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Pansharpening of multispectral images using the nonseparable framelet lifting transform with high vanishing moments

Yan Shi [a], Xiaoyuan Yang [b,*], Ting Cheng [b]

[a] State Key Laboratory of Software Development Environment, Beihang University, Beijing 100191, China
[b] Key Laboratory of Mathematics, Informatics, and Behavioral Semantics, Ministry of Education, Department of Mathematics and Systems Science, Beihang University, Beijing 100191, China

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ABSTRACT

This paper proposes a novel nonseparable lifting scheme for wavelet frames with high vanishing moments. A specific nonseparable framelet lifting transform (NFLT), combined with a modified covariance intersection (CI) algorithm, has been applied to pansharpening of multispectral images. Experiments are carried out on the multispectral and panchromatic images acquired by the SPOT, QuickBird and Landsat spaceborne sensors. Benefiting from the high order of vanishing moments, the proposed NFLT can distinguish the low- and high-frequency efficiently and can compact most of the energy into the low-pass subband. Thus the spectral distortion can be minimized. Experimental results show that the NFLT-CI method reduces the spectral distortion while improves the spatial resolution simultaneously, and outperforms the other state-of-the-art methods derived from various transforms and injection models.

1. Introduction

Remote sensing images usually have limitations in either spectral or spatial resolution. On one hand, the panchromatic (PAN) images, captured by wide-band sensors, provide a high-resolution quality but lack of essential spectral information. On the other hand, the multispectral (MS) images, obtained by various narrow-band sensors, possess specific spectral information but have a poor quality in spatial resolution. For this reason, it is desirable to increase the spatial resolution of MS images by using the spatial information of PAN images while retaining the fidelity of spectral information as much as possible. This process is called pansharpening [1].

Over the last two decades, a number of pansharpening techniques have been proposed. Component-substitution-based (CS) approaches such as intensity hue saturation (IHS) [2,3] have been widely used due to the fast implementation and high sharpening ability. Since the intensity component I of MS image is substituted with the PAN image, it may yield large spectral distortion even if the PAN is histogram-matched to I [1]. Other CS-based methods such as principle component analysis (PCA) [4] and Gram–Schmidt (GS) [5] suffer from the same problem. Although a variety of modified algorithms [1,6–8] have been proposed to compensate for such distortion, the limitation of CS-based methods does not be fully overcame.

Recently a variety of methods based on multiresolution analysis (MRA) have demonstrated a superior capability of injecting high-frequency components from PAN image into MS low-frequency subband with low spectral distortion. Among them the widely recognized approximation tools are "à trous" wavelet transform [9,10], generalized Laplacian pyramid [11], as well as the anisotropic frame-based transforms such as curvelet [12,13] and nonsubsampled contourlet [14,15]. As the MRA-based multiscale transform can efficiently decompose the image into high-pass (HP) and low-pass (LP) subbands, not only does it have an advantage on minimizing the spectral distortion, but it also provides a flexibility to define how the HP coefficients of PAN are injected into the LP subband of MS. Initial works [4,9] suggested directly inserting the HP coefficients into the LP subband of MS. However many methods using the ARSIS concept [16,17] adjust the coefficients based on specified models [11,18–20]. Usually these models feature in adaptive injection of information according to the local correlation between PAN and MS images, and outperform the directly injecting method [1].

The vanishing moment, as an essential characteristic of wavelets, stands for the ability of representing polynomials or information of signals [21]. Explicitly, if the wavelet has vanishing moments of order N, then the polynomials of degree up to N convolved with the wavelet will vanish to be zero, that is

* Corresponding author. Tel.: +86 13910906994.
E-mail addresses: shiyan200245@163.com (Y. Shi), xiaoyuanyang@vip.163.com (X. Yang), xiaochengting0425@126.com (T. Cheng).

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$$\int x^p\psi(x)\mathrm{d}x = 0, \quad \text{for } |p| < N.$$

As many image processing tasks [22,23] indicate, a high number of vanishing moments is preferred since it can compress the regular parts of the signal thus leading to a sparse representation. However few works in the literature have considered the vanishing moments' effect on the fusion. This motivates us to develop a new MRA-based approximation tool with high vanishing moments.

In this paper, we aim to provide a specific nonseparable framelet lifting transform (NFLT) derived from the lifting scheme for wavelet frames. The 1-D lifting factorization of wavelet frames has been explicitly discussed in our previous works [24–26]. The method of increasing the order of vanishing moments for univariate wavelets has been demonstrated, which involves Laurent polynomial factorization. For higher dimensions, however, factoring a multivariate polynomial is nontrivial and it becomes increasingly cumbersome. Therefore the scaled version of Neville filters, which is a generalization of the original [21], is introduced for constructing wavelet frames with vanishing moments of desirable orders. In addition, a modified algorithm based on the covariance intersection (CI) [27] is proposed for merging the coefficients. CI is originally derived from Kalman filters [27] and recently it has been applied to image fusion [28,29]. It provides a consistent estimate when the cross-correlations between multi-sources are unknown. Since the NFLT possesses high vanishing moments, most of the essential information of MS is compacted into the LP subband while the HP subbands refer to the highly irregular information such as edges and textures. It can be expected that the NFLT-based fusion reduces the spectral distortion while improves the spatial resolution of MS simultaneously. To sum up, the contribution of this paper has three aspects:

- A novel nonseparable framelet lifting transform with high vanishing moments aiming at compacting the MS spectral information.
- A scaled version of Neville filters as generalizations of the traditional ones.
- A modified CI algorithm suitable for merging intra-band HP coefficients.

This paper is organized as follows. In Section 2, we recall some notations and basics which will be used hereafter. In Section 3, the scaled Neville filter as well as its properties are proposed. Section 4 is the main contribution of this paper, where the lifting scheme for wavelet frames with preserved vanishing moments are presented, followed by a specific NFLT. In Section 5, the effect of increasing vanishing moments on keeping spectral information is first discussed. Then the proposed NFLT is applied to PAN and MS image fusion. Experimental results and comparison with other state-of-the-art methods are shown. Finally Section 6 is the conclusion.

2. Preliminaries

2.1. Notations

A multidimensional signal $x = \{x(\boldsymbol{k}), \boldsymbol{k} \in \mathbb{Z}^d\}$ convolved with a finite impulse response (FIR) filter $H = \{h(\boldsymbol{k}), \boldsymbol{k} \in \mathbb{Z}^d\}$ is defined as $Hx := (H * x)(\boldsymbol{n}) = \sum_{\boldsymbol{k}\in\mathbb{Z}^d} h(\boldsymbol{n}-\boldsymbol{k})x(\boldsymbol{k})$. It is equivalently denoted in z-transform as $H(\boldsymbol{z})X(\boldsymbol{z})$, where $H(\boldsymbol{z}) = \sum_{\boldsymbol{k}} h(\boldsymbol{k})\boldsymbol{z}^{-\boldsymbol{k}}$ and $X(\boldsymbol{z}) = \sum_{\boldsymbol{k}} x(\boldsymbol{k})\boldsymbol{z}^{-\boldsymbol{k}}$. Here $\boldsymbol{z} = e^{i\omega}, i = \sqrt{-1}$ and $\boldsymbol{z}^{\boldsymbol{k}}$ is defined as $\boldsymbol{z}^{\boldsymbol{k}} = \prod_{j=1}^d z_j^{k_j}$. The size of the multi-index is $|\boldsymbol{k}| = \sum_{j=1}^d k_j$.

The multivariate differentiation operator is

$$D^{\boldsymbol{n}} = \frac{\partial^{|\boldsymbol{n}|}}{\partial\omega_1^{n_1}\cdots\partial\omega_d^{n_d}}.$$

And the scaled differentiation operator [21] is given by

$$\Delta^{\boldsymbol{n}} = \frac{\partial^{|\boldsymbol{n}|}}{i^{|\boldsymbol{n}|}\partial\omega_1^{n_1}\cdots\partial\omega_d^{n_d}}.$$

Note that the operator $\Delta^{\boldsymbol{n}}$ is always respect to $\boldsymbol{\omega}$. Thus $\Delta\boldsymbol{z}^{\boldsymbol{k}} = \boldsymbol{k}\boldsymbol{z}^{\boldsymbol{k}}$ and for a filter H,

$$\Delta^{\boldsymbol{n}}H(\boldsymbol{z}) = \sum_{\boldsymbol{k}} h(-\boldsymbol{k})\boldsymbol{k}^{\boldsymbol{n}}\boldsymbol{z}^{\boldsymbol{k}}. \tag{1}$$

The upsampling of a filter H is denoted in z-domain as $H_u(\boldsymbol{z}) = H(\boldsymbol{z}^{\mathbf{M}})$, where $\mathbf{M}$ is the subsampling matrix, $\boldsymbol{z}^{\mathbf{M}} = (\boldsymbol{z}^{\boldsymbol{m}_1}, \ldots, \boldsymbol{z}^{\boldsymbol{m}_d})^T$ and $\boldsymbol{m}_i$ is the i-th column vector of $\mathbf{M}$. In this paper, the quincunx case is considered, i.e.,

$$\mathbf{M} = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}.$$

Since $\det\mathbf{M} = 2$, the lattice $\mathbb{Z}^d$ is split into the "even" lattice $\mathbf{M}\mathbb{Z}^d$ and the "odd" one $\mathbf{M}\mathbb{Z}^d + \boldsymbol{t}$, where $\boldsymbol{t} = (1,0)^T$.

2.2. Wavelet frame and its lifting structure

Let $\mathcal{S}(\Psi)$ denote a wavelet system $\mathcal{S}(\Psi) := \{\psi_{i,j,\boldsymbol{k}}(\boldsymbol{x}) = |\det\mathbf{M}|^{jd/2}\psi_i(\mathbf{M}^j\boldsymbol{x} - \boldsymbol{k}) | \psi_i \in \Psi, i = 1,\ldots,L-1, j\in\mathbb{Z}, \boldsymbol{k}\in\mathbb{Z}^d\}$. A system $\mathcal{S}(\Psi)$ is a *frame* if there exist positive constants C_1, C_2 such that

$$C_1\|f\|^2_{L_2(\mathbb{R}^d)} \leqslant \sum_{\psi_{i,j,k}\in\mathcal{S}(\Psi)} |\langle f, \psi_{i,j,k}\rangle|^2 \leqslant C_2\|f\|^2_{L_2(\mathbb{R}^d)}, \quad \forall f \in L_2(\mathbb{R}^d).$$

The elements in $\mathcal{S}(\Psi)$ are referred to as *framelets*. A pair of systems $\{\mathcal{S}(\Psi), \mathcal{S}(\widetilde{\Psi})\}$ is called a *bi-frame* if each of the systems is a frame, and satisfies the perfect reconstruction: $f = \sum_{i,j,k}\langle f, \widetilde{\psi}_{i,j,k}\rangle \psi_{i,j,k}$, $\forall f \in L_2(\mathbb{R}^d)$.

According to the multiresolution analysis (MRA) of wavelet frames [30], there exist impulse responses $\{h_i(\boldsymbol{k})\}$ such that

$$\varphi(\boldsymbol{x}) = \sum_{\boldsymbol{k}} h_0(\boldsymbol{k})\varphi(\mathbf{M}\boldsymbol{x} - \boldsymbol{k}),$$

$$\psi_i(\boldsymbol{x}) = \sum_{\boldsymbol{k}} h_i(\boldsymbol{k})\varphi(\mathbf{M}\boldsymbol{x} - \boldsymbol{k}), \quad i = 1,\ldots,L-1.$$

Given a bi-frame $\{\mathcal{S}(\Psi), \mathcal{S}(\widetilde{\Psi})\}$, the corresponding analysis and synthesis filter banks (dual and primal) are denoted as $\{\widetilde{H}^i(\boldsymbol{z}), i = 0,\ldots,L-1\}$ and $\{H^i(\boldsymbol{z}), i = 0,\ldots,L-1\}$, respectively. According to the lifting factorization theorems developed in our previous works [24–26], the polyphase matrix of wavelet frames can be decomposed into a series of ladder matrices. Here the lifting factorization theorem of $\det\mathbf{M} = 2$ is briefly introduced as follows.

Proposition 2.1 [26]. *For the polyphase matrix $\widetilde{\mathbf{H}}_p(z)$ defined as*

$$\widetilde{\mathbf{H}}_p(z) = \begin{pmatrix} \widetilde{H}^0_e(z) & \widetilde{H}^0_o(z) \\ \vdots & \vdots \\ \widetilde{H}^{L-1}_e(z) & \widetilde{H}^{L-1}_o(z) \end{pmatrix},$$

where $\widetilde{H}_e, \widetilde{H}_o$ represent the even and odd components respectively, there exists a factorization given by

$$\widetilde{\mathbf{H}}_p(z) = \prod_{s=1}^{S}\left[\left(\mathbf{I} + \sum_{1\leqslant j\leqslant L-1} U^s_j(z)\boldsymbol{e}_1\boldsymbol{e}^T_{j+1}\right)\left(\mathbf{I} - \sum_{1\leqslant i\leqslant L-1} P^s_i(z)\boldsymbol{e}_{i+1}\boldsymbol{e}^T_1\right)\right] \cdot \mathbf{R}(z)\mathbf{K}, \tag{2}$$

where $\boldsymbol{e}_k$ is the unit vector whose elements are all zeros except the k-th one equals to 1. $P^s_i(z), U^s_j(z)$ are Laurent polynomials, referred to as 'prediction' and 'update' filters hereafter. $\mathbf{I}$ is the $L \times L$ identity matrix, and