Remote Sensing Image Sequence Segmentation Based on the Modified Fuzzy C-means

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***Abstract*—Remote sensing image with characteristics of multiple gray level, more informative, fuzzy boundary, complex target structure and so on, there is no completely reliable model to guide the remote sensing image segmentation. In response to these issues, the article presents a remote sensing image sequence segmentation method based on improved FCM (fuzzy c-means) algorithm. The color space selects the lower relevance of HSI (hue, saturation, intensity) and adopts standard covariance matrix—the Mahalanobis distance formula, which is more suitable for the use of remote sensing image. It can solve the initial centers selection problems of fuzzy C-means clustering algorithm by the use of ECM. By using the partition of S component, it can divide the image into high S regions and low S regions. We can do FCM segmentation respectively with H component and I component of these two parts. The segmentation results can be achieved after the merger. The program experimental result shows that this method will enable FCM to converge to global optimal solution with less iteration, and has good stability and robustness. It has good effect on improving the accuracy of threshold segmentation and efficiency for remote sensing images, which can be used for content-based remote sensing image retrieval systems.**

***Index Terms*—remote sensing image, fuzzy c-means, sequence segmentation, evolving clustering method, content-based image retrieval**

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I. Introduction

Image segmentation is the process and technology that to divide images into the regions with distinctive features and extract the target interested in. Features can be gray, color, texture and so on, target can correspond to single region, may also correspond to a number of regions [1]. Remote sensing image segmentation means the process and technology of the processing, analysis, extracted target. Remote sensing image with characteristics of multiple gray level, more informative, fuzzy boundary, complex target structure and so on, which make it ask for higher requirements to remote sensing image segmentation whether in the efficiency or the effect, but lack of a reliable model to guide it completely, it block the application of segmentation technology in the field of remote sensing to some extent [2], [3].

Segmentation is an essential issue in image description or classification [4]. Threshold-based segmentation is a basic method of image segmentation -- simply way and High-speed deal -- but it is not suitable for image segmentation fuzzy boundary region as its hard partition method. Unsupervised clustering method used regularly for the fuzzy boundary region partition, like K-Means, Fuzzy C-Means [5], [6], ISODATA [7], etc [8], [9], [10]. Many different segmentation approaches have been developed that cannot be generalized under a single

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scheme. The fuzzy C-means algorithm (FCM) has been utilized in a wide variety of image processing applications such as medical imaging [11], [12] and remote sensing [13], [14]. The algorithm and various modifications of it with focus on practical applications in both industry and science are discussed. Its advantages include a straightforward implementation, fairly robust behavior, applicability to multichannel data, and the ability to model uncertainty within the data. FCM is more effective to the fuzzy boundary region segment, but the biggest disadvantage is that no better way to determine the C value of clustering and the initial cluster centers, essentially, FCM is a local search optimization algorithm, it will converge to the local minimum point and this clustering effect would have a greater impact if the initial selection value are not properly [15], [16].

In this paper, a new method of image sequence segmentation is put forward by combining the evolving clustering method with the improved FCM algorithm. The color space selects the lower relevance of *HSI* (hue, saturation, intensity) and adopts standard covariance matrix—the Mahalanobis distance formula, which is more suitable for the use of remote sensing image. It can solve the initial centers selection problems of fuzzy C-means clustering algorithm by the use of ECM. By using the partition of *S* component, it can divide the image into high *S* regions and low *S* regions. We can do FCM segmentation respectively with *H* component and *I* component of these two parts. The segmentation results can be achieved after the merger. The program experimental result shows that this method will enable FCM to converge to global optimal solution with less iteration, and has good stability and robustness. It has good effect on improving the accuracy of threshold segmentation and efficiency for remote sensing images, which can be used for content-based remote sensing image retrieval systems.

This paper is organized as follows. Section 2 introduces the FCM algorithm and its problems, and put forward the improved FCM algorithm. Section 3 describes our approach, including color space, the choice of distance measure, and put forward the method of remote sensing image sequence segmentation. Results from the implemented algorithm are shown and discussed in Section 4; while our conclusions are given in Section 5.

II. The Improved FCM Algorithm

A. *Fuzzy C-means Algorithm*

Fuzzy C-means [17], [18] is a clustering method which allows a piece of data to belong to two or more clusters, which is frequently used in computer vision, pattern recognition and image processing. The FCM algorithm obtains segmentation results by fuzzy classification [19]. Unlike hard classification methods which group a pixel to belong exclusively to one class, FCM allows a pixel to belong to multiple classes with varying degree of memberships [20]. FCM approach is quite effective for image segmentation. Several segmentation algorithms based on fuzzy set theory and FCM were reported.

Fuzzy C-means is a clustering algorithm that used membership degree to determine each data point belongs to a certain cluster. FCM divided the n vectors $x_i \ (i = 1, 2, ..., N)$ into *c* fuzzy group, and computing the cluster center of each group, making value function of non-similarity index to achieve the minimum. FCM algorithm making each of the given data points with values between $0,1$ membership to determine its degree of belonging to various groups through fuzzy partition. And to suit the introduction of fuzzy partition, the membership matrix U allowed the element value between $0,1$.

In addition to normalized provides the membership degree sum of a data set equivalent to 1:

$$\sum_{i=1}^{C} u_{ij} = 1, \forall j = 1, 2, ..., N \tag{1}$$

Then, the values function of FCM (objective function) as follows:

$$\begin{aligned} &J(U, v_1, ..., v_C) \\ &= \sum_{i=1}^{C} J_i = \sum_{i=1}^{C} \sum_{j=1}^{N} (u_{ij})^m (d_{ij})^2 \end{aligned} \tag{2}$$

u_{ij} ranged between $0,1$ here, v_i is the cluster center of fuzzy group i, $d_{ij} = \left\| x_j - v_i \right\|$ is the Euclidean distance between the first i cluster center with the first j data point, $m \in [1, \infty)$ is a weighted index.

The new constructed objective function can be obtained necessary condition so that (2) to achieve the minimum:

$$\begin{aligned} &\bar{J}(U, v_1, ..., v_c, \lambda_1, ..., \lambda_n) \\ &= J(U, v_1, ..., v_c) + \sum_{j=1}^{N} \lambda_j \left(\sum_{i=1}^{C} u_{ij} - 1\right) \\ &= \sum_{i=1}^{C} \sum_{j=1}^{N} (u_{ij})^m (d_{ij})^2 + \sum_{j=1}^{N} \lambda_j \left(\sum_{i=1}^{C} u_{ij} - 1\right) \end{aligned} \tag{3}$$

In (3), the λ_j ($j = 1, 2, ..., N$) is Lagrange multiplier of n of constrained formulas of (1). Derivation of each input parameter, so that (2) to reach the minimum necessary conditions are as follows:

$$v_i = \sum_{j=1}^{N} (u_{ij})^m x_j \Big/ \sum_{j=1}^{N} (u_{ij})^m \tag{4}$$

and

$$u_{ij} = \left[\sum_{k=1}^{C} \left(d_{ij} / d_{kj} \right)^{2/(m-1)} \right]^{-1} \tag{5}$$

From the above two necessary conditions, Fuzzy C-means is a simple iterative process. In the run-time of batch mode, FCM with the following steps to determine the cluster centers v_i and the membership matrix U .

Step1. Using a random number in value between $0,1$ to initialize the membership matrix U, to meet constraints of (1).

Step2. Computing the cluster centers v_i ($i = 1, 2, ..., c$) by using (4).

Step3. Calculating the values function with (2). The algorithm to stop if it is less than a determined threshold or its previous value of the relative change in function value is less than a certain threshold.

Step4. Calculation of the new matrix U by (5), return step 2.

The above algorithm can also initialize cluster center firstly, and run the iterative process after. The algorithm does not guarantee an optimal solution to the convergence, so its performance depends on the initial cluster centers. Therefore, another fast algorithm can be used to determine the initial cluster centers, or start the algorithm with different initial clusters center every time, running FCM repeatedly.

B. Evolving Clustering Method

Evolving clustering method is a clustering algorithm of kind of evolution, on-line and bounding by a maximum distance. It increases the number of cluster or adjusts the centers and the radius real-time dynamically as entered sample data increasing [21], [22]. In any one cluster, the maximum distance between the example of cluster points and the corresponding maximum distance are less than the threshold $D_{threshold}$, $D_{threshold}$ selection will have a direct impact on the clustering numbers. Examples of clustering process from a data stream, the whole process start clustering from an empty set. Some of the created clusters to be updated through depend on the location of the current example in the input space as well as changing the location of the cluster centers and increasing the radius of the cluster with the new examples appearance, it will no longer to be updated when its radius meet the threshold.

RGB (red, green, blue) space is selection by space of images color -- pre-set the cluster radius for $D_{threshold}$ -- can implement the initial partition in pixels for a radius of $D_{threshold}$ through the scan of whole image. The algorithm is:

Step1. Reading pixel information from image data stream in line, simply select the first pixel x_1 *RGB* value from the input data stream as clustering center v_1 of the *RGB* value to create the first cluster V_1, set the cluster radius $r_1 = 0$.

Step2. The algorithm close if all the pixels are processed in data stream. Otherwise, computing distance $d_{ij} = \|x_i - v_j\|$, $j = 1, 2, ..., N$ between the current input pixel x_i, and N of the cluster center v_j.

Step3. If there is a d_{ij} less than or equal to the one of r_j at least, which means that x_i belong to the first m cluster V_m, namely, $d_{im} = \|x_i - v_m\| = \min(\|x_i - v_j\|)$, $j = 1, 2, ..., N$, it has been bounded by $d_{im} \le r_m$. Under these circumstances, neither to create a new cluster nor update any existing clusters. Algorithm to return to step 2, otherwise, go into step 4.

Step4. Calculate $s_{ij} = d_{ij} + r_j$, $j = 1, 2, ..., N$, select the clustering center v_a that was provided with s_{ia}, in order to identify the cluster V_a, and $s_{ia} = d_{ia} + r_a = \min(s_{ij})$, $j = 1, 2, ..., N$.

Step5. x_i does not belong to any existing cluster if $s_{ia} > 2 \times D_{threshold}$. Create a new cluster similar step 1, then back to step 2.

Step6. Update V_a through move v_a and increase the value of r_a, if $S_{ia} \le 2 \times D_{threshold}$. Make v_a^{new} located the connection at x_i and v_a, further, meet $\|v_a^{new} - x_i\| = r_a^{new}$ when $r_a^{new} = s_{ia} / 2$, the algorithm back to step 2.

C. Optimization of Cluster Center

Each cluster center from evolution algorithm to be optimized by FCM, the steps are:

Step1. Set of fuzzy clustering coefficient value b and algorithm termination threshold ε, number of iterations $t = 1$, permit the maximum number of iterations $t_{\max}$, and c of the cluster centers $v_{C_i} (1 \le i \le C)$ from evolution algorithm as the initial cluster centers for FCM.

Step2. Calculate membership function with the current cluster center according (5).

Step3. Update all types of cluster centers with the current membership function according (4).

Step4. Select a suitable matrix norm, if $\|V^{(t+1)} - V^{(t)}\| \le \varepsilon$ or $t \ge t_{\max}$, then operation stop, otherwise, update the cluster center value $t = t + 1$, return to step 3.

When the algorithm convergence, it can get each clustering centers and the membership degrees of various clusters samples, completing the partition of fuzzy clustering, and finally through the elimination of fuzziness into a certainties classification, to achieve final clustering segmentation.

D. Set Partitioning of Image Pixel

Scanning the data stream, re-determine the classification of each pixel for the c of optimized cluster center. If there is a cluster center v_j, the distance

$d_{ij} \le r_j (j=1,...,C)$, then x_i belong to cluster V_m that it meet the minimum distance $d_{im} = \|x_i - v_m\| = \min(\|x_i - v_j\|)$.

III. OUR APPROACH

A. Color Model Selection

Directly making use of these components will affect the results, because the *RGB* (red, green, blue) color space has a high relevance among the three components. To reduce the pertinence between various feature components in characteristic space of color use, HSI space, which the vision system based on human perception of color characteristics of image processing is adopted in this paper for the purpose of the convenience specific application of remote image segmentation.

For practical image segmentation tasks, the *HSI* color model should have two principal advantages. First, the *I* component is de-coupled from the color information in the image. Second, the *H* and *S* components are intimately related to the way with which human beings perceive color [23].

To better take the advantages of the color contents of images, the color image segmentation can be carried out in *HSI* space. The conversion from *RGB* component s to *HSI* components can be carried out according to the following formulas.

$$H = \arccos\left(\frac{(R-G)+(R-B)}{2\sqrt{(R-G)^2+(R-B)(G-B)}} \right),$$

$$R \ne G \text{ or } R \ne B, \ B > G, H = 2\pi - H \tag{6}$$

$$S = 1 - \frac{3}{R+G+B}\left[\min(R,G,B)\right] \tag{7}$$

$$I = \frac{R+G+B}{3} \tag{8}$$

In the *HSI* model space, every single uniformity color region corresponds to relatively consistent hue *H*, which means that hue can be used to conduct segmentation in a shadow-independent color region.

B. Distance Measure Selection

Conventional fuzzy C-means clustering method is based on Euclidean distance, i.e. the clustering method of isotropy. However, the actual scatter of remote sensing image show that the distribution of pixel is not subject to isotropic or spherical distribution. Therefore, the desired results cannot be often achieved in the applications [24], [25].

First of all, the distribution of different categories tends to super-ellipsoid scatter in the feature space because of the indeterminacy of remote sensing images and the existence of mixed pixels, which are not suitable for the use of distance-based Euclidean distance between points. Secondly, FCM clustering algorithm can only be used to cluster spectrum information and does not reflect the dependence between samples in the field of remote sensing.

$d_{ij} = \|x_j - v_i\|$ is equal to the Euclidean distance and can be applied to the distribution of the same or sphere in the classical FCM algorithm. Due to the indeterminacy of remote sensing information and the existence of mixed pixels, the distribution of different categories tends to super-ellipsoid scatter in the feature space. Thus clustering results by using the FCM algorithm are not satisfactory. For this reason, we focus on the characteristics of remote sensing image and improve the distance algorithm in FCM by using the Mahalanobis distance formula, which is based on standard covariance matrix and suitable for the remote sensing image even more.

First of all, the covariance matrix of three-channel and the standard covariance matrix C should be calculated. Then the inverse matrix of standard covariance matrix can be calculated and the equation for computing the distance is as follows:

$$(d_{ij})^2 = (x_j - v_i)^T C^{-1} (x_j - v_i) \tag{9}$$

In (9), C^{-1} is the inverse matrix of the standard covariance matrix C. When $C^{-1} = I$ (I is unit matrix), the equation (9) is changed into Euclidean distance. The essence of Mahalanobis distance is to introduce the weighted matrix C^{-1} in the distance calculation of sample X and the center V. This weighted matrix is a inverse matrix of normalized fuzzy discrete class; intuitively, that is, the weighted is relatively less in the biggish dispersion direction, whereas in the lesser dispersion direction weighted is relatively bigness. In this way, we can achieve the super ellipsoid fuzzy clustering, which can more effectively detect the distribution of the various categories in super ellipsoid.

C. Sequence Segmentation Sstrategy

Remote sensing image segmentation takes a step-by-step strategy. For most proposed algorithms of color segmentation using *HSI* model, the three components of a color image are taken simultaneously in the process. Because *HSI* three components are mutually independent, it is possible to turn this 3-D search problem into three 1-D search problems. In the article, the method of the sequence segmentation of different components is adopted and the flow chart is shown as in Fig.1.

(1) Separate the image into high and low saturation regions by S component.

(2) Split high saturation regions by using value *H*, as threshold. In the high *S* regions, the *H* component provides a powerful discriminating tool for segmentation.

(3) Split low saturation regions by using value *I*, as threshold. In the low *S* regions, the *I* component has the comparable ability.

Segmentation in the above three steps can be splitted by using both different methods and the same method.

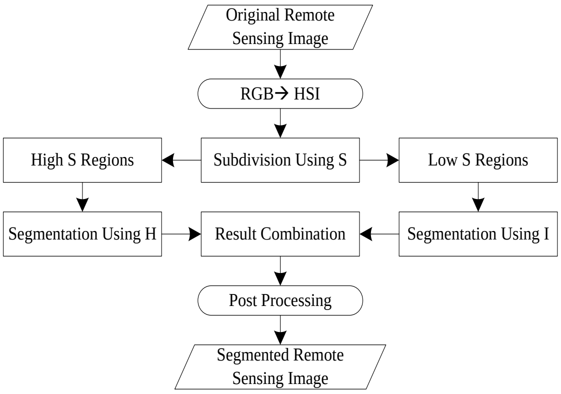
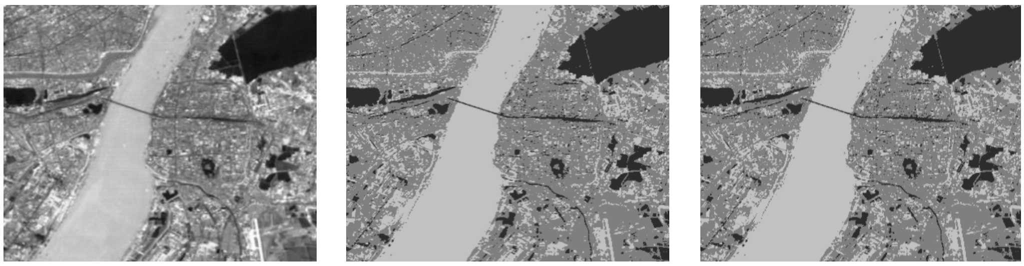


Figure 1. Flow chart of image sequential segmentation.

II. EXPERIMENTAL RESULTS AND DISCUSSION

A. Experimental Results with Improved FCM Algorithm

This paper presents a remote sensing image segmentation results for the purpose of verifying the validity of the algorithm. Fig.2 is given segmentation results of a remote sensing image based on the improved FCM algorithm. Fig.2(a) is a random sample image of 395×405 pixels from a large number of remote sensing images, fig.2(b) is the result of the remote sensing image clustering segmentation based on ECM and GA (genetic algorithm), fig.2(c) is the result based on ECM and FCM. In the experiment, each pixel take the color of its cluster center - $D_{threshold}$ parameters takes 199.6, the optimized threshold of 0.01 - in the 12th iterative when the difference between the old and the new center value is less than 0.01, to meet the limit of the difference degree and withdraw from iterative cycle.



(a) original image (b) result based on ECM and GA (c) result based on ECM and FCM

Figure 2. Segmentation results with improved FCM algorithm.

According to a large number of experiments were found that using genetic algorithms combined with ECM on the same image segmentation to optimize the initial cluster centers from ECM make use of genetic algorithm, the definition of evaluation function for the sum of each pixel to it corresponding center distance, the end of the conditions of algorithm is optimal individual evaluation function for two generations difference is less than 0.01 or the evolution of the 500 generation, the results showed that the time the algorithm used was far less than the above-mentioned methods used in, the difference is more obvious when larger images and more category of image content. The effect of two methods is not very different from artificial evaluation.

As for image segmentation on the same image with the same algorithm, it is also found that the time spending on the combination of ECM and FCM is basically stable; while the time and the number of iteration on the combination of ECM and GA are not the same. The segmentation effect is not very different from artificial judgment when the cluster radius is appropriately set. The experiment results show that the segmentation effect with the improved FCM algorithm is better when the cluster radius is appropriately set.

Fig.3 shows the iteration numbers curve of two algorithms with the cluster radius changes under the same experimental conditions. The iteration numbers for the combination of ECM GA are taken by computing the average for 10 times with the same parameters. It can be seen that the convergence curve is superior to the combination of ECM and genetic algorithm, which indicates that algorithm proposed in this paper is reasonable and effective.

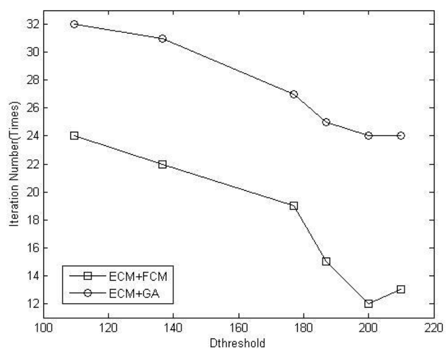
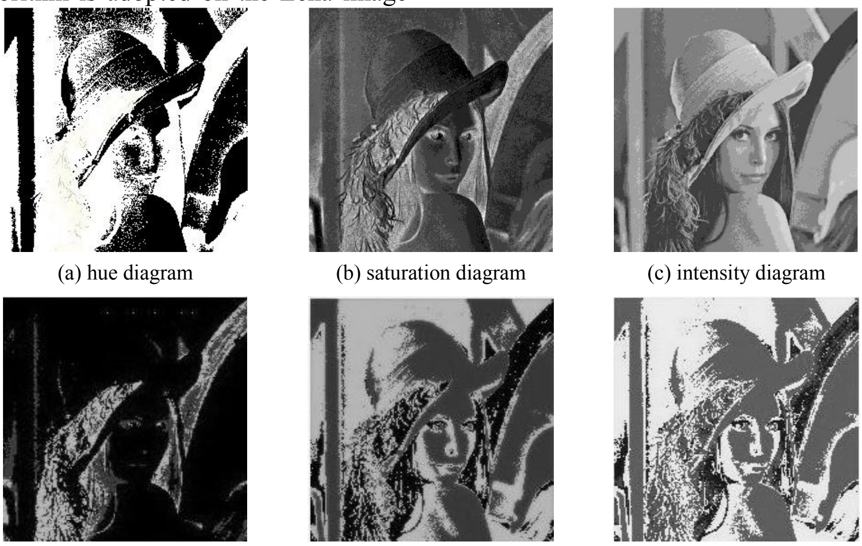


Figure 3. Algorithm convergence curve comparison.

B. Experimental Results with Sequence Segmentation

In order to verify the validity of the above-mentioned method, according to the technical route, *HSI* space is selected as the image color space and a more suitable for remote sensing images Mahalanobis distance formula is taken as distance measure. And then the sequence segmentation strategy is adopted. A Lena image (size 512 × 512 pixels) and a remote sensing image is selected to carry out the program experiment. The experiment results are shown in Fig.4 and Fig.5. The remote sensing image data adopt SPOT5 multi-spectral images with a spatial resolution of 10m and a study area size of 395 × 405 pixels.

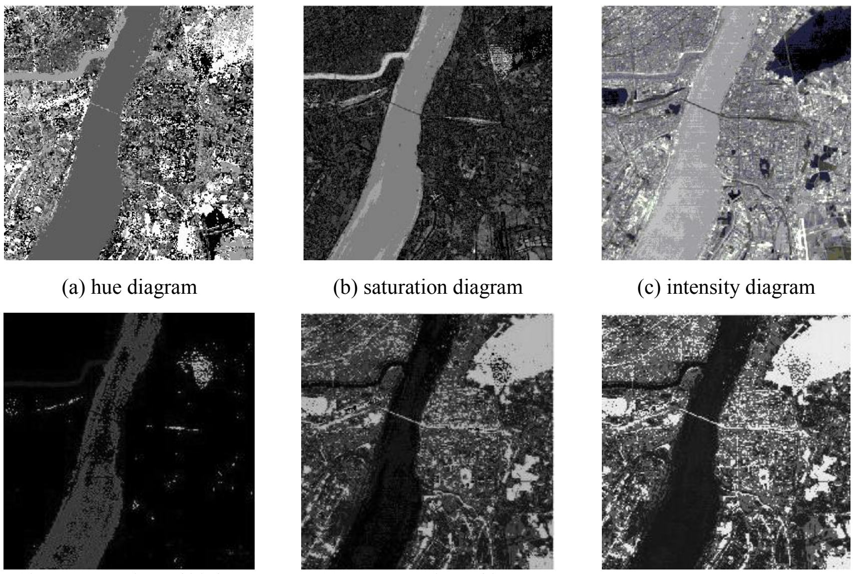
The proposed algorithm — the above-mentioned improved FCM algorithm is adopted on the Lena image sequence segmentation experiments. Fig.4(a) is the hue diagram for Lena image. Fig.4(b) is the saturation diagram. Fig.4(c) is the intensity diagram, Fig.4(d) is the thresholding segmentation of high *S* regions in Lena image with value *H* that is used the improved FCM algorithm. Fig.4(e) is the thresholding segmentation of low *S* regions in Lena image with value *I* that is used the improved FCM algorithm. Fig.4(f) is the segmentation results after the merger.



(a) hue diagram (b) saturation diagram (c) intensity diagram

(d) segmentation of high S regions with value H (e) segmentation of low S regions with value I (f) merging results

Figure 4. Sequence segmentation results on Lena image.



(a) hue diagram (b) saturation diagram (c) intensity diagram

(d) segmentation of high S regions with value H (e) segmentation of low S regions with value I (f) merging results

Figure 5. Sequence segmentation results on remote sensing image.

The proposed algorithm — the above-mentioned improved FCM algorithm is adopted on the remote sensing image sequence segmentation experiments. Fig.5(a) is the hue diagram for remote sensing image. Fig.5(b) is the saturation diagram. Fig.5(c) is the intensity diagram. Fig.5(d) is the thresholding segmentation of high *S* regions in remote sensing image with value *H* that is used the improved FCM algorithm. Fig.5(e) is the thresholding segmentation of low *S* regions in remote sensing image with value *I* that is used the improved FCM algorithm. Fig.5(f) is the segmentation results after the merger.

Judging from the results, using the proposed algorithm and strategies for remote sensing image segmentation can offer less iterations times to converge to global optimal solution. At the same time, it has good stability and robustness. Its good effect of segmentation can improve accuracy and efficiency of remote sensing image thresholding segmentation.

IV. CONCLUSIONS

Image segmentation is an important research area including pattern recognition, image understanding, computer vision, and so on, although the use of Fuzzy C-means and its improvement methods with a brief description, easy to implement, good partition effect in image segmentation, there are still some problems, such as weak robustness of distance measure, requirements of setting the initial number of clusters in advance, without considering local image feature, which limits its further application. Moreover, the remote sensing images with large-scale lead to the processing efficiency of the algorithm have certain requirements.

In response to these issues, the article presents a remote sensing image sequence segmentation method, which is based on the combining of the evolving clustering method with the modified FCM algorithm. The color space selects the lower relevance of *HSI* (hue, saturation, intensity) and adopts standard covariance matrix — the Mahalanobis distance formula, which is more suitable for the use of remote sensing image. It can solve the initial centers selection problems of fuzzy C-means clustering algorithm by the use of ECM. The sequence segmentation is carried out in accordance with the strategy and the results can be performed on the new digital global platform. The program experimental result shows that this method will enable FCM to converge to global optimal solution with less iteration, and has good stability and robustness. It has good effect on improving the accuracy of threshold segmentation and efficiency for remote sensing images, which can be used for content-based remote sensing image retrieval systems.

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