarity metric between kth pixel and ith cluster center. We can adjust the ratio between the two features linearly.

Global intensity (color) similarity metric F reflects the intensity or color difference between pixels each cluster center. The greater the intensity or color difference is, the lower their similarity is. The global intensity (color) similarity can be expressed as follows:

$$F_{ik} = \exp\left(-\beta_1 \cdot \left|I_k - I_i\right|\right) \tag{7}$$

where I_k and I_i represent the intensity value or color vector-valued at the kth pixel and ith cluster center, respectively. β_1 represents a free parameter, is used to adjust the weight of intensity (color) feature in the distance metric.

A novel global spatial similarity metric is proposed to improve the performance of the FCM based image segmentation algorithm, and it depends on the spatial relationship between two nodes. The global spatial similarity can be defined as follows:

$$S_{ik} = \exp\left(\frac{-\beta_2 \cdot \max\left(\left|X_k - X_i\right|, \left|Y_k - Y_i\right|\right)}{\max\left(M, N\right)}\right) \tag{8}$$

where $\left(X_k, Y_k\right)$ and $\left(X_i, Y_i\right)$ represent the space coordinates at the kth pixel and ith cluster center, respectively. M and N are the image length and width, respectively. β_2 is a free parameter, is used to adjust the weight of the spatial location feature in the distance metric. Figure 1, shows the value of the global spatial similarity for all the pixels centered around ith cluster center with different free parameter β_2.

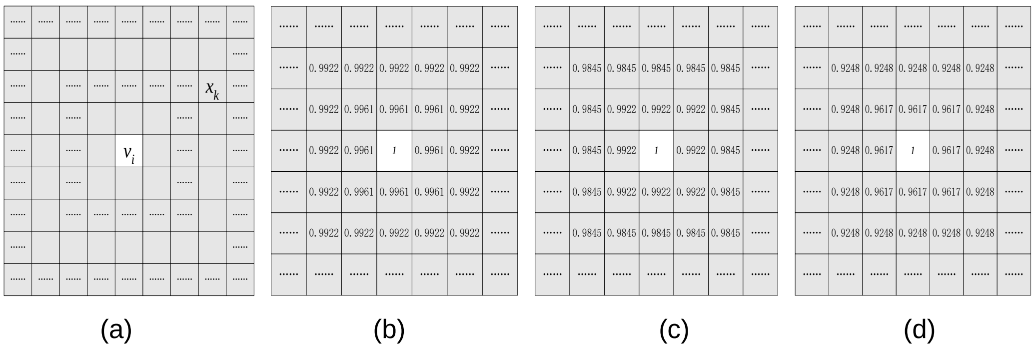

FIGURE 1. Spatial Similarity between Pixels and Cluster Centers at Different Free Parameter (a) Spatial Location of Image Window (b) the Value of Spatial Similarity between Pixels and Cluster Centers when β_1=1 (c) the Value of Spatial Similarity between Pixels and Cluster Centers when β_1=2 (d) the Value of Spatial Similarity between Pixels and Cluster Centers when β_1=10

4. Maximal Similarity Based on Class Merging

The global space similarity metric, enhance the continuity of the segmentation results in spatial distribution. However, the global space similarity metric also limits the spatial distribution of pixels in each class. To solve this problem, we increase the number of cluster centers.

(1) In this work, we set c'=2c (c' is the new number of the cluster centers). After the

FCM segmentation, we obtain the segmentation results with 2c classes. We use color histogram as a region descriptor and calculate the similarity of any two classes, and adopt a maximal similarity based class merging method to merge the classes with maximal similarity.

(2) The input images are taken in the RGB color space, and the color histogram is built in RGB color space in this work. We uniformly quantize each color channel into 16 levels, and calculate the color histogram of each class by discretization of the colors into 16×16×16=4096 bins. Let HistRi and HistRj be the normalized histogram of classes Ri and Rj, the Bhattacharyya distance b(Ri, Rj) is used to measure the similarity between two different classes Ri and Rj.

$$b_{R_i,R_j} = \sum_{u=1}^{4096} \sqrt{Hist_{R_i}^{u} \cdot Hist_{R_j}^{u}} \tag{9}$$

where the superscript u represents the uth element of the normalized histogram HistRi and HistRj. The Bhattacharyya distance indeed reflects the similarity between two classes. The larger the Bhattacharyya distance is, the higher the similarity between two classes is.

The color histogram as a descriptor is a simple yet powerful way to represent the classes. With the help of the Bhattacharyya distance, we can accurately measure the similarity between classes. It has been successfully used in interactive image segmentation [9] and object tracking [10]. A maximal similarity based class merging mechanism is employed to guide the merging process, and then the final segmentation results will be obtained.

5. Experimental Results

Experiments were conducted with nebula image and infrared images. They are given to verify the feasibility of our proposed algorithm. In our experiments, three algorithms are taken into account, including the traditional FCM based image segmentation algorithm (FCM), kernel-induced FCM based image segmentation algorithm [4] (KFCM), and our proposed algorithm (GSSBFCM).

Figure 2, compares the performance of our proposed algorithm with that of the other two algorithms. Figure 2(a), shows the original image, Figure 2(b), shows the segmentation results by FCM, Figure 2(c), shows the segmentation results by KFCM, Figure 2(d) shows the segmentation results by GSSBFCM. Here, free parameter values β_1 and β_2 are set to 1 and 0.5, respectively. As show in Figure 2(a), in the nebula image, since a nebula is formed by interstellar cloud of dust, hydrogen gas, helium gas and other ionized gases, the color spatial distribution of nebula is irregular, which makes the objective of nebula image difficult to be accurately separated out. In the human infrared thermal image and the PCB infrared thermal image, the segmentation results are easily influenced by background disturbances which make the image difficult to be accurately segmented. Now we can subjectively evaluate the segmentation results of the three methods. As can be seen from Figure 2(b)-(d), our proposed method produces more accurate segmentation results.

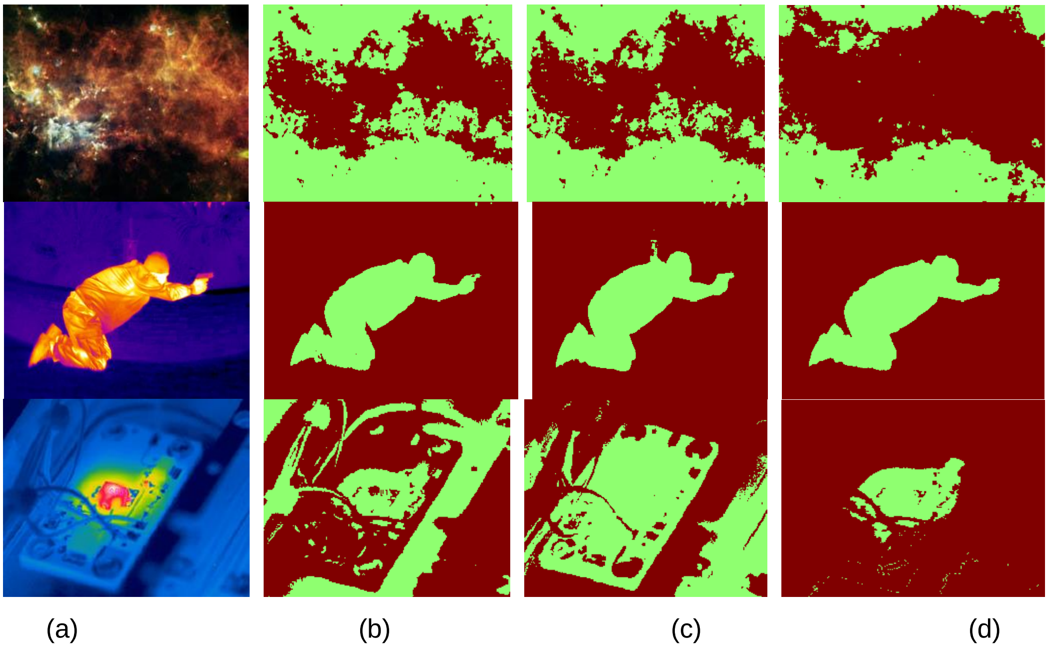

FIGURE 2. The Segmentation Results of PCB with Three Methods (a) Original Image (b) The Segmentation Result Obtained by FCM (c) The Segmentation Result Obtained by KFCM (d) The Segmentation Result Obtained by GSSBFCM

6. Conclusion

A modified FCM algorithm for image segmentation is proposed. To enhance the continuity of the segmentation results in spatial distribution, a novel global space similarity metric is proposed that used in a novel distance metric between pixels and cluster centers. In addition, a maximal similarity based class merging mechanism is applied to the proposed method for more effective segmentation. Simulation results show that the better segmentation results can be obtained by the proposed algorithm, compared with the conventional FCM based and the KFCM based image segmentation algorithm. In the future, both FCM and KFCM will be applied on real practice that can be used in space image, underwater image and police video image.

Acknowledgments

This work is partially supported by National Natural Science Foundation of PR China under Grant 71471006, Social Science Planning Foundation of Liaoning Province in China under Grant L15AGL016 and National Social Science Planning Foundation of PR China under 2016 Cultivation Projection. The authors also gratefully acknowledge the helpful comments and suggestions of the reviewers, which have improved the presentation.

References

[1] N. A. M. Isa, S. A. Salamah and U. K. Ngah, “Adaptive fuzzy moving K-means clustering algorithm for image segmentation”, IEEE Transactions on Consumer Electronics, vol. 55, no. 4, **(2009)**, pp. 2145-2153.

[2] M. R. Sabuncu, B. T. T. Yeo and K. V. Leemput, “A Generative Model for Image Segmentation Based on Label Fusion”, IEEE Transactions on Medical Imaging, vol. 29, no. 10, **(2010)**, pp. 1714-1729.

[3] X. W. Yang, G. Q. Zhang and J. Lu, “A Kernel Fuzzy c-Means Clustering-Based Fuzzy Support Vector Machine Algorithm for Classification Problems with Outliers or Noises”, IEEE Transactions on Fuzzy Systems, vol. 19, no. 1, **(2011)**, pp. 105-115.

[4] S. C. Chen and D. Q. Zhang, “Robust image segmentation using FCM with spatial constraints based on new kernel-induced distance measure”, IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics, vol. 34, no. 4, **(2004)**, pp. 1907-1916.
[5] Z. X. Ji, Q. S. Sun and D. S. Xia, “A framework with modified fast FCM for brain MR images segmentation”, Pattern Recognition, vol. 44, no. 5, **(2011)**, pp. 999-1013.
[6] G. Stefan and S. Robin, “Anti-aliased Euclidean distance transform”, Pattern Recognition Letters, vol. 32, no. 2, **(2011)**, pp. 252-257.
[7] C. Euisun and L. Chulhee, “Feature extraction based on the Bhattacharyya distance”, Pattern Recognition, vol. 36, no. 8, **(2003)**, pp. 1703-1709.
[8] R. D. Maesschalck, D. J. Rimbaud and D. L. Massart, “The Mahalanobis distance”, Chemometrics and Intelligent Laboratory Systems, vol. 50, no. 1, **(2000)**, pp. 1-18.
[9] J. F. Ning, L. Zhang and D. Zhang, “Interactive image segmentation by maximal similarity based region merging”, Pattern Recognition, vol. 43, no. 2, **(2010)**, pp. 445-456.
[10] D. Comaniciu, V. Ramesh and P. Meer, “Kernel-based object tracking”, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 25, no. 5, **(2003)**, pp. 564-577.

Authors

Yufeng Yi, He received his Ph.D. degree from Northeastern University. He is currently a engineer in Academy of Opt-Electronics, China Electronic Technology Group Corporation, China. He is primary research interests in Intelligent Algorithm and Imagine Segmentation.

Lei Wang, He received his Ph.D. degree from University of Science and Technology Beijing. He is currently a assistant professor in Department of Public Order, National Police University of China. He is primary research interests in Intelligent Algorithm, Imagine Segmentation and Information System.