

Using Fuzzy Logic to Enhance the Large Size Remote Sensing Images

Trung Nguyen Tu, Huy Ngo Hoang, and Thoa Vu Van

Abstract—The image enhancement methods based on fuzzy clustering make image which quality clearly higher the traditional methods. However, actually, the methods have problems with the large size remote sensing, that is the inherent disadvantage of the fuzzy clustering algorithms. In addition, the methods only work on each band, therefore the color of image is not conserved after enhancement. This paper presents a new algorithm of image enhancement with combination of two fuzzy clustering levels and multiple bands grey level adjust model which can surmount the above disadvantages.

Index Terms—Image enhancement, fuzzification, defuzzification, grey level adjust.

I. INTRODUCTION

Remote sensing images often have large size and high resolution. They can also contain noises. For noise reduction and image enhancement, we need to use the image quality enhancing methods. Quality Enhancement includes two separate phases: Image Enhancement and Restore. Noises in remote sensing images include common noises like color images and specific noises as mist, cloud... For specific noises we need specific methods of noise reduction such as removing cloud and mist using Mallat algorithm [1]. For common noises, we can use the common noise reduction methods such as noise filter, image smoothing; contrast enhancement, adjusting grey levels of images; ... Many common contrast enhancement methods apply the global approach to enhance all brightness levels of images. This can loss the local contrast information and details in bright and dark regions. In [2], the authors combine the fuzzy clustering and the grey level adjusting formulas to enhance contrast of medical images. However, in reality, the methods have problems with the large size remote sensing images, that is the inherent disadvantage of the fuzzy clustering algorithms. In addition, the methods only process each band. In [2], the medical images are the grey images. So, if the methods apply to multiple band images, such as color images, the color of image is not often conserved after enhancement.

This paper presents a new algorithm of image enhancement based on fuzzy clustering which can perform with the large size remote sensing images and process simultaneously multiple bands, combining auto thresholds computing following each cluster.

Remaining sections of this paper are presented as follow.

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Section II presents the algorithm of enhancing the large size remote sensing images based on fuzzy technique. Experiments are presented in Section III. Section IV is the conclusion of the paper.

II. ENHANCING THE LARGE SIZE REMOTE SENSING IMAGES BASE ON FUZZY TECHNIQUE

My fuzzy image enhancement algorithm is implemented with three stages as in Table I.

TABLE I: ENHANCING IMAGE WITH ALGORITHM

Stage	Task
Stage 1	Fuzzification with lsiFCM
Stage 2	Creating the grey level adjust model
Stage 3	Defuzzification with the grey level adjust model

A. Fuzzification with lsiFCM

1) FCM clustering algorithm

Fuzzy c-Means clustering algorithm [3] of fuzzy segmentation is widely used. While considering fuzzy logic set, the algorithm is developed based on k-Means clustering algorithm. In this algorithm, each pixel does not only belong to any cluster and represented by multiple membership of each cluster. Clustering algorithm is performed with iterating optimization of minimizing fuzzy objective function (J_m) which is defined as equation 6 ([4], [5]).

$$J_m = \sum_{i=1}^c \sum_{k=1}^n (\mu_{ik})^m d^2(x_k, V_i) \quad (1)$$

where:

c : number of clusters.

n : number of pixels of image.

μ_{ik} : membership value of i th cluster of k th pixel

m : fuzzy parameter

x_k : vector of k th pixel

V_i : center vector of i th cluster

$d^2(x_k, V_i)$: Euclidean distance between x_k and V_i

Membership(μ_{ik}) is estimated with distance between x_k and V_i and bounded as following:

$$\begin{cases} 0 \leq \mu_{ik} \leq 1 \\ \sum_{k=1}^n \mu_{ik} = 1 \\ 0 \leq \sum_{k=1}^n \mu_{ik} \leq 1 \end{cases} \quad (2)$$

Center of cluster V_i and the member matrix μ_{ik} (of the member matrix μ) can be computed by the formula:

$$V_i = \frac{\sum_{k=1}^n (\mu_{ik})^m x_k}{\sum_{k=1}^n (\mu_{ik})^m}, 1 \leq i \leq c \quad (3)$$

$$\mu_k = \left[\sum_{j=1}^c \left(\frac{d(x_k, V_j)}{d(x_k, V_i)} \right)^{\frac{2}{m-1}} \right]^{-1}, 1 \leq i \leq c, 1 \leq k \leq n \quad (4)$$

Therefore, J_m can be minimized by iterating through equations (3) and (4). The first step of iterating is initializing fixed cluster number c , fuzzy parameter m , convergence threshold ε , then computing μ_{ik} and V_i using equations (3) and (4). Iterating is finished when the change of V_i between two iterations is smaller than ε . Finally, each is classified into a combination of memberships of clusters.

2) Remote sensing image clustering with lsiFCM

The fuzzy enhancing methods only process each band. In [2], the medical images are the grey images. Inherently, FCM algorithm [3] can perform clustering with multiple bands. Actually, this algorithm is used effectively for color image clustering. Therefore, we improve some grey level adjust functions (see section 2.B) to use this utility for clustering multiple bands of remote sensing images.

A different problem needs to be solved. The FCM algorithm [3] cannot perform for large size images such as remote sensing images. FCM algorithm process to cluster directly input image. It is not sure this can be executed with large size remote sensing images. The fuzzy clustering has problem when being executing large size images which are remote sensing images with high resolution. The problem is due the member matrix μ . According to formula 4 (section 2.A.1), size of μ is computed as following:

$$Size_{\mu} = c.n.8 \quad (\text{Byte}) \quad (5)$$

where, c is cluster count, n is pixel count of image.

Supposing we have a image with size 2048×2048 , we need segment to 20 clusters. Then, $Size_{\mu}$ is $2048 \times 2048 \times 20 \times 8(B) = 640(MB)$. This matrix is stored in RAM. In this case, we need RAM 1GB to store the matrix. However, if we want to segment to 40 clusters, $Size_{\mu}$ is $1280(MB) > 1024 (MB) = 1GB$. It means if we have only RAM 1GB then it will not contain enough elements of the matrix. Then, to execute FCM algorithm, we must increase RAM.

If the size of image is 16000×16000 , cluster count $c = 20$, $Size_{\mu}$ is $16000 \times 16000 \times 20 \times 8(B) = 640(MB) = 39062.5 (MB) \approx 39 (GB)$. With the above image size and the above cluster count, even with largest size RAM at the moment, PC (personal computer) can not also contain the matrix, which leads to the fact that FCM unable to execute if this matrix is stored in RAM. Therefore, we can think of using hard disk to store this. However, then, even with the common color images, executing time of FCM is very low. With remote sensing, this time can be up to day unit. Therefore, it is not effective. The above analysis explains the reason why FCM [3] has problems with large size images that are specific remote sensing images.

If FCM algorithm [3] for large size remote sensing images is improved, images enhancement algorithm will solve the above problem. Therefore, we propose algorithm of fuzzy clustering, which we call lsiFCM (large size image Fuzzy cMeans), for large size remote sensing images. Algorithm diagram is described in Fig. 1.

Step 1: Divide cells

We can describe images under pixels set. Supposing image has size $M \times N$. Then, we have:

$$Image = \{Pix(i, j): 1 \leq i \leq M, 1 \leq j \leq N\} \quad (6)$$

Original Image is divided to $P \times Q$ cells, each cell has a

size not exceeding $1024 \times 1024 (Mc \times Nc)$ pixels to assure that FCM procedure can be executed. Horizontally, two consecutive cells have stacked a part as large as a half of each cell $Cell(x, y)$. Vertically, two consecutive cells have stacked a part as large as a half of each cell. Then, we have a new description of images as following:

$$Image = \{Cell(x, y): 1 \leq x \leq P, 1 \leq y \leq Q\} \quad (7)$$

where:

$$Cell = \{Pix(i, j): 1 \leq i \leq Mc, 1 \leq j \leq Nc\} \quad (8)$$

$$Mc, Nc < 1024$$

Hence, we have a set of cells. Rewriting (6) in the one direction form of cells, we have a representation of image following:

$$Image = \{Cell(i): 1 \leq i \leq n\} \quad (9)$$

where, $Cell(i)$ is equivalent to $Cell(x, y)$ in (7) and $n = P \times Q$.

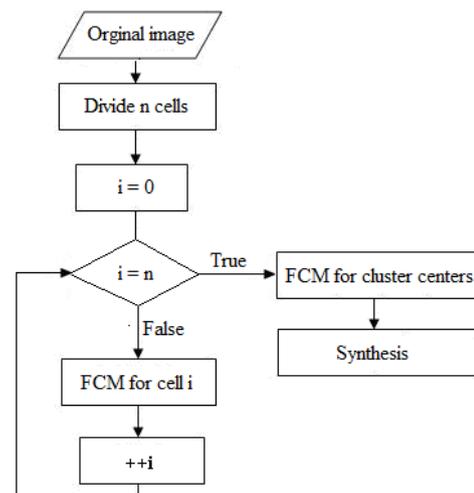


Fig. 1. Diagram of lsiFCM algorithm.

Step 2: FCM clustering for each cell

Perform clustering each cell $Cell(x, y)$ with FCM algorithm. After all cells are clustered, we obtain the center set as following:

$$V_{Image} = \{V_{Image}(x, y, k): 1 \leq x \leq P, 1 \leq y \leq Q, 1 \leq k \leq c\} \quad (10)$$

Step 3: FCM clustering for cluster centers set

After collecting cluster centers set of all cells, we perform FCM clustering on this set. Then, we will cluster centers set with c final centers.

Step 4: Synthesis

From c cluster centers which are obtained in Step 3, recalculate membership values of each pixel in original image for each cluster center.

B. Creating the Grey Level Adjust Model

In this stage, we will construct the grey level adjust function to enhance each cluster. This function is created from grey level stretch fomula following:

$$g' = 255 \times \frac{g - \min}{\max - \min} \quad (11)$$

The grey level adjust function is formulated following:

$$T_i(g, lower_{V_i}, lower_{V_i}) = 255 \times \frac{g - lower_{V_i}}{upper_{V_i} - lower_{V_i}} \quad (12)$$

where, min is minimum value, max is maximum value, $lower_{V_i}$ is lower boundary, $upper_{V_i}$ is upper boundary, g is old grey level value, g' is new grey level value.

Then, the thresholds $upper_{V_i}$ and $lower_{V_i}$ is computed follow each band and each cluster V_i .

Suppose, $d(g)$ is called the distributed function of the g grey level following each cluster. $d(g)$ and the parameters: V_i , $upper_{V_i}$, $lower_{V_i}$ is showed in Fig. 2.

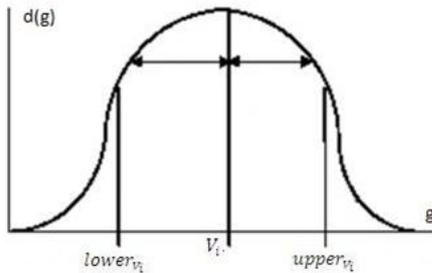


Fig. 2. Distributed function and thresholds.

The thresholds $upper$ and $lower$ is determined by selecting so that area of subregion between $upper_{V_i}$ and $lower_{V_i}$ values equalize 95% area of region buildt by graph of the distributed function. Table II list the most of the grey adjust fomulas in [2].

TABLE II: THE GREY LEVEL ADJUST FOMULAS IN [2]

Meaning	Adjust formulas $T_i(g)$ / intermediate parameters
Possibility Distribution	$g * \left(2 * \left(\frac{g - b_{i,l}}{V_i - b_{i,l}} \right)^2 \right), \quad b_{i,l} \leq g < \frac{b_{i,l} + V_i}{2}$ $g * \left(1 - \left(\frac{g - V_i}{V_i - b_{i,l}} \right)^2 \right), \quad \frac{b_{i,l} + V_i}{2} \leq g < V_i$ $g * \left(1 - \left(\frac{g - V_i}{b_{i,u} - V_i} \right)^2 \right), \quad V_i \leq g < \frac{b_{i,u} + V_i}{2}$ $g * \left(2 * \left(\frac{g - V_i}{b_{i,u} - V_i} \right)^2 \right), \quad \frac{b_{i,u} + V_i}{2} \leq g \leq b_{i,u}$
Intensification Operator	$b_{i,u} - F_d * (\mu')^{-1.5}$ <p>Where:</p> $F_d = \frac{b_{i,u} - V_i}{0.5^{-1.5}}$ $\mu = \left(1 + \frac{b_{i,u} - g}{F_d} \right)^{-2}$ $\begin{cases} \mu' = 2 * \mu^2, & 0 \leq \mu \leq 0.5 \\ \mu' = 1 - 2 * (1 - \mu)^2, & 0.5 < \mu \leq 1 \end{cases}$
Hyperbolization	$\left(\frac{255}{e^{-1} - 1} \right) \left[e^{-\mu^2(g)} - 1 \right]$ <p>Where:</p> $\mu = \begin{cases} 0, & g < b_{i,l} \\ \frac{g - b_{i,l}}{b_{i,u} - b_{i,l}}, & b_{i,l} \leq g \leq b_{i,u} \\ 1, & b_{i,u} \leq g \leq 255 \end{cases}$

where:

g : original gray value.

$b_{i,u}$: upper boundary for stretching of i th cluster.

$b_{i,l}$: lower boundary for stretching of i th cluster.

V_i : center of i th cluster.

C. Defuzzification with the Multi Bands Grey Level Adjust Model

Defuzzification is process of image transformation from membership space back to the gray level space. Based on the grey level adjust model for each built in section 2.2, grey values of each pixel are enhanced to new values. This enhancing function has a general form as following: $g \mapsto g' = T(g)$. Where,

$$T(g) = \sum_{i=1}^c T_i(g, lower_{V_i}, lower_{V_i}) \quad (13)$$

$$0 \leq T(g) \leq 255$$

The enhancing algorithms only built grey level adjust functions for a band [2]. So, fuzzification also only performs on each band (see section 2.1). Assuming each pixel P has 3 grey values corresponding 3 bands is (g_1, g_2, g_3) Fuzzification, which is performed independently on each band, leading to g_1, g_2, g_3 will have corresponding 3 sets membership values with sets of cluster on each band that isn't related together. This leads to the loss of the relationship of 3 grey values in the same pixel. Then, new values after transformation $T(g_1), T(g_2), T(g_3)$ also lose this feature. So, the color of enhanced image is not conserved. However, if we perform simultaneously fuzzification on multiple bands, each pixel $P(g_1, g_2, g_3)$ or (g_1, g_2, g_3) has the same set of membership values with same set of clusters. This means the relation of grey values in the same pixel does not break.

Based on formula (13) and applying simultaneously FCM for multiple bands (see section 2A.1), we modify grey level function for multiple bands and the function with 3 bands stated as following:

$$(g_1, g_2, g_3) \mapsto (g'_1, g'_2, g'_3) = T(g_1, g_2, g_3) \quad (14)$$

$$T(g_1, g_2, g_3) = [T(g_1, g_2, g_3)] \quad (15)$$

$$0 \leq g_1, g_2, g_3, g'_1, g'_2, g'_3 \leq 255$$

where, (g_1, g_2, g_3) is old grey values of pixel P and (g'_1, g'_2, g'_3) new grey values of pixel P .

III. EXPERIMENTS

We performed two experiments. The first experiment is performed with a sample which is small size image. The second experiment is performed with a sample which is large size image. In both experiments, enhanced image is compared with the histogram equalized image based on Entropy Index.

A. Experiment 1

Input image is a remote sensing image which have low contrast. Table III list input image, histogram equalized image and enhanced image of our improved method. Visually, we can see the enhanced image of improved method is more highlight than the stretched image and the histogram equalized image.

TABLE III: ENHANCED IMAGE BY THE METHODS

Meaning	Image
Orginal image	
Histogram equalization	
Grey level stretch	
Enhanced image by Improved algorithm	

In Table IV and Fig. 3, we see Entropy of image which is resulted by our improving algorithm higher than Entropy of original image and image which is resulted by histogram equalization algorithm.

TABLE IV: COMPARE ENTROPY OF THE METHODS

Band	His Eq	Stretch	Enh
1	5.21	5.23	7.65
2	4.72	4.74	7.40
3	4.50	4.52	7.51

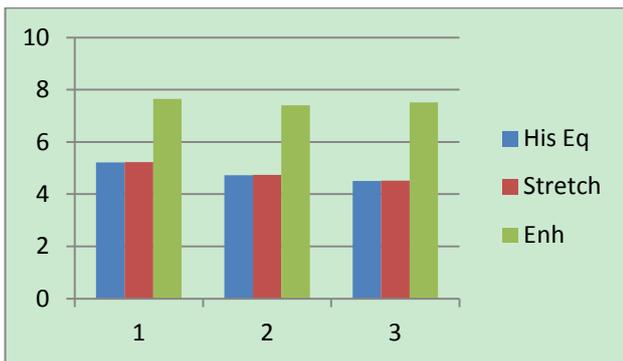


Fig. 3. Comparison entropy of each band of remote sensing image.

B. Experiment 2

Input image is a large size image which have low contrast, its size is 6385 × 5337. Table V lists input image, histogram equalized image and enhanced image of our improved method. Visually, we can see the enhanced image of improved method is more highlight than the stretched image and the histogram equalized image. In addition, color of histogram equalized image is changed.

In Table VI and Fig. 4, we see Entropy of image which is resulted by our improving algorithm higher than Entropy of

original image and image which is resulted by histogram equalization algorithm.

TABLE V: ENHANCED IMAGE BY THE METHODS

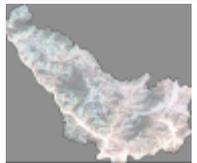
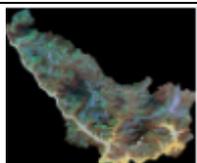
Meaning	Image
Orginal image	
Histogram equalization	
Grey level stretch	
Enhanced image by Improved algorithm	

TABLE VI: COMPARE ENTROPY OF THE METHODS

Band	His Eq	Stretch	Enh
1	2.95	3.04	4.47
2	3.23	3.32	4.50
3	3.21	3.30	4.41

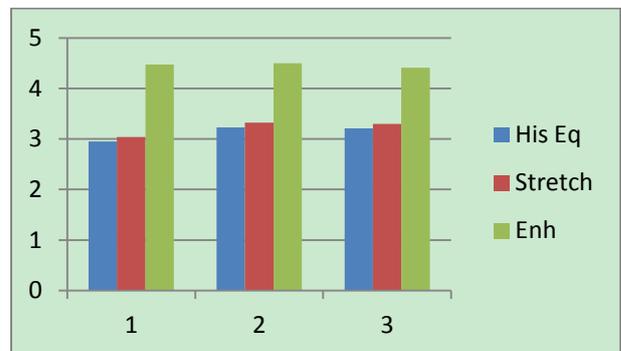


Fig. 4. Comparison entropy of each band of large size remote sensing image.

IV. CONCLUSION

In this research, we propose a new algorithm for large size remote sensing image enhancement. Firstly, image is fuzzificated by fuzzy clustering for large size image lsiFCM which we proposed. Then, image is enhanced following fuzzy clusters and performed simultaneously on multiple bands. Experiment Results show that the improved method makes quality of enhanced image higher than quality of histogram equalization and linear stretch and performs well for large size remote sensing images.

In the next work, we are going to parallel lsiFCM algorithm based on a model of parallel computation to increase processing speed of this algorithm.

REFERENCES

- [1] X. F. Zhu and F. Wu, "An improved approach to remove cloud and mist from remote sensing images based on mallat algorithm," presented International Symposium on Photoelectronic Detection and Imaging 2007, Beijing 2007.
- [2] A. E. Hasaniien and A. Badr, "A comparative study on digital mamography enhancement algorithms based on fuzzy theory," *Studies in Informatics and Control*, vol. 12, no. 1, March 2003.
- [3] J. C. Bezdek, R. Ehrlich, and W. Full, "FCM: The fuzzy c-Means clustering algorithm," *Computers & Geosciences*, vol. 10, no. 2-3, pp. 191-203, 1984.
- [4] J. C. Bezdek, *Pattern Recognition with Fuzzy Objective Function Algorithm*, New York: Plenum Press, 1981.
- [5] T. J. Ross, *Fuzzy Logic with Engineering Applications, Fuzzy Classifying*, Hoboken, NJ: John Wiley, pp. 379 -387, 2004.



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