# A FUZZY-BASED METHOD FOR REMOTE SENSING IMAGE CONTRAST ENHANCEMENT

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**ABSTRACT:**

Many conventional contrast enhancement techniques adopt a global approach to enhance all the brightness level of the image. However, it is usually difficult to enhance all land cover classes appearing in the satellite images, because local contrast information and details may be lost in the dark and bright areas. In this study, a fuzzy-based image enhancement method is developed to partition the image pixel values into various degrees of associates in order to compensate the local brightness lost in the dark and bright areas. The algorithm contains three stages: First, the satellite image is transformed from gray-level space to membership space by Fuzzy c-Means clustering. Second, appropriate stretch model of each cluster is constructed based on corresponding memberships. Third, the image is transformed back to the gray-level space by merging stretched gray values of each cluster. Finally, the performance of the proposed scheme is evaluated visually and quantitatively. The results show that the proposed method can enhance the image to a quality visualization and superior index measurement.

## 1. INTRODUCTION

With the development of remote sensing technology, the satellite can provide images with resolution of 1 or 2 meters. Although there are many feature detection algorithms developed for automatic purposes, manual interpretation and image visualization are still of basic importance for many areas of application. In general, raw satellite images have a relatively narrow range of brightness values; hence, contrast enhancement is frequently used to enhance the image for better interpretation and visualization. Many image enhancement algorithms have been developed to improve the appearance of images. These algorithms may be broadly categorized into three classes. The first is spatial domain methods, which normally operate with local window algorithm. Each pixel on the image is enhanced with corresponding local contrast which is derived from designed filters (Polesel et al., 2000). The second is transform-based methods. The techniques normally transform the images into the frequency domain by using 2-D discrete cosine transform, Fourier transform, or other transforms. Then various algorithms could be developed to enhance the image. Generally, the main purpose of the approaches is to reduce the noises and enhance the shapes of features on the frequency domain (Kover, 2006; Aghagolzadeh and Ersoy, 1992). Finally, the third is histogram adjustment methods. Since the brightness and contrast of the image could be estimated by image mean value and the dynamic range of the histogram, respectively, thus, an image could be enhanced by modifying the histogram with the above information (Kim, 1997). However, the conventional contrast enhancement techniques normally have difficulties enhancing all land cover classes appear in the image. For example, the dark forest regions generally become darker and bright urban areas normally appear brighter after contrast enhancement. Accordingly, the conventional contrast enhancement ends up with an image containing enough mid-brightness contrast, while losing local brightness details in the dark and bright areas. In this study, a fuzzy-based image enhancement method is developed to partition the image pixel value into various degrees of associates in order to compensate the local brightness lost in the dark and bright areas.

## 2. METHODOLOGY

Since the conventional enhancement method usually involves losing local brightness details in the highly dark and bright areas, a partition enhancement method based on fuzzy set theory is developed in this study. The purpose of using fuzzy set theory is to avoid discontinuity of gray values caused by the conventional partitions. Zadeh (1965) introduced the fuzzy set theory an extension of the traditional notion of the crisp set. The main concept of the theory is that the elements of sets have degrees of membership valued in an interval [0, 1] instead of binary value. Accordingly, a complicated process could be regarded as a combination of several simple processes, which could operate respectively. After each sub-process is completed, the original complicated process could be reconstructed. Base on this idea, a three-stage algorithm is developed. First, the satellite image is classified by Fuzzy c-Means clustering (FCM) algorithm. Each classified pixel comprises several memberships of corresponding clusters when the image is fuzzified and transformed from gray-level space to membership space. Second, appropriate stretch model of each cluster is individually constructed based on corresponding memberships. Third, the image is defuzzified and transformed back to the gray-level space by merging stretched gray values of each cluster. Thereafter, the quality of the enhancement result is evaluated and compared with other typical methods. The entire procedure of the proposed algorithm is shown in Figure 1.

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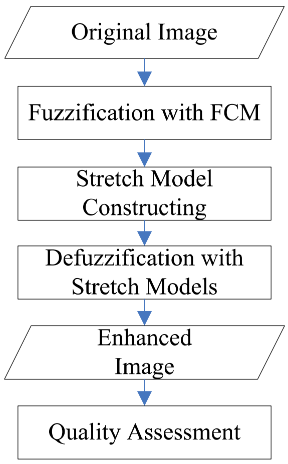



Figure 1. Procedure of the proposed method

## 2.1 Fuzzy c-Means Clustering

Fuzzy c-Means clustering is a widely used algorithm of fuzzy classification. While considering the fuzzy set logic, the algorithm is developed based on k-means clustering. In this algorithm, each pixel does not belong exclusively to any one cluster but is represented by several memberships of each cluster instead. The clustering algorithm is performed with an iterative optimization of minimizing a fuzzy objective function ($J_m$) defined as Eq.1 (Bezdek, 1981; Ross, 2004).

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

where $c$ = number of clusters
$n$ = number of pixels
$\mu_{ik}$ = membership value of $i$th cluster of $k$th pixel
$m$ = fuzziness for each fuzzy membership, when $m$ is close to 1, the algorithm is similar to k-means clustering.
$x_k$ = 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 $V_i$

The membership ($\mu_{ik}$) is estimated by the distance between $k$th pixel and center of $i$th cluster, and is constrained as follows:

$$\begin{cases} 0 \le \mu_{ik} \le 1 & \text{for all } i,k \\ \sum_{i=1}^{c}\mu_{ik} = 1 & \text{for all } k \\ 0 < \sum_{k=1}^{n}\mu_{ik} < n & \text{for all } i \end{cases} \tag{2}$$

where $\mu_{ik}$ = membership value of $i$th cluster of $k$th pixel
$c$ = number of clusters
$n$ = number of pixels

The center of cluster ($V_i$) and the membership value ($\mu_{ik}$) could be calculated by Eq.3 and Eq.4, respectively.

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

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

Therefore, $J_m$ can be minimized by the iteration through Eq.3 and Eq.4. The first step of the iteration is to initialize a fixed $c$, a fuzziness parameter ($m$), a threshold $\varepsilon$ of convergence, and an initial center for each cluster, then computing $\mu_{ik}$ and $V_i$ using Eq.3 and Eq.4 respectively. The iteration is terminated when the change in $V_i$ between two iterations is smaller than $\varepsilon$. Finally, each pixel is classified into a combination of memberships of clusters.

## 2.2 Stretch Model Constructing

After the clustering process, the image is transformed into membership space from gray level space. Each pixel comprises various combinations of memberships. A simple linear stretch model is designed to smoothly enhance each cluster. The stretching algorithm includes two steps. First, the histogram of each cluster is generated by counting the corresponding membership value of each pixel instead of frequency which is generally used. Thus, the count of each bin of the histogram is floating number, but the sum of floating counts of each histogram is still equal to the number of pixels of the image. Second, the stretch model is built base on the corresponding floating histogram of each cluster as the following equation:

$$m_i(g) = \frac{g - b_{i,l}}{b_{i,u} - b_{i,l}} \times (L-1) \tag{5}$$

where $m_i(g)$ = stretched gray value
$g$ = original gray value
$L$ = number of gray level
$b_{i,u}$ = upper boundary for stretching of $i$th cluster
$b_{i,l}$ = lower boundary for stretching of $i$th cluster

The upper boundary ($b_{i,u}$) and the lower boundary ($b_{i,l}$) are determined by two proportion parameters of $p_u$ and $p_l$, as shown in Eq.6.

$$\begin{aligned} b_{i,l} &= h_i^{-1}\left(p_l \times \sum_{g=0}^{L-1} h_i(g)\right), \\ b_{i,u} &= h_i^{-1}\left((1-p_u) \times \sum_{g=0}^{L-1} h_i(g)\right) \end{aligned} \tag{6}$$

where $h_i(g)$ = distribution function of $i$th cluster
$p_u$, $p_l$ = proportion parameters

### 2.3 Defuzzification

After the stretch model of each cluster is built, the image could be transformed back to the gray level space. According to the stretch model of each cluster (Eq.5), gray values of the original image could be enhanced to various values. These enhanced values are then weighted with corresponding membership values (Eq.7). In order to prevent over-saturation of the pixel value, the result of the enhancement is constrained by Eq.8.

$$m'(g) = \sum_{i=1}^{c} \mu_{ik} \times m_i(g) \quad (7)$$

$$0 \le m'(g) \le L - 1 \quad (8)$$

where $\mu_{ik}$ = membership value of $i$th cluster of $k$th pixel
$g$ = original gray value of pixel $k$
$L$ = number of gray level
$m_i(g)$ = mapping function of $i$th cluster

## 3. EXPERIMENTAL RESULTS

### 3.1 Test Data

The proposed algorithm is tested with a FORMOSAT-2 satellite image. The ground resolution of the image is 8 meter and the size of the image is 3000×2300 pixels. There are various land cover classes appearing on the images, including forests, urban areas, river, and others.

In FCM step, the number of cluster ($c$) is given by 5 and the fuzziness ($m$) is given by a value of 2 for purposes of efficient computation. Furthermore, proportion parameters ($p_u$) and ($p_l$), are both given by 0.015 to build the stretch model of each cluster.

Figure 2 shows the original image and enhanced images using conventional methods and the proposed method. The original image obviously appears that the brightness is dark and the contrast is low. By using the conventional enhancement methods, the gray values with extremely dark or bright are visibly over saturated. As Figure 2 shows, the proposed method provides better visualization in colour and details than other methods. Figure 3, 4, and 5 show the comparisons of the enlarge images of urban area, forests, and river, respectively. In these areas, the conventional enhancement methods tend to lose the tiny details of the images, while the proposed method could provide more details and better contrast in the image.

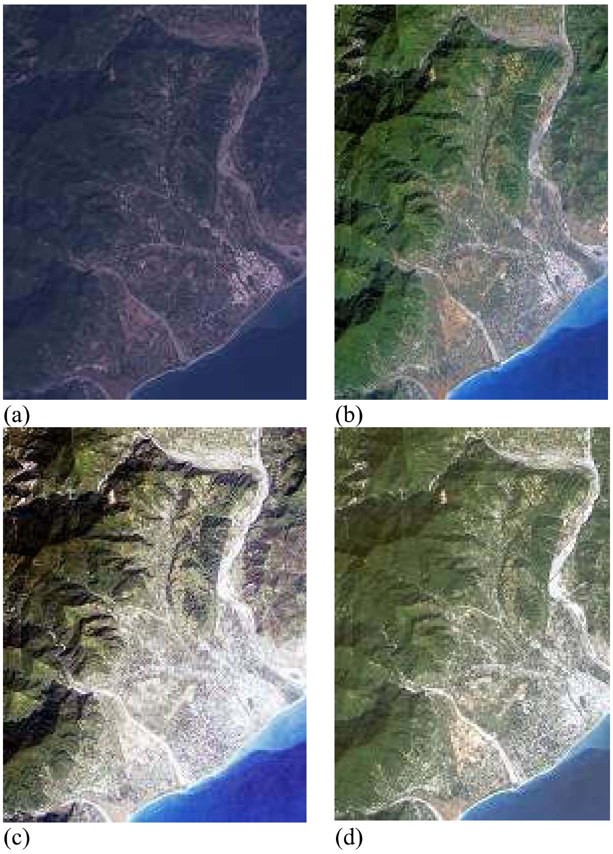



Figure 2. Original image and comparative results. (a) original image, (b) the proposed method, (c) histogram equalization, (d) linear contrast stretch.

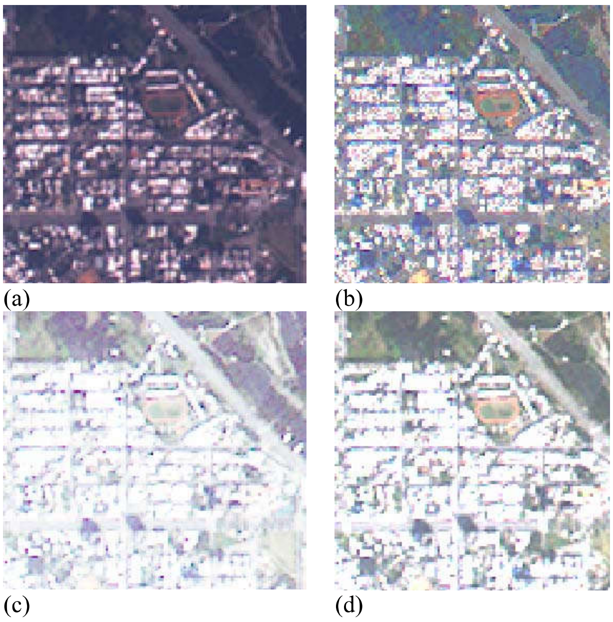
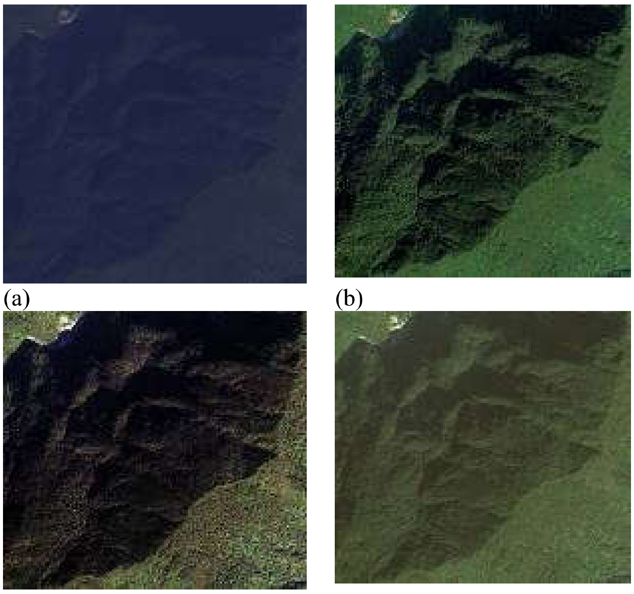
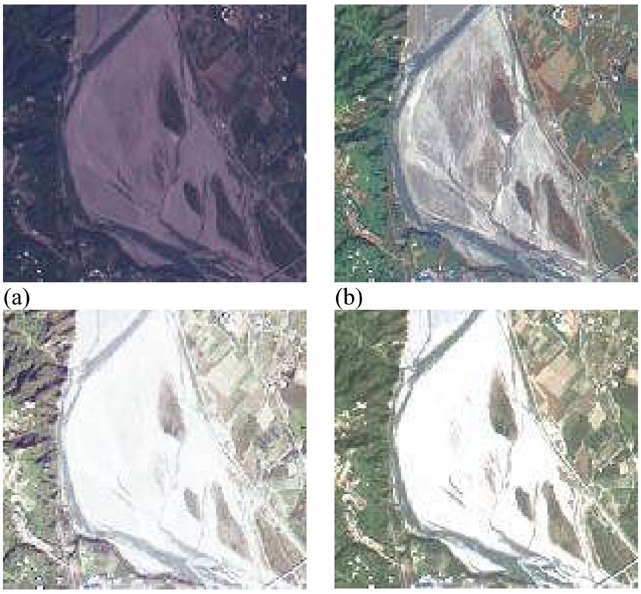



Figure 3. Local enlarge images (urban area) for comparison. (a) original image, (b) the proposed method, (c) histogram equalization, (d) linear contrast stretch.



(a) (b) (c) (d)

Figure 4. Local enlarge images (forests) for comparison. (a) original image, (b) the proposed method, (c) histogram equalization, (d) linear contrast stretch.



(a) (b) (c) (d)

Figure 5. Local enlarge images (river) for comparison. (a) original image, (b) the proposed method, (c) histogram equalization, (d) linear contrast stretch.

### 3.2 Quality Assessment

As shown in Figure 2, 3, 4, and 5, the proposed method provides significantly better contrast and details for human visual perception than the conventional enhancement methods. However, the visual performance of the contrast enhancement approach is difficult to evaluate and compare with different methods objectively. Hence, a metric index is required to estimate the result. In this study, two indices, entropy and Image Quality Measure, are used to evaluate the results.

#### 3.2.1 Shannon Entropy

Shannon Entropy (or information entropy) is a method to measure the uncertainty of the information. Assume there are $n$ events in the sample space, the probability of each event is $p_i$ ($i$= 1, 2, …, $n$), each $p_i$ is equal or greater than zero, and the sum of $p_i$ is defined to be 1. Therefore, a function $H$ could be defined to measure the uncertainty of the sample space (Jaynes, 1957). For image processing, $n$ is given by the number of gray level. Then the $H$ could be described as Eq.9. From the values of the entropy, it appears that the information of the image is richer when entropy is higher. Since the test data is multi-spectral image, the entropy in this study is calculated by averaging all bands. The entropy results are shown in Table 1. Entropy of the image enhanced by the proposed method is 5.071 which is higher than the values of images enhanced by the conventional methods.

$$H = -\sum_{i=0}^{L-1} p_i \ln\left(p_i\right) \tag{9}$$

where $L$ = number of gray level

$p_i$= probability of level $i$ in the histogram

#### 3.2.2 Image Quality Measure

Nill and Bouzas (1992) proposed a method to measure the quality of natural scene based on human visual system. The algorithm performs as the following steps. First, the image is transformed to power spectrum using Fourier transform. Second, the power spectrum is normalized by brightness and size of the image. Third, a vision filter is used to incorporate with the human visual system model. Moreover, the system needs a noise filter to control the noise of the image and a directional scale factor to treat the images obliquely acquired. Finally, the measure is obtained from the power spectrum weighted by the above processes. Eq.10 shows the IQM index. It appears that the image quality seems better when IQM index is higher. Table 1 also shows the IQMs of the images enhanced by the proposed method and the conventional methods. The comparison indicates that the image enhanced by the proposed method can obtain higher IQM, and accordingly, better quality than the conventional methods

$$IQM = \frac{1}{M^2} \sum_{\theta=-180°}^{180°} \sum_{\rho=0.01}^{0.5} S(\theta_1) W(\rho) A^2(T\rho) P(\rho,\theta) \tag{10}$$

where $M^2$ = image size

$S(\theta_1)$ = directional image scale parameter

$W(\rho)$ = modified Wiener noise filter

$A^2(T\rho)$ = modulation transfer function of human visual system

$P(\rho, \theta)$ = brightness normalized image power spectrum

$\rho, \theta$ = spatial frequency in polar coordinates

| Index | Algorithm | | |
|---|---|---|---|
| | Fuzzy-based Enhancement | Histogram Equalization | Linear Contrast Stretch |
| Entropy | 5.071 | 4.099 | 4.011 |
| IQM | $4.72\times10^{-3}$ | $4.30\times10^{-3}$ | $2.92\times10^{-3}$ |

Table 1. Quality assessment of different algorithms

## 4. CONCLUSIONS

Most conventional contrast enhancement algorithms usually fail to provide detailed contrast information in the dark and bright areas of remotely sensed images. This study proposed a fuzzy-based approach to enhance all the contrast and brightness details of the image. The test results indicate that the proposed method could provide better contrast image than the conventional enhancement methods in terms of visual looks and image details. Moreover, two image quality indices are used to evaluate the performance of the enhancement technique. The comparison shows that the proposed method can produce better measurements than the conventional enhancement techniques. However, the stretch method used to enhance each cluster in this study is generated by a linear model with stretch parameters given by experience. In future work, the linear stretch model would be modified and constructed automatically with an optimization procedure in order to provide the image enhancement more feasible and efficient.

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