

Nonlocal Patch-Based Fully-Connected Tensor Network Decomposition for Multispectral Image Inpainting

Wen-Jie Zheng, Xi-Le Zhao, Yu-Bang Zheng, and Zhi-Feng Pang

Abstract—Multispectral image (MSI) inpainting plays an important role in real applications. Recently, fully-connected tensor network (FCTN) decomposition has been shown the remarkable ability to fully characterize the global correlation. Considering the global correlation and the nonlocal self-similarity (NSS) of MSIs, this paper introduces the FCTN decomposition to the whole MSI and its NSS groups, and proposes a novel nonlocal patch-based FCTN (NL-FCTN) decomposition for MSI inpainting. More specially, the NL-FCTN decomposition-based method, which increases tensor order by stacking similar small-sized patches to NSS groups, cleverly leverages the remarkable ability of FCTN decomposition to deal with higher-order tensors. Besides, we propose an efficient proximal alternating minimization-based algorithm to solve the proposed NL-FCTN decomposition-based model with a theoretical convergence guarantee. Extensive experiments on MSIs demonstrate that the proposed method achieves the state-of-the-art inpainting performance among all compared methods.

Index Terms—Multispectral image (MSI) inpainting, nonlocal self-similarity (NSS), tensor order increment, fully-connected tensor network (FCTN) decomposition.

I. INTRODUCTION

MULTISPECTRAL images (MSIs) contain a wealth of spatial and spectral information, which makes them widely applied in various applications [1]–[3]. In practice, however, MSIs obtained are often incomplete due to some unavoidable factors, such as dead pixels and cloud cover. In order to improve the subsequent practicability, it is important to estimate missing elements by MSI inpainting [4]–[6]. The core problem of MSI inpainting is to characterize the intrinsic prior of MSIs [7]–[11].

Global correlation is an important prior of MSIs. Since MSIs are usually modeled as higher-order tensors, whose global correlation can be captured by tensor decomposition.

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There are various types of tensor decomposition, such as CAN-DECOMP/PARAFAC (CP) decomposition, Tucker decomposition, tensor singular value decomposition (t-SVD), tensor train (TT) decomposition, and tensor ring (TR) decomposition. All of them have been increasingly applied to MSI inpainting and achieved promising results. For example, Liu et al. [12] proposed a CP decomposition-based MSI denoising model, and Ng et al. [13] introduced a Tucker decomposition-based adaptive weighted sum of the nuclear norm (SNN) for MSI inpainting. Based on t-SVD, Fan et al. [14] employed tensor nuclear norm (TNN) to MSI inpainting, and Zheng et al. [15] further expanded TNN to convex three-directional TNN and non-convex three-directional log-based TNN, and proposed two models for mixed noise removal. TT and TR decompositions, two representative tensor network decompositions, received extensive applications in image restoration, since they have the superior capability to deal with higher-order tensors. For example, Bengua et al. [16] first proposed a TT decomposition-based image inpainting model, and Ding et al. [17] further embedded a total variation (TV) regularization into TT decomposition to improve the capability of image details recovery. Based on TR decomposition, Yuan et al. [18] and He et al. [19] proposed an image inpainting method by combining factor regularization and TV regularization, respectively.

However, the above methods directly considered the global correlation, which ignored the redundancy of repeated local patches across the spatial modes of MSIs, i.e. nonlocal self-similarity (NSS). One way to fully utilize NSS prior is to apply tensor low-rank method, such as log-based SNN [20] and TNN, to each NSS group [21], which is a new tensor obtained by stacking similar small-sized patches. By taking a third-order MSI as an example, each original NSS group is a fourth-order tensor, including two spatial modes, one spectral mode, and one similar-group mode. However, traditional methods usually reshaped two spatial modes in each NSS group to one mode, which cannot better preserve the spatial structure of each NSS group. Therefore, Ding et al. [22] exploited TT rank minimization to the original fourth-order NSS groups and achieved promising completion results. But TT decomposition only characterizes the correlation between adjacent two modes, causing a limited characterization for the NSS groups.

Recently, a fully-connected tensor network (FCTN) decomposition has been proposed, which establishes an operation between any two modes and has the powerful capability to capture the global correlation of tensors [23]. Based on FCTN decomposition, this paper makes two-fold contributions listing

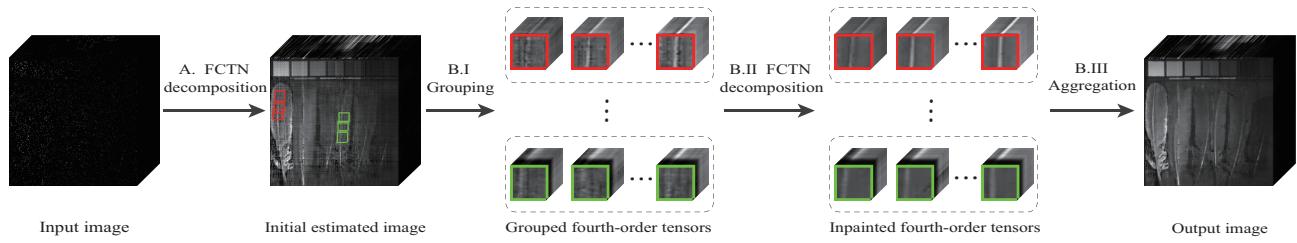


Fig. 1. Flowchart of the proposed MSI inpainting method. It involves two stages: A. initial FCTN decomposition inpainting and B. NL-FCTN decomposition inpainting. B includes three steps consisted of grouping, grouped FCTN decomposition inpainting, and aggregation.

TABLE I
NOTATION DECLARATIONS.

Notations	Interpretations
$x, \mathbf{x}, \mathbf{X}, \mathcal{X}$	scalar, vector, matrix, tensor
$\mathcal{X}(i_1, i_2, \dots, i_N)$	the (i_1, i_2, \dots, i_N) th element of \mathcal{X}
$\mathcal{X}_{1:d}$	$(\mathcal{X}_1, \mathcal{X}_2, \dots, \mathcal{X}_d)$
$\ \mathcal{X}\ _F$	$\sqrt{\sum_{i_1, i_2, \dots, i_N} \mathcal{X}(i_1, i_2, \dots, i_N) ^2}$

as follows:

First, we suggest a novel nonlocal patch-based FCTN (NL-FCTN) decomposition-based MSI inpainting model, the flowchart of which is illustrated in Fig 1. As shown in Fig 1, the proposed model has two advantages. On the one hand, employing FCTN decomposition to the whole MSI and its NSS groups fully captures the global correlation and the NSS of MSIs. On the other hand, NL-FCTN decomposition-based method regards the process of stacking similar small-sized patches to NSS groups as a tensor order increment operation, which cleverly leverages the remarkable ability of FCTN decomposition for characterizing higher-order tensors.

Second, we develop a proximal alternating minimization (PAM)-based algorithm to solve the NL-FCTN decomposition-based model with a theoretical guarantee of convergence. Extensive experiments show that the proposed method outperforms the state-of-the-art methods on MSI inpainting.

II. NOTATIONS

We summarize the notations throughout this paper in Tab. I, and introduce a generalized tensor unfolding operation following [23]. Supposing that \mathbf{n} is a reordering of the vector $(1, 2, \dots, N)$, the generalized tensor unfolding represents an N th-order tensor $\mathcal{X} \in \mathbb{R}^{I_1 \times I_2 \times \dots \times I_N}$ as a matrix $\mathbf{X} \in \mathbb{R}^{\prod_{i=1}^d I_{n_i} \times \prod_{i=d+1}^N I_{n_i}}$, which is denoted by $\mathbf{X}_{[n_1:d; n_{d+1:N}]} = \text{GenUnfold}(\mathcal{X}, \mathbf{n}_{1:d}; \mathbf{n}_{d+1:N})$. On the contrary, its inverse operation is denoted by $\mathcal{X} = \text{GenFold}(\mathbf{X}_{[n_1:d; n_{d+1:N}]}, \mathbf{n}_{1:d}; \mathbf{n}_{d+1:N})$.

III. PROPOSED MSI INPAINTING METHOD

In this section, we start with a brief introduction to the definition and properties of FCTN decomposition, and then introduce the proposed NL-FCTN decomposition-based method for MSI inpainting in detail.

A. FCTN Decomposition

Compared with TT and TR decompositions, FCTN decomposition is more efficient and more general. Specifically, by factorizing an N th-order tensor into a sequence of small-sized N th-order factor tensors and establishing the relationship between any two factors, FCTN decomposition has the remarkable ability to fully characterize the global correlation of tensors. Mathematically, given an N th-order tensor $\mathcal{X} \in \mathbb{R}^{I_1 \times I_2 \times \dots \times I_N}$, FCTN decomposition denotes each element of \mathcal{X} by

$$\begin{aligned} \mathcal{X}(i_1, i_2, \dots, i_N) = & \\ & \sum_{r_{1,2}=1}^{R_{1,2}} \sum_{r_{1,3}=1}^{R_{1,3}} \dots \sum_{r_{1,N}=1}^{R_{1,N}} \sum_{r_{2,3}=1}^{R_{2,3}} \dots \sum_{r_{2,N}=1}^{R_{2,N}} \dots \sum_{r_{N-1,N}=1}^{R_{N-1,N}} \\ & \{ \mathcal{G}_1(i_1, r_{1,2}, r_{1,3}, \dots, r_{1,N}) \\ & \quad \mathcal{G}_2(r_{1,2}, i_2, r_{2,3}, \dots, r_{2,N}) \dots \\ & \quad \mathcal{G}_k(r_{1,k}, r_{2,k}, \dots, r_{k-1,k}, i_k, r_{k,k+1}, \dots, r_{k,N}) \dots \\ & \quad \mathcal{G}_N(r_{1,N}, r_{2,N}, \dots, r_{N-1,N}, i_N) \}, \end{aligned} \quad (1)$$

where $\mathcal{G}_k \in \mathbb{R}^{R_{1,k} \times R_{2,k} \times \dots \times R_{k-1,k} \times I_k \times R_{k,k+1} \times \dots \times R_{k,N}}$ ($k = 1, 2, \dots, N$) are called the FCTN-factors and the vector $(R_{1,2}, R_{1,3}, \dots, R_{1,N}, R_{2,3}, \dots, R_{2,N}, \dots, R_{N-1,N})$ is called the FCTN-rank. For the sake of simplicity, the equation (1) can be expressed as $\mathcal{X} = \text{FCTN}(\mathcal{G}_1, \mathcal{G}_2, \dots, \mathcal{G}_N)$.

Fig. 2 vividly illustrates the graphic structure of FCTN decomposition. In Fig. 2, we can clearly observe that any two FCTN factors are linked by a line, representing a multi-linear operation, i.e. tensor contraction [23], between them.

B. NL-FCTN Decomposition-Based MSI Inpainting Method

The following is a detailed derivation of the proposed NL-FCTN decomposition-based model for MSI inpainting with the Fig. 1. The model consists of two stages. In stage A, we employ FCTN decomposition to the whole MSI as an initialization process, which not only utilizes the global correlation of whole MSI but also guarantees the high accuracy of the subsequent group matching.

In stage B, there are three steps. In step B.I, we divide the initial MSI into small-sized patches and stack similar patches as NSS groups. By taking an MSI $\mathcal{F} \in \mathbb{R}^{I_1 \times I_2 \times I_3}$ as an example, we divide it into overlapped cubes $\{\mathcal{F}_t \in \mathbb{R}^{p \times p \times I_3}\}_{t=1}^T$ with patch size p and row/column stride 1, where $T = ((I_1 - p + 1) \times ((I_2 - p + 1))$ is the number of total patches. Similarly, we obtain key patches from \mathcal{F} by setting row/column stride to $p - 1$ and the number of key patches

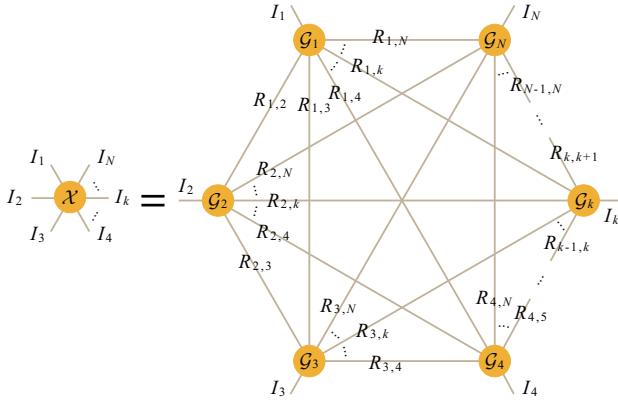


Fig. 2. Illustration of FCTN decomposition.

is $L = ((I_1 - p)/(p - 1) + 1) \times ((I_2 - p)/(p - 1) + 1)$. The way to obtain each NSS group is to utilize the Euclidean distance to access similarity between each key patch and all total patches, and cluster the first s similar patches. The NSS groups of MSI are denoted by $\{\hat{\mathcal{F}}_l \in \mathbb{R}^{p \times p \times I_3 \times s}\}_{l=1}^L$. Thus, a third-order MSI \mathcal{F} transforms into a set of fourth-order NSS groups $\{\hat{\mathcal{F}}_l\}_{l=1}^L$ by group matching. Following a similar step described above, a fourth-order time-series MSI with the size of $I_1 \times I_2 \times I_3 \times I_4$ transforms into a set of fifth-order NSS groups with the size of $p \times p \times I_3 \times I_4 \times s$. More generally, an N th-order tensor naturally transforms into a set of $(N+1)$ th-order NSS groups.

In step B.II, we regard an NSS group as a basis inpainting unit because of its strong global correlation, and introduce FCTN decomposition to each NSS group. For FCTN decomposition, this step not only makes full use of the remarkable ability to characterize the global correlation, but also cleverly leverages the advantage of dealing with higher-order tensors by NSS-based tensor order increment operation.

Without loss of generality, we consider an $(N+1)$ th-order NSS group $\hat{\mathcal{F}}_l$ and employ FCTN decomposition to obtain the inpainted NSS group $\hat{\mathcal{X}}_l$, which can be formulated as

$$\begin{aligned} & \min_{\hat{\mathcal{X}}_l, \mathcal{G}_l} \frac{1}{2} \|\hat{\mathcal{X}}_l - \text{FCTN}(\mathcal{G}_{l,1}, \mathcal{G}_{l,2}, \dots, \mathcal{G}_{l,N+1})\|_F^2 \\ & \text{s.t. } \mathcal{P}_{\Omega_l}(\hat{\mathcal{X}}_l) = \mathcal{P}_{\Omega_l}(\hat{\mathcal{F}}_l), \end{aligned} \quad (2)$$

where $\mathcal{P}_{\Omega_l}(\cdot)$ is the projection operator that maps the entries in Ω_l to themselves and others to zero, and Ω_l is the index of known elements in $\hat{\mathcal{F}}_l$. Since (2) is convex for $\hat{\mathcal{X}}_l$ and its FCTN-factors $\mathcal{G}_{l,i}$ ($i = 1, 2, \dots, N+1$) independently, PAM [24] is introduced to obtain the solution as follows:

$$\left\{ \begin{array}{l} \mathcal{G}_{l,i}^{(q+1)} = \underset{\mathcal{G}_{l,i}}{\operatorname{argmin}} \left\{ \frac{1}{2} \|\hat{\mathcal{X}}_l^{(q)} - \text{FCTN}(\mathcal{G}_{l,1:N-1}^{(q+1)}, \mathcal{G}_{l,i}, \mathcal{G}_{l,i+1:N+1}^{(q)})\|_F^2 \right. \\ \quad \left. + \frac{\rho}{2} \|\mathcal{G}_{l,i} - \mathcal{G}_{l,i}^{(q)}\|_F^2 \right\}, \quad i = 1, 2, \dots, N+1, \\ \hat{\mathcal{X}}_l^{(q+1)} = \underset{\mathcal{P}_{\Omega_l}(\hat{\mathcal{X}}_l) = \mathcal{P}_{\Omega_l}(\hat{\mathcal{F}}_l)}{\operatorname{argmin}} \left\{ \frac{1}{2} \|\hat{\mathcal{X}}_l - \text{FCTN}(\mathcal{G}_{l,1:N+1}^{(q+1)})\|_F^2 \right. \\ \quad \left. + \frac{\rho}{2} \|\hat{\mathcal{X}}_l - \hat{\mathcal{X}}_l^{(q)}\|_F^2 \right\}, \end{array} \right. \quad (3)$$

where $\mathcal{G}_{l,i}^{(q)}$ and $\hat{\mathcal{X}}_l^{(q)}$ are the results of the q th iteration of $\mathcal{G}_{l,i}$ and $\hat{\mathcal{X}}_l$, respectively, and $\rho > 0$ is a proximal parameter.

Algorithm 1 PAM-Based Algorithm for NL-FCTN Decomposition-Based MSI Inpainting Model

Input: The degraded MSI $\mathcal{T} \in \mathbb{R}^{I_1 \times I_2 \times \dots \times I_N}$, the index set Ω , the patch size p , the similar patch number s , and the FCTN-rank R of each NSS groups.

Initialization: The initial iterations $q = 0$, the maximum iterations $q_{\max} = 100$, and $\rho = 0.01$.

- 1: **Stage A. initial FCTN decomposition inpainting**
- 2: Inpaint the degraded MSI \mathcal{T} via FCTN decomposition and obtain an initial MSI \mathcal{F} .
- 3: **Stage B. nonlocal FCTN decomposition inpainting**
- 4: (I) Group similar patches over all bands of \mathcal{F} and obtain a set of $(N+1)$ th-order NSS groups $\{\hat{\mathcal{F}}_l\}_{l=1}^L$.
- 5: (II) Inpaint each NSS group $\hat{\mathcal{F}}_l$ via FCTN decomposition
- 6: **for** $l = 1 : L$ **do**
- 7: **for** $q = 1 : q_{\max}$ **do**
- 8: Update $\mathcal{G}_{l,i}^{(q+1)}$ via (5).
- 9: Update $\hat{\mathcal{X}}_l^{(q+1)}$ via (5).
- 10: **end for**
- 11: **end for**
- 12: (III) Aggregate the inpainted NSS groups $\{\hat{\mathcal{X}}_l\}_{l=1}^L$ to form the inpainted MSI \mathcal{X} .

Output: The inpainted MSI \mathcal{X} .

According to Theorem 4 in [23],

$$\hat{\mathbf{X}}_{l(i)} = (\mathbf{G}_{l,i})_{(i)} (\mathbf{M}_{l,i})_{[m_{1:N}; n_{1:N}]},$$

where $\mathcal{M}_{l,i} = \text{FCTN}(\{\mathcal{G}_{l,i}\}_{i=1}^{N+1}, / \mathcal{G}_{l,i})$ is a composition of $\mathcal{G}_{l,1}, \mathcal{G}_{l,2}, \dots, \mathcal{G}_{l,i-1}, \mathcal{G}_{l,i+1}, \dots, \mathcal{G}_{l,N+1}$,

$$m_j = \begin{cases} 2j, & \text{if } j < i, \\ 2j-1, & \text{if } j \geq i, \end{cases} \quad \text{and} \quad n_j = \begin{cases} 2j-1, & \text{if } j < i, \\ 2j, & \text{if } j \geq i. \end{cases}$$

Thus, the $\mathcal{G}_{l,i}$ ($i = 1, 2, \dots, N+1$)-subproblems are given by

$$\begin{aligned} \mathcal{G}_{l,i}^{(q+1)} &= \underset{\mathcal{G}_{l,i}}{\operatorname{argmin}} \left\{ \frac{\rho}{2} \|\mathcal{G}_{l,i} - \mathcal{G}_{l,i}^{(q)}\|_F^2 \right. \\ & \quad \left. + \frac{1}{2} \|\hat{\mathbf{X}}_{l(i)}^{(q)} - (\mathbf{G}_{l,i})_{(i)} (\mathbf{M}_{l,i}^{(q)})_{[m_{1:N}; n_{1:N}]} \|_F^2 \right\}. \end{aligned} \quad (4)$$

It is easy to find that (3) and (4) have the closed-form solutions as

$$\left\{ \begin{array}{l} \mathcal{G}_{l,i}^{(q+1)} = \text{GenFold} \left(\left[\hat{\mathbf{X}}_{l(i)}^{(q)} (\mathbf{M}_{l,i}^{(q)})_{[n_{1:N}; m_{1:N}]} + \rho (\mathbf{G}_{l,i}^{(q)})_{(i)} \right. \right. \\ \quad \left. \left. [(\mathbf{M}_{l,i}^{(q)})_{[m_{1:N}; n_{1:N}]} (\mathbf{M}_{l,i}^{(q)})_{[n_{1:N}; m_{1:N}]} + \rho \mathbf{I}]^{-1} \right) \right], \\ \quad i = 1, 2, \dots, N+1, \\ \hat{\mathcal{X}}_l^{(q+1)} = \mathcal{P}_{\Omega_l} \left(\frac{\text{FCTN}(\{\mathcal{G}_{l,i}^{(q+1)}\}_{i=1}^{N+1}) + \rho \hat{\mathcal{X}}_l^{(q)}}{1+\rho} \right) + \mathcal{P}_{\Omega_l}(\hat{\mathcal{F}}_l). \end{array} \right. \quad (5)$$

In step B.III, we aggregate the inpainted NSS groups $\{\hat{\mathcal{X}}_l\}_{l=1}^L$ to their original positions and obtain the whole inpainted MSI \mathcal{X} .

The above NL-FCTN decomposition-based method for MSI inpainting is summarized in Algorithm 1. Its theoretical convergence can be similarly proved following [23].

IV. NUMERICAL EXPERIMENTS

In this section, we test the performance of NL-FCTN decomposition-based method for MSI inpainting on 32

TABLE II
THE AVERAGE PSNR, SSIM, SAM, AND RUNNING TIME OF 32 TESTING MSIs OBTAINED BY DIFFERENT COMPARED METHODS.

MR	98%				95%				90%				80%			
Method	PSNR	SSIM	SAM	Time (s)	PSNR	SSIM	SAM	Time (s)	PSNR	SSIM	SAM	Time (s)	PSNR	SSIM	SAM	Time (s)
KBR-TC	22.640	0.642	20.400	150.89	33.548	0.911	6.809	151.05	41.729	0.977	3.446	155.14	48.536	0.994	1.972	162.95
NL-SNN	16.570	0.642	17.900	1985.5	29.648	0.864	6.111	2032.6	41.303	0.977	2.537	2044.3	47.365	0.991	1.712	2048.3
NL-TNN	19.822	0.656	26.313	69.608	31.698	0.921	8.629	70.766	36.773	0.970	3.947	71.294	44.186	0.993	1.761	72.850
NL-TT	26.371	0.786	15.267	301.30	31.486	0.905	6.680	305.40	34.736	0.947	3.914	306.17	38.426	0.975	2.516	309.41
FCTN-TC	25.994	0.662	19.188	36.168	33.022	0.863	9.832	55.352	37.726	0.937	6.673	91.170	43.682	0.976	4.212	155.88
NL-FCTN	28.494	0.804	11.952	542.20	37.537	0.959	3.985	544.17	44.286	0.990	2.070	542.31	49.717	0.996	1.336	542.38

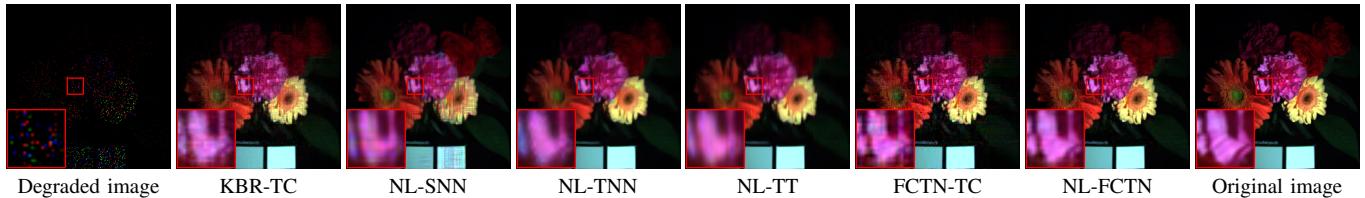


Fig. 3. Restoration results of *flowers* with MR=95%. The pseudo color images are composed of bands 29, 14, and 5.

MSIs (third-order tensors) and two time-series MSIs (fourth-order tensors). The compared methods are global tensor decomposition-based tensor completion (TC) methods including KBR-TC [25] and FCTN-TC [23], and nonlocal patch-based tensor decomposition for TC including NL-SNN [20], NL-TNN [21], and NL-TT [22]. All hyper-parameters of each compared method are set for the optimal performance according to the authors' paper and code. Three evaluation indexes contain the peak signal to noise rate (PSNR), the structural similarity (SSIM), and the spectral angle mapping (SAM). Here, the PSNR and SSIM values are obtained by averaging the values of PSNR and SSIM of all bands. The SAM values are obtained by averaging the values of SAM of all spectral vectors.

1) *MSI Inpainting*: We test the CAVE Database¹ with 32 MSIs. Each test MSI is resized to 256 × 256 × 31. The missing rate (MR) is defined as the rate of the unknown elements in the total elements. We test four MRs: 98%, 95%, 90%, and 80%. Tab. II reports the average values of PSNR, SSIM, SAM, and running time of all 32 MSIs obtained by all compared methods under each MR. We observe that the proposed method performs better than the compared methods for PSNR, SSIM, and SAM, while costing moderate running times. This is because the NL-FCTN introduces FCTN-TC to the whole MSI and its NSS groups, which boosts the performance of FCTN decomposition on higher-order tensors.

Fig. 3 shows the pseudo color images of restoration results with MR=95% of *flowers*. As observed, the proposed method achieves superior inpainting results visually. In particular, the spatial textures of MSIs can be better preserved, such as the petals.

2) *Time-Series MSI Cloud Removal*: We test two datasets of the time-series sentinel-2 images. *Morocco*² is taken over Morocco, which is resized to 200 × 200 × 4 × 6. To simulate the cloud mask of real scene on *Morocco*, we set that 1) at different time nodes, the clouds are located at different location; and 2) at the same time node, the clouds are located

at the same location in all bands. *Bratislava*³ is taken over Bratislava with a real cloud mask detected by multi-scale convolutional feature fusion [26], which is resized to 200 × 200 × 6 × 7. Tab. III reports the PSNR, SSIM, SAM, and running time on cloud removal results of *Morocco* obtained by all compared methods. We observe that the proposed method achieves outstanding results regardless of RSNR, SSIM, or SAM within an acceptable time.

Fig. 4 shows the pseudo images of simulated cloud removal results of *Morocco* at the second time node. Especially in the red box, we observe that KBR-TC can not better preserve the spectral information and causes color loss; NL-SNN, NL-TNN, and NL-TT blur the detail textures of the spatial images; FCTN-TC preserves the details but causes some artifacts; NL-FCTN achieves the closest result to the original images among all compared methods. Fig. 5 displays the pseudo images of the real cloud removal results of *Bratislava* at the fifth time node. As observed, the results obtained by KBR-TC, NL-SNN, and NL-TNN are over-smoothed and lose local details, and the results obtained by NL-TT and FCTN-TC contain artifacts. On the contrary, NL-FCTN obtains the best visual result, both in global structure recovery and local details preserving.

V. CONCLUSION

In this paper, we proposed an NL-FCTN decomposition-based method for MSI inpainting. We introduced FCTN decomposition to the whole MSI and its NSS groups to fully characterize the global correlation and the NSS of MSIs. From another perspective, we combined the FCTN decomposition with the nonlocal patch-based tensor order increment operation, which cleverly leverages its remarkable ability on higher-order tensors. The NL-FCTN decomposition-based model was solved by a PAM-based algorithm with a theoretical convergence guarantee. Extensive experiments proved that the proposed method performed better than all compared methods.

¹<https://www.cs.columbia.edu/CAVE/databases/multispectral/>.

²<https://theia.cnes.fr/atdistrib/rocket/#/home>.

³<https://earthexplorer.usgs.gov>.

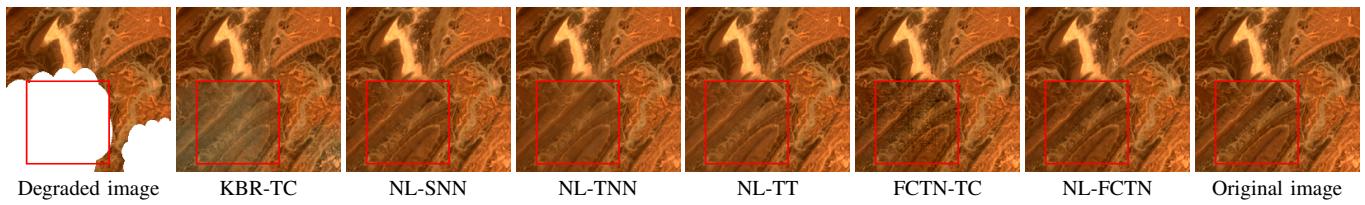


Fig. 4. Simulated cloud removal results of *Morocco*. The pseudo color images are composed of bands 3, 2, and 1 at the second time node.

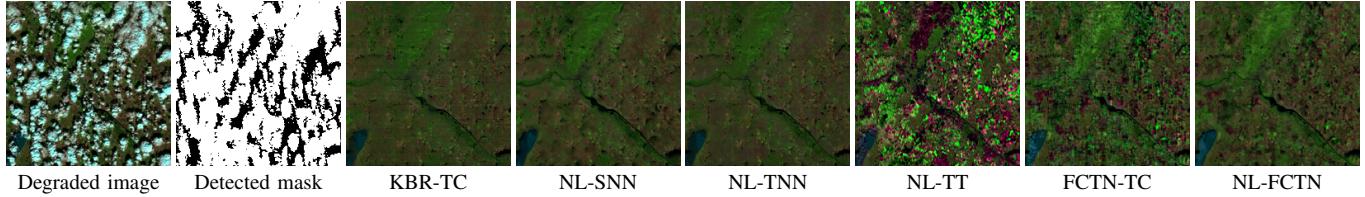


Fig. 5. Real cloud removal results of *Bratislava*. The pseudo color images are composed of bands 5, 3, and 1 at the fifth time node.

TABLE III

THE PSNR, SSIM, SAM, AND RUNNING TIME OF *Morocco* OBTAINED BY DIFFERENT COMPARED METHODS.

Method	PSNR	SSIM	SAM	Time (s)
KBR-TC	33.853	0.970	2.745	100.21
NL-SNN	46.891	0.988	0.336	63.553
NL-TNN	43.089	0.981	0.446	341.81
NL-TT	39.777	0.907	1.249	190.23
FCTN-TC	44.128	0.982	0.363	240.69
NL-FCTN	48.132	0.994	0.243	686.86

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