Improving the Spatial Resolution of Landsat TM/ETM+ Through Fusion With SPOT5 Images via Learning-Based Super-Resolution

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Abstract—To take advantage of the wide swath width of Landsat Thematic Mapper (TM)/Enhanced Thematic Mapper Plus (ETM+) images and the high spatial resolution of Système Pour l’Observation de la Terre 5 (SPOT5) images, we present a learning-based super-resolution method to fuse these two data types. The fused images are expected to be characterized by the swath width of TM/ETM+ images and the spatial resolution of SPOT5 images.

To this end, we first model the imaging process from a SPOT image to a TM/ETM+ image at their corresponding bands, by building an image degradation model via blurring and downsampling operations. With this degradation model, we can generate a simulated Landsat image from each SPOT5 image, thereby avoiding the requirement for geometric coregistration for the two input images. Then, band by band, image fusion can be implemented in two stages: 1) learning a dictionary pair representing the high- and low-resolution details from the given SPOT5 and the simulated TM/ETM+ images; 2) super-resolving the input Landsat images based on the dictionary pair and a sparse coding algorithm. It is noteworthy that the proposed method can also deal with the conventional spatial and spectral fusion of TM/ETM+ and SPOT5 images by using the learned dictionary pairs. To examine the performance of the proposed method of fusing the swath width of TM/ETM+ and the spatial resolution of SPOT5, we illustrate the fusion results on the actual TM images and compare with several classic pansharpening methods by assuming that the corresponding SPOT5 panchromatic image exists. Furthermore, we implement the classification experiments on both actual images and fusion results to demonstrate the benefits of the proposed method for further classification applications.

Index Terms—Landsat Thematic Mapper (TM) or Enhanced Thematic Mapper Plus (ETM+) image, spatial resolution, Système Pour l’Observation de la Terre 5 (SPOT5) image, super-resolution, swath width.

I. INTRODUCTION

W

ITH the emergence of a wide variety of remote sensing instruments and the widespread application of remote

sensing data, multisensor multiresolution image fusion is becoming increasingly more important [1]. A common feature among these satellite sensors is that they trade off between spatial resolution and other sensor properties, including spectral resolution, temporal resolution, and swath width, caused by technical and budget limitations. Two examples are the Thematic Mapper (TM) or the Enhanced Thematic Mapper Plus (ETM+) sensor aboard the Landsat satellite (we will take the Landsat TM sensor as an example in this paper) and the High Resolution Geometrical (HRG) instrument on the commercial satellite Système Pour l’Observation de la Terre 5 (SPOT5).

Although launched by different agencies, SPOT (1–6 have currently been launched) and Landsat (1–8 have currently been launched) satellites have provided large amounts of data for various fields since the launch of the first one. With the launch of the new SPOT and Landsat satellites in the future, studying the fusion of data from these two platforms will greatly promote their applications.

Landsat TM provides unique resources for global change research and applications in such areas as agriculture, cartography, and geology [2], with a spatial resolution of 30 m, at most, of the seven bands (except band 6 with a spatial resolution of 120 m) and a swath width of 185 km, whereas SPOT5 HRG aims for high-spatial-resolution images featured by four multispectral bands [green, red, near-infrared (NIR)] with a spatial resolution of 10 m, and short-wave infrared (SWIR) with a spatial resolution of 20 m) and one panchromatic band with a swath width of 60 km. Obviously, these two sensors are complementary in their spatial resolution and swath width properties, i.e., the TM sensor is characterized by lower spatial resolution but wider swath width, whereas the SPOT5 sensor is characterized by higher spatial resolution but narrower swath width. However, higher spatial resolution and a greater cover area may be simultaneously needed in practical applications, e.g., in large-area land cover/land use mapping with high spatial resolution [3], [4] or in cases where higher spatial resolution data are required but only low-resolution TM/ETM+ data are available for the study scene. Thus, we propose to enhance the spatial resolution of TM images by merging with an available SPOT5 image.

In fact, the fusion of Landsat TM/ETM+ and SPOT5 images has been explored by many researchers in the past two decades [5]–[7]. However, most of them focused mainly on the fusion of TM/ETM+ multispectral and SPOT5 panchromatic images to integrate the good spectral property of the former and the good spatial property of the latter, respectively. This spatial and
s spectral fusion task is usually referred to in previous literature [8], [9] as pansharpening, i.e., the fusion of the panchromatic (Pan) and multispectral (MS) images. Suppose that the Pan and MS images cover the same geographic area, a pansharpening method proportionally injects the spatial high-frequency information of the Pan band into the MS bands to obtain MS images at higher spatial resolution. Popular pansharpening methods include three categories: projection–substitution, relative spectral contribution, and methods that belong to the Amélioration de la Résolution Spatiale par Injection de Structures (ARSIS) concept. For fusion of TM MS and SPOT5 Pan images, these methods encounter three important challenges [8]: 1) These two data types should be well registered geometrically; 2) dissimilarities exist between these two data sets caused by different times of acquisition; 3) spectral distortion exists in the fused MS images due to their different spectral bands of acquisition. The proposed fusion method in this paper provides feasible solutions to these problems from new perspectives. First, we build an image degradation model from SPOT5 to TM at a specific image band, e.g., at the NIR band of SPOT5 and TM, by simulating the imaging process. This degradation model is then utilized to generate the simulated TM images from given SPOT5 images, which, thus, avoids the requirements of accurate geometrical coregistration and the same capture time between the input TM and SPOT5 images. Second, we correlate the high-frequency details of the simulated TM and SPOT5 band images by learning a dictionary pair in each band, which can then be applied to the TM MS bands to predict the corresponding high-frequency details at a higher spatial resolution. Since the low-frequency information in the original TM MS bands is not changed during the fusion procedure, the spectral distortion phenomena can be alleviated to a certain degree.

Apart from handling the spatial and spectral fusion of TM MS and SPOT5 Pan, the main innovation of the proposed method lies in increasing the spatial resolution of TM MS images when the corresponding SPOT5 data are not available in the study scene. Given a SPOT5 MS image and a TM MS image, which covers a smaller study scene and a larger study scene, respectively, we first use their overlapping area to build dictionary pairs by means of sparse representation theory [10]. We can then super-resolve the TM study areas where the SPOT5 data are not available via a sparse coding algorithm [11]. With a comparable spatial resolution as the actual SPOT5 image, we can also deem the fused image as a spatially extended SPOT5 image, which, thus, largely broadens the application potential of the raw TM and SPOT5 images.

As the main technical strategy adopted in this paper, super-resolution originally aims at fusing multiple low-resolution (LR) images with different subpixel shifts to obtain a high-resolution (HR) image [12]. With the development of sparse representation theory in the image processing field, including sparse coding and dictionary learning algorithms, the super-resolution has been evolved to reconstruct an HR image from a single LR image based on a dictionary pair learned from other prior images [13], [14]. The main idea in these learning-based methods for super-resolution is that the high-frequency details in images, such as edges and textures, can be sparsely represented by a linear combination of a few fundamental atoms denoted by a predefined dictionary. In addition, there is one important assumption concerning these methods, i.e., similar spatial structures or high-frequency details exist between prior images and the image in the study, so that the representation atoms can be learned from these prior images. Fortunately, this assumption was reasonably well validated by previous literature [13]. In this study, we borrow this single-image super-resolution strategy to improve the spatial resolution of TM to that of SPOT5 and develop a new dictionary learning strategy at the same time.

Based on an image degradation model from SPOT5 to TM and the sparsity-regularized super-resolution algorithm, we seek to improve the spatial resolution of TM MS bands on study scenes, where the spatially corresponding SPOT5 data are not available, by utilizing available SPOT5-TM image pairs. Consequently, we can merge both spectral information and swath width of TM data with the spatial information of SPOT5 data. Three main contributions are made in this paper. First, we are the first to propose the fusion of swath width and spatial resolution on Landsat TM/ETM+ and SPOT5 images. Second, we propose to relate images from two types of sensors by a degradation model and, thus, liberate the geometric coregistration requirement, which is usually a strong prerequisite in multisensor image fusions. Third, we improve the dictionary-pair learning procedure by combining the joint learning and the K singular value decomposition (K-SVD) dictionary training algorithm.

The remainder of this paper is organized as follows. We first introduce the related studies regarding the image degradation model, single-image super-resolution, and sparse representation theories in Section II. Our proposed method is then illustrated in detail in section III. Section IV shows the experimental results on the evaluation of the proposed dictionary-pair learning method, fusion performance on actual TM images, and classification tests on fusion images. Finally, this paper is concluded in Section V with discussion.

II. RELATED STUDIES

A. Image Degradation Model

According to the imaging procedure of camera sensors, a degradation model can be built between an observed LR image \(X^{LR}\) and an HR image \(X^{HR}\) that is desirable [12], i.e.,

\[
X^{LR} = SHFX^{HR} + N \tag{1}
\]

where \(F\) denotes a geometric motion operator, \(H\) represents a blur matrix, \(S\) is a sensor spatial subsampling matrix, and \(N\) is the system additive noise. The operator \(F\) may include shifting and rotation; \(H\) may consist of optical blur, motion blur, and the sensor’s point spread function (PSF) effect, which can be approximated by an isotropic 2-D Gaussian kernel with a covariance parameter \(\sigma^2_{PSF}\) or a circular disk with a radius parameter \(r\) [15]; the matrix \(S\) can be assumed to be a uniform sampling operator; the noise \(N\) can be modeled by Gaussian distribution, Laplacian distribution, or Possion distribution. Building this degradation model is the first step
in the multiframe super-resolution task relating the original HR image to the observed LR images [12]. With appropriate assumptions and solving for the operators in (1), each LR pixel can be defined as a weighted sum of the related HR pixels with additive noise.

B. Single-Image Super-Resolution Based on Sparse Representation

In traditional multiframe-image super-resolution algorithms, most of them depend on the redundant information among multiple LR images and the degradation model in (1) for solving [12], [16], [17]. In contrast, learning-based single-image super-resolution algorithms exploit the existence of similar high-frequency information in prior images and directly relate the LR and HR images by enforcing their representation atoms in correspondence spatially. In recent years, these learning-based methods have been frequently studied due to the increasing popularity of sparse representation in image processing, including remote sensing image fusion [18]–[21]. For spatial–temporal fusion, i.e., fusing the high spatial resolution of images from one sensor and the high temporal resolution of images from another sensor, we proposed the application of a learning-based super-resolution technique in [18] and [19], where we directly super-resolve the low-spatial-resolution images (or difference images). In this paper, we first propose a dictionary-pair learning method for bridging SPOT5 and TM sensors images (or difference images). In this paper, we first propose a joint dictionary training method by first combining these two data sets in \( X = [X^{HR}; X^{LR}] \) and then optimizing the following objective function:

\[
\min_{D, \Lambda} \|X - DA\|_F^2 + \lambda\|\Lambda\|_1, \quad \|d_i\|_2^2 \leq 1, i = 1, 2, \ldots, K
\]  

(5)

where \( \Lambda \) is \( X \)'s representation coefficient matrix, \( \lambda \) is a regularization parameter, \( D = [D^{HR}; D^{LR}] \), and \( d_i \) is the \( i \)th column of \( D \). The optimization of (5) is performed in an alternative manner over \( D \) and \( \Lambda \), i.e., fixing one and updating another in each time until convergence. Zeyde et al. [14] developed another dictionary-pair learning method based on the K-SVD algorithm [22]. The first step in this method is to learn \( D^{LR} \) by applying the K-SVD procedure to \( X^{LR} \) with the following objective formula:

\[
\{D^{LR}, \Lambda^*\} = \arg \min_{D^{LR}, \Lambda} \|X^{LR} - D^{LR}\Lambda\|_2^2,
\]

\[
\|\alpha_i\|_0 \leq T, \quad i = 1, 2, \ldots, M
\]

(6)

where \( \alpha_i \) is the \( i \)th column of \( \Lambda \). With the solved coefficient matrix \( \Lambda^* \) in (6), the next step is to reconstruct \( D^{HR} \) via a pseudo-inverse expression (given that \( \Lambda^* \) has full row rank), i.e.,

\[
D^{HR} = X^{HR}\Lambda^{*T}(\Lambda^{*}\Lambda^{*T})^{-1}.
\]

(7)

Compared with the alternative-updating dictionary training algorithm in [13], the advantage of the K-SVD method is its efficiency and simplicity.

Given an overcomplete dictionary \( D \), sparse coding solves the problem of finding sparse representations of the signals with respect to \( D \), similar to that in (3). In recent years, substantial efforts have been put into studying sparse coding algorithms [11]. Among them, two categories obtained wide application due to their efficiency and accuracy: those based on greedy pursuit and those based on convex relaxation. One simple and efficient greedy pursuit algorithm is orthogonal matching pursuit (OMP) [23], which solves the \( l_0 \)-norm-constrained sparseness problem via iteratively refining the current estimate for the coefficient vector by modifying one or several coefficients chosen to yield a substantial improvement in approximating the signal. In convex relaxation algorithms, the \( l_0 \)-norm is replaced by the \( l_1 \)-norm to yield convex optimization problems that admit tractable algorithms. It has been demonstrated that these methods produce optimal or near-optimal solutions to sparse approximation problems in a variety of settings. A detailed description about these two categories of sparse coding algorithms can be found in [11].
III. PROPOSED METHODOLOGY

The flowchart in Fig. 1 shows the principal steps of the proposed methodology. The whole procedure includes two main stages: training and reconstruction. In the training stage, several available SPOT5 images are first used to generate the corresponding TM images according to a degradation model. The flowchart in Fig. 1 shows the principal steps of the proposed methodology. The whole procedure includes two main stages: training and reconstruction. In the training stage, several available SPOT5 images are first used to generate the corresponding TM images according to a degradation model. Then, the high-frequency feature images of input data are extracted for further collection of HR and LR training samples. Subsequently, a dictionary pair is learned from these training samples via a joint K-SVD dictionary learning algorithm and the OMP sparse coding algorithm for each band. While in the reconstruction stage, the TM images are first preprocessed, similar to radiometric intercalibration and interpolation, after which the feature images are extracted, as in the training stage. The collected LR reconstruction set from the LR feature images is then sparsely represented with respect to the LR dictionary via the OMP algorithm. With the derived sparse coefficients from this LR image representation procedure and the available HR dictionary, the HR images can be predicted by means of simple matrix multiplication.

A. Degradation Model Between SPOT5 and TM

During the fusion of remote sensing images from different sensors, their geometric coregistration is an important challenge, particularly for high-resolution images, such as SPOT5. The main reason for this challenge is that each image acquisition system produces unique geometric distortions, which are mainly caused by the acquisition system (platform, imaging sensor, and other measuring instruments), atmosphere (refraction and turbulence), and Earth [24]. Apart from these geometric distortions, another factor preventing the fusion of SPOT5 and TM is their capture time interval, which may cause land-cover type changes. Since the revisit periods of TM and SPOT5 are 16 and 26 days, respectively, it cannot guarantee that the two available study images are acquired on exactly the same date. To mitigate the problems caused by these two factors, we build a degradation model between these two types of images to mimic how to derive a TM image from a SPOT5 image. The study in [25] has shown that the TM sensor and the SPOT5 HRG sensor have similar total sensor PSF shapes, which can be depicted by the blurring operator in (1). Inspired by this linkage, we thus apply (1) to relate the TM and SPOT5 images in green, red, NIR, and SWIR bands, whose spectral comparison is shown in Table I. From this table, we can observe that the bandwidths of SPOT5 are a little narrower or very close to those of TM, which enables the reasonability of bridging these two sensors via a degradation model. By generating the simulated TM images from the corresponding SPOT5 images, we can thus correlate the spatial high-frequency details of TM and SPOT5 bands via building a dictionary pair (which will be introduced in the following section).

Since the degradation factors in (1) are mainly determined by the sensor properties, we assume that the degradation model is the same for all bands, i.e., green, red, NIR, and SWIR of SPOT5 and TM. It should be noted that the radiometric difference between SPOT5 and TM images caused by the different settings of the sensors themselves is not considered in the designed degradation model because this difference will not affect their correspondence in spatial details. In this study, we choose the NIR band to build the degradation model. Due to the requirement of geometric correspondence during the fusion of TM and SPOT5, the geometric motion operator in (1) is omitted. For the sampling operator and noise in (1), we adopt a uniform sampling $S$ and the Gaussian noise $N$. For the blurring kernel herein, we assume that they are spatially varying considering the changing atmospheric conditions. Joshi et al. [32] proposed a blurring function estimation method, which first predicts a sharp version of a blur input image and then uses the two images to derive the blurring function. This method performs well for estimating small-scale blur with spatial variance. Recently, Sun et al. [33] proposed another edge-based blur kernel estimation approach by first learning some edge patch priors and then iteratively restoring the image gradients (in coarse-to-fine) by using the patch priors to coerce image primitives. Based on these two blur estimation methods, we propose a nonparametric approach to estimate the blurring kernels between TM and SPOT5 images for each local neighborhood (e.g., a $20 \times 20$ window). In the following paragraph, the procedure for determining the blurring kernels will be introduced.

Given a SPOT5 image scene and a TM image scene, we assume that they cover a smaller area and a larger area, respectively, with an overlapping area. Theoretically, these two images should be captured as close together in time as possible; however, this is not a strict requirement as long as there are proper unchanged regions between their capture dates. To determine the blurring kernels in (1), we first choose, by visual inspection, two regions of interest (ROI 1 and ROI 2) that have almost no land-cover type changes from the two input images.

### Table I: Bandwidth Comparison Between SPOT5 and TM

<table>
<thead>
<tr>
<th>Band name</th>
<th>Band-width of SPOT5 (nm)</th>
<th>Band-width of TM (nm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>green</td>
<td>500-590</td>
<td>520-600</td>
</tr>
<tr>
<td>red</td>
<td>610-680</td>
<td>630-690</td>
</tr>
<tr>
<td>NIR</td>
<td>780-890</td>
<td>760-900</td>
</tr>
<tr>
<td>SWIR</td>
<td>1,580-1,750</td>
<td>1,550-1,750</td>
</tr>
</tbody>
</table>
Subsequently, we derive the edge patch priors as in [33] from the SPOT5 ROIs with normalization. To simulate the spatially varying blurring kernels, we search for a set of latent edge priors for each patch of the local neighborhood and then solve a set of blur kernels in the whole TM image scene [32], [33]. To reduce the computation complexity, we merge blur kernels with small Gaussian distance (less than 10% of the average mean of all blurs). Corresponding with this set of blurring kernels, we derive a set of degradation models. In generating the simulated TM images for training from the corresponding SPOT5 images, we randomly apply the degradation model set to the whole image scene.

B. Dictionary-Pair Learning

The starting point of the dictionary-pair learning is the collection of LR and HR training samples. For the given SPOT5 study image, we first extract several subscenes with different land-cover types, such as vegetation, buildings, and roads, which are then used to generate the corresponding simulated TM (denoted as sTM in the following description) images via the degradation models described in Section III-A. The sTM images are then upsampled to the same size as the corresponding SPOT5 images for feature extraction. The HR image features are extracted by computing the difference images between each SPOT5 image band and the corresponding sTM image band. The reason for this step is the need to focus the training on characterizing the relationship between the LR images and the high-frequency details within the corresponding HR ones. As for the LR image features, they are generated by filtering each LR image with two high-pass filters, i.e., gradient and Laplacian. Subsequently, the LR and HR training samples can be extracted from the corresponding image features in patches (e.g., 7 × 7), which are then concatenated into vectors (for LR training samples, each one includes two filtered patches). We denote the collected HR and LR training samples as $X^{HR}$ and $X^{LR}$, respectively.

With the HR and LR training samples, the dictionary pair in one band (e.g., NIR band) can be learned. As introduced in Section II-C, the K-SVD dictionary learning method is more efficient than the alternative-updating one proposed in [13] by performing an SVD operation on residual data matrices and updating the dictionary atoms and coefficient vectors simultaneously. As demonstrated in [14], the dictionary-pair learning method based on K-SVD in a separate way (i.e., the LR dictionary is trained from LR samples and then predicts the HR dictionary by pseudo-inverse multiplication, as described in Section II-C) has better performance for image super-resolution in both accuracy and speed than the method of Yang et al. in [13]. However, this separate K-SVD method for dictionary-pair learning mainly depends on the information in the LR samples. A possible consequence of this approach is that the predicted HR dictionary cannot adequately represent the HR training samples, whereas the joint dictionary-pair learning strategy in [13] can avoid this problem by simultaneously training the LR and HR dictionaries on the concatenation of LR and HR samples. To make full use of the information in both LR and HR samples, we thus propose a joint K-SVD method for training the dictionary pair. Denoting the combined training samples as $X = [X^{HR}; X^{LR}]$, the K-SVD-based optimization function is

$$D^j = \arg \min_D \| X - D \alpha \|_2^2, \quad \| \alpha_i \|_0 \leq T, \ i = 1, 2, \ldots, M \quad (8)$$

where $T$ is a preset constant of the sparsity constraint, and $M$ is the number of training samples. Since the derived $D^j$ in (8) is a normalized matrix, we first get the dictionary atoms corresponding to $X^{LR}$ and then normalize it to obtain $D^{LR}$. With the same scaling coefficients in deriving $D^{LR}$, $D^{HR}$ is derived by scaling the dictionary atoms of $D^j$ corresponding to $X^{HR}$. The reason for using the same scaling coefficients in deriving $D^{LR}$ and $D^{HR}$ is to consider the norm difference between LR and HR samples.

Instead of stacking all the RGB bands together for training as in [27] to keep the spectral information, we implement the reconstruction in band-by-band format because of the maintaining of spectral information in TM bands. Since different bands in the spectrum are characterized by different levels of spatial structures, we learn one dictionary pair for each band (i.e., green, red, NIR, and SWIR, as shown in Table I). For TM blue and SWIR2 bands that are not covered by SPOT5, we super-resolve them by applying the learned dictionary pair for the green and SWIR bands, respectively, under the assumption that adjacent bands in the spectrum have a similar level of spatial structures.

C. Fusion Image Reconstruction

There are two application scenarios for the super-resolved TM images. The first one is multisensor image mosaicking [28]. With comparable bandwidths in green, red, NIR, and SWIR, as shown in Table I, the actual TM images with the four bands can be super-resolved to be those with comparable spatial resolution as SPOT5 images. The super-resolved TM images can then be mosaicked with SPOT5 images. In this application scenario, the input TM images should be preprocessed by orthorectification and radiometric cross-calibration [29]. In the second application scenario, the spectral information of TM MS images can be kept, and the spatial resolution of all bands can be enhanced. In this case, the aforementioned preprocessing steps in the first scenario are not necessary. However, for both scenarios, the input TM images are first interpolated as in the training phase before image reconstruction.

After image interpolation, the LR feature images can be extracted from each TM band image as in the training stage. We then collect the LR reconstruction set from the feature images, which is denoted as $Y^{LR}$. From (8), we know that the $D^{LR} - D^{HR}$ pair is trained by enforcing the LR and HR samples with the same representation coefficients. Thus, the corresponding HR feature patches can be reconstructed by predicting the representation coefficients of the LR reconstruction set. With the LR dictionary $D^{LR}$, the coefficients of $Y^{LR}$ can be solved via the OMP algorithm with the following optimization formula:

$$\alpha_i^{LR} = \arg \min_\alpha \| Y^{LR} - D^{LR} \alpha \|_2^2, \quad \text{s.t. } \| \alpha_i \|_0 \leq T_0. \quad (9)$$
Then, the HR feature image can be reconstructed by $Y_{HR} = D_{HR}A_{LR}$. According to the designing procedure of the HR feature image, the fused image can be predicted by adding the corresponding LR image to the predicted HR feature image.

IV. EXPERIMENTAL RESULTS AND COMPARISONS

A. Data Set Description

Here, we apply the proposed fusion method to the second application scenario, i.e., enhancing the spatial resolution of all TM bands. When the corresponding SPOT5 Pan image is available, this problem can also be solved via pansharpening methods. To qualitatively evaluate the fusion results and to compare with classic pansharpening algorithms, we chose a TM image and a SPOT5 MS image covering the same area of Hong Kong (including part of Shen Zhen), China. These two study images were captured on January 10, 2003 and November 8, 2002, respectively. Due to the climatic similarity in these two time periods and the stability of surface types in Hong Kong and Shen Zhen, the two chosen images are comparable in both radiometric and spatial information. The TM image is featured by six spectral bands within spectrum 0.45–2.35 μm (bands 1–5 and band 7) and a spatial resolution of 30 m, whereas the SPOT5 MS image includes four bands, i.e., green, red, NIR, and SWIR, with a spatial resolution of 10 m for the first three bands and 20 m for SWIR. Here, we only use the 10-m bands of SPOT5 for illustration. For the training purpose of our method, we chose five subscene images from the given SPOT5 image with sizes of approximately 500 × 500 to extract the training samples (assuming that they are prior images). In the reconstruction stage, we chose two subscenes with different land-cover types from both TM and SPOT5 images to examine the performance of the proposed method and the comparison methods. For our method, the SPOT5 images are utilized for qualitative evaluation, whereas for the comparison pansharpening methods, the SPOT5 images are also employed for approximating the Pan band.

B. Evaluation for the Proposed Degradation Model

To examine the proposed degradation model between the input TM and SPOT5 images, we chose two ROIs with sizes of 56 × 96 and 129 × 119, respectively, as shown in Fig. 2 with NIR–red–green as R–G–B composite. Fig. 2(a) and (d) shows the SPOT5 ROIs, whereas Fig. 2(b) and (e) shows the corresponding TM ROIs. By referring to the prior edge patches and solving for the blurring kernels for each 20 × 20 neighborhood of TM ROIs, the simulated TM ROIs generated from the SPOT5 ROIs are shown in Fig. 2(c) and (f), respectively. Compared with the actual TM ROIs in Fig. 2(b) and (e), we can observe that the simulated TM ROIs are very similar to the actual TM ROIs in spatial details, except for some radiometric differences caused by their capture time interval. To quantitatively evaluate this spatial similarity, we calculate the structural similarity index measure (SSIM) indexes between the actual and simulated TM ROIs. The value range of SSIM is [0, 1] with higher SSIM indicating more similarity in spatial structures between the input images, and vice versa. The SSIM results for ROI1 and ROI2 are 0.9235 and 0.9310, respectively, implying the rationality of the estimated degradation model.

C. Evaluation for the Proposed Joint K-SVD Method

To evaluate the effectiveness of the proposed joint K-SVD method in training the dictionary pair, we compare it with the dictionary-pair learning method in [14] (referred to as the separate K-SVD method in this section). For fair comparison, the parameters for both methods are set the same. Via empirical tuning, we set the patch size as $7 \times 7$ and the sparsity parameter as 3. Considering the balance between computation and reconstruction quality, the dictionary atom number is set to 1000. Then, we learn a dictionary pair for each band from the training samples via the joint K-SVD method (abbreviated as J-K-SVD) and the separate K-SVD method (abbreviated as S-K-SVD), separately. For quantitative evaluation purposes, we use a simulated TM image to examine the performance of these two methods at predicting the SPOT5-like images. For the subscene SPOT5 image shown in Fig. 3(a), we can derive the simulated TM image shown in Fig. 3(b). Via the proposed image reconstruction method, the fusion results from the S-K-SVD method and the J-K-SVD method are demonstrated in Fig. 3(c) and (d), respectively. Compared with the actual SPOT5 image in Fig. 3(a), we can observe that there are more spatial details in the fusion result of J-K-SVD than that of S-K-SVD. By comparing with the actual SPOT5 image, the quantitative evaluation results for these two fusion images in terms of peak signal-to-noise ratio, SSIM, the error relative global adimensionnelle de synthèse, and the spectral angle mapper are illustrated in Table II, from which we can conclude that the J-K-SVD method performs better than S-K-SVD at keeping both spectral and spatial information.
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D. Experiments With Actual TM Images

Here, we evaluate the performance of the proposed fusion method on super-resolving the actual all-band TM images (except band 6) by comparing with three representative pansharpening algorithms. The first one is the wavelet-transform-based (WTB) fusion method in [5], which was proposed to merge Landsat TM and SPOT panchromatic data. This WTB method includes two main steps: 1) The TM images are geometrically registered onto the SPOT Pan image and resampled to the same spatial size of SPOT Pan; and 2) the wavelet coefficients representing the spatial details of SPOT Pan are projected onto the TM image band by band after histogram matching. The second one is the generalized Laplacian pyramid with context-based decision (GLP-CBD) in [30], which relies on a model of the modulation transfer functions and the generalized Laplacian pyramid (GLP). As recommended in [30], the window size of GLP-CBD is set to 5. The third one is the sparse fusion of images for pansharpening (SparseFI) in [34], which directly constructs a coupled dictionary pair from the patches of the panchromatic image and its degraded version and then reconstructs the fused image by the sparse coding algorithm. We use the recommended parameters for SparseFI as [34] in our experiments. Even under different auxiliary conditions, i.e., the learned dictionary pair (from prior images) for the proposed method and the SPOT5 Pan band for the comparison algorithms, we compare them to demonstrate the superiority of the proposed method in keeping both spectral and spatial information for super-resolving all-band TM images. Due to the unavailability of the SPOT5 Pan image, we use the average of the SPOT5 MS bands in the visual spectrum (green, red, and NIR) to approximate the Pan band for the comparison methods.

For experimental purposes, we chose two TM images located at the Shen Zhen urban area and Hong Kong suburban area, respectively, as shown in Figs. 4(a) and 6(a) with NIR–red–green as R–G–B composite. The corresponding SPOT5 images are clipped at the same time for qualitatively evaluating the fusion results and acting as the high-spatial-resolution input data in the comparison methods, as shown in Figs. 4(g) and 6(g), respectively. During preprocessing, the TM and SPOT5 images are first orthorectified separately and then coregistered by manually selecting the ground control points. It should be noted that these geometric preprocessings cannot totally remove the geometric distortions caused by the acquisition system. We, thus, do not conduct the quantitative evaluation for the spatial details of the fusion results (see Fig. 5).

With the available SPOT5 Pan image for the comparison methods, the fusion results on the two actual TM images are shown in Figs. 4(b)–(e) and 6(b)–(e), respectively. To clearly inspect the spatial details of the fusion results, two zoomed-in blocks (a road network and a building set) corresponding to Fig. 4 are shown in Fig. 5, from which we can observe that the spatial details increased in all fusion results compared with the input TM images (the first column). WTB (the second column) has the worst performance in increasing the spatial details as well as keeping the spectral information. GLP-CBD (the third column) is better than WTB in increasing the spatial
Fig. 6. Illustration of fusion results on the second TM image with NIR–red–green as R–G–B composite. (a) Actual TM image. (b) Fusion result of WTB. (c) Fusion result of GLP-CBD. (d) Fusion result of SparseFI. (e) Fusion result of our method. (f) Actual SPOT5 image.

details but is also weak in keeping the spectral information. The reasons leading to their poor performance are the inherent geometrical distortion of sensors and the spectrum range of SPOT5 MS images not entirely consistent with that of TM images. SparseFI (the fourth column) and our method (the fifth column) improved a lot in keeping the spectral information over WTB and GLP-CBD; however, our method is the best in increasing the spatial details. To quantitatively evaluate the preservation of spectral information in the fusion results, we compute band by band the correlation coefficients (spectral CC) between the downsampled fusion results and the TM images. The spectral CC results on two study images are demonstrated in Table III, from which we can observe that our method is the best in preserving spectral information.

E. Classification Test on Fusion Images

To examine the benefits of fusion results on classification performance, we conduct classification on both images of before and after image fusion by adopting the unsupervised ISODATA classification method [31]. By setting the class number as 5 (including vegetation type 1, vegetation type 2, road/cement, building, and shadow/water), the classification maps on data of before fusion, i.e., the given TM and SPOT5 images, and after fusion are shown in Fig. 7. Comparing the maps on the given TM image [see Fig. 7(a)] and the SPOT5 image [see Fig. 7(b)], we can conclude that higher spatial resolution data obtain more meticulous classification results. The classification maps on the fusion results of WTB, GLP-CBD, SparseFI, and our method are shown in Fig. 7(c)–(f), respectively, from which we can observe that the noise is the most in the map of the WTB result. It should be noted that there are some land-cover type changes between the input TM and SPOT5 data [refer to Fig. 4(a) and (f)] due to their capture time interval, which leads to the differences between the classification maps of the fusion results and the SPOT5 data.

To further quantitatively evaluate the classification accuracy for the fused images, we selected ground truth samples for the five classes in Fig. 4(a) by visual inspection and by referring to the SPOT5 image in Fig. 4(f). The pixel numbers of selected

<table>
<thead>
<tr>
<th>ROI</th>
<th>method</th>
<th>B1</th>
<th>B2</th>
<th>B3</th>
<th>B4</th>
<th>B5</th>
<th>B7</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>WTB</td>
<td>0.86</td>
<td>0.88</td>
<td>0.91</td>
<td>0.87</td>
<td>0.91</td>
<td>0.91</td>
</tr>
<tr>
<td></td>
<td>GLP-CBD</td>
<td>0.92</td>
<td>0.91</td>
<td>0.92</td>
<td>0.86</td>
<td>0.89</td>
<td>0.89</td>
</tr>
<tr>
<td></td>
<td>SparseFI</td>
<td>0.92</td>
<td>0.92</td>
<td>0.93</td>
<td>0.92</td>
<td>0.89</td>
<td>0.90</td>
</tr>
<tr>
<td></td>
<td>Our method</td>
<td>0.93</td>
<td>0.94</td>
<td>0.95</td>
<td>0.94</td>
<td>0.92</td>
<td>0.92</td>
</tr>
<tr>
<td>2</td>
<td>WTB</td>
<td>0.80</td>
<td>0.84</td>
<td>0.90</td>
<td>0.89</td>
<td>0.91</td>
<td>0.91</td>
</tr>
<tr>
<td></td>
<td>GLP-CBD</td>
<td>0.95</td>
<td>0.95</td>
<td>0.95</td>
<td>0.88</td>
<td>0.93</td>
<td>0.94</td>
</tr>
<tr>
<td></td>
<td>SparseFI</td>
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<td>0.97</td>
<td>0.97</td>
<td>0.95</td>
<td>0.96</td>
<td>0.96</td>
</tr>
<tr>
<td></td>
<td>Our method</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
</tr>
</tbody>
</table>
TABLE IV
CLASSIFICATION ACCURACY RESULTS ON THE FUSION RESULTS AND THE SPOT5 IMAGE

<table>
<thead>
<tr>
<th>Classification map</th>
<th>Overall accuracy (%)</th>
<th>Kappa coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>WTB</td>
<td>73.0</td>
<td>0.663</td>
</tr>
<tr>
<td>GLP-CBD</td>
<td>82.3</td>
<td>0.778</td>
</tr>
<tr>
<td>SparseFI</td>
<td>83.1</td>
<td>0.788</td>
</tr>
<tr>
<td>Our method</td>
<td>85.0</td>
<td>0.812</td>
</tr>
<tr>
<td>SPOT5</td>
<td>87.8</td>
<td>0.847</td>
</tr>
</tbody>
</table>

samples for vegetation type 1, vegetation type 2, road/element, building, and shadow/water are 200, 100, 180, 150, and 150, respectively. To compare the classification performance on the SPOT5 data, we calculate the overall classification accuracy and the Kappa coefficient on the classification maps of the WTB fusion result, the GLP-CBD fusion result, the SparseFI fusion result, our method fusion result, and the SPOT5 image by comparing with ground truth on selected pixel locations. The accuracy assessment results are shown in Table IV. The poor performance on the WTB fusion result and GLP-CBD result may ascribe to spectral distortion. The overall accuracy and kappa coefficient on the fusion result of our method demonstrate that the proposed fusion method has great potential to approximate the actual SPOT5 image for classification tasks. This is particularly beneficial for cases when the SPOT5 images are not available on the study area.

V. CONCLUSION

This paper has presented a new image fusion method of combining the best properties of Landsat TM/ETM+ and SPOT5 HRG sensors, i.e., the swath width and spectral properties of TM/ETM+ and the spatial resolution of SPOT5 MS. Before image fusion, we first build an image degradation model from SPOT5 to TM in their corresponding bands by utilizing the available TM and SPOT5 image pairs. With the degradation model, the simulated TM images can be generated from given SPOT5 images, which are then utilized to train a dictionary pair representing the spatial high-frequency details of HR and LR images, respectively. In the image reconstruction stage, the actual TM images can be super-resolved via the dictionary pair and the sparse coding algorithm. Since neighboring bands are characterized by a similar level of spatial structures, we can super-resolve TM bands that are not covered by SPOT5 data via the learned dictionary pairs in other corresponding bands, which, thus, incorporates the classic spatial and spectral fusion of TM and SPOT data into the proposed fusion framework. The fusion results on actual TM images demonstrate that the proposed method is superior to the classic fusion methods at keeping both the spectral information of TM data and the spatial details of SPOT5 data. Further classification experiments illustrate that the proposed fusion method has great potential for high-level applications.

The main contributions of this paper are as follows: 1) Instead of directly learning a dictionary pair from the given SPOT5 and TM images, we first build an image degradation model and then train the dictionaries on the SPOT5 and simulated TM images; and 2) we propose a new dictionary-pair learning method by combining the joint strategy and the efficient K-SVD algorithm. The former provides an effective way of avoiding fine registration between two categories of sensor data, and the latter promotes the development of dictionary-pair learning in the image super-resolution field. Apart from these techniques, the main contribution of this paper is that we propose to improve the spatial resolution of TM data when the corresponding high-resolution SPOT5 data are not available, which, thus, will simultaneously improve the spatial resolution of TM data and extend the spatial extent (or swath width) of SPOT5 data. The key issue of the proposed fusion method is that the degradation model between the two study sensors should be as accurate as possible, which is achievable by building a spatially varying blurring kernel in the degradation formula. Furthermore, there is still room in the proposed method for improving the spatial details of TM images, which can be observed from the experimental results on both fusion and classification.

REFERENCES
