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RESEARCH ARTICLE

Research on Color Correction Processing of Multi-Hyperspectral Remote Sensing Images Based on FCM Algorithm and Wallis Filtering

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ABSTRACT This study proposes an improved color correction algorithm based on Fuzzy c-means (FCM) clustering algorithm and Wallis filtering to address the problem of spectral drift in image stitching. The proposed method can be applied to general multi-hyperspectral remote sensing images and focuses on color correction processing of images with and without overlapping areas. To ensure color correction, the color gamut is transformed using the color gamut transformation method, and an improved color matching algorithm based on Wallis filtering is used. For non-overlapping areas or hyperspectral remote sensing images, a feature class matching relationship is established using the class matching as the overlapping area for color correction processing, inspired by the application of FCM clustering in image segmentation. The experimental results show that the improvement of the histogram matching algorithm using Wallis filtering achieves a performance improvement of about 9.3%, and this performance is indexed by the spectral distortion. Also, the average gradient value of the image to be homogenized was significantly improved in the image color correction task without overlapping regions, where the false color image improvement was about 27.2%. The proposed approach is time-efficient and robust, while ensuring the quality of color correction processing.

INDEX TERMS Color correction, color gamut transformation, FCM cluster matching, Wallis filtering.

I. INTRODUCTION

In order to address the color and brightness deviation challenges in multi-hyperspectral remote sensing images, color correction processing is a critical step. It can ensure the consistency of data distribution among similar objects in different images and produce visually appealing uniform color images, which is essential for subsequent image processing and analysis.

A plethora of research efforts have been invested into the field of multi-hyperspectral remote sensing image leveling, including the enhancement of the MASK uniform light processing algorithm in [1]. This algorithm separates color and brightness, mitigating color distortion caused by uneven subband processing, but falls short in addressing inherent color inconsistencies among images. In [2], a team analyzed image information entropy for multi-camera stitching uniform color, but selecting the optimal reference image remains a challenge. A novel regularized conditional generative adversarial network (GAN) for image transfer was introduced in [3], which eliminates differences in grayscale, texture, and style among multispectral images, albeit at the cost of longer processing time. In [4], a group studied the color image segmentation algorithm based on clustering and region merging, and analyzed the application and development of ordinary c-means clustering in image segmentation. In order to improve the robustness and efficiency of the segmentation algorithm, [5] proposed an improved fuzzy C-mean image segmentation algorithm with neighborhood information combined with Markov random fields, and a neural network image segmentation model with multimodal fuzzy clustering algorithm label learning for human brain magnetic resonance

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imaging (MRI) images. Reference [6] conducted research on image fuzzy clustering and segmentation algorithms and analyzed the pros and cons of various clustering methods. The Wallis filtering-based tile image leveling algorithm proposed in [7] has been improved upon the original traditional Wallis filtering algorithm. In the realm of color gamut transformation, a standardized method for creating realistic color images of HSI has been developed through an algorithm described in [8]. A new adaptive and efficient brightness enhancement method [9], called the adaptive trigonometric transform function (ATTF), has been proposed to enhance the visual quality of digital color images captured by unmanned aerial system (UAS). ATTF is derived from a tangent-based transformation function that adapts its characteristics according to changes in image brightness. By combining ATTF with Laplacian operator and color restoration process, a well-balanced color image can be obtained. The effectiveness of the proposed technology was evaluated on various UAS-based images and compared with other IE technologies. In [10], a seamless transition was introduced in the overlapping area of the target image after the histogram matching step, to eliminate the difference between the geometric shapes. The effectiveness of this method was evaluated through visual interpretation and by calculating the weighted average of the difference between the reference histogram and the matching histogram. Results demonstrate that the proposed histogram matching-based method is a practical and effective mosaic method that can be used to generate high-resolution, large coverage satellite image data sets.

In [11], a new method based on histogram matching and polynomial regression was proposed to correct chromatic aberration, regardless of parallax. Experimental results show that this method is effective in achieving good results. In [12], a novel color-correction model comprising a series of local grid linear models was proposed to generate a composite image with visually consistent color. However, the original color information may be destroyed by this method. In [13], a two-stage color correction process was proposed, where the color of downsampled images was first corrected via low-frequency modeling and replacement, followed by mapping the color of downsampled images to original images through local modeling and super-resolution color correction. A new thermal image enhancement algorithm was proposed in [14], which employs combined processing of local and global images in the frequency domain. The proposed method leverages the logarithmic relationship between stimulus and perception. The basic idea is to apply log-transform histogram and spatial equalization method matching to different image blocks. The resulting image is obtained by taking the weighted average of all processed blocks, where the weight of each local and global enhanced image is determined by optimized enhancement measures (EME). In order to effectively address the aforementioned issues, [15] proposes an automatic piecewise polynomial fitting method. This study establishes a mapping between the collected RGB value and the standard RGB value through the calibration of the X-rite Color Checker. The color difference is represented by computing Δ E in the CIELab color space. To address the limitations of hard methods, a novel method was proposed in [16], which utilizes fuzzy C-means optimized by fractional Darwin particle swarm optimization algorithm. To expedite the clustering process, the original image data is substituted with an image intensity histogram during clustering. Additionally, the proposed clustering approach is coupled with support vector machine classification to accurately classify hyperspectral images. A comparative study on clustering performance was conducted via simulation experiments, and the validity function suggested on the FCM clustering algorithm was compared with the known typical validity function [17]. For optimizing image luminance and contrast in the luminance channel, the block-based Wallis transform method was employed. In the chromaticity channel, a spline curve was employed as a model to optimize color differences. The color differences were expressed as a cost function and resolved via convex quadratic programming [18].

Our proposed method includes the use of a color gamut conversion method to transform the color gamut and an improved color matching algorithm based on Wallis filtering to achieve color matching between images in another spatial coordinate system. In addition, we solve the problem of non-overlapping regions by establishing feature class matching relationship between the image to be homogenized and the reference image based on FCM clustering algorithm. Our experimental results show that the improved histogram matching algorithm based on Wallis filter improves the spectral distortion index by 9.3%. Meanwhile, in the remote sensing image leveling task without overlapping regions, the average gradient value of true color image leveling improved by about 4.4%; while the false color image leveling improved by 27.2%. Because of the improved way of using Wallis filtering, it makes the proposed method have good robustness and stability, and effectively improves the color correction processing of multi-hyperspectral remote sensing images. Meanwhile, the FCM clustering algorithm solves the dilemma of color uniformity of remote sensing images in non-overlapping regions by feature approximation matching, which provides a new solution idea for color correction processing of multi-hyperspectral remote sensing images in non-overlapping regions.

The main contributions of this study are: firstly, it improves the color correction algorithm for processing overlapping regions, combining Wallis filtering to enhance image information locally and histogram matching to level out the color globally. Secondly, it is the first time to introduce FCM cluster matching method to achieve class overlap between images without overlapping regions, thus enabling the use of improved color correction algorithm for leveling between images with overlapping regions when there are no overlapping regions.

II. METHODOLOGY

To achieve consistent color across multi-hyperspectral remote sensing images, a comprehensive approach that leverages multiple techniques is required. This includes careful selection of reference images, effective use of Wallis filtering and histogram matching, FCM cluster matching, and appropriate color gamut transformation methods. By combining these techniques, remote sensing images can be processed to achieve a uniform color appearance that is visually appealing and facilitates more accurate analysis and interpretation.

A. REFERENCE IMAGE SELECTION

To select the most suitable reference image for achieving uniform color in multi-hyperspectral remote sensing images, it is essential to consider the amount of information and richness of features in each image. The selection process involves the following steps:

Step 1: Information entropy is used to measure the information content of an image. For a single image, the gray distribution can be represented by $p = \{p_1, p_2, p_3, \ldots, p_n\}$, where each gray value is treated as an independent sample. The information entropy of each image is then calculated:

$$\mathrm{H} = -\sum_{i=0}^{n-1} p_i \log_2 p_i \tag{1}$$

where i is the gray level, n is the number of gray levels.

Step 2: The reference value of each image is calculated based on a weighted average of the information entropy and feature richness, with equal weights of 50% for each factor. The calculation formula is as follows:

$$Q = \frac{H}{H_{\max}} * 50\% + \frac{N}{N_{\max}} * 50\% \tag{2}$$

where Q is the reference value, H is the information entropy, the maximum value in the information entropy, and N is the type of the included feature, which is the maximum value of the included feature type.

Select the image with the highest Q value as the reference image and participate in the leveling algorithm of the image to be leveled.

B. WALLIS FILTERING ALGORITHM

This approach solely utilizes the grayscale mean and standard deviation information from both the reference and the image to be leveled. Wallis filtering works by leveling the color to be processed and the reference image using the grayscale mean and standard deviation. The mean value of a grayscale image conveys the overall brightness, while the standard deviation indicates the contrast. This relationship is exploited by the Wallis filter algorithm, which performs color leveling between the image to be leveled and the reference image by utilizing the grayscale mean and standard deviation. The method involves replacing the gray average value of the image to be processed with that of the reference image, while simultaneously redefining the gray value of the image to be processed using the standard deviation of the reference image's gray level.

Furthermore, from the algorithm, we can comprehend that the uniform color processing of the remote sensing image based on the Wallis filter is a form of local image uniformity, which enhances the contrast of areas with small gray value contrast in the image to be processed and reduces the contrast of areas with large gray value contrast correspondingly. Ultimately, the contrast of the entire image becomes balanced. Thus, the Wallis filtering uniform color algorithm is used to uniformly color the panchromatic remote sensing image.

The Wallis algorithm differs significantly from histogram matching in that it primarily utilizes the mean and standard deviation of the gray value of the image. The specific implementation method can be described as follows:

(1) Calculate the mean and standard deviation of the gray value of the color to be leveled and the reference image separately

Suppose the image to be leveled is $g(x, y)$, the mean gray value is m_g and the standard deviation is s_g; the reference image is $f(x, y)$, the mean gray value is m_f and the standard deviation is s_f.

$$\mathrm{m}_g = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} g(i, j) \tag{3}$$

$$\mathrm{m}_f = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} f(i, j) \tag{4}$$

$$s_g = \sqrt{\frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} [g(i, j) - m_g]^2} \tag{5}$$

$$s_f = \sqrt{\frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} [f(i, j) - m_f]^2} \tag{6}$$

(2) Bring the above results into the mathematical expression of Wallis filter and analyze

$$g'(x, y) = [g(x, y) - m_g] \frac{cs_f}{cs_g + (1-c)s_f} + [bm_f + (1-b)m_g] \tag{7}$$

where c is the standard deviation expansion coefficient, the value range $(0 \le c \le 1)$; b is the brightness expansion coefficient, the value range $(0 \le b \le 1)$; c is between (0.7∼0.8), b is between (0.6∼0.7) The effect is more ideal in the actual operation process.

C. FCM CLUSTER MATCHING ALGORITHM

The Fuzzy C-means (FCM) algorithm is an improvement over the conventional C-means algorithm. While the conventional C-means algorithm is rigid in data division, the FCM algorithm allows for flexible fuzzy division. Fuzzy clustering establishes an uncertain description of the sample to the category, which can more objectively reflect the image characteristics, making it a widely used technique.

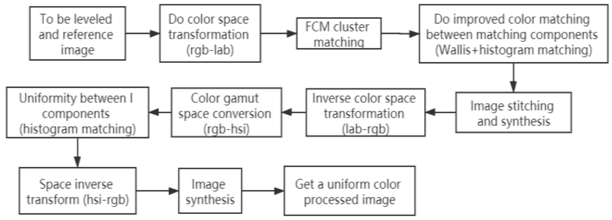


FIGURE 1. Flow chart of research on color correction processing of weightless multi-hyperspectral remote sensing images based on fcm algorithm and wallis filtering.

The FCM algorithm defines an evaluation function that uses membership as a weight to iterate the distance, usually using the Euclidean distance formula to evaluate the distance, to minimize the objective function. The objective function is given by the following equation:

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^{m} d^2(x_i, v_j) \tag{8}$$

Among them, $X = \{x_1, x_2, \ldots, x_i, \ldots, x_N$ is the set of pixels of the gray image X_β to be divided, N is the number of pixels in the image X_β to be divided, $i = \{1,2,\ldots,N\}$, C is the number of clustering categories, $2 \leq C \leq N$; u_{ij} represents the degree of membership of pixel x_i to the jth category, v_j represents the clustering center of the jth category, $j = \{1,2,\ldots,C\}$;

$d^2(x_i, v_j)$ represents the similarity between the pixel x_i and the cluster center v_j, that is, the distance metric, generally Euclidean distance; m is the fuzzy index, also known as the smoothing index, the larger the value of m, the greater the degree of blurring, generally $m = 2$; The process of selecting the number of cluster categories should be consistent with the number of feature categories (farmland, rivers, mountains, etc.) of the reference image rather than the image to be leveled;

According to minimizing the value of the evaluation function, that is, solving for $\min J_m$, the Lagrange multiplier method can be used to solve this type of extreme value problem.

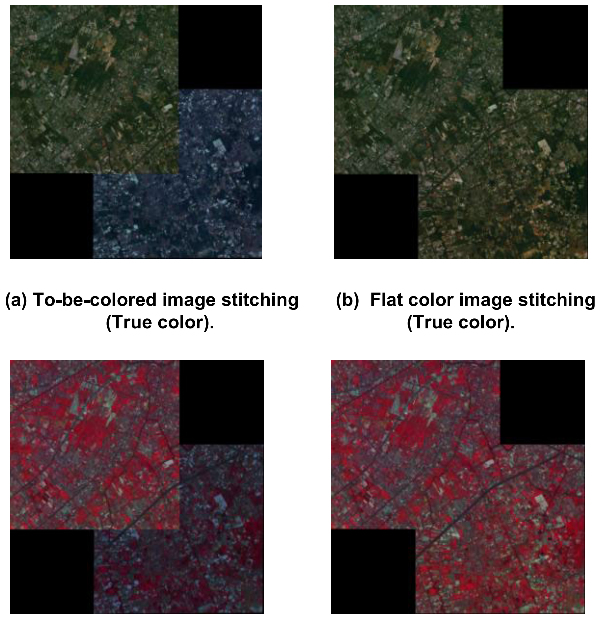
$$F_m = \sum^{N}\sum^{C} u_{ij}^{m}\left\|x_i, v_j\right\|^2 + \lambda(1 - \sum^{C} u_{ij}) \tag{9}$$

Find the derivative of u_{ij} for F_m as follows:

$$u_{ij} = \left(\frac{\lambda}{m\left\|x_i, v_j\right\|^2}\right)^{\frac{1}{m-1}} \tag{10}$$

Combining the constraint $\sum_{j=1}^{C} u_{ij} = 1, \forall i$, the required u_{ij} is brought into the following formula:

$$\sum_{j=1}^{C}\left(\frac{\lambda}{m\left\|x_i, v_j\right\|^2}\right)^{\frac{1}{m-1}} = 1 \tag{11}$$



(a) To-be-colored image stitching (True color).
(b) Flat color image stitching (True color).
(c) To-be-colored image stitching (False color).
(d) Flat color image stitching (False color).

FIGURE 2. Stitching of true/false color images with overlapping areas. Used MIID Obite data: taiguowan_20190223 (1219 × 1270×32) and taiguowan_20190307 (1219 × 1270×32).

According to Equation (11), solve λ

$$\lambda = \frac{m}{\left(\sum_{j=1}^{C}\left(\frac{1}{m\|x_i, v_j\|^2}\right)^{\frac{1}{m-1}}\right)^{\frac{1}{m-1}}} \tag{12}$$

Substituting the required λ into Equation (10), the membership function containing only the central variable of the cluster is solved.

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{\|x_i, v_j\|^2}{\|x_i, v_k\|^2}\right)^{\frac{1}{m-1}}} \tag{13}$$

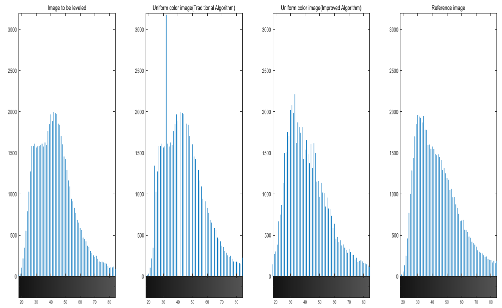
Derivation of clustering center v_j, the solution is:

$$v_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} x_i}{\sum_{i=1}^{N} u_{ij}^{m}} \tag{14}$$

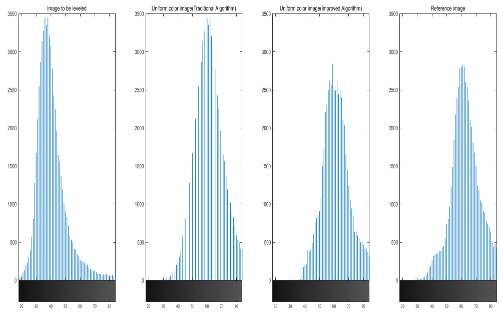
III. EXPERIMENT DESIGN

A. DATASETS

In this study, we used the following datasets taken by the Gaofen-1 satellite, Gaofen-2 satellite: GF1_130926 (1536×1536×4), GF1_140916 (1536×1536×4), GF2_0302 (2560×2560×4), GF2_0415 (2560×2560×4), GF2_150906 (450×2934×4), GF2_160628 (450×2934×4), GF2_160821 (450×2934×4). And MIID Obite data: taiguowan_20190223 (1219×1270×32), taiguowan_20190307 (1219×1270×32).



(a) True color contrast histogram



(b) False color contrast histogram

FIGURE 3. Comparison of the uniform color result of each algorithm with the reference image histogram.

B. RESEARCH ON COLOR CORRECTION OF WEIGHTED MULTI-HYPERSPECTRAL REMOTE SENSING IMAGES BASED ON COLOR GAMUT TRANSFORMATION AND WALLIS FILTERING

Another color gamut space transformation algorithm worth considering is the *rgb-lαβ* color gamut space transformation algorithm. The core of this algorithm is to first transform the input image into the *lαβ* color space, perform improved uniform color processing on each channel of the transformed image, synthesize a new image, and then transform it back into the RGB color space. After that, the image is transformed into the HSI color space, where the brightness component I is adjusted to complete the image leveling process. Experimental results have shown that after the above leveling process, the color and brightness differences between the input and reference images are significantly reduced, resulting in an overall improved color rendering effect.

This algorithm can achieve a better overall and local uniform color effect, and can achieve smooth transitions between two or more images without compromising the visual effect. The resulting uniform color contrast image processed by this improved algorithm is illustrated in section IV.

C. RESEARCH ON LEVELING OF WEIGHTLESS MULTI-HYPERSPECTRAL REMOTE SENSING IMAGES BASED ON COLOR GAMUT TRANSFORMATION AND IMPROVED FCM CLUSTER MATCHING

This section mainly focuses on solving the color matching problem of multi-hyperspectral remote sensing images in non-overlapping areas, by utilizing color gamut transformation and improved FCM cluster matching. The algorithm aims to achieve uniform color for weightless multi-hyperspectral remote sensing images by combining the advantages of the color gamut transformation method and the FCM cluster matching method in solving color unevenness and image segmentation, respectively. Figure 1 illustrates the specific flow of the algorithm.

The algorithm considers the issue of color distortion due to the inconsistent ratio between various hyperspectral bands during the image processing, and addresses it by improving the color gamut transformation. As the processed image is a general hyperspectral image, and there is generally no overlapping area between them, it is necessary to match the similar features between images using the FCM cluster matching method. Finally, the improved uniform color algorithm is applied to perform the uniform color processing between the matched features. For multi-hyperspectral remote sensing images, the algorithm levels each set of three bands at a time. For example, a nine-band multi-spectral remote sensing image can be divided into three groups, each containing three bands of image information for color matching. In section IV, we will see the specific uniform color processing of true color and standard false color remote sensing images.

TABLE 1. Average gradient index of histogram matching algorithm and improved algorithm.

Average gradient index	R	G	B	Average
Image to be leveled	1.7925	1.8819	2.1630	1.9458
Histogram matching algorithm	1.9843	1.8815	2.0038	1.9565
Improved algorithm	1.9153	1.9157	2.1329	1.9880

TABLE 2. Spectral distortion of histogram matching algorithm and improved algorithm.

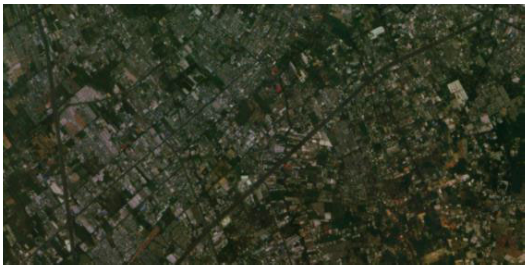
Spectral distortion	R	G	B	Average
Image to be leveled	0.3755	2.2083	22.0093	8.1977
Histogram matching algorithm	5.2692	3.2808	4.0521	4.2007
Improved algorithm	5.1071	2.8436	3.4811	3.8106

D. COMPARISON AND VERIFICATION METHODS

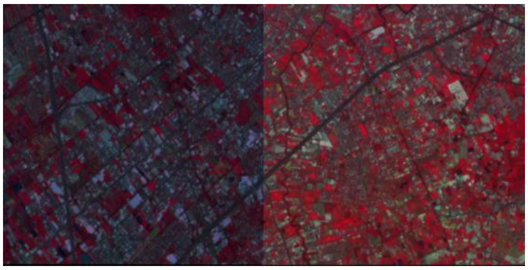
The paper compares the proposed algorithm with two other methods: histogram comparison and average gradient index comparison. Spectral distortion is used to verify the effectiveness of the uniform color results.

The average gradient index comparison method is based on gradient calculations, which reflects the overall contrast of

(a) To-be-colored image stitching (True color).



(b) Flat color image stitching (True color).



(c) To-be-colored image stitching (False color).

(d) Flat color image stitching (False color).

FIGURE 4. Stitching of true/false color images without overlapping areas. Used MIID Obite data: taiguowan_20190223 (1219 × 1270×32) and taiguowan_20190307 (1219 × 1270×32).

the image. A higher value of the average gradient index (AGI) indicates higher contrast, clearer image, and better overall visual effect. The formula for calculating the AGI($\nabla\overline{g}$) is as follows:

$$\nabla\overline{g} = \frac{\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\sqrt{\frac{\nabla_i^2 f(i,j)+\nabla_j^2 f(i,j)}{2}}}{(M-1)(N-1)} \tag{15}$$

TABLE 3. The true color average gradient index of the improved algorithm.

Average gradient index	R	G	B	Average
Reference image	1.9614	1.8989	1.7935	1.8846
Image to be leveled	1.7925	1.8819	2.1630	1.9458
Color correction image	1.9872	1.9693	2.1353	2.0306

TABLE 4. The false color average gradient index of the improved algorithm.

Average gradient index	NIR	R	G	Average
Reference image	1.8518	1.9614	1.8989	1.9040
Image to be leveled	1.4413	1.7925	1.8819	1.7052
Color correction image	1.8861	2.2913	2.3288	2.1687

where $f(i,j)$ is the grayscale image, and i and j are the pixel coordinates; M and N are the maximum values of the abscissa and the ordinate, respectively.

Assume that the trichromatic value of the uniform color image at coordinates (i,j) is $(R_{\mathrm{ij}}G_{ij}B_{ij})$, and the trichromatic value of the uniform color image at coordinates (i,j) is $(R'_{ij}G'_{ij}B'_{ij})$. The average difference D_R, D_G, D_B of the R, G, B channels on the image can be expressed as:

$$D_R = \frac{1}{n}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\left|R_{ij} - R'_{ij}\right| \tag{16}$$

$$D_G = \frac{1}{n}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\left|G_{ij} - G'_{ij}\right| \tag{17}$$

$$D_B = \frac{1}{n}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\left|B_{ij} - B'_{ij}\right| \tag{18}$$

IV. RESULTS AND ANALYSIS

A. RESULTS AND ANALYSIS OF WEIGHTED MULTI-HYPERSPECTRAL REMOTE SENSING IMAGE LEVELING BASED ON COLOR GAMUT TRANSFORMATION AND WALLIS FILTERING

1) IMAGE STITCHING EFFECTS

In Figure 2, (a) and (b) show the comparison graphs of the stitching effect of the true color remote sensing images before and after the processing of the improved algorithm based on Wallis filter (improved algorithm). (c) and (d) show the comparison of the stitching effect of the corresponding false color remote sensing images. It is intuitively shown that the Improved Algorithm effectively solves the color inhomogeneity problem in multispectral images with overlapping regions. Especially at the junction of images, Wallis filtering makes the transition between images more natural.

2) HISTOGRAM COMPARISON

In Figure 3, the histogram comparison analysis shows that the improved algorithm is closer to the reference image compared to the histogram matching algorithm, which indicates its superior performance. Where (a) shows the histogram comparison of the true color image; (b) shows the histogram comparison of the false color image. The first one is the image to be leveled in the overlapped area, the second one is the leveled image processed by the histogram matching algorithm, the third one is the leveled image processed by the improved algorithm based on Wallis filter, and the fourth one is the reference image in the overlapped area. It is obvious that both in the true color image and in the false color image, the third one always has a data distribution closer to that of the fourth histogram compared to the second one. The reason for this is that the images to be homogenized by the difference in information content always carry less local information than the reference image, and therefore the data distribution tends to be concentrated (the second image in a)) or just shifted in parallel (the second image in b)) during histogram matching. Because the use of Wallis filter, the local details of the image are enhanced, and this local fine-grained enhancement can bring better matching results for histogram matching.

3) AVERAGE GRADIENT INDEX COMPARISON AND SPECTRAL DISTORTION EVALUATION

In Table 1, the improved algorithm achieves a higher average gradient index of 1.9880, which is higher than the average gradient index of 1.9565 of the histogram matching algorithm, and especially achieves a 6.4% improvement in the B channel. This reflects that the improved algorithm has richer detail information, which brings more operation space for future image processing. Meanwhile, in Table 2, by calculating the spectral distortion between the results of the two algorithms and the reference image, we can know which algorithm's processing effect is closer to the reference image. The average spectral distortion of the improved algorithm is 3.8106, which is smaller than the average spectral distortion of the histogram matching algorithm of 4.2007, with an improvement of about 9.3%, especially in the B channel where a 14.1% improvement is achieved. It shows that the improved algorithm achieves spectral characteristics closer to the reference image. The experimental results verify the effectiveness of the proposed multispectral remote sensing image color matching algorithm based on color gamut transform and Wallis filtering.

B. RESULTS AND ANALYSIS OF WEIGHTLESS MULTI-HYPERSPECTRAL REMOTE SENSING IMAGE LEVELING BASED ON COLOR GAMUT TRANSFORMATION AND IMPROVED FCM CLUSTER MATCHING

1) IMAGE STITCHING EFFECTS

In Figure. 4, (a) and (b) show the comparison of the stitching effect of true color remote sensing images before and after processing by the improved algorithm based on FCM cluster matching algorithm and Wallis filtering. (c) and (d) then show the comparison graphs of the stitching effect of the corresponding false color remote sensing images. The algorithm effectively solves the color uniformity problem in the non-overlapping regions of multispectral remote sensing images. In order to overcome the color distortion problem caused by the inconsistent ratio of various hyperspectral bands, the color gamut transformation method is adopted and the FCM cluster matching method is applied for feature matching. the Wallis filter is also integrated into the algorithm to further enhance the uniformity effect and suppress the noise. The algorithm achieves a better overall equalization effect and preserves local details, resulting in a homogeneous image with high quality.

2) AVERAGE GRADIENT INDEX COMPARISON

When evaluating the performance of the algorithm by the average gradient method, Table 3 shows that the average gradient index of the true-color color correction image is 2.0306, which is better than that of the image to be homogenized by 1.9458, with an improvement of about 4.4%. The performance in the R channel is excellent, with an improvement of 10.9%. Similarly, for the false color image in Table 4, the average gradient index of the color correction image is 2.1687, which is better than that of the to-be-leveled image of 1.7052, with an improvement of about 27.2%. There is a large improvement in the NIR, R, and G channels, with an increase of 30.9%, 27.8%, and 23.7%, respectively, and the results show the richness of image information and the flexibility of post-image processing applications.

Therefore, the experimental results validate the effectiveness of the proposed multi-hyperspectral remote sensing images color correction processing based on FCM algorithm and Wallis filtering for non-overlapping regions.

V. CONCLUSION

In this study, an improved color correction processing for multi-hyperspectral remote sensing images based on local Wallis filtering and global histogram matching is proposed. Meanwhile, the FCM cluster matching algorithm is combined to solve the multi-hyperspectral remote sensing images color correction processing without overlapping areas, and the multi-hyperspectral remote sensing images color correction processing algorithm based on FCM algorithm and Wallis filtering is proposed. The improved histogram matching algorithm based on Wallis filtering improves the spectral distortion index by 9.3% compared with the histogram matching algorithm in dealing with the multispectral remote sensing image color correction processing with overlapping areas. In the multi-hyperspectral remote sensing image color correction task without overlapping regions, the average gradient value of true color image leveling improved by about 4.4%; while the false color image leveling improved by 27.2%. The results show that the two improvement works proposed in this study have better performance in solving the problem of color correction processing of multi-hyperspectral remote sensing images without overlapping regions as well as with overlapping regions. Because of the improved way of using Wallis filtering, it makes the proposed method have good robustness and stability, and effectively improves the color uniformity of multi-hyperspectral remote sensing images. Meanwhile, the FCM clustering algorithm solves the dilemma of color correction of remote sensing images in non-overlapping regions by feature approximation matching, which provides a new solution idea for color correction processing of remote sensing images in non-overlapping regions. However, it is worth noting that the algorithm in this study is only effective in the color correction processing among multi-hyperspectral remote sensing images in large scale space. Because the method of FCM clustering is used, the method only plays the role of grouping targets with similar features into one category, and does not have the ability to specify labels, so it can only have good matching effect between images with similar feature categories. Subsequent studies can make better improvement work for this point.

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