Automatic Reference Image Selection for Color Balancing in Remote Sensing Imagery Mosaic

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***Abstract*— Selection of a reference image is an important step in color balancing. However, the past research and currently available methods do not focus on it, leading to the lack of an effective way to select the reference image for color balancing in remote sensing imagery mosaic. This letter proposes a novel automatic reference image selection method that aims to select the reference images by assessing multifactors according to the land surface types of the target images. The proposed method addresses the limitations caused by the use of a single assessment factor as well as the selection of a single image as the reference in traditional methods. In addition, the proposed method has a wider range of applications than those requiring no reference image. The visual experimental results indicate that the proposed method can select the suitable reference images, which benefits the color balancing result, and outperforms the other comparative methods. Moreover, the absolute mean value of skewness metric of the proposed method is 0.0831, which is lower than the values of the other comparison methods. It indicates that the result of the proposed method had the best performance in the color information. The quantitative analyses with the metric of absolute difference of mean value indicate that the proposed method has a good ability in maintaining the spectral information, and the spectral changing rates had been reduced at least 10.66% by the proposed method when compared with the other methods.**

***Index Terms*— Ground features, land surface type, multifactors, reference image assessment index.**

I. INTRODUCTION

COLOR balancing is one of the important steps in the image mosaic process. A great deal of the related past research has addressed the color balancing process, which can be categorized as direct methods, path propagation methods, and global optimization methods. The direct methods adjust the color information of every target image to that of the reference image directly, such as the Wallis color balancing method [1] and the histogram matching method [2]. The propagation methods utilize the adjacent relationships between images to determine the color information transfer paths, through which the color difference between images can be eliminated one by one, such as the network-based radiometric equalization approach [3], [4]. The global optimization methods transmute the color balancing problem into a global optimization problem, which can solve the normalization regression models of all images simultaneously, such as the quadratic programming color harmonization method [5].

Although the theories among the three kinds of color balancing methods are different, almost all of them require a reference image before the normalization process, which points up the important role of the reference image in most color balancing methods. However, past color balancing studies that addressed how to select the reference image are insufficient, which means that there is no consensus on the criterion for determining the reference image.

There are two approaches to selecting the reference image. The first approach selects the reference image from an external image that is not one of the target images. Thus, the user often needs to interact with the process and a suitable external image cannot always found. The second approach selects the reference image from the target images and needs no extra information, which also means it has a wider range of application than the first approach. In this letter, we focus on the second approach.

Ibrahim *et al.* [6] provided a strategy to automatically select the best reference image for panoramic stitching. In order to get the best reference image, the authors used the iterative strategy to select the reference image in order to achieve the best performance. However, their method is most suitable when the target images are small in size and quantity, and, therefore, not suitable for remote sensing image applications, since the selection process would be time-consuming and remote sensing images are generally large. Xiong and Pulli [7] selected the reference image from the target images arbitrarily or by user interaction. It is obvious that these methods are not the best choice for the color balancing process. Canty and Nielsen [8] considered the clearest image to be the reference image. However, the definition of "clearest" was not specified in their studies. Pan *et al.* [3] and Chen *et al.* [4] regarded the image in the middle with the minimum distance to the others as the reference image, but their approach did not consider the image's quality, which may yield inadequate results. Cresson and Saint-Geours [5] and Zhou [9] proposed methods that do not require a reference image. Cresson and Saint-Geours [5] assume that the sum of the mean values as well as the standard deviations of the target images is equal to that of the result images. However, their assumption may not work when the color information of the target images is distributed in a disorderly fashion. Zhou [9] employs the color surface models to fit the distribution of the color information in the target images. However, the color surface model may not reflect the complexity of the color distribution of the images.

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The selection of a reference image is conducted in accordance with certain specified rules, which is similar to the process of image quality assessment (IQA). Most of the indexes for IQA can only measure the distortion/similarity between two images of the same scene with different qualities [10]. However, the measurements of different images with different scenes are needed in the selection of a reference image, which means that the indexes for IQA are not suitable for the selection of a reference image. However, the concept of the building index of IQA can be utilized for the selection of a reference image.

Inspired by the well-known structural similarity index [11] in IQA, a novel reference image selection method is proposed in this letter that can produce a suitable and practicable reference image in the color balancing process. The kernel contribution of the proposed method is putting forward a novel reference image assessment index, which consists of three complementary components: quality factor, color factor, and location factor. Considering the diversity of land surface type of the target images, the strategies of classification and clustering are employed, which can divide the target images into different types according to their ground features. Therefore, the proposed method consists of two parts: 1) classification and clustering of the target images and 2) selection of reference images with the reference image assessment index based on different types. Different from traditional methods with a single reference image, the proposed method considers the ground features of the target images to select the reference images, by which more than one reference image can be selected based on the real conditions. Moreover, multifactors are employed to evaluate the target images in the proposed method as opposed to traditional methods, which are limited to considering only one factor. Finally, when compared with the methods, which do not require reference images, the proposed method has a wider range of application due to its consideration of the real conditions of the target images.

II. METHOD

A. Reference Image Assessment Indexes

1) Quality Factor: First of all, the image selected as the reference image should be of good quality, and the contrast of an image is typically perceived as the important factor in image quality measurement [6], [12]. Because of the cross measurement among images with different scenes, the metrics employed in the proposed method are context-free. Hence, the context-free contrast metric [13] is used to measure the quality of the experimental images. The equation is shown as follows:

$$q(i) = p_0(h_1 - h_0) + \sum_{k=2}^{K} p_k(h_k - h_{k-1}) \quad (1)$$

where $q(i)$ is the contrast of a gray-scale image i of b bits with a histogram h of K nonzero entries, $h_0 < h_1 < \cdots < h_{k-1}$, $0 < K \leq L = 2^b$, and p_k is the probability of gray level h_k, $0 \leq k < K$.

Since multifactors are employed in the proposed method, each of the factors must be normalized before they are combined. Therefore, the final quality factor is shown as follows:

$$Q(i) = \frac{q(i) - q_{\min}}{q_{\max} - q_{\min}} \quad (2)$$

$$q_{\min} = \min(q(i)|i \in N) \quad (3)$$

$$q_{\max} = \max(q(i)|i \in N) \quad (4)$$

where $Q(i)$ is the final quality factor of image i, $q_{\min}$ is the minimum value among the target images, $q_{\max}$ is the maximum value among the target images, and N represents the number of target images.

2) Color Factor: The objective of the color-balancing method is elimination of the color difference among the target images. The color factor, therefore, is also an important element in the selection of the reference image. Generally, in order to maintain the spectrum characteristics of the target images after color balancing, the color information of the reference image must be as close as possible to that of the target images. Hence, the color information of the reference image must have the closest color distance among the other target images. The Euclidean distance of color information is a commonly used measurement to evaluate the difference between different color information. Moreover, the mean value of the image, which is easily obtained and widely used, is often regarded as the accepted representation of color information. Therefore, the Euclidean distance of the mean values between different images is employed as the color factor in the proposed method. Since a smaller value of Euclidean distance means closer color information between the images, the relationship between the Euclidean distance and the color factor is negative. The color factor formula is shown as follows:

$$c(i) = -\frac{\sum_{n=1}^{N}\sqrt{\sum_{b=1}^{B}\left(m_i^b - m_n^b\right)^2}}{N-1} \quad (5)$$

$$C(i) = \frac{c(i) - c_{\min}}{c_{\max} - c_{\min}} \quad (6)$$

$$c_{\min} = \min(c(i)|i \in N) \quad (7)$$

$$c_{\max} = \max(c(i)|i \in N) \quad (8)$$

where $c(i)$ is the temporary color factor of image i, B is the number of image bands, m_i^b is the mean of band b in image i, m_n^b is the mean of band b in image n, $C(i)$ is the final color factor of image i, $c_{\min}$ is the minimum value among the target images, and $c_{\max}$ is the maximum value among the target images.

3) Location Factor: The location of the reference image also plays an important role in color balancing. Chen *et al.* [4] considered the image with the minimum sum of distance to the other images as the reference image, which could minimize normalization errors. In a similar way, the sum distance of one image to the other images is utilized as the location factor in the selection of reference image in the proposed method. The format of the location factor is similar to that of the color factor

$$l(i) = -\frac{\sum_{n=1}^{N}\sqrt{(x_i - x_n)^2 + (y_i - y_n)^2}}{N-1} \quad (9)$$

$$L(i) = \frac{l(i) - l_{\min}}{l_{\max} - l_{\min}} \quad (10)$$

$$l_{\min} = \min(l(i)|i \in N) \quad (11)$$

$$l_{\max} = \max(l(i)|i \in N) \quad (12)$$

where $l(i)$ is the temporary location factor of image i, (x_i, y_i) is the geographic coordinates in the center of image i, (x_n, y_n) is the geographic coordinates in the center of image n, $L(i)$ is the final location factor of image i, $l_{\min}$ is the minimum value

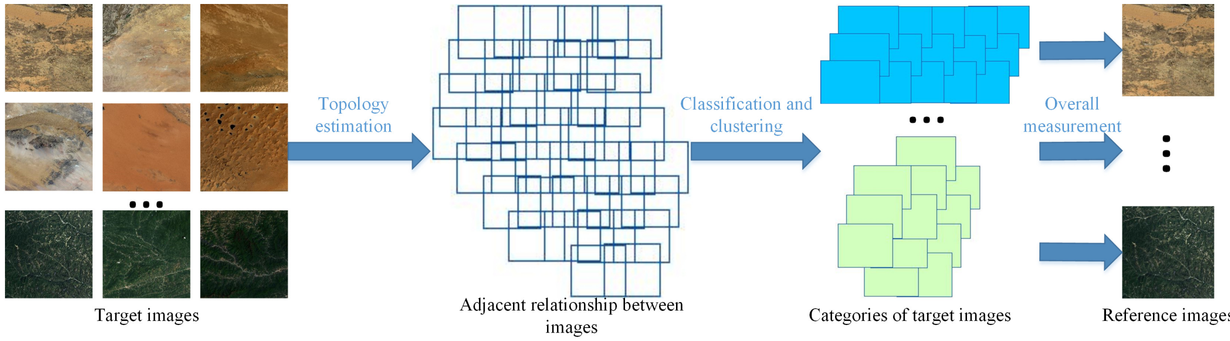

Fig. 1. Flowchart of the proposed reference image selection method.

among the target images, and $l_{\max}$ is the maximum value among the target images.

While it is obvious that the above-mentioned three factors are independent of each other, they are combined together to yield an overall image measurement index

$$R(i) = Q(i)^{\alpha} * C(i)^{\beta} * L(i)^{\gamma} \tag{13}$$

where $R(i)$ is the overall measurement index of image i, and α, β, and γ are used to control the influence of different factors, in the proposed method, $\alpha = \beta = \gamma = 1$.

Then, each image is evaluated with the overall measurement index, and the image with the maximum value of R is selected as the reference image.

B. Classification and Clustering

Generally speaking, satellite images that must be mosaicked cover large geographic areas, which means that there are many ground categories within the area of interest, such as town, forest, and desert. Different ground objects also have different spectral reflectance values. Therefore, images with different ground objects have different colors. In the process of color balancing in image mosaicking, if only one image is selected as the reference, the diversity of the images is ignored, which may lead to distortion of the color balancing result. The ground categories of the target images are taken into consideration in the selection of the reference image in the proposed method. In other words, the reference images are selected based on the distribution of ground objects in the target images. In order to determine the land surface type of the image, classification and clustering are employed in the proposed method. Numerous methods for classification and clustering are available [14], [15]. The support vector machine (SVM) [14] and region grow [15] algorithms, which are simple and effective, are employed to classify and cluster the images in the proposed method. The process of classification and clustering is outlined in the following.

1) Training: The existing imagery data sets are classified into town, forest, desert, and so on. Then, the features, such as the mean and variance of the images, are extracted and then used in the training of prediction model training by the SVM algorithm.

2) Prediction: The features of the target images are extracted. Then, the SVM algorithm within the prediction model is employed to classify the images.

3) Clustering: The images, which are adjacent to each other with the same land surface type, are clustered together. If the number of images in one class set is larger than a threshold, such as 6, the class set will be saved. Then, the major categories of the target images are obtained corresponding to the ground features distribution of the target images.

C. Overall Process

In general, the proposed reference image-selection method contains two parts, as is shown in Fig. 1. In the preprocess step, the adjacent relationship between the target images is built based on the geographic coordinates of the images. Since this step is simple, it is not discussed earlier. Then, the major categories of the target images are acquired with the process of classification and clustering. Next, the images are evaluated with the overall measurement index in each land surface type. Finally, the reference image in each land surface type is obtained.

III. Experiment and Analysis

A. Color Balancing Method Used for Experiment

The purpose of a reference image is to provide the color standard for color balancing. Therefore, the color balancing results are one of the important ways to evaluate the performance of the reference image selection method. In order to evaluate the performance of the proposed method, the existing quadratic programming color balancing method [8] was used for comparison. It is worth noting that the origin equality constraints used in the quadratic programming color balancing method were replaced by the conditions that the mean and standard deviation of the reference images are equal before and after the color balancing process

$$\mu' = \mu \tag{14}$$

$$\sigma' = \sigma \tag{15}$$

where μ and σ are the mean and standard deviation values of the reference image before processing; and μ' and σ' are the corresponding values of the reference image after processing, respectively.

B. Study Data

Thirty-eight satellite images from Landsat8 OLI, which are located in the provinces of Shan Xi, Nei Menggu, Ning Xia, and Gan Su of China, were used as experimental data [see Fig. 2(a)]. Since current display devices can only show 8-b images with three bands, all the experimental data were consisted of three bands [including band 4 (red), 3 (green), and 4 (blue)] and converted into 8 b. All of the color balancing results below were mosaicked with the same method.

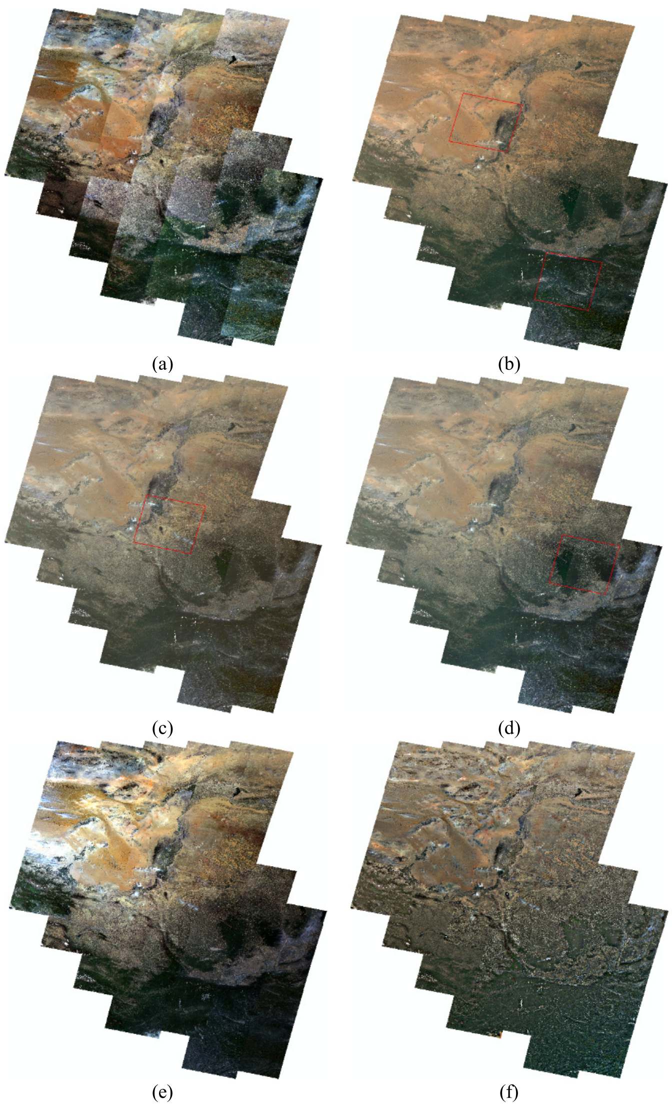

Fig. 2. Thumbnail results of the experimental data with different methods. (a) Mosaicked target images. (b) Mosaicked color balancing result of the proposed method. (c) Mosaicked color balancing result of the "Middle" method. (d) Mosaicked color balancing result of the "Clearest" method. (e) Mosaicked color balancing result of the "NO1" method. (f) Mosaicked color balancing result of the "NO2" method.

C. Results and Analysis

Using the proposed method, the experimental data were classified as forest and desert, and the reference images were extracted from the two categories, as is shown in the images within the red box in Fig. 2(b). The mosaicked color balancing results also are shown in Fig. 2(b). In addition, other reference image selection methods were applied to the experimental data and their results were compared with the results of the proposed method. The first comparison method, proposed by Chen *et al.* [4], regards the image in the middle with the minimum distance to the other images as the reference (hereinafter referred as "Middle"). The reference image selected by "Middle" is shown within the red box in Fig. 2(c). The second comparison method, proposed by Canty and Nielsen [8], regards the clearest image as the reference (hereinafter referred as "Clearest"). The reference image selected by "Clearest" is shown within the red box in Fig. 2(d). The third comparison method, proposed by Cresson and Saint-Geours [5], requires no image as a reference (hereinafter referred as "NO1") [see Fig. 2(e)]. The fourth comparison method, proposed by Zhou [9], requires no image as a reference (hereinafter referred as "NO2") [see Fig. 2(f)]. The comparison methods of "Middle," "Clearest," and "NO1" also utilize the quadratic programming color balancing method with their own constraint to obtain the final results shown in Fig. 2(c)–(e). The fourth comparison method ("NO2") utilizes the color balancing method proposed by Zhou [9] to get the final result shown in Fig. 2(f).

In Fig. 2(a), there is a noticeable difference among the different images in the original experimental data. Although the difference was eliminated in the results of all the methods, their performance varied greatly. The results shown in Fig. 2(b) processed by the proposed method maintained the color characteristics of the forest and desert in the corresponding areas. However, a color cast is apparent in the results of the comparison methods of "Middle" and "Clearest." As is shown in Fig. 2(c), the color of the desert area appears in shades of green because the reference image came from the forest area. Similarly, the color of the forest area is slightly yellow in hue since the reference image came from the desert area [see Fig. 2(d)]. In the methods of "Middle" and "Clearest," only one image was selected as the reference, leading to the neglect of ground object diversity when the target images contain more than one land surface type, resulting in color distortion in the final color balancing result, as is shown in Fig. 2(c) and (d). Furthermore, the two methods considered only one factor in the selection of the reference image. For instance, the method "Middle" focused on the image in the middle with the minimum distance to the other ones as the reference (i.e., only the location factor was considered), which may yield poor results when the selected reference image is of poor quality. For the third comparison method, as is shown in Fig. 2(e), the luminance of the desert area was very high, while that of the forest was low. As is mentioned above, the method requires no reference image as the constraint. However, the assumption of the sum of the mean values as well as the standard deviations of the target images is equal to that of the result images may not work when the color information of the target images are distributed in a disorderly fashion, which may lead to a color cast in the color balancing results. Color surface models were employed in the fourth comparison method to fit the distribution of the color information in the target images, which also required no reference image in the color balancing process. However, the color surface model could not reflect the complexity of the color distribution of the images, which resulted in color distortion in the color balancing result as is shown in Fig. 2(f). Nevertheless, in the proposed method, the land surface types of the target images were extracted, and the multifactor assessments were employed, both of which benefit the selection of suitable reference images. The above analyses demonstrate that the proposed method, which selects the reference images based on the categories, outperformed all the other methods.

Finally, the metrics of skewness [16] and absolute difference of the mean value (ADMean) [17] were employed to further evaluate the results of the different methods quantitatively. Skewness is a measurement of the asymmetry of a set of

TABLE I
EVALUATION COMPARISON OF THE RESULT WITH DIFFERENT METHODS

	Band \ Method	Proposed	Middle	Clearest	No1	No2
Skewness	1	**-0.0196**	0.0328	0.0525	-0.7697	-0.4905
	2	**0.0273**	0.0611	0.1054	-0.7284	-0.3305
	3	0.2025	0.2714	0.3052	-0.3672	**0.0653**
ADMean	1	**15.5653**	25.7837	27.3308	28.4124	26.4782
	2	**14.9458**	23.7957	28.7477	31.7256	24.6414
	3	**17.9782**	25.0639	25.3554	33.7038	24.2116

statistical data, which is used to make judgments about the color surface of an image. A smaller absolute value of skewness indicates better results in the color information of the image. The "ADMean" is employed to evaluate the spectral differences between the images before and after color balancing. A small value of "ADMean" indicates a good result. The statistical results are shown in Table I. The numbers marked in bold in each row represent the best value among the different methods. As is shown in Table I, three bands in the results of "NO1" had the highest values of skewness, which indicates that the distortion of the color information in the results was the most serious. In addition, even though the third band in the results of "NO2" had the best performance in skewness, the other two bands did not perform well, yielding an unsatisfactory overall visual performance in the results. The purpose of color balancing is to obtain high quality images with no color difference. In this letter, the absolute mean values of the skewness for the results of each method were 0.0831, 0.1218, 0.1544, 0.6218, and 0.2954, respectively. The proposed method had the lowest skewness values, which indicates that the result of the proposed method had the best performance in the color information. However, the comparison methods of "NO1" and "NO2" with the higher skewness values were shown as unsuitable for the color balancing process due to the color distortions in their results. Moreover, the mean values of the "ADMean" for the results of each method were 16.1631, 24.8811, 27.1446, 31.2806, and 25.1104, respectively. And the overall mean value of all the target images is 81.7782. Therefore, the spectral changing rates between the images before and after color balancing for each method were 19.76% (=16.1631/81.7782), 30.42% (=24.8811/81.7782), 33.19% (=27.1446/81.7782), 38.25% (=31.2806/81.7782), and 30.71% (=25.1104/81.7782), respectively. It was obvious that the proposed method had the best "ADMean" values, and the spectral changing rates had been reduced at least 10.66% (=30.42%−19.76%) by the proposed method when compared with the other methods, indicating that the proposed method outperformed the others in maintaining the spectral information. In general, among the other three methods shown in Table I, the proposed method was shown to have performed the best as far as skewness, and "ADMean" and therefore provided the best overall performance.

IV. Conclusion

The main contribution of this letter is the introduction of a novel automatic reference image selection method for color balancing in image mosaic. In the proposed method, the multi-factors of quality, color, and location are considered to evaluate the images comprehensively, which benefit the selection of suitable reference image. Moreover, the land surface types of the target images are considered, and the classification and clustering process are employed in the proposed method, from which the suitable reference images can be selected in different land surface types to achieve better color balancing results. The experimental results in this letter confirm that the reference images selected by the proposed method performed better in the ensuing color balancing process compared with those of the traditional methods.

References

[1] M. W. Sun and J. Q. Zhang, "Dodging research for digital aerial images," *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.*, vol. 37, p. 276, Jan. 2008.

[2] E. H. Helmer and B. Ruefenacht, "Cloud-free satellite image mosaics with regression trees and histogram matching," *Photogramm. Eng. Remote Sens.*, vol. 71, no. 9, pp. 1079–1089, Sep. 2005.

[3] J. Pan, M. Wang, D. Li, and J. Li, "A network-based radiometric equalization approach for digital aerial orthoimages," *IEEE Geosci. Remote Sens. Lett.*, vol. 7, no. 2, pp. 401–405, Apr. 2010.

[4] C. Chen, Z. Chen, M. Li, Y. Liu, L. Cheng, and Y. Ren, "Parallel relative radiometric normalisation for remote sensing image mosaics," *Comput. Geosci.*, vol. 73, pp. 28–36, Dec. 2014.

[5] R. Cresson and N. Saint-Geours, "Natural color satellite image mosaicking using quadratic programming in decorrelated color space," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 8, no. 8, pp. 4151–4162, Aug. 2015.

[6] M. T. Ibrahim, R. Hafiz, M. M. Khan, and Y. Cho, "Automatic selection of color reference image for panoramic stitching," *Multimedia Syst.*, vol. 22, no. 22, pp. 379–392, Jun. 2015.

[7] Y. Xiong and K. Pulli, "Fast panorama stitching for high-quality panoramic images on mobile phones," *IEEE Trans. Consum. Electron.*, vol. 56, no. 2, pp. 298–306, May 2010.

[8] M. J. Canty and A. A. Nielsen, "Automatic radiometric normalization of multitemporal satellite imagery with the iteratively re-weighted MAD transformation," *Remote Sens. Environ.*, vol. 112, pp. 1025–1036, Mar. 2008.

[9] X. Zhou, "Multiple auto-adapting color balancing for large number of images," *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.*, vol. 40, p. 735, Jan. 2015.

[10] X. Zhu and P. Milanfar, "Automatic parameter selection for denoising algorithms using a no-reference measure of image content," *IEEE Trans. Image Process.*, vol. 19, no. 12, pp. 3116–3132, Dec. 2010.

[11] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: From error visibility to structural similarity," *IEEE Trans. Image Process.*, vol. 13, no. 4, pp. 600–612, Apr. 2004.

[12] Z. Wang and A. C. Bovik, "A universal image quality index," *IEEE Signal Process. Lett.*, vol. 9, no. 3, pp. 81–84, Mar. 2002.

[13] X. Wu, "A linear programming approach for optimal contrast-tone mapping," *IEEE Trans. Image Process.*, vol. 20, no. 5, pp. 1262–1272, May 2011.

[14] I. W. Tsang, J. T. Kwok, and P.-M. Cheung, "Core vector machines: Fast SVM training on very large data sets," *J. Mach. Learn. Res.*, vol. 6, pp. 363–392, Apr. 2005.

[15] P. Yu, A. K. Qin, and D. A. Clausi, "Unsupervised polarimetric SAR image segmentation and classification using region growing with edge penalty," *IEEE Trans. Geosci. Remote Sens.*, vol. 50, no. 4, pp. 1302–1317, Apr. 2012.

[16] I. Motoyoshi, S. Nishida, L. Sharan, and E. H. Adelson, "Image statistics and the perception of surface qualities," *Nature*, vol. 447, pp. 206–209, May 2007.

[17] L. Zhang, C. Wu, and B. Du, "Automatic radiometric normalization for multitemporal remote sensing imagery with iterative slow feature analysis," *IEEE Trans. Geosci. Remote Sens.*, vol. 52, no. 10, pp. 6141–6155, Oct. 2014.