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Review of the pansharpening methods for remote sensing images based on the idea of meta-analysis: Practical discussion and challenges

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ABSTRACT

In this paper, the development of pansharpening methods from traditional understanding to the current understanding is comprehensively reviewed. Furthermore, the performance of the different categories of pansharpening methods developed between 2000 and 2016 is evaluated based on the idea of meta-analysis. This is innovatively performed by making a statistical analysis of the studies ever published. In the proposed scheme, based on strict selection criteria, 48 representative articles, which were selected from more than 1000 articles, were applied for the statistical analysis. This paper aims to provide a holistic review of the pansharpening methods, and highlights the development process from the traditional understanding to the current understanding. In addition, the experiments were implemented from a new perspective based on the idea of meta-analysis.

1. Introduction

With the rapid development of satellite sensors, remote sensing images have become widely used. However, due to the technical limitations of the sensors and other factors, the existing remote sensing sensors have to make a fundamental tradeoff between the spatial and spectral resolutions [1]. Specifically, there are two main limitations [2–4]. (1) The incoming radiation energy into the sensor. In general, the high spatial resolution (HR) panchromatic (PAN) image has broader bandwidth, and the low spatial resolution (LR) multispectral (MS) image has narrower bandwidth. To collect more photons and ensure the signal-to-noise ratio (SNR), the size of the MS detector should be larger (i.e., a larger instantaneous field of view (IFOV), and then a lower spatial resolution). (2) The data volume collected by the sensor. It should be noted that the data volume of the HR MS image is significantly larger than that of the bundled LR MS and HR PAN images. Therefore, this can overcome the difficulty of the limited on-board storage capacity and the data transmission from platform to ground. Fortunately, PAN/MS image fusion, which is typically referred to as "pansharpening", can be used to integrate the geometrical detail of the HR PAN image and the spectral information of the LR MS image to obtain an HR MS image [4], and it can overcome the tradeoff between the spatial and spectral resolutions of satellite sensors.

To the best of our knowledge, pansharpening methods originated in the 1980s [5]. Since 1986, the Système Pour l' Observation de la Terre-1 (SPOT-1) system has provided two LR MS images together with one HR PAN image, so pansharpening methods have got rapid development over a period of 30 years. The development of the pansharpening methods has been motivated by several factors. Firstly, it has been motivated by the advance in remote sensing sensors. This mainly focuses on the variation of the number of spectral bands and the difference of the spectral range between the MS and PAN images. Specifically, this has varied from the previous MS images with only three bands and PAN image covering only the visible spectrum (such as SPOT-1, SPOT-2, etc.); to MS images with four bands and a PAN image covering the visible and near-infrared (NIR) spectrum (such as IKONOS, QuickBird, etc.); up to MS images with six or more bands and only part of them covered by the PAN image (such as Landsat ETM + , OLI, WorldView-2, etc.). Secondly, the development of the pansharpening methods has been motivated by the application of the relevant new emerging theories or other hot-spot mathematical researches. For example, the pansharpening methods based on sparse representation [6,7] have been a hot research topic in recent years. In addition, the pansharpening methods based on deep learning [8–11] are attracting more and more attentions. However, it should be noted that whether some new emerging theories or hot-spot mathematical researches could better solve the problems for pansharpening should be further fully tested and verified. Thirdly, the development of the pansharpening

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methods has been motivated by the demands of practical engineering and remote sensing applications. For example, effective pansharpening methods to obtain HR MS images for thematic mapping [12,13], visual interpretation [14], and change detection [15,16], etc., are highly desirable. In addition, it is noteworthy that, in fact, different applications may have different requirements for more spectral fidelity or more spatial enhancement. Therefore, the development of the application-oriented pansharpening methods is attracting ever-increasing attentions. On the whole, the development of the pansharpening methods has been characterized by a gradual process from the previous unitarily (few methods and categories) [5,17–21] to multiplicity [22,23]; from the very simple linear operators (such as the Brovey method, the traditional intensity-hue-saturation (IHS) methods, etc.) [5,17–21,24,25] to the consideration of nonlinear features [10,26]; and from independent development [14,20,24 25 27,28] to general fusion frameworks [29–34].

To date, a large number of pansharpening methods have been proposed [20,22,35], and these methods have been classified in several different ways. Baronti et al. [36] classified the existing pansharpening methods into two major categories, i.e., the component substitution (CS)-based methods and the multiresolution analysis (MRA)-based methods. Li et al. [37] classified the existing pansharpening methods into the CS-based methods, the MRA-based methods, and the regularized-based methods. In addition, Zhang et al. [29] classified them into the CS-based methods, the MRA-based methods, and the Bayesian-based methods, and Shen et al. [1] classified them into the CS-based methods, the MRA-based methods, the model-based optimization (MBO)-based methods, and the sparse reconstruction (SR)-based methods. It should be noted that the major fusion process of the regularized-based methods, the Bayesian-based methods, the MBO-based methods, and the SR-based methods are based on or converted to the optimization of a variational model, they can be hence generalized into the variational optimization (VO)-based methods. Besides, Kwan et al. [38,39] classified the existing pansharpening methods based on whether or not the point spread function (PSF) is used. However, hardly few papers have provided the comprehensive review of the CS-based methods, the MRA-based methods, and the VO-based methods, especially the review of the VO-based methods. Excitingly, Garzelli [40] firstly performed a comprehensive review of the VO-based methods based on super-resolution concept.

In this paper, based on the above categories, three major categories of pansharpening methods are classified. They are (1) the component substitution (CS)-based methods; (2) the multiresolution analysis (MRA)-based methods; and (3) the variational optimization (VO)-based methods. In addition, the deep learning (DL)-based pansharpening methods [8,10,41] have been proposed in recent years, which can be regarded as a new generation of pansharpening methods. The performance of the different categories of pansharpening methods has been reviewed in many papers [2,3,14,20,22,23,26,30,42-49], which have made a great contribution to the development of the pansharpening methods. However, the performance of different categories of pansharpening methods has resulted in controversy. For example, some papers [50–52] hold the viewpoint that the CS-based methods have poor spectral information preservation. However, many CS-based pansharpening methods [48,53,54] developed in recent years refute this viewpoint. To the best of our knowledge, there are two main reasons for this. On the one hand, much of the understanding on the performance of the different categories of pansharpening methods is based on the traditional pansharpening methods or a particular part of the popular pansharpening algorithms. However, pansharpening algorithms have been improved, and a number of state-of-the-art methods have been proposed in recent years. Therefore, the understanding may be inaccurate. On the other hand, the experimental verification of the algorithms in most of the existing studies has only been implemented on a few datasets [30,31,34]. In addition, the experimental datasets applied in some studies may be from specific regions or with specific surface features. Therefore, this cannot comprehensively verify the performance of the methods, which leads to controversy. However, in a single study, it seems to be impossible to implement all the algorithms, and it is also difficult to verify the performance of the algorithms through a large number of experiments, due to the limitations on the acquirement of remote sensing datasets. Fortunately, there have been many published studies that have reported on the performance of the pansharpening methods. Therefore, how to take advantage of these previously published articles to make a more robust and reliable evaluation is an inspiring and feasible idea. The idea of meta-analysis [55] provides a feasible solution. It involves taking the results from primary research articles and quantitatively analyzing and synthesizing these data in an attempt to arrive at more robust conclusions, and it has been widely used in many areas, including ecology [56], medicine [57], and sociology [58], etc.

In this paper, the performance of the different categories of pansharpening methods published from 2000 to 2016 is analyzed based on the idea of meta-analysis. In the proposed scheme, based on strict selection criteria, as many published studies as possible in the pansharpening field were collected. The statistical analysis was then performed on the reported quantitative experimental results of the pansharpening methods, including the proposed methods and other methods for comparison, etc., in these collected studies to make a reliable evaluation. It should be noted that due to the amounts of the researches on the DL-based pansharpening methods are insufficient, the DL-based methods are not included in the statistical analysis. On the whole, this paper makes three main contributions. (1) The development of the pansharpening methods is comprehensively reviewed. (2) This is the first time that the idea of statistical analysis has been applied to the review of the pansharpening methods, and this is a novel and feasible strategy to make use of large amounts of published studies. (3) The proposed scheme avoids the very huge cost of implementing a large number of pansharpening algorithms, especially the VO-based methods, and the insufficient datasets used in the previous studies. The statistical results in this paper provide a reliable evaluation on the performance of the different categories of pansharpening methods.

2. Pansharpening methods

The three main categories of pansharpening methods, i.e., the CS-based methods, the MRA-based methods, and the VO-based methods, are comprehensively reviewed, including the process of development from the traditional understanding to the current understanding, the characteristics of each category, and the main directions for their improvement in the process of development.

2.1. Component substitution (CS)-based methods

The CS-based methods are the simplest and the most widely used in the pansharpening family, and as such, they are provided in most of the professional remote sensing software, including ENVI, ERDAS Imagine, PCI Geomatica, etc. The traditional understanding of the CS-based methods is that the MS bands are first projected into a new space based on the spectral transformation, one of the components that represents the spatial information is then substituted by the HR PAN image, and the inverse projection is finally performed to obtain the fused image. Therefore, they are also generally referred to as "projection-substitution" methods [26]. The representative methods include the IHS methods [20,59], the principal component analysis (PCA) methods [20,60,61], the Gram-Schmidt (GS) methods [28], etc. Fig. 1(a) shows the flowchart of the traditional understanding of the CS-based pansharpening methods.

Subsequently, Tu et al. [31] demonstrated that the CS-based methods can be generalized to a new formalization, without explicit calculation of the forward and backward transformation, and this was then extended in [30,34]. Accordingly, the understanding of the CS-

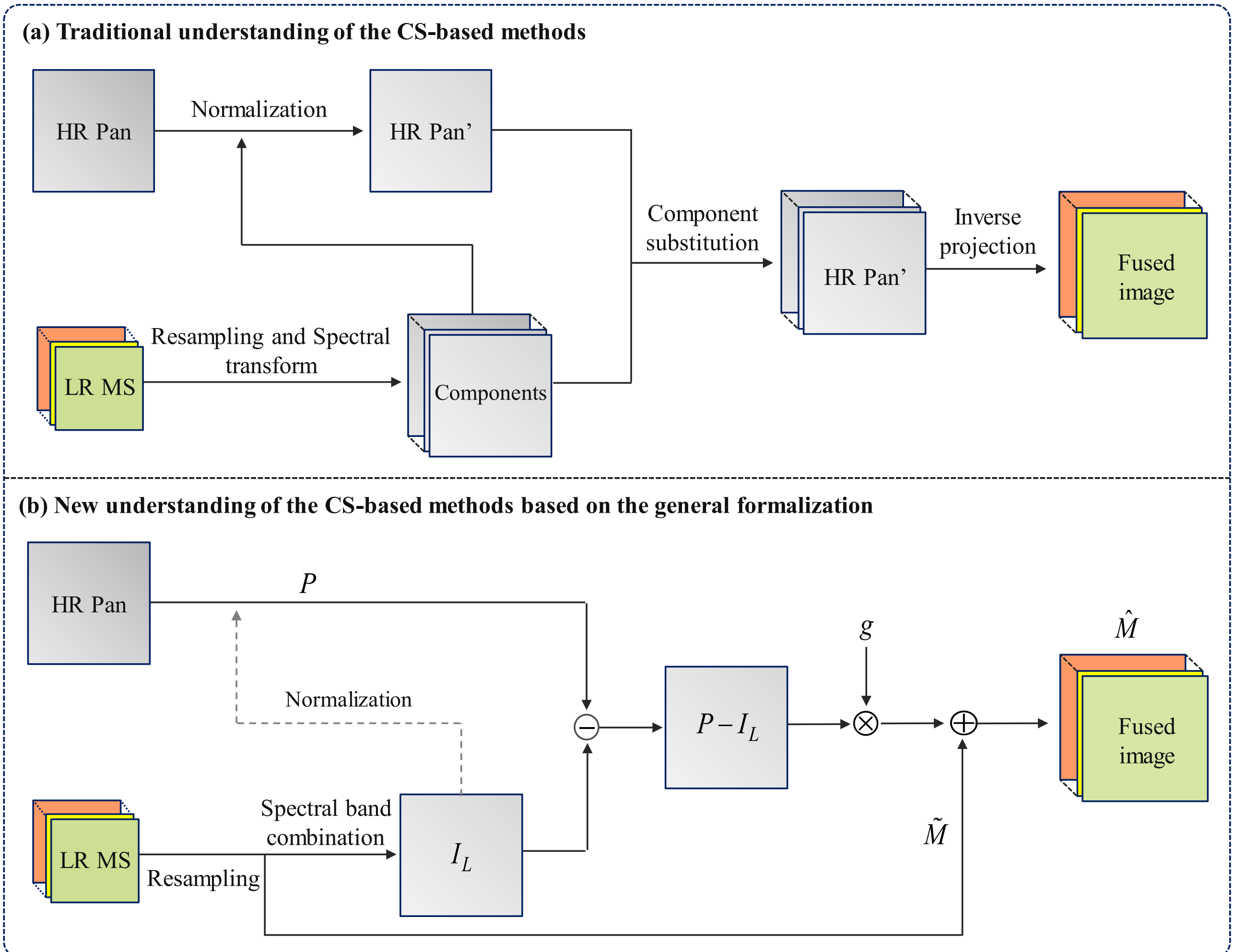

Fig. 1. Flowchart of the CS-based pansharpening methods. (a) The traditional understanding of the CS-based pansharpening methods. (b) The new understanding of the CS-based pansharpening methods based on the general formalization.

based methods has become more general. The new understanding, as shown in Fig. 1(b), is that this category of methods is based on the simple substitution of a single component by the PAN image, and the component is generally obtained by a linear combination of the spectral bands of the MS images, such as the typical GSA (adaptive GS) [62] and BDSD (band-dependent spatial detail) [63] methods, etc. It is noteworthy that, in effect, this involves extracting the high spatial structure information of the PAN image through the difference between the PAN image and the component, and the extracted high spatial structure information is then injected into the MS images by an appropriate injection scheme. This can be represented as:

$$\widehat{\mathbf{M}} = \widetilde{\mathbf{M}} + g(\mathbf{P} - \mathbf{I}_L) \tag{1}$$

where $\widehat{\mathbf{M}}$ is the fused image, $\widetilde{\mathbf{M}}$ is the resampled MS image, $\mathbf{I}_L$ denotes the component to be substituted, $\mathbf{P}$ denotes the PAN image, which is generally normalized (e.g. through histogram matching) with $\mathbf{I}_L$ to reduce the spectral distortion, and g represents the injection weight.

The general formalization of the CS-based methods has two advantages: 1) it leads to a faster implementation of the traditional methods. However, it should be noted that this should satisfy the premise that the component to be substituted is linearly generated from the available spectral bands. For example, the hyperspherical color sharpening (HCS) method [64] is based on the nonlinear hyperspherical coordinate transformation, and hence it does not admit a fast Algorithm. 2) It opens up new horizons for the development of this kind of methods, and a number of improved methods have been subsequently proposed. In general, the improvements for the CS-based methods have mainly focused on the optimal determination of component $\mathbf{I}_L$ and the injection weight g. Among them, the calculation of $\mathbf{I}_L$ is based on the assumption that the greater the correlation between the component and the PAN image, the better the fused result. In conclusion, there are several popular solutions. On the one hand, $\mathbf{I}_L$ is calculated from the earlier simple averaging of the spectral bands of the MS image [27,28,59], to the optimization by the spectral response functions of the sensors [34,65], and the optimal calculation by least squares regression [62,66,67]. On the other hand, it is calculated from global solutions [20,27,60,61] to optimal solutions by consideration of the local features [54,68]. For the determination of the injection weight g, a variety of solutions can be applied [2,22,23]. On the one hand, in the spatial dimension, the injection weight can be determined by a global model [62] or a local model [53]. On the other hand, in the spectral dimension, the injection weight may be equal for all the spectral bands [31], or determined by a band-dependent solution [28].

2.2. Multiresolution analysis (MRA)-based methods

The MRA-based methods originated in the 1980s [21]. The forerunners of this kind of method were based on single-level decomposition, such as the high-pass filter (HPF) method [20,21], and the pioneering formal MRA-based pansharpening methods were strictly based on the decimated wavelet transform (DWT) [69]. The traditional understanding of the MRA-based methods is [70]: “The source images are

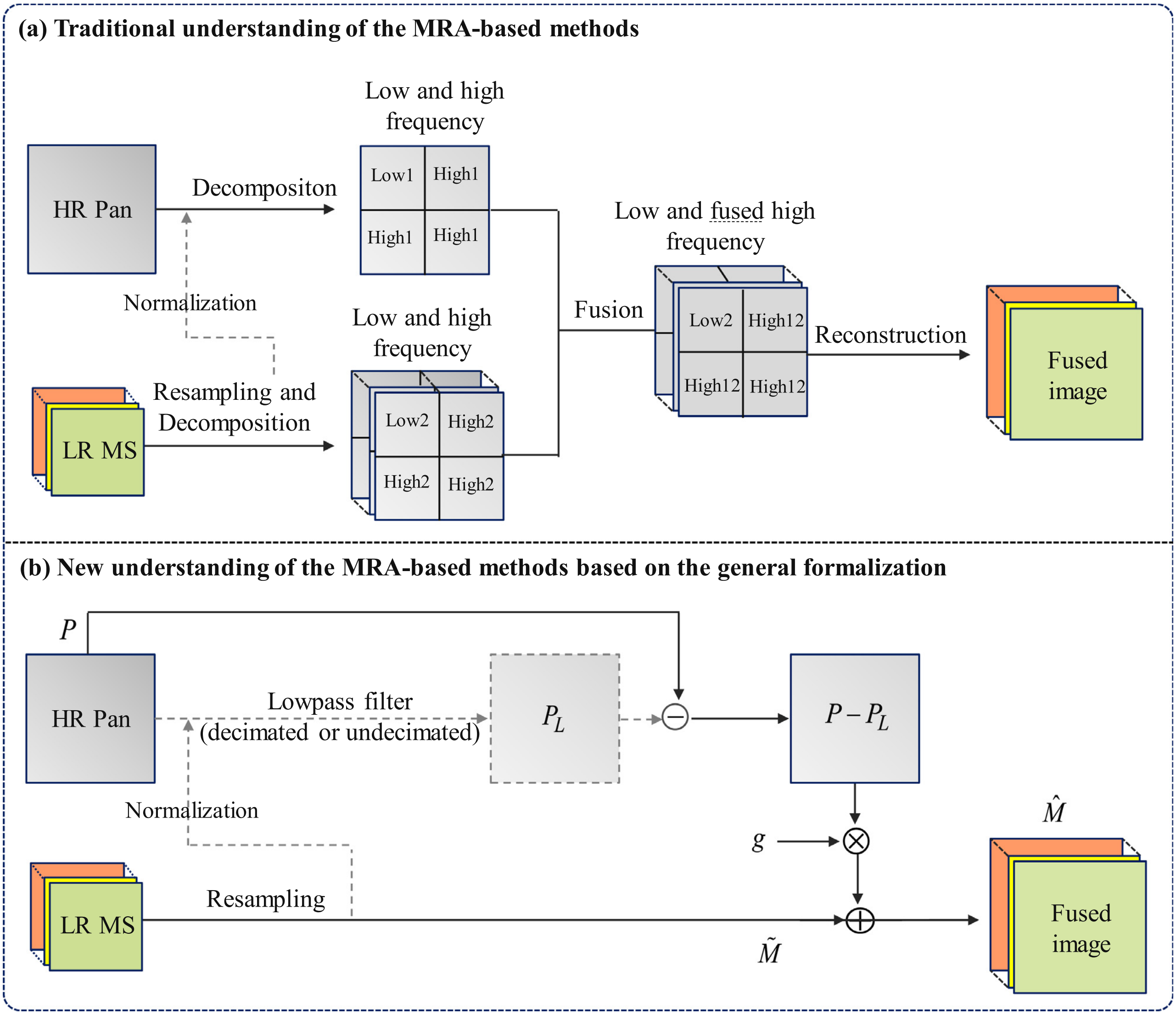

Fig. 2. Flowchart of the MRA-based pansharpening methods. (a) The traditional understanding of the MRA-based pansharpening methods. (b) The new understanding of the MRA-based pansharpening methods based on the general formalization.

decomposed into a series of bandpass channels based on wavelet transform or Laplacian pyramids, etc. Then, the high-frequency channels coming from the PAN decomposition are inserted into the corresponding MS band channels before the reconstruction step." Fig. 2(a) shows the flowchart of the traditional understanding of the MRA-based pansharpening methods.

The traditional understanding of the MRA-based methods has subsequently been extended. It is denoted as the popular ARSIS in [71], to highlight that the purposes of these methods are to preserve the whole content of the LR MS image and add the further high spatial structure information of the HR PAN image [22,23,72]. Tu et al. [31] subsequently extended the MRA-based methods based on the general formalization, and this general formalization was further extended in [23,30,70] as a unifying framework. It is demonstrated that the mathematical representation of most of the MRA-based methods can be represented as:

$$\widehat{\mathbf{M}} = \widetilde{\mathbf{M}} + g(\mathbf{P} - \mathbf{P}_L) \tag{2}$$

where $\mathbf{P}_L$ is the low-pass version of the PAN image. It can be seen that the main difference between the MRA-based methods and the CS-based methods depends on how they extract the spatial details. For the MRA-based methods, the high spatial structure information is obtained by the difference between the PAN image $\mathbf{P}$ and its low-pass version. The flowchart of the MRA-based pansharpening methods based on the general formalization is shown in Fig. 2(b).

It should be noted that the different MRA-based methods are uniquely characterized by how they obtain the image $\mathbf{P}_L$ and the injection weight g. For the solution of $\mathbf{P}_L$, there is a number of ways. These range from the methods based on single-level decomposition; to the methods based on formal multiresolution analysis algorithms; and to the methods based on more general MRA framework. Specifically, in the early stage, the HPF method is the representative approach. Subsequently, the pansharpening methods based on multiresolution DWT [69,73,74] have grown in popularity as a result of their better spectral preservation ability. However, due to the existence of subsampling in the wavelet decomposition, artifacts generally appear in the spatial structures. Therefore, pansharpening methods based on undecimated discrete wavelet transform (UDWT) [75,76], especially the à trous wavelet transform method [52,70,77,78], have been proposed and are attracting more and more attentions, such as the popular additive wavelet luminance proportional (AWLP) method [42,52]. In addition, MRA-based pansharpening methods using the generalized Laplacian pyramid (GLP) [79,80], the contourlet transform [81,82], and the curvelet transform [50] have also become popular. On the whole, the calculation of the $\mathbf{P}_L$ with the above different kinds of filters can be divided into two ways, i.e., the calculation based on decimated filters and undecimated filters. For the calculation with the undecimated filters, the low-pass version $\mathbf{P}_L$ has the same spatial dimension with the $\mathbf{P}$. For the calculation with the decimated filters, such as the DWT filter, the low-pass version $\mathbf{P}_L$ has to go through the downsampling and interpolation operation, and this generally introduce the spatial aliasing artifacts. However, it is noteworthy that the MRA-based methods would perform better if the filters used are closely tuned to match the modulation transfer function (MTF) of the sensor [42,79,80], such as the typical MTF-GLP method [80]. For the determination of the injection weight g, this is similar to the CS-based methods. The popular injection models include high-pass modulation (HPM) [83], the context-based decision (CBD) model [84], and the spectral distortion minimizing (SDM) model [84], the representative methods including the MTF-GLP-HPM and MTF-GLP-CBD [84], etc.

2.3. Variational optimization (VO)-based methods

The VO-based methods are an important category of the pansharpening family. The major process of this category of pansharpening methods is generally based on or converted to the optimization of a variational model. The VO-based methods include two major parts: (1) the construction of the energy functional; and (2) the optimization solution. Fig. 3 shows the schematic of the VO-based pansharpening methods.

For the construction of the energy functional, the methods based on observation model [85–91] and the sparse representation [37,92–94] are the most popular. Among them, the model-based methods regard the fusion process as an ill-posed inverse optimization problem, and the energy functional is constructed based on the observation models between the ideal fused image and the degraded observations, as shown in Fig. 3. Generally, the energy functional can be summed up as three terms: (1) the spectral fidelity model; (2) the spatial enhancement model; and (3) the prior model. It can be generally represented as the following expression:

$$E(\mathbf{x}) = f_{spectral}(\mathbf{x}, \text{LR MS}) + f_{spatial}(\mathbf{x}, \text{HR PAN}) + f_{prior}(\mathbf{x}) \tag{3}$$

where $\mathbf{x}$ denotes the ideal fused image. The first term is the spectral fidelity model, the second term is the spatial enhancement model, and the third term is the prior model. Among them, the spectral fidelity model relates the ideal fused image to the LR MS image. It is generally constructed based on the assumption that the observed LR MS image can be obtained by blurring, downsampling, and the noise operators performed on the HR MS image [1,32,91,95,96]. The spatial enhancement model relates the ideal fused image to the HR PAN image. In general, it is constructed based on two assumptions. The first is that the spectral degradation between the HR MS image and the HR PAN image, i.e., the wide PAN band is assumed to be a linear combination of the narrow bands of the HR MS image [91,95,97]. The second is the assumption that the spatial structures of the ideal fused image are approximately consistent with the HR PAN image [98–101]. This is generally represented by gradient features [98,99,102], wavelet coefficients [101], or other approaches [88,103]. The prior model imposes constraints on the ideal fused image, and many VO-based pansharpening methods based on a Laplacian prior [104], a Huber-Markov prior [91], a total variation (TV) prior [90], a nonlocal prior [105], and a low-rank priors [106], etc., have been proposed. To the best of our knowledge, a certain number of fusion energy functions can be generally simplified as the following two basic expression:

$$\begin{aligned} E(\mathbf{x}) &= \lambda_1 \|LR\ MS - \mathbf{DSx}\| + \|HR\ PAN - \mathbf{Cx}\| + \lambda_2 prior(\mathbf{x}) \\ E(\mathbf{x}) &= \lambda_1 \|LR\ MS - \mathbf{DSx}\| + \sum_{\mathrm{b}=1}^{B} \|\mathbf{W}{*}HR\ PAN - \mathbf{W}{*}\mathbf{x}_{\mathrm{b}}\| + \lambda_2 prior(\mathbf{x}) \end{aligned} \tag{4}$$

where the $\mathbf{D}$ and $\mathbf{S}$ denote the downsampling and blurring matrix, respectively, the $\mathbf{C}$ denotes the spectral combination matrix, and the $\mathbf{W}$ represents the operator to extract the high spatial structure information. The λ_1 and λ_2 are two model parameters to balance the three terms. It can be seen that an obvious characteristic of the two representative energy functions in (4) depends on the two classical assumptions of the spatial enhancement models. In addition, it can also find an interesting phenomenon that the two assumptions are highly correlated to the basic ideal of the spatial structure extraction of the CS-based methods and the MRA-based methods, respectively.

The sparse-based methods are mainly based on sparse representation theory. It is assumed that the signals of the remote sensing images are sparse in a basis set [107], and they can be represented by a linear combination of relatively few base elements in a basis or an overcomplete dictionary. This is generally represented as $\mathbf{x} = \Psi\boldsymbol{\alpha}$, where the $\boldsymbol{\Psi}$ denotes the dictionary, and the $\boldsymbol{\alpha}$ denotes the sparse coefficients. The sparse-based pansharpening methods were first proposed by Li and Yang [37], and since then, they have got rapid development. It is noteworthy that the acquisition of the dictionary is relatively important

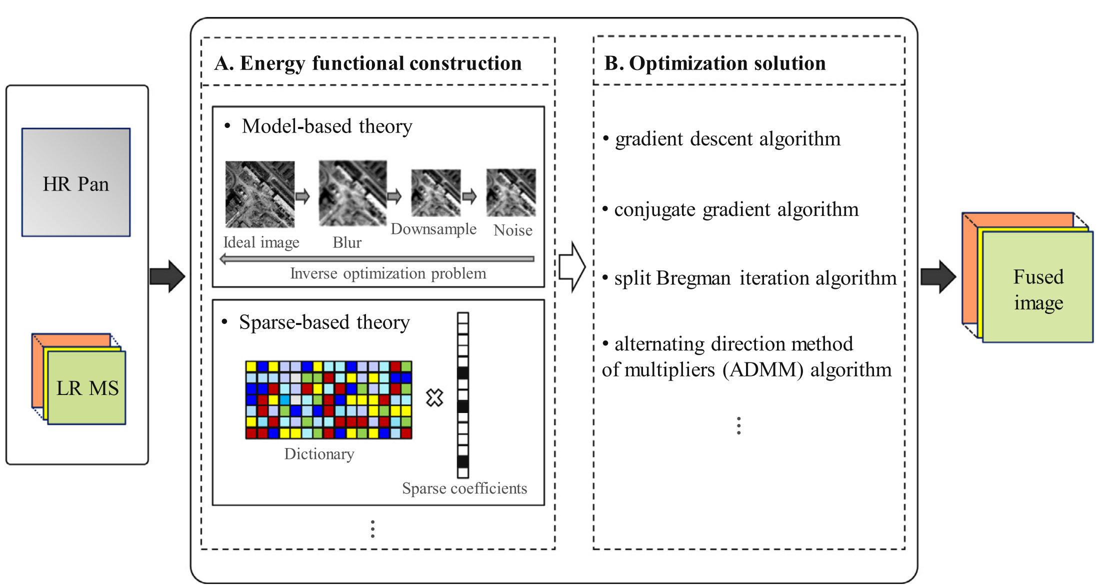

Fig. 3. Flowchart of the VO-based pansharpening methods.

for this kind of pansharpening methods. For the dictionary acquisition, the early sparse-based methods mainly rely on external database to train the dictionary, therefore, this type of methods is also called the offline dictionary training methods [37,93]. However, they acquire a large collection of external images, which is computationally expensive. To deal with this problem, the online dictionary training methods [92,94,108] were developed. They directly train the dictionary from the source images, and they are also the current mainstream methods to obtain the dictionary. It is noteworthy that the model-based and the sparse-based approach do not have the rigid distinction. Such as many methods [37,93] are both based on sparse representation theory and the observation model.

The optimization solution of the fusion model is generally based on an iterative optimization algorithm [1,109], such as the gradient descent algorithm [91,110], the conjugate gradient algorithm [1], the split Bregman iteration algorithm [86], and the alternating direction method of multipliers (ADMM) algorithm [96], etc. For most of the optimization solution, the fused image was solved iteratively. In addition, an optimization solution based on the Sylvester equation [96,111], without any iterative update step, has been proposed for the VO-based methods, and it can effectively accelerate the efficiency. On the whole, to the best of our knowledge, there are three key points in the VO-based pansharpening methods. The first is the construction of the optimal fusion energy functional; the second is the adaptive selection of the model parameters; and the third is the fast optimal solution. It is noteworthy that the low efficiency has seriously hindered the application of the VO-based pansharpening methods, and it should be given more attentions.

2.4. Relations among CS-based, MRA-based, VO-based methods

In this section, the relations among the CS-based methods, the MRA-based methods, and the VO-based methods are reviewed and discussed.

2.4.1. Relations between the CS-based methods and MRA-based methods

The CS-based methods and MRA-based methods have been developed from the traditional understanding to the current new general understanding. For the new understanding of both the CS-based and MRA-based methods, most of them can be generalized into two major steps, i.e., (1) the extraction of the high spatial structures of the HR PAN image; (2) the injection of the extracted high spatial structures into the resampling MS image to obtain the fused image. In addition, the mathematical representation, i.e., the Eq. (1) and (2), of the two categories of pansharpening methods is similar. Then, how to distinguish the CS-based methods and the MRA-based methods under the new general understanding? This is dependent on the way to extract the high frequency information of the PAN image. On the one hand, if the extracted high frequency information, which is generally implemented by a spatial filter or other spatial operators, is individually dependent on the PAN image, such as Fig. 2 and Eq. (2), then they are regarded as the MRA-based methods. Therefore, the MRA-based methods are also called the spatial methods [42]. On the other hand, if the high frequency of the PAN image is extracted based on both the PAN and the intensity component, which is generally obtained by the linear combination of the spectral bands of MS image, as shown in Fig. 1 and Eq. (1), then they are regarded as the CS-based methods. Therefore, the CS-based methods are also called the spectral methods [42]. For example, the AWLP method [52] involved both the spectral transformation of the MS image and the à trous wavelet transform; however, the high frequency is only extracted on the PAN image based on à trous filter. Therefore, the AWLP method is classified into the MRA-based pansharpening methods in this paper.

2.4.2. Relations between CS-based/MRA-based methods and VO-based methods

The VO-based methods [85,89] developed relatively later compared with the CS-based methods and MRA-based methods. On the one hand, there is obvious difference between the VO-based methods and the CS-based/MRA-based methods. The basic principle of the general CS-based and MRA-based methods is to explicitly extract the high spatial structures of the HR PAN firstly, and then inject them into the MS image in terms of a weighting scheme to obtain the fused image [112]. Different from the CS-based and MRA-based methods, the VO-based methods mainly integrate the spatial structure injection of the HR PAN and the spectral fidelity of the LR MS into a constraint energy model, based on the relationship between the desired fused image and the observations, and the prior knowledge of the desired fused image is generally utilized in the model. In addition, the major solution generally depends on the iterative optimization algorithms. On the other hand, there is correlation between the VO-based methods and the CS-based/MRA-based methods. For example, an interesting phenomenon is the idea of the spatial enhancement term of two typical VO-based fusion models, which is based on the linear spectral band combination and the similarity of the high spatial structure, respectively. It can be easily find that they are highly correlated to the basic ideal of the spatial structure extraction of the CS-based and MRA-based methods, respectively.

Therefore, the CS-based methods, the MRA-based methods, and the VO-based methods should be learned from each other. On the one hand, the future development of the CS-based and MRA-based methods can be learned from the VO-based methods. On the other hand, the development of the VO-based methods should be further learned from the idea of the CS-based and MRA-based methods.

3. Materials and methods

In this paper, we propose to innovatively evaluate the performance of the three categories of pansharpening methods developed between 2000 and 2016 based on a statistical analysis of the collected published studies, in which each study is focused on the performance of the pansharpening methods. The schematic of the proposed method is

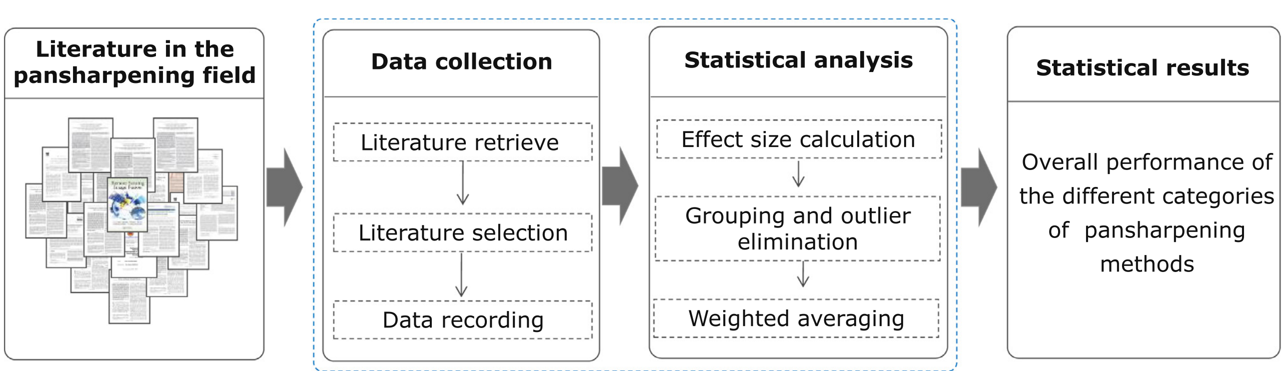

Fig. 4. The schematic of the proposed method.

shown in Fig. 4. It can be seen that the process of the proposed method includes two main steps: (1) data collection; and (2) statistical analysis. In the process of the data collection, as many published studies as possible are firstly retrieved; the satisfactory studies are then selected based on the strict selection criteria to ensure the reliability of the statistical analysis; and finally, the performances of the pansharpening methods in each selected study are recorded. After the data collection, the implementation of the statistical analysis follows. Firstly, the effect sizes, which denote the basic unit for the statistical analysis, are calculated. Secondly, all the data used in the analysis are grouped based on the pansharpening categories and the different effect sizes. In addition, the obvious abnormal outliers are eliminated. Finally, the weighted averaging is performed on the data in each group. Through the statistical analysis of the collected studies, the overall performance of the three categories of pansharpening methods is obtained.

3.1. Data collection

Firstly, the relevant studies in the pansharpening field from 2000 to 2016 were retrieved from the Web of Science, and more than 1000 studies were searched. It is noteworthy that the retrieval period was determined based on the objective of this paper, i.e., the performance evaluation of the three categories of pansharpening methods with controversy. To the best of our knowledge, most of the improved pansharpening methods were published after 2000, especially, since Tu et al. [31] proposed a general framework for the CS-based methods and MRA-based methods. Therefore, the controversy with regard to the performance of the different categories of pansharpening methods generally existed in the studies published after 2000. The performances of the earlier traditional methods, such as IHS [20,59], PCA [20,60,61], the Brovey [27], etc., are straightforward. Therefore, they are not in the scope of this study. Secondly, the satisfactory articles were selected based on strict criteria, and 48 representative articles (see the supplementary file) were finally selected from the more than 1000 studies. The selection criteria were as follows: (1) The quantitative evaluation results should be reported, as they are the only feasible statistical indicators to certify the performance of the pansharpening methods. In addition, it is important that at least one of the three popular quantitative evaluation indices—the dimensionless global error in synthesis (ERGAS) index [113], the spectral angle mapper (SAM) index [91,114], and the Q4 index [115] should be included. This is because, on the one hand, according to statistics, these three quantitative evaluation indices are the most widely used in the pansharpening studies; on the other hand, they are more robust to the difference between experimental datasets. (2) The experimental datasets should be introduced, and this mainly includes the introduction of the remote sensing sensor types or the spectral bands. In this paper, the studies in which the spectral bands of the MS image to be fused were approximately covered by the PAN image were selected to ensure homogeneity. Such as the QuickBird images and the IKONOS images, etc. They are also the primary experimental datasets in the past researches of pansharpening methods. In addition, it should be noted that for the WorldView-2 and ETM + datasets, etc., if they are implemented based on a subset of MS spectral bands, which is approximately covered by the spectral rang of the HR PAN image, then they are also admitted. (3) A common pansharpening method should be reported in each selected article, and it is regarded as a reference to ensure the feasibility and the objectivity of the statistical analysis. The selected common method should satisfy two essential criteria. On the one hand, it should be popular and widely used in experiments to ensure the sufficiency of the statistical data. On the other hand, it should be performed by professional commercial software, such as ENVI, to ensure consistency and avoid controversy. To the best of our knowledge, and based on the collected studies, the GS pansharpening method [28] is the optimal choice. Finally, the relevant information was extracted and recorded from the selected articles. This information was: the authors; the year of publication; the pansharpening methods applied in the experiments; the quantitative evaluation results of the ERGAS, SAM, and Q4; and the basic information of the experimental datasets. Through the collection, the experimental datasets including the QuickBird, IKONOS, Pléiades, GeoEye-1, WorldView-2 (implemented on parts of the MS bands covered by the spectral rang of PAN), and the ETM + (implemented on parts of the MS bands covered by the spectral rang of PAN), etc., were collected and statistically analyzed.

3.2. Statistical analysis

The effect size is regarded as the basic unit for the statistical analysis, and it should be firstly determined. In the collected studies, the quantitative evaluation indices were generally used to objectively evaluate the performance of the pansharpening methods. However, different experimental datasets were generally utilized in the different articles, and the recorded quantitative evaluation results in the selected studies may have been influenced by the difference between the experimental datasets. Hence, a statistical analysis directly using the original quantitative evaluation results is not suitable. In this paper, the effect size, including the adjusted ERGAS, the adjusted SAM, and the adjusted Q4, is calculated for the analysis. This is represented as:

$$S_{index} = (F_{index} - R_{index})/R_{index} \tag{5}$$

where S_{index} denotes the adjusted evaluation results with $index = [\text{ERGAS}, \ \text{SAM}, \ \text{Q4}]$. F_{index} represents the original evaluation results of a pansharpening method in an experiment; and R_{index} denotes the quantitative evaluation results of the common reference pansharpening method, i.e., the GS method, in the corresponding experiment.

After the adjusted evaluation results of all the studies were obtained, they were then divided into three primary groups based on the three categories of pansharpening methods. In addition, each primary group included three specific groups based on the three different effect sizes, i.e., the adjusted ERGAS, the adjusted SAM, and the adjusted Q4. To ensure the robustness and effectiveness of the final statistical results, the obvious abnormal outliers were eliminated [116]. It should be noted that if an outlier in a group was eliminated, then the corresponding collected data in other groups should be removed. Such as an outlier in the group of adjusted ERGAS was eliminated, then the corresponding values in the group of adjusted SAM and Q4 should be also removed. In addition, for a specific pansharpening method in each group, at least two evaluation results should be included. Finally, the weighted averaging was performed on the statistical data in each group. This can be represented as:

$$\begin{aligned} &O_{m,n} = \sum_{i=1}^{K_{m,n}} w_{m,n}(i)\, S_{m,n}(i) \\ &\textit{with} \quad m = [\text{CS}-\text{based methods},\ \text{MRA}-\text{based methods},\ \text{VO}-\text{based methods}]; \\ &\qquad\quad n = [\text{adjusted ERGAS},\ \text{adjusted SAM},\ \text{adjusted Q4}]; \end{aligned} \tag{6}$$

where $O_{m,\ n}$ denotes the results of the $(m,\ n)$ group, with m corresponding to the index of the three categories of pansharpening methods, and n corresponding to the index of the three different effect sizes. $w_{m,\ n}(i)$ denotes the weight for the ith record of the $(m,\ n)$ group, and the weight of $1/K_{m,\ n}$ is applied, where $K_{m,\ n}$ is the total number of records of the corresponding group. The 95% confidence interval is further calculated to provide reliable statistical results, and it is calculated as $O_{m,\ n} \pm 1.96\,\rho(S_{m,\ n})$, with $\rho(S_{m,n}) = \sigma/\sqrt{K_{m,n}}$ denoting the standard error for the statistical data of the $(m,\ n)$ group, and σ is the standard variance.

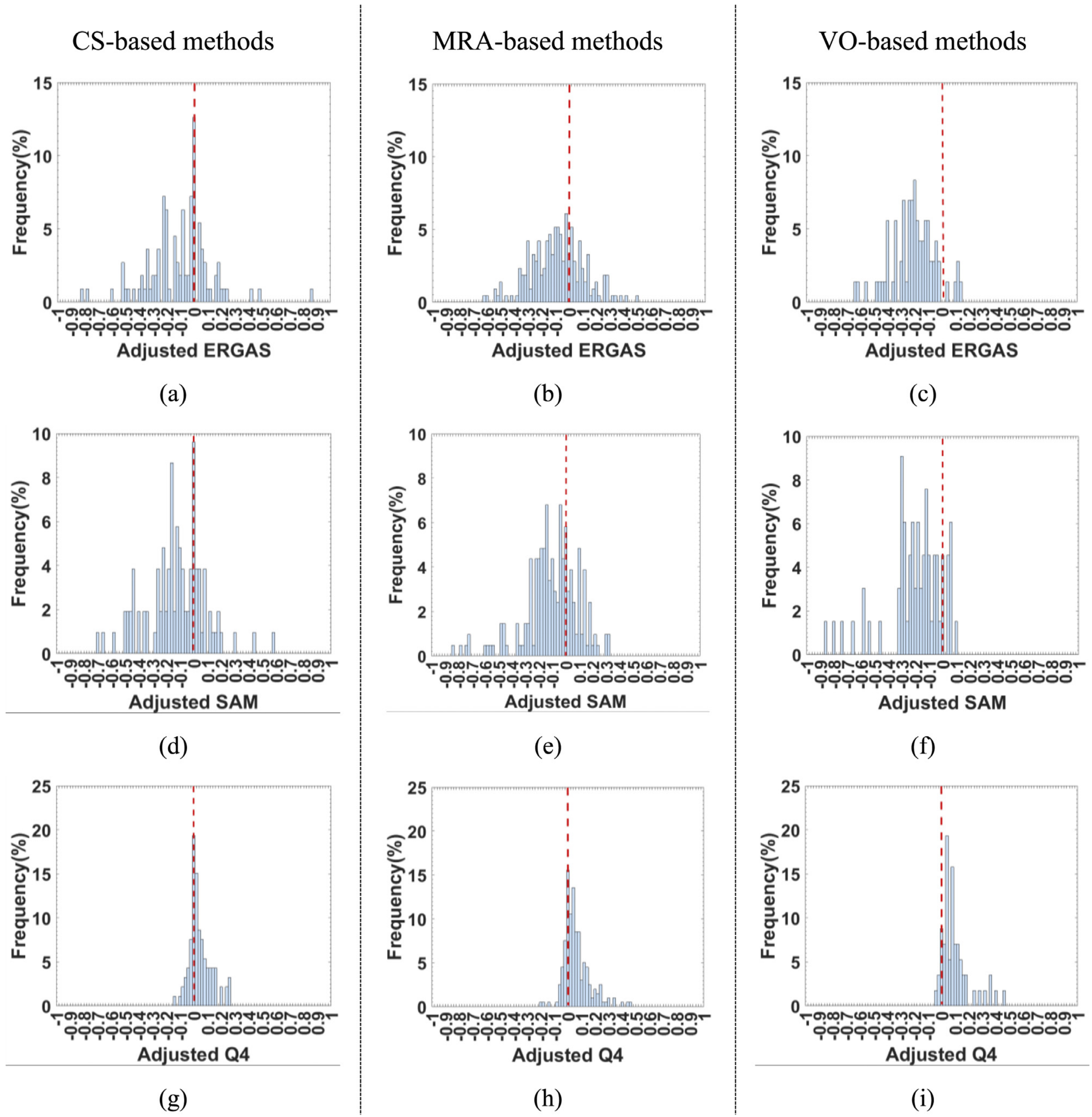

Fig. 5. The frequency distribution of the statistical data for each group (the vertical lines are drawn at zero). (a)–(c) The frequency distribution of the adjusted ERGAS for the three categories of pansharpening methods. (d)–(f) The frequency distribution of the adjusted SAM for the three categories of pansharpening methods. (g)–(i) The frequency distribution of the adjusted Q4 for the three categories of pansharpening methods.

4. Results and discussion

4.1. Results

To reveal the characteristics of the statistical data, their frequency distribution for each group is shown in Fig. 5. The abscissa denotes the adjusted evaluation results, and the vertical axis represents the frequency. In addition, the vertical lines at zero are drawn to intuitively show the characteristics of the distribution. It should be noted that the smaller the adjusted ERGAS, the smaller the adjusted SAM, and the bigger the adjusted Q4, then the better the result.

Fig. 5(a)–(c) show the frequency distribution of the adjusted ERGAS for the CS-based methods, the MRA-based methods, and the VO-based methods, respectively. The frequency distribution of the adjusted SAM for the three categories of pansharpening methods is shown in Fig. 5(d)–(f), and the corresponding adjusted Q4 is shown in Fig. 5(g)–(i). It can be clearly seen that the total frequency distribution of all the adjusted ERGAS, the adjusted SAM, and the adjusted Q4 for the CS-based methods and the MRA-based methods are similar. The frequency distribution for the VO-based pansharpening methods has obvious differences with the other two types of methods, and it is more obviously gathered at one side of the red line. This shows that most of the VO-based methods generally perform better than the CS-based methods and the MRA-based methods.

The statistical results of the three categories of pansharpening methods from 2000 to 2016 are shown in Fig. 6 and Table 1. Among

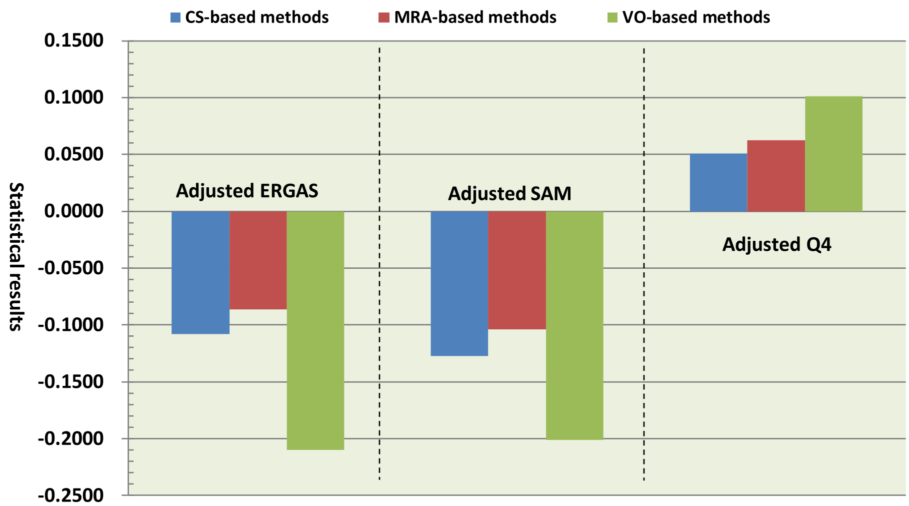

Fig. 6. Statistical results (average) of the three categories of pansharpening methods from 2000 to 2016 in terms of the three adjusted evaluation indices, i.e., the adjusted ERGAS, the adjusted SAM, and the adjusted Q4.

Table 1
The detailed statistical results of the three categories of pansharpening methods from 2000 to 2016 in terms of the three adjusted evaluation indices.

	Methods	Average	Confidence interval (95%)	Variance
Adjusted ERGAS	CS	−0.1078	[−0.1513, −0.0643]	0.0546
	MRA	−0.0864	[−0.1125, −0.0604]	0.0378
	VO	−0.2101	[−0.2472, −0.1731]	0.0257
Adjusted SAM	CS	−0.1274	[−0.1730, −0.0818]	0.0595
	MRA	−0.1042	[−0.1317, −0.0766]	0.0407
	VO	−0.2010	[−0.2509, −0.1512]	0.0427
Adjusted Q4	CS	0.0508	[0.0310, 0.0707]	0.0100
	MRA	0.0622	[0.0487, 0.0757]	0.0094
	VO	0.1012	[0.0730, 0.1293]	0.0117

them, the overall performance is visualized in Fig. 6, and it is noteworthy that, for Fig. 6, the longer the bar, the better the performance of the methods.

It can be clearly seen that the VO-based pansharpening methods show the best performance, and they have obvious advantages over the CS-based methods and the MRA-based methods in terms of the three quantitative evaluation indices. The statistical results between the CS-based methods and the MRA-based methods have little difference. In comparison, the CS-based methods perform slightly better in the adjusted ERGAS and the adjusted SAM; however, they perform slightly worse in the adjusted Q4. The detailed statistical results are shown in Table 1. In the table, the average column corresponds to Fig. 6. The 95% confidence interval and the variance are further applied to show more precise results and the robustness of the statistical analysis. It can be seen that the confidence intervals of all three quantitative evaluation indices for the VO-based methods further indicate their better performance. In addition, the performance of the CS-based and MRA-based methods is similar. The low variances and concentrated confidence intervals both indicate the reliability and robustness of the results. On the whole, the statistical results show that the VO-based methods perform the best. The CS-based methods and MRA-based methods perform slightly worse, and their performances are similar.

4.2. Discussion

The statistical results indicate that the VO-based pansharpening methods perform the best, and the CS-based methods and the MRA-based methods perform slightly worse. On the whole, the CS-based methods and the MRA-based methods show similar performances. However, it should be noted that this denotes the overall performance of the three categories of pansharpening methods, and it does not indicate the performance of each specific method. For example, the statistical results show that the VO-based methods perform better than the MRA-based and CS-based methods; however, some methods in the VO-based category may perform worse than the methods in the other two categories. Though it has a great significance to evaluate the performance of the individual methods within each category; however, this is limited by the amount of the collections of the statistics. In this paper, it is assumed that a robust statistical result depends on large amounts of statistical datasets. Therefore, by seriously considering the reliability of the statistical results for each specific method, the statistical analysis for individual methods was not shown. Furthermore, it does not indicate specific factors in the performance of the pansharpening methods, such as the performance of the pansharpening methods for different surface features, and this will be studied in our future work.

In this paper, the performance of the pansharpening methods has been statistically analyzed based on the quantitative evaluations, and the qualitative evaluations were not involved. This is because the quantitative evaluation is objective, and it is also the sole feasible statistical indicator for the analysis. In the statistical analysis of the quantitative evaluation, the weight was set to $1/K_{m,\ n}$ in (6), which is feasible when considering the specific objective and the characteristics of the data in this study. Finally, some interesting statistical analysis are limited by the amount of the collections, such as the quantitative evaluation of the real experiments. It is noteworthy that the quality evaluation is one of an open problem for pansharpening. For example, a method performs good in the simulated experiment may be poor in the real experiment in some case. Although a quantitative evaluation result of the simulated experiment cannot fully represent the performance of the pansharpening methods in the real experiments, the overall performance between them will not vary substantially. In addition, Palsson et al. [117] have demonstrated that the consistency property in the real experiments and the synthesis property in the simulated experiments show high correlated for the ranking of the pansharpening methods. In addition, it should be noted that some non-reference evaluation indices have been proposed for the real experiments, such as the popular QNR [118] and GQNR [119] metrics, etc. However, Palsson et al. [117] demonstrated that the QNR metric cannot effectively reflect the performance of the pansharpening methods, and it is also limited by the spectral rang between the PAN and MS images [119]. In addition, the efficiency of the pansharpening methods has not been statistically analyzed. This is because the efficiency was generally not reported in most of the articles, and hence the amount of corresponding statistical data is insufficient. However, to the best of our knowledge, most of the

VO-based pansharpening methods are less efficient than the CS-based methods and the MRA-based methods, especially for datasets of large dimensions. In comparison, the CS-based methods and the MRA-based methods are more suitable for practical engineering applications, and the CS-based methods are generally routinely used duo to their greater robustness to MS-to-PAN misalignments.

In addition, there is an interesting phenomenon that the CS-based pansharpening methods and the MRA-based pansharpening methods show similar statistical results, and this is different from the general understanding that the CS-based methods tend to bring serious spectral distortions. To the best of our knowledge, it is because the general understanding on the performance of the CS-based methods is still based on the traditional pansharpening methods or a particular part of the popular pansharpening algorithms, such as the IHS pansharpening method, the PCA pansharpening method, and the GS pansharpening method, etc. However, it should be noted that the CS-based methods have been improved, and a number of state-of-the-art methods have been proposed. Especially since 2000, the CS-based methods have been simplified and generalized into the unifying framework, and various advanced strategy can be applied to improve their performance. Therefore, the approaching performance of the advanced CS-based methods to the MRA-based methods is understandable and encouraging.

5. Future challenges

As the above description, the pansharpening methods have went through a remarkable development over thirty years, and numbers of pansharpening methods have been developed. However, at the present time, there are still many open-ended problems. In this section, we put forward some future challenges on this topic.

5.1. Difference of the spectral response between MS and PAN images

This has been one of the main reasons to cause the distortions for pansharpening. Such as most of the popular pansharpening methods can be directly applied to the fusion of HR PAN and 4-band LR MS for IKONOS, QuickBird, GaoFen-1/GaoFen-2 satellite images; however, what about the fusion of all the spectral bands of the MS and PAN images for the WorldView-2, Landsat-8 OLI, and Sentinel-2? Most of the popular pansharpening methods maybe perform worse in these cases. This is because only part of the MS spectral bands are covered by the spectral range of the PAN image, the larger difference of the spectral response, the less correlation between images to be fused, and generally the worse of the fusion performance. Therefore, how to design more effective pansharpening methods to overcome the difference of the spectral response between MS and PAN images is a challenging work. Future exploration in this direction can be further conducted.

5.2. MS-to-PAN misalignments with moving objects

The misalignments generally introduce spatial artifacts of the fused image, and this has been one of the key problems in pansharpening [120], especially for the MRA-based methods. The misregistration problem is generally inevitable for very high-resolution remote sensing images, especially for the images located in city region with moving objects existed. For these images, geometrical registration can be performed to satisfy the general fusion requirements for most regions; however, it seems to be helpless to realize a high precise registration for the local regions with moving objects, such as vehicles. Though the CS-based methods are relatively robust to MS-to-PAN misalignment, this will also affect the spectral fidelity of the fused image to some extent. Therefore, future exploration on pansharpening methods with greater robust to MS-to-PAN misalignments should attract more attentions.

5.3. Application-oriented pansharpening methods

To date, a number of pansharpening methods have been developed; however, few algorithms can be applied to engineering applications. On the one hand, for the CS-based and MRA-based methods, several popular pansharpening methods have been commercialized in some professional software; however, most of them generally introduce spectral distortions. On the other hand, for the VO-based methods, they generally have higher fusion accuracy as shown above; however, the low efficiency has seriously hindered their applications, especially the fusion tasks for large regions. In addition, though many pansharpening methods have been proposed, most of them don't have good robustness to remote sensing images from different scenes. Therefore, on the one hand, it is incontrovertible that the fast high-fidelity pansharpening methods should be further developed to satisfy the engineering applications. On the other hand, it is noteworthy that, in fact, different applications may have different requirements for more spectral fidelity or more spatial enhancement. Therefore, the development of the application-oriented pansharpening methods should attract more attentions.

6. Conclusion

This paper has presented a comprehensive review of the pansharpening methods for remote sensing images. In addition, the performance of the three main categories of pansharpening methods, i.e., the CS-based methods, the MRA-based methods, and the VO-based methods developed between 2000 and 2016, has been innovatively statistically analyzed based on the articles ever published. Nevertheless, the future work can potentially expand the research into the performance evaluation of the individual methods within each category of pansharpening methods, and the specific factors, such as the different ground features, for the pansharpening methods.

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Supplementary material

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