A Study on Quality Evaluation Methods of Hyperspectral Image

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Abstract. Because of great theoretical value and application prospects in civil and military affairs, hyperspectral image quality assessment method has been a hot research issue in current target recognition and remote sensing information processing field. In this article, firstly, we explicitly described evaluation methods which affect the quality of hyperspectral image based on two aspects of image quality and spectral quality evaluation. Afterwards, we used data cube provided by Australia Airborne Imaging Spectrometer Hymap as ideal raw spectral data to separately restored the degraded images by using Wiener Recovery, R-L Recovery and CGA Recovery, and then verified the recovery results through image quality assessment methods and spectral assessment methods introduced in this article, and finally made a general judgement on the merits of each method.

1. Introduction
As a new type of earth observation technology, hyperspectral imaging technology can obtain the geometric image and spectral information of ground objects, achieving the integration of imager and spectrometer and effective inversion of the physical properties, improving the recognition accuracy of objects, exposing camouflages and reducing the false alarm rate. Therefore, it has been widely used in many fields for economical development[1,2]. With the increasing application of hyperspectral imaging technology, its evaluation methods have drawn researcher’s more attention.

The essence of evaluation of hyperspectral imaging quality is to assess the processing method and algorithm of selected images. The result is favorable to selecting the image processing method and formulating the plan in future applications of hyperspectral image.

With the increasingly rich sources of spatial image information, further investigating high spatial-temporal resolution remote sensing imaging technology and improving the quality of remote sensing images have become two key research areas in remote sensing, digital photogrammetry, geographic information systems and related sciences[3,4]. Therefore, the study on the method of high spectral image quality evaluation is more and more valuable.

2. The Classification of Quality Evaluation Methods for Hyperspectral Remote Sensing Data
The quality evaluation of hyperspectral remote sensing data is divided into subjective evaluation and objective evaluation[5]. Subjective evaluation takes place when human observe the images under a standard test condition. According to the specified scoring scale, human subjectively judge quality of the observed images. Afterwards, the final evaluation results are obtained by the statistical average of the multi-group evaluation results. Objective evaluation is a quantitative evaluation process based on a series of indicators of the related physical characteristics.
Subjective evaluation method is widely applied because it’s simple and usually authoritative. But limited to their physical ability, human cannot always understand the quality of image information completely or objectively during the observation procedure, which leads to subjectivity and individuality in the actual observation, and cannot be described through mathematical model.

Due to quantitative evaluation measured by specific indexes, the results of objective quality evaluation can avoid the disadvantages of subjective methods. The objective evaluation method can achieve batch processing, and it is easy to deduce the rules from the changes of image quality and find out existing problems, which is used for guidance of the image restoration. In objective quality evaluation, there are many parameters based on different principles, and these parameters play different roles in the evaluation. Therefore, their analysis and explanation to the corresponding evaluation results vary. Objective quality evaluation can be divided into three categories: reference quality evaluation, reduce reference quality evaluation and non-reference quality evaluation.[6-8]. The regular parameter of reference quality assessment includes absolute error (MAE), mean square error (MSE), normalized squared error (NMSE), signal -to-noise ratio (SNR), and peak signal-to-noise ratio (PSNR) [9-11]. The no-reference quality assessment includes Gray Mean Grads (GMG) and Laplacian (LS) and so on.

Hyperspectral image quality analysis can also be classified by image quality analysis and spectral quality analysis.

3. The Factors Influencing the Quality Evaluation of Hyperspectral Remote Sensing Data and the Introduction of Each Evaluation Method

In terms of hyperspectral remote sensing images, the main factors that influence their qualities are S/N, image resolution and characteristic spectrum etc[12].

3.1. The Evaluation Methods of Image Quality

The common evaluation methods of image quality include mean absolute error (MAE), mean square error (MSE), the normalized mean square error (NMSE), signal noise ratio (SNR) and peak signal noise ratio (PSNR), the Gray Mean Grads (Gray Mean Grads, GMG). As for the restoration of motion blurred images, there is another function to evaluate the restoration effect: the sum of gray-scale gradient vector modes ( $G_k^{-1}$ ) and the sum of squares of gray-scale gradient vector modes ( $G_k^{-1}$ ).

Presently, motion image quality evaluation is not usually assessed by the motion of image points, and there are mainly three methods to evaluate the quality: the optical axis errors and the Rayleigh distribution limit evaluation method, the motion optical transfer function method, and the probability of obtaining a clear photo[13-15].

The average absolute error is calculated by dividing the sum of absolute value of the gray difference between the evaluated image and the original image with the size of the image. The smaller the value is, the smaller the deviation compared with the original image is, and the better the image quality is.

$$MAE = \frac{1}{M\times N} \sum_{i=1}^{M} \sum_{j=1}^{N} |g(i, j) - f(i, j)|$$

The mean square error is one of the most common algorithms for measuring image quality. The smaller the value is, the better the image quality is. The calculation formula is:

$$MSE = \frac{1}{M\times N} \sum_{i=1}^{M} \sum_{j=1}^{N} (g(i, j) - f(i, j))^2$$

Normalized mean square error (NMSE) is a measuring method based on energy normalization. Compared with mean square error whose denominator is the size of images, its denominator is sum of squares of the original image’s each pixel’s gray level. Similarly, the smaller the value is, the better the image quality is. The calculation formula is:

$$NMSE = \frac{1}{M\times N} \sum_{i=1}^{M} \sum_{j=1}^{N} (g(i, j) - f(i, j))^2$$
\[
NMSE = \left( \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} (g(i, j) - f(i, j))^2}{\sum_{i=1}^{M} \sum_{j=1}^{N} (g(i, j))^2} \right) / \left( \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} (g(i, j))^2}{\sum_{i=1}^{M} \sum_{j=1}^{N} (g(i, j))^2} \right)
\] (3)

Signal noise ratio and peak signal noise ratio are also used to compare the quality between the evaluated image and the original image. The higher the signal noise ratio or peak signal noise ratio is, the better the image quality is. Their expressions are as follows:

\[
SNR = 10 \log_{10} \left( \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} (g(i, j))^2}{\sum_{i=1}^{M} \sum_{j=1}^{N} (g(i, j) - f(i, j))^2} \right)
\] (4)

\[
PSNR = 10 \log_{10} \left( \frac{255^2 \times M \times N}{\sum_{i=1}^{M} \sum_{j=1}^{N} (g(i, j) - f(i, j))^2} \right)
\] (5)

The Gray Mean Grads (GMG) reflects the contrast ratio and the character of texture changes of the image. The larger the value is, the better the image quality is, and the clearer the image is. The formula is:

\[
GMG = \frac{1}{(M-1)(N-1)} \sum_{i=1}^{M-1} \sum_{j=1}^{N-1} \frac{\Delta I_i^2 + \Delta I_j^2}{2} = \frac{1}{(M-1)(N-1)} \sum_{i=1}^{M-1} \sum_{j=1}^{N-1} \frac{[g(i, j+1) - g(i, j)]^2 + [g(i+1, j) - g(i, j)]^2}{2}
\] (6)

The calculation of Gray Mean Grads is to obtain the square root of sum of squares which is the difference of the adjacent pixel gray value in the direction of image length and width respectively.

As for restoration of motion blurred images, there is a special function to evaluate the result of the recovery. This function can provide more objective evaluation with the restoration. Consequently, it has become an objective measure to evaluate image quality and an important basis for evaluating image restoration algorithm.

For a digital image \(f(x, y)\), its gradient is expressed as:

\[
\nabla f(x, y) = \left( \frac{\partial f}{\partial x}, \frac{\partial f}{\partial y} \right)
\] (7)

If the differential is substituted by difference, the gradient mode is expressed as:

\[
\nabla f(x, y) = \left( f(x+1, y) - f(x, y), f(x, y+1) - f(x, y) \right)
\] (8)

For the kth (k=1, 2,..., M) image of the image sequence, the sum of the grayscale gradient vector modes \(G_k\) and the sum of the squares of the grayscale gradient vector modes \(\tilde{G}_k\) in a certain image window \(w\) respectively are:

\[
G_k = \sum_{(x,y)\in w} \left( f_k(x,y) - f(x+1,y) \right)^2 + \left( f_k(x,y) - f(x,y+1) \right)^2
\] (9)

\[
\tilde{G}_k = \sum_{(x,y)\in w} \left( f_k(x,y) - f(x+1,y) \right)^2 + \left( f_k(x,y) - f(x,y+1) \right)^2
\] (10)

\(G_k\) and \(\tilde{G}_k\) can also be used as an evaluation function for motion blurred images. For the kth (k=1, 2,..., M) image of the image sequence, we take the Laplacian operator towards each pixel in the 3×3 neighborhood to obtain the 8-neighborhood differential value in the image window \(w\), followed by a summation:

\[
L_k = \sum_{(x,y)\in w} \left( f_k(x,y) - f_k(x+1,y) - f_k(x-1,y) - f_k(x,y+1) - f_k(x,y-1) - f_k(x+1,y+1) - f_k(x+1,y-1) - f_k(x-1,y+1) - f_k(x-1,y-1) \right)
\] (11)

After normalization, it becomes:

\[
L = \frac{\sum_{(x,y)\in w} \left( f_k(x,y) - f_k(x+1,y) - f_k(x-1,y) - f_k(x,y+1) - f_k(x,y-1) - f_k(x+1,y+1) - f_k(x+1,y-1) - f_k(x-1,y+1) - f_k(x-1,y-1) \right)}{(M-2)(N-2)}
\] (12)

M, N are the numbers of rows and columns of the image matrix, respectively.
For a blurred image, the smaller the pixel gray value change around each pixel, the smaller the value of \( L \) is. \( L \) reaches its maximum when the outline of the image is clear for a focused image. All the directions of \( L \) in 8 neighborhoods was considered, and it possesses a lot of characters such as good bias, strong unimodality, obvious change trend near the clear image and high sensitivity, etc.

For dynamic imaging quality assessment, it is not usually assessed by the movement of image points. At present, there are three methods to evaluate the dynamic imaging quality: the optical axis errors and the Rayleigh distribution limit evaluation method, the motion optical transfer function method, and the probability of obtaining a clear photo.

3.1.1. The optical axis errors and the Rayleigh distribution limit evaluation method
This method firstly defines the visual axis error in two forms generally: one is to define the change of the visual axis pointing direction of the optical system as the visual axis error, and the other is to use the imaging position changes of the object point on the image plane. Once the visual axis error is defined, we can determine the error value allowed by the system resolution according to the Rayleigh distribution limit. The value is called the limit visual axis error. It is easy to judge the quality of the images by using the visual axis and the extreme visual axis error vibration of the optical system.

3.1.2. The motion optical transfer function method
The image quality imaged by optical system may be affected by many factors such as optics, atmospheric jitter, vibration, and image shift. All these factors can be regarded as linear-low pass filter of space object. Because degradation of the imaging quality caused by mechanical vibration plays an important role in the resolution of the entire system, the image shift caused by mechanical vibration and the analysis of decline in optical transfer function has drawn increasing attention. At present, there are mainly two methods for research. The first method is to deduce an optical transfer function based on the institution change when the object images through the optical system, which can be applied for calculating the function of uniform linear motion or high frequency sinusoidal motion. The second method is to calculate the motion of objects based on the motion probability density within the exposure time. But this method is only applicable to some typical forms of movement and one-dimensional problems.

3.1.3. The probability of getting a clear photo
Not all the vibration modes can be evaluated via the motion optical transfer function method. One example is low-frequency sinusoidal motion. It's very difficult to express this kind of motion in a unified transfer function because the relative motion between the target and the image is related to the exposure moment. Only by dividing the exposure progress into several stages according to different exposure moment, can we obtain different transfer functions. In order to compensate the shortcoming of dynamic optical system imaging evaluated by motion optical transfer function, we use the probability of obtaining clear images to describe how vibration affects image quality from optical systems. Its calculation makes this method applicable to various motion forms.

In this methodology, the diameter of Airy spot that can be distinguished by optical system or the minimum motion optical transfer function should be calculated at first. Next, the motion diameter or motion optical transfer function which are caused by image spot vibration within the exposure time will be calculated. If the motion diameter is less than that of Airy spot or the motion optical transfer function is larger than the minimum motion optical transfer function, it means that the vibration does not affect the resolution. A multi-exposure in one vibration process, the probability that the image can be identified can express the effect of the vibration on the imaging quality.

3.2. The Evaluation Methods of Spectral Quality
There are many spectral quality evaluating methods. Generally, we can choose one or more according to our own demand. But no matter which one we choose, spectral curve will be inevitably used. From the spectral curve, we pick up a specified point whose distribution of the spectral curve reflects the point’s reflectivity situation at different waveband positions. The spectral quality assessment, also called spectral similarity or spectral discrimination, evaluates whether the spectrum and the theoretical
distribution of the spectrum are consistent or similar. Common methods are: Relative Spectral Mean Square Error(SMSE), Spectral Angle(SA), Spectral Correlation Angle(SCA), Spectral Information Divergence(SID), Spectral Gradient Angle(SGA), Spectral Correlation Coefficient, and so on[16-18].

If the n bands of the two pixels in a hyperspectral image respectively are: and , the evaluation methods of various spectral similarity are as follows.

Spectral mean square error(SMSE):

\[
\text{SMSE}(x, y) = \sqrt{\frac{1}{N^2} \sum_{i=1}^{N} (x_i - y_i)^2}
\]  

(13)

Spectral angle(SA):

\[
\text{SA}(x, y) = \cos^{-1}\left(\frac{\sum_{i=1}^{N} x_i y_i / \left(\sqrt{\sum_{i=1}^{N} x_i^2} \cdot \sqrt{\sum_{i=1}^{N} y_i^2}\right)}{\sqrt{\sum_{i=1}^{N} x_i^2} \cdot \sqrt{\sum_{i=1}^{N} y_i^2}}\right)
\]  

(14)

Spectral angle is that spectral curve is regarded as a two-dimensional variant to calculate the generalized angles of the two variants, aiming for characterizing the level of similarity. The smaller the generalized angle is, the more similar the two variants are.

Spectral correlation angle(SCA):

\[
\text{SCA}(x, y) = \cos^{-1}(\text{SCC}(x, y) + 1) / 2
\]  

(15)

The spectral correlation angle can reflect the change of the spectrum relative to the mean.

Spectral information divergence(SID):

\[
\text{SID}(x, y) = \frac{1}{N^2} \sum_{i=1}^{N} (p(x_i) - p(y_i)) \cdot (\log(p(x_i)) - \log(p(y_i)))
\]  

(16)

In this equation, \( p(x_i) = x_i / \sum_{i=1}^{N} x_i \), \( p(y_i) = y_i / \sum_{i=1}^{N} y_i \), this method differentiates the similarity based on information theory and compares spectrums from the overall perspective.

Spectral correlation coefficient(SCC):

\[
\text{SCC}(x, y) = \frac{\sum_{i=1}^{N} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N} (x_i - \bar{x})^2} \cdot \sqrt{\sum_{i=1}^{N} (y_i - \bar{y})^2}}
\]  

(17)

In this equation, \( \bar{x} = \frac{1}{N} \sum_{i=1}^{N} x_i \), \( \bar{y} = \frac{1}{N} \sum_{i=1}^{N} y_i \), the spectral correlation coefficient is between -1 and 1, and the larger the value is, the higher the spectral similarity is.

Spectral Gradient Angle:
The gradient vectors of the spectral vectors x and y relatively are:

\[
SG(x) = (x_2 - x_1, x_3 - x_2, x_4 - x_3, ..., x_n - x_{n-1})
\]  

(18)

\[
SG(y) = (y_2 - y_1, y_3 - y_2, y_4 - y_3, ..., y_n - y_{n-1})
\]  

(19)

The generalized Angle of the gradient vector can be expressed as:

\[
\text{SGA}(x, y) = \cos^{-1}\left(\frac{\langle SG(x), SG(y) \rangle}{\|SG(x)\| \cdot \|SG(y)\|}\right)
\]  

(20)

The spectral gradient angle reflects the partial characteristics variation of the spectrum, especially the slope of the spectrum trend.

The hyperspectral image correlation can be divided into spatial correlation and inter-spectral correlation, and it has been a comprehensive evaluation index for image and spectrum[19]. Spatial correlation represents the similarity between a pixel and its neighboring pixels in one specific spectral segment. Inter-spectral correlation refers to the similarity of the pixels in the same spatial position of
each spectral segment. Since each monochromatic image of the spectral data cube reflects the imaging
of the same region in different wavelength bands, the spectral correlation the images possess. Due to a
single ground targets, all the monochromatic maps share the same spatial topology.

Autocorrelation function is defined as:

\[
R(\tau) = f(t) f(-t) = \int_{-\infty}^{\infty} f(t) f(t + \tau) dt
\]

(21)

For a generalized stationary random signal \(X(n)\) with a discrete mean of zero, the autocorrelation
function is defined as:

\[
R_x(m) = E[x(n)x(n + m)]
\]

(22)

For hyperspectral data cubes, the autocorrelation function refers to the spatial correlation of each
monochromatic band image.

Definition of cross-correlation function:

\[
R_{fg}(\tau) = f(t) g(-t) = \int_{-\infty}^{\infty} f(t) g(t + \tau) dt
\]

(23)

Random signals neither have limited energy nor periodicity, so it cannot be described with a
definite time function. Cross-correlation can reflect the similarity level of two functions in different
relative positions, and describe the spatial energy distribution through statistical average. The
reflectivity curve of the same object shows similarity, which implies the correlation between the
spectra of hyperspectral data cubes.

4. Experimental Verification

The data cube provided by the Australian Airborne Imaging Spectrometer Hymap was chosen as the
ideal spectral data, as is shown in Figure 1.

Figure 1. The spectral data cube provided by Hymap.

Figure 2 shows some certain single-band monochromatic image in the original cube, and Fig.4.3
exhibits its vibration-blurred image. The monochrome image in the data cube was processed
separately using Wiener recovery[20], Richardson-Lucy iterative recovery (RL) [21-23] and chaotic
genetic algorithm recovery (CGA) [24-28]. The results are shown in Figure 4, 5, and 6.

Figure 2. The original image

Figure 3. The vibration fuzzy image
Figure 4. The Wiener recovery image  
Figure 5. The R-L iterative recovery image.

Figure 6. The CGA recovery image.

By subjective evaluation, we can see that compared to the original image, the vibration-blurred image is fuzzier, less clear in contour and lacks details. Recovered by Wiener Recovery method and R-L iterative algorithm, the definition of image improved in a large degree with clearer contour and eliminated smear. But, the ringing effect is very serious and there is still a big gap compared to the original image. The image recovered by the CGA algorithm is shown in Figure 4.6. It is not difficult to see that the result is better than that of Wiener Recovery method or the R-L iterative algorithm.

Subsequently, in order to verify the recovery algorithm, we take different evaluation methods, including the Gray Mean Grads (GMG) and Laplacian (LS) including no-reference quality assessment and the signal noise ratio (RNS), peak signal noise ratio (PSNR). The results of the evaluation are shown in Table 1.

For hyperspectral images, we should consider not only the definition of spatial images but also the restoration of spectral quality. We sampled the spectra data of certain image points (121, 96), (210, 142) from the spectral data cube and compared the original spectrum, degradation spectrum and various restoration spectra. As is shown in figure 7 and figure 8, it can also be seen that chaotic genetic algorithm is more effective than other restoration algorithms.

Because the spectral degradation of each image point relates to the spectra of around points, some points may obtain good recovery. However, they do not represent the entire spectral data cube. Therefore, the quality of spectral data cube is measured by the spectral information divergence and gradient angle. The obtained data is shown in Table 1.

Table 1. The objective evaluation of image quality.

| Image                     | The reference evaluation | The no-reference evaluation |
|---------------------------|--------------------------|-----------------------------|
|                           | SNR          | PSNR         | GMG          | LS            |
| The original image        | —            | —            | 26.8461      | 133.0786      |
| The degenerate image      | 5.8286       | 14.7744      | 18.6588      | 84.4696       |
| The Wiener recovery image | 8.5837       | 21.5960      | 27.2249      | 138.1417      |
| The R-L iterative image   | 11.8607      | 22.6780      | 27.4468      | 123.6392      |
| The CGA recovery image    | 12.2324      | 24.0014      | 27.9728      | 143.7321      |
Because the spectral degradation of each image point relates to the spectra of around points, some points may obtain good recovery. However, they do not represent the entire spectral data cube. Therefore, the quality of spectral data cube is measured by the spectral information divergence and gradient angle. The obtained data is shown in Table 2.

Table 2. The spectral quality evaluation table of spectral Cube

| The spectral data cube.                  | The spectral information divergence (SID) | The spectral gradient angle (SGA) |
|-----------------------------------------|------------------------------------------|---------------------------------|
| The original spectral cube              | ---                                      | ---                             |
| The distorted spectral cube             | 1.3124                                   | 0.9928                          |
| The wiener recovery spectral cube       | 1.1419                                   | 0.9943                          |
| The R-L recovery spectrum cube          | 0.9851                                   | 0.8073                          |
| The CGA recovery n spectrum cube        | 0.7289                                   | 0.6853                          |

5. Conclusion
The article describes a variety of hyperspectral image quality assessment methods in detail. We took the data cube provided by Australia Airborne Imaging Spectrometer as the ideal raw spectral data, recovering the hyperspectral data by using the improved chaotic genetic algorithm, and comparing the results with those processed by the traditional Wiener filtering restoration method and R-L restoration method. We find that the chaotic genetic algorithm works well in recovering vibration blurred spectral images and it could improve both the definition and the quality of spatial images.
What is noteworthy is that the method to evaluate image quality and spectral quality described in this paper is suitable for common hyperspectral data. When it comes to the spectral cubes for motion imaging degeneration and correction, a highly sensitive and robust evaluation parameter should be used to achieve objective evaluation on the recovery.

Accurate evaluating the spectral image quality is an important part of image processing. It is a challenge to select a better spectral image in the large quantity of remote sensing image all the time. Therefore, proposing the new spectral quality evaluation index, as well as effective and precise reflecting the similarity and discrimination of the spectra is important orientations in our future research.

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