In this paper we combined the projection–substitution with ARSIS (French acronym for “Amélioration de la Résolution Spatiale par Injection de Structures”, i.e., Improving Spatial Resolution by Structure Injection) concept assumption for fusion of panchromatic (PAN) and multispectral (MS) images. Firstly support value filter (SVF) is used to establish a new multiscale model (MSM), support vector transform (SVT), and adaptive principal component analysis (APCA) is then employed to select the principal components of MS images by means of a statistical measure of the correlation between MS and PAN images; secondly, a local approach is used to check whether a structure should appear in the new principal component and PAN high frequency structures are transformed by high resolution interband structure model (HRIBSM) before inserting in the MS modalities. Because SVT is an undecimated, dyadic and aliasing transform with shift-invariant property, the fused image can avoid ringing effects suffered from sampling. Additionally, the ARSIS concept can make full use of the remote sensing physics to reduce the spatial and spectrum distortion in the structure injection. Texture extraction is also employed to avoid the spectral distortion caused by the mistaken injection of low-pass components into the MS images. Experimental results including visual and numerical evaluation also proves the superiority of the proposed method to its counterparts.

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1. Introduction

The fusion of low resolution multispectral (MS) and high resolution panchromatic (PAN) images is a useful technique for enhancing the spatial quality of MS images [1]. A variety of image-fusion techniques have been devoted to merge MS and PAN images which exhibit complementary characteristics of spatial and spectral resolutions. These classical methods can be classified into three categories: statistical technique based methods, mathematical technique based methods and intensity based methods. The statistical technique based approaches convert inter-correlated multispectral bands into a new set of uncorrelated components by statistical tools such as principal components analysis (PCA), and the higher resolution image is used to replace the calculated principal component [4]. The mathematical technique based fusion methods are based on the mathematical combination of the multispectral images and high resolution PAN image such as Brovey method [2]. Its basic idea is that each normalized multispectral image is multiplied by the PAN image to add the spatial information to the fused image. The third category modify the PAN image to look more like the intensity component, with replacing the high frequency part of the intensity component with that from the PAN image [3,4]. Some variation of these classical fusion methods are also discussed, for example, Tu et al. [5] presented a fast IHS fusion approach with spectral adjustment for IKONOS data, later Choi [6] introduced a tradeoff parameter in fast HIS, and Alparone [7] proposed a generalized intensity modulation way by setting a threshold to modulate the intensity component. In recent years, there is an increasing of interests in this field [8–13], for example, Wang et al. [8] proposed a comprehensive framework for general fusion of MS and PAN images; Fasbender [9] suggested an approach within a Bayesian framework; Otazu et al. [10] considered the physical electromagnetic spectrum responses of sensors during the fusion process for better fusion result; Garzelli et al. [11] proposed an optimum algorithm in the minimum mean-square-error (MMSE) sense, whose solution can minimize the squared error between the MS images and the fusion result obtained by spatially enhancing a degraded version of the MS images.

For the fusion of PAN and MS images, a general framework is to sharpen low resolution MS image by injecting high-pass details taken from the higher resolution PAN image [14,15], namely, projection–substitution approach. Some multiresolution analysis tools like wavelets [16–18] and pyramids [19] have been used to reduce
spectral distortion. Recently developed multiscale geometric analysis (MGA) tools are also considered to improve the performance of fusion, for example, Choi et al. [20] applied Curvelet transform to enhance the spatial resolution of the fused image since Curvelet can represent edges better than wavelets; Shah [21] presented a combined adaptive PCA–Contourlet approach for PAN-sharpening, which uses nonsubsampled Contourlets for spatial transformation to capture intrinsic geometrical structures of the objects efficiently.

The main strength of projection–substitution approach lies in good consistency of PAN and MS images. However, high frequencies extracted from the PAN representation and those of an MS image are not exactly equivalent. The higher the correlation between PAN and each MS modality, the better performance of projection–substitution methods can be obtained. When images are poorly correlated, projection–substitution will be inefficient. In recent years, in the fusion community more and more attentions are being paid on the remote sensing physics, which should be carefully considered while designing the fusion process [30–32]. The ARSIS (French acronym for “Amélioration de la Résolution Spatiale par Injection de Structures”, i.e., Improving Spatial Resolution by Structure Injection) concept, whose fundamental assumption is that the missing spatial information in MS modalities can be inferred from the high frequencies, permits to synthesize the MS image at the resolution of PAN image that is as close as possible to reality. To synthesize MS images close to those that would have been collected by the corresponding sensor if it had the high spatial resolution, we applied transformation of PAN high frequency structures to adjust these details to the MS representation before inserting in the MS modalities, which is called the high resolution interband structure model (HRIBSM). In the ARSIS frame, a multiscale model (MSM) represented by a pyramidal structure is firstly applied on PAN and MS images to obtain a scale-by-scale description of the information content of PAN and MS images.

In the case of high frequency or high frequency structure injection, spatial distortions, typically ringing or aliasing effects, originating shifts or blur of contours and textures may occur, especially when the MSM underlying detail injection is not shift-invariant. Paper [32] indicated that provided the choice of an efficient MSM avoiding aliasing, the consistency property is checked, and the spectral distortion will be limited in the projection–substitution. Although the multiresolution, localization, critical sampling, and limited directionality (horizontal, vertical, and diagonal directions) properties have made wavelets a popular MSM [16–18], wavelets fail to capture the smoothness along the contours. Additionally with the increase of the decomposed level of MSM, the extracted high frequency component of PAN image may contain both the textures and low-frequency smooth regions, which will distort the spectrum of the fused image.

Nowadays the machine learning techniques have brought abundant outcomes for image processing. Support value transform (SVT) uses the mapped least squares support vector machine (LS-SVM [23,29]) to efficiently calculate the support values of images, which represent the importance related to the visual result of images. Considering the aliasing, isotropic and shift-invariant properties of SVT, in this paper we presented a SVT and adaptive principal component analysis (APCA) based fusion method under the concept of ARSIS, and a texture extraction scheme from high frequency spatial component is proposed to reduce the spectral and spatial distortions. Firstly APCA is used to extract the principal component (PC) of MS image on which SVT is performed to extract the spatial detail information; then the texture information of PAN image are extracted and is subtracted from PC; thirdly the texture information of PAN image is transformed by HRIBSM, in which AABP (Alazziz, Alparone, Baronti and Pippin) model is employed to establish a local relationship between the detail of PAN and MS images. Finally an injection is made and an inverse PCA is performed to obtain the fused image. Some experiments are performed on comparing the new algorithm with some other existing fusion methods. The experimental results show that the proposed fusion algorithm is effective and can provide a better performance than some available approaches.

The remainder of this paper is organized as follows. Section 2 introduces the SVT based ARSIS fusion approach for fusion of MS and PAN images, a mathematical of SVT is depicted in detail firstly, and then a new fusion approach based on APCA and texture extraction followed by AABP is proposed. In Section 3, some experiments will be conducted and their results together with relevant discussions will be reported. The conclusions are finally summarized in Section 4.

2. SVT and APCA based fusion of MS and PAN images

High correlation among the spectral bands has made PCA popular in the MS and PAN images fusion. PCA has been used for spectral transformation because the first principal component (PC1) consists of the most variance, making it a suitable choice to replace the PAN component. However, this method will provide spectral artifacts for injecting the low-frequency component of PC1 to PAN images. To overcome this problem, Gonzalez-Audicana et al. proposed a PAN-sharpening method based on a wavelet–PCA merger where only the details of PC1 are replaced by the details of the PAN image [18]. However, it is not based on any statistics between PAN image and the PC1 of MS image. A higher variance of PC1 does not necessarily mean that it has higher correlation with the PAN image. Thus an APCA based method can be employed to improve the fusion result by adaptively selecting the component for the substitution or injection of high spatial details [24], which is adopted in our method. Taking the dependency between the PCs of MS images and PAN image into consideration, a statistical measure, based on the cross-correlation coefficient, is incorporated into the process to adaptively determine the appropriate PC components that is to be injected with detail information. SVT makes avail of the approximation capability of LS-SVM to represent an image, and proves to present better outcome than other approaches in the fusion of optical and remote sensing images [22,23,29]. Therefore, we use a SVT based MSM inspired by machine learning to overcome the limitation of the wavelets in capturing salient geometric structures of the objects, and the ringing or aliasing effects brought by downsampling.

2.1. Support value transform (SVT)

Firstly we discuss the construction of the support value transform. Given the training data \( \{(x_i, y_i)\}_{i=1}^{N} \) with \( x_i \in \mathbb{R}^2 \), \( y_i \in \mathbb{R} \) denotes the positions and the corresponding pixel of the ith sample. Assume that the relationship between \( x_i \) and \( y_i \) is described by the function \( f \), i.e., \( y_i = f(x_i) \), we can provide an approximation of images using \( f \):

\[
f(x) = \sum_{i=1}^{N} \alpha_i K(x, x_i) + b,
\]

where \( \alpha_i \) is the support value of \( x_i \) and the kernel function

\[
K(x, x_i) = \Phi(x)^T \Phi(x_i), \quad i = 1, \ldots, N
\]

satisfies the Mercer’s condition with nonlinear mapping \( \Phi(\cdot) \). Under the frame of LS-SVM, we can write the conditions for optimality as the solution to the following set of linear equations

\[
\begin{bmatrix}
0 & \bar{I}^T & b \\
\bar{I} & \Omega & \alpha \\
\end{bmatrix}
\begin{bmatrix}
0 \\
Y \\
\end{bmatrix}
= \begin{bmatrix}
0 \\
Y \\
\end{bmatrix}
\]

(3)
where $\Omega = K + I/\gamma; K_q = K(x_i, x_j), Y = [y_1, \ldots, y_N]^T, \alpha = [\alpha_1, \ldots, \alpha_N]^T$. If Gaussian kernel function is considered with the form of

$$K_{ij} = K(x_i, x_j) = \exp \left( -\frac{||x_i - x_j||^2}{2\sigma^2} \right) \quad (4)$$

The support value analysis is developed by designing a series of multiscale support value filters, which are obtained by filling zeros in the basic support value filter (SVF) deduced from the above mapped LS-SVM to match the resolution of the desired level. The SVF is deduced by the approximation of the mapped LS-SVM of images, and the SVT is performed based on these SVFs and ‘àtrous’ algorithm. The determination of SVF can be described as follows.

1. Given the parameter $\gamma$ of LS-SVM and the spread parameter $\sigma$ of Gaussian RBF kernel $K(x_i, x_j)$, and the input vectors are denoted as $[x_i, i = 1, \ldots, N]$;
2. Calculate the matrix $\Omega_{ij} = K_{ij} + I_{ij}/\gamma = K(x_i, x_j) + I_{ij}/\gamma \quad i, j = 1, \ldots, N \quad (5)$
3. Calculate the matrices $A, B$ and the $N \times N$ matrix $Q$ as follows,

$$A = \Omega^{-1}, B^2 = \frac{\Omega^{-1}}{\Omega^{-1} + I} \quad (6)$$

$$Q = A(I - \Omega B^2) \quad (7)$$
4. Extract the central row vectors of matrix $Q$ and reshape it into a weight kernel, then the support value filter can be obtained. Eq. (8) shows a support value filter when the size of the mapped vector space is set to be $5 \times 5$ pixels, the spread parameter in Gaussian RBF kernel $\sigma$ is set to be 0.3 and $\gamma$ set to be 1.

$$[-0.0158 \ -0.0136 \ -0.0102 \ -0.0136 \ -0.0158]$$
$$[-0.0136 \ -0.0130 \ -0.0602 \ -0.0130 \ -0.0136]$$
$$[-0.0102 \ -0.0602 \ -0.5051 \ -0.0602 \ -0.0102]$$
$$[-0.0136 \ -0.0130 \ -0.0602 \ -0.0130 \ -0.0136]$$
$$[-0.0158 \ -0.0136 \ -0.0102 \ -0.0136 \ -0.0158] \quad (8)$$

Given an original image $P$, a series of support value $\{S_1, S_2, \ldots, S_r\}$ could be obtained using the formula (9) by using the parallelepiped framework and “àtrous” algorithm. The support values $S_j$ of the original image is.

$$S_j = SV_j + P_j \quad (9)$$

$$P_{j+1} = P_j - S_j, \quad j = 1, \ldots, r; \quad P_1 = P \quad (10)$$

Denote the decomposition level as $r$, the approximation image is the sum of the support values and the residual image.

$$P = P_{r+1} = \sum_{j=1}^{r} S_j \quad (11)$$

2.2. SVT and APCA based fusion scheme

In our scheme, firstly PCA is applied on the normalized MS images (normalized to zero mean) to extract its first component; secondly, because the similarity between images can be measured by the correlation coefficient [35], we calculate the cross-correlation coefficient (CC) between the decomposed PCs and the PAN image, then the PC having the highest absolute CC value is selected. The value of the coefficient varies from $-1$ to $1$, with a value close to 1 indicating a strong similarity between two images, whereas a value of $-1$ represents images not only with dissimilarity but also signifies that there is a strong inverse relationship between these two images. For a given two $M \times N$ pixels images, the CC is given by [25] as follows:

$$\text{Corr}(A, B) = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} (A_{ij} - \bar{A})(B_{ij} - \bar{B})}{\sqrt{\sum_{i=1}^{M} \sum_{j=1}^{N} (A_{ij} - \bar{A})^2 \sum_{i=1}^{M} \sum_{j=1}^{N} (B_{ij} - \bar{B})^2}} \quad (12)$$

It should be noted that if CC value is negative, we need to inverse the PAN image before performing histogram matching; thirdly, the PAN image is histogram-matched with the selected principal component (SPC), and the histogram-matched PAN image and the SPC of MS images are both decomposed by SVT. When the high frequency component of the PAN image and the SPC of MS images are obtained, a smooth filtering is employed to obtain the spatial high frequency smooth component textures; fourthly, the high frequency information of the histogram-matched PAN image is transformed by AABP and used to update the SPC of MS images; finally an inverse PCA is used to obtain the fused image, as shown in Fig. 1.

The procedure of SVT and APCA scheme can be described as below:

Procedure:

Step 1: Perform PCA on the normalized MS images to get $PC^1, PC^2, \ldots, PC^N$.

Step 2: Calculate the CCs between the PCs and the PAN image, then select the PC having the highest absolute CC value.

Step 3: Perform histogram matching of the selected PC (SPC) with the PAN image.

Step 4: Perform SVT on the SPC and the histogram-matched PAN image, and extract their spatial high frequency components $dSPC$ and $dPAN$.

Step 5: Use a $5 \times 5$ smooth filter window to obtain the high frequency smooth components $sdSPC$ and $sdPAN$ for $dSPC$ and $dPAN$.

Step 6: Calculate the high frequency texture components $tdSPC$ and $tdPAN$ using the formula (13),

$$tdSPC = dSPC/sdSPC - 1; \quad tdPAN = dPAN/sdPAN - 1 \quad (13)$$

Fig. 1. The flowchart of our proposed method based on SVT, adaptive PCA and texture extraction.
3. Simulations

In this section, we give several illustrative examples to demonstrate the effectiveness of our proposed method by taking the example of the 512 × 512 QuickBird image shown in Fig. 2. The MS image of QuickBird data has four bands: blue band (450–520 nm), green band (520–600 nm), red band (630–690 nm) and near infrared (NIR) band (760–900 nm), the resolution of MS is 2.44 m. The resolution of PAN image (450–900 nm) is 0.61 m. The simulations are conducted in MATLAB R2006 on PC with Intel Core2/1.8G/1G. For evaluating the performance of the proposed approach, some experiments are designed and the computed results are compared by visual quality subjectively and by some guidelines in PAN and MS images fusion.

3.1. Experiment 1: advantages of SVT over UWT in high-pass detail injection

Firstly we compare the outcome of the two MSM, SVT and UWT used in paper [18]. The decomposed components of the PAN and principal component of MS images at different scale are shown in Fig. 3. For the PAN image shown in Figs. 2a and 3a–j show the extracted high frequency components decomposed by five level SVT and UWT respectively, where a–e are the obtained multiscale components by UWT and f–j show the obtained support value images by SVT. The same operations are performed on the first component of the MS image in Fig. 2b, and the extracted components are compared and their differences with that of the PAN image are calculated, the results are shown in Fig. 3k–l. From the result of UWT shown in Fig. 3k–o we can see a remarkable nonzero difference, which will distort the spectrum of the fusion image. Fig. 3p–t show the result of SVT, from which we can see that the differences are smaller than that of UWT, which will decrease the spectrum distortion of the fused image.

We compare the extracted high-pass details of our method and SVT, and Fig. 4 shows the obtained texture of our method (a) and UWT (b). To observe a clear visual result, the pixels of the two images are amplified fivefold. It can be seen that Fig. 4b contains some smooth component, while only texture component are existed in Fig. 4a.

3.2. Experiment 2: advantages of our proposed method over IHS, PCA and UWT

In this experiment IHS, PCA and the Gonzalez-Audicana’s improved UWT mergers [18] are compared with our proposed fusion approach. In SVT, σ = 0.3, γ = 1, n = m = 5. We set the decomposition level of UWT as 2, which proves to present the optimal result in paper [18]. The decomposition level of SVT is set as 5. In this experiment the HRIBSM does not used in our scheme (that is, the step 5 is omitted). The fused images are shown in Fig. 5, where Fig. 5a–d are the fused result of IHS, PCA, Gonzalez-Audicana’s approach and our method respectively, and Fig. 5e–l are the corresponding amplified version of one local region in Fig. 5a–d. As to visual result, we can see that there are some remarkable spectrum distortions in IHS and PCA based method, but UWT and our proposed method can achieve higher spatial resolution, moreover, less spectral distortion than the UWT method can be observed in the fused image. The visual differences are very small, so we amplified some local regions in the second line and third line in Fig. 5. In the third line, two regions indicated by white and red blocks are compared, and we can see that in the white block, our method presents clearer shapes and contours than that of UWT, and in the red block more vegetable textures can be observed.

The spatial correlation coefficient (SCC) [33], RASE (relative average spectral error index) [33], universal image quality index (UIQI) [26] total image quality index (Q4) [34] and average gradient (AG) [33] are often used to estimate the fusion result of remote sensing images. UIQI combined the spatial correlation, wrap of mean and variance together, and it can embody the comparability between the fused image and MS images. It is defined as:

\[
\text{Step 7: Update the tdSPC using the AABP model to establish HRIBSM under the ARSIS assumption,}
\]

\[
\text{tdSPC} = \alpha \times \text{tdPAN}
\]

where \( \alpha \) is determined by

\[
\alpha = \min \left\{ \frac{\sigma_{\text{tdSPC}}}{\sigma_{\text{tdPAN}}}^{3} \right\} \quad \text{if } \rho_{c} > 0
\]

\[
0 \quad \text{if } \rho_{c} < \theta
\]

Here \( \sigma_{\text{tdSPC}} \), \( \sigma_{\text{tdPAN}} \) are the standard deviations of \( \text{tdSPC} \) and \( \text{tdPAN} \) respectively; \( \rho_{c} \) is the linear correlation coefficient of Pearson for the sliding window (in this paper 7 × 7 window is adopted); \( \theta \) is a constant threshold ranging in 0.2–0.5.

\[
\text{Step 8: Calculate the new component using the formula (16).}
\]

\[
\text{SPC} = \text{SPC} - \text{tdSPC} + \text{tdPAN}
\]

\[
\text{Step 9: Use the new SPC and other PCs to perform an inverse PCA to get the fused image } f.
\]
\[ Q = \frac{\sigma_{AB}}{\sigma_A \sigma_B} \frac{2|\mu_A \cdot |\mu_B|}{\mu_A^2 + \mu_B^2} \frac{2\sigma_A \sigma_B}{\sigma_A^2 + \sigma_B^2} \]  

where \( \sigma_{AB} \) is the covariance of the fused source images \( A \) and \( B \), \( \sigma_x \) and \( \mu_x \) are the standard variance and the mean of the image \( x \).
respectively. UIQI is very suitable for estimate the subjective vision effect.

$Q_4$ is a new quality index of spectral image which refers to the global quality of spectral resolution. Here we use it to estimate the reservation of spectral information. Firstly the images are divided into $N \times N$ subblocks, and $Q_4$ is calculated using the formula (19).

$$Q_4 = \frac{E[|x \cdot y'| - \bar{x} \cdot \bar{y}|]}{E[|x|^2 + E[|y|^2] - |y|^2]}$$

where $x, y$ are both quaternions (for example, for the element $v$ of $x, v = [v_0 + jv_1 + jv_2 + kv_3]$, $y'$ represent complex conjugate, $\bar{x}$ is the mean of quaternion $x$ and $|| \cdot ||$ represent module. Besides these indexed, the average gradients is also estimated, which can reflect the clarity of images.

$$\bar{g} = \frac{1}{(M-1)(N-1)} \sum_{i=1}^{M-1} \sum_{j=1}^{N-1} \sqrt{\left( \frac{\partial f(x_i, y_i)}{\partial x_i} \right)^2 + \left( \frac{\partial f(x_i, y)}{\partial y_i} \right)^2 / 2}$$

The statistical results about the three indexes of the fused images are shown in Table 1.

The conditions of our method are the same with that of experiment 1. We also compare our result with a nonsubsampled contourlet transform (NSCT) based method in paper [21] (without texture extraction when compared with our method), a non-adaptive PCA version of our method (that is, the first principal component is selected) and Gram-Schmidt (GS) spectral sharpening method [27]. In the PDFB implementation of NSCT, the LP filter is ‘db3’ and NSDFB is ‘9–7’ type; the decomposition level of LP is also five. From the table we can see that our proposed method outperformed the PCA, GS and UWT based methods about the UIQI, $Q_4$ and AG. For our method, the adaptive PCA outperformed the non-adaptive method for Blue and NI Bands, but obtained the same result in the other two bands, which means the first principal component is selected. On the other hand, NSCT based method performed best about the UIQI in the red band and IHS performed best about the AG in the NI band. However, the average result of our proposed method is better than that of IHS, PCA, UWT and NSCT based fusion schemes.

3.3. Experiment 3: fusion scheme based on ARSIS concept consumption

In the experiment 2, we have examined the result of SVT and adaptive PCA about the visual result and global quality of spectral resolution. In this experiment, we introduced the HRIBSM in the fusion to transform the PAN high frequency structures before inserting in the MS modalities. Because the ARSIS concept can
make full use of the remote sensing physics to reduce the spatial and spectrum distortion in the structure injection, the quality indexes about the distortion, such as Bias, CC, RMSE, VRMSE, ERGAS and SAM are used to estimate the result of our proposed method. The RMSE \( \sqrt{\text{MSE}} \) is calculated to help analyzing the spectra of the different clusters. Vectorial Root Mean Square Error (VRMSE) is an index that measures the overall radiometric distortion. ERGAS (from the French “Erreur Relative Globale Adimensionnelle de Synthèse”) is a global criteria computed with the standard deviation taken into account the number of bands and the ratio of the PAN and MS resolutions, which means relative dimensionless global error in synthesis. Spectral angle mapper (SAM) denotes the absolute value of the spectral angle between two vectors. SAM equal to zero denote absence of spectral distortion.

In this experiment, SVT are firstly applied onto these images to obtain a scale-by-scale description of the information content of PAN image and MS images, generally represented by a pyramidal structure. Then the ARSIS concept consumption is used and the ARSIS concept assumption. As a redundant, aliasing and shift-invariant model of Aiazzi, Alparone, Baronti and Pippi (AABP) is used to establish HRIBSM in the fusion. Table 2 reports some average and global indexes calculated for the images at reduced resolution [28], with the bold number indicating the superiority of SVT–APCA–ARSIS to the other methods.

The proposed fusion methods also show better performances with slight differences among each other. For all six indices, the proposed methods attain scores better than those of the other methods, followed by SVT–APCA, SVT–PCA, NSCT, UWT and GS.

4. Conclusions

Combining projection–substitution with the ARSIS concept assumption for fusion of panchromatic (PAN) and multispectral (MS) images is gaining popularity because it can improve the spatial resolution by structure injection. The ARSIS concept permits to synthesize the principal component of MS image at the resolution of PAN image that is as close as possible to reality. It is based on the assumption that the missing information is linked to the high frequencies in the PAN and MS images. An accurate high-pass component injecting is important because the low frequency information is useless for improving the spatial clarity of fused images. In this paper, a new method of PAN-sharpening based on the merger of the APCA, SVT and textures extraction is proposed under ARSIS concept assumption. As a redundant, aliasing and shift-invariant MSM, SVT can effectively represent the salient feature of images and extract the detail information of images more efficiently, at the same time avoiding the ringing effects. So it is used as a MSM to obtain the hierarchical decomposition of source images under the ARSIS concept. Moreover, the obtained difference of high frequency information between the PAN images and the principal component of MS image is smaller than that of UWT, which can reduce the distortion in the fusion. On the other hand, in our method we only inject the texture information of the PAN image into the MS images, which can preserve the spectral information of MS images well and improve the clarity of the fused images. Some experiments are taken on comparing our proposed method with a number of fusion method sws, and the results demonstrate that SVT can decrease the spectrum distortion of the fused image when compared with other multiscale tools. By adaptively selecting the component for the substitution or injection of high spatial details, we can improve the global quality of the fusion result. Moreover, the ARSIS concept consumption also helps to reduce the spectral and radiometric distortion.

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