A Low-rank Tensor Model for Hyperspectral Image Sparse Noise Removal

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ABSTRACT Hyperspectral image (HSI) has been widely used in target detection and classification. However, various kinds of noise in HSIs affect the applications of HSIs. In this paper, we propose a low-rank tensor recovery model to remove noise. Considering the HSI is a three-dimensional (3-D) HSI data, and the underlying low-rank tensor property are used in the model. Then according to the similarity of adjacent bands images, the regularization on the difference of adjacent bands images are considered. The experiments of removing noise from different noisy HSIs show that our method can achieve better performance on removing sparse noise, especially for strips removal.

INDEX TERMS Hyperspectral image, sparse noise removal, low-rank, tensor

I. INTRODUCTION

HYPERSPECTRAL images (HSIs) have widely applications in target detection [1] and classification [10] since the high spectral resolution. However, HSIs often suffer from various noise, such as stripes, pulse noise and random noise, due to the physical limitations of sensor, atmospheric effects, and calibration error [3]. These noise will affect the subsequent applications of HSIs. Therefore, denoising is a necessary and important preprocessing step for HSIs applications and analysis.

In recent years, different HSIs denoising methods have been proposed [4]–[6]. To data, traditional HSIs denoising methods always convert three-dimensional (3-D) HSI data to 2-D matrices. In [7], a nonlocal means algorithm based on nonlocal averaging of all pixels in the image is proposed. In [8], a two-phase matrix decomposition scheme is presented, in which the HSI data matrix is decomposed into signal component and noise component. In [9], Zhao et al. proposed a denoising method in which the global and local redundancy, and the correlation in spatial/spectral domains are jointly used. Recently, methods based on low-rank (LR) matrix recovery have been proposed. In [10], a low-rank matrix recovery (LRMR) method is proposed by rearranging HSI data as a 2-D matrix and using the low-rank property of HSI. The method can simultaneously remove various noise, such as random noise, stripes, dead lines and dead lines. In [11], He et al. proposed a HSI denoising method by using a noise-adjusted iterative low-rank matrix approximation (NAILRMA). Then in [12], a total variation (TV)-regularized low-rank matrix factorization (LRTV) method was proposed, in which the TV regularization, nuclear norm and L1-norm are jointly used. In [13], a multitask sparse nonnegative matrix factorization (MTSNMF) method is developed in which spectral-spatial structure of HSI are considered. However, most LR-based methods are based on matrix obtained by convert 3-D HSI data to 2-D, so that the HSI inter structural information are lost. In order to using the 3-D structural information, tensor-based denoising methods were proposed [14]. In [15], a denoising method based on low-rank tensor recovery is proposed to simultaneously remove various sparse noise, in which the sparsity property of noise and the low-rank tensor property of the clean HSI data are utilized. In [16], a denoising method based on Tucker decomposition and principal component analysis (PCA) was proposed. In [17], a denoising method based on group sparse and low-rank tensor decomposition (GSLRTD) was proposed to remove various noise. In [18], a newly-designed structure tensor is constructed and used to formulate a regularization for HSI denosing.

In this paper, a HSI denoising method based on a low-
rank tensor recovery is proposed to remove various noise. In our model, the low-rank property of clean HSI data is used, and the similarity of the adjacent bands image is considered to introduce a sparse regularization on the difference of the adjacent bands image. The performance of our method is verified by comparing the denoising performance with different methods. The outline of this paper is as follows. We introduce the theory and method in Section II, and give the optimization process in Section III. In Section IV, some experimental results are shown to verify the performance of our method. Section V draws the final conclusions.

II. OUR MODEL

Assuming that the degraded HSI image can be seen as the sum of clean HSI image, sparse noise and Gaussian noise, written as following

\[ F = U + S + N \] (1)

where \( F, U, S, N \in \mathbb{R}^{M \times N \times B} \) denote the obtained degraded HSI image, clean HSI image, sparse noise (including impulse noise, dead lines, stripes, and so on), and Gaussian noise, respectively. \( M, N \) are spatial dimensions of HSI image and \( B \) is the number of bands.

The purpose of denoising is to obtain the clear HSI image \( U \) from the degraded HSI image \( F \). As it is known that the clean HSI image has low-rank tensor property, a tensor robust principal component analysis model was proposed [19] by using the low-rank property of tensor

\[
\min_{U,S} \|U\|_* + \lambda_1 \|S\|_1 \\
\text{s.t.} \quad F = U + S
\] (2)

where \( \| \cdot \|_* \) and \( \| \cdot \|_1 \) denote nuclear norm and \( L_1 \) norm, respectively. \( \lambda_1 \) is a parameter which controls the recovery accuracy.

In this paper, a HSI denoising method model is proposed based on the following considerations. Firstly, the underlying low-rank tensor property of clean HSI data is considered. Then, it is known that the adjacent bands images have high similarity, although it is different between the images corresponding to different spectral bands. Thus, the difference image between the adjacent bands are sparse. Based on above considerations, a HSI denoising method model is given as

\[
\min_{U,S} \|U\|_* + \frac{\lambda_1}{2} \|F - U - S\|_2^2 \\
\quad + \frac{\lambda_2}{2} \|S\|_1 + \frac{\lambda_3}{2} \|D_2U\|_2^2
\] (3)

where \( D_2 \) is the difference operators, and \( D_2U \) denotes the difference image between the adjacent bands. \( \| \cdot \|_2 \) denotes \( L_2 \) norm.

III. OPTIMIZATION

In order to solve Eq.(3), we introduce the auxiliary variable \( M \) and \( U_Z \), and get

\[
\min_{U,S,M,U_Z} \|U\|_* + \frac{\lambda_1}{2} \|F - U - S\|_2^2 \\
\quad + \frac{\lambda_2}{2} \|S\|_1 + \frac{\lambda_3}{2} \|D_2U\|_2^2 \\
\text{s.t.} \quad U = M \\
\quad D_2U = U_Z
\] (4)

Then the augmented Lagrangian function can be adressed as follows:

\[
L(U, S, U_Z, M) = \|M\|_* + \frac{\lambda_1}{2} \|F - U - S\|_2^2 \\
\quad + \frac{\lambda_2}{2} \|S\|_1 + \frac{\lambda_3}{2} \|U_Z\|_2^2 \\
\quad + \alpha \|M - U - B_1\|_2^2 \\
\quad + \frac{\beta}{2} \|U_Z - D_2U - B_2\|_2^2
\] (5)

where \( B_1 \) and \( B_2 \) are Lagrangian multipliers.

Then we use alternating direction method of multiplier (ADMM) algorithm to minimize Problem (5).

For updating \( M \), we have

\[
M^{k+1} := \arg \min_M \|M\|_* + \frac{\alpha}{2} \|M - U - B_1\|_2^2
\] (6)

Then we can obtain

\[
M^{k+1} = U \left[ \text{soft} \left( \sum \frac{1}{\alpha} \right) \right] V^T
\] (7)

where \( U \) and \( V \) are obtained from singular value decomposition (SVD) of \( (U + B_1) \), written as

\[
U + B_1 = USV^T
\] (8)

and

\[
\text{soft} \left( \sum \frac{1}{\alpha} \right) = \text{sign} \left( \sum \right) \max \left( 0, \left| \sum \right| - \frac{1}{\alpha} \right)
\] (9)

For updating \( U \), we have

\[
U^{k+1} := \arg \min_U \frac{\lambda_1}{2} \|F - U - S\|_2^2 \\
\quad + \frac{\alpha}{2} \|M - U - B_1\|_2^2 \\
\quad + \frac{\beta}{2} \|U_Z - D_2U - B_2\|_2^2
\] (11)

Then we can obtain

\[
U^{k+1} = F^{-1} \left\{ \frac{F \left[ \lambda_1 (F - S) + \alpha (M - B_1) + \beta D_2^T(U_Z - B_2) \right]}{\lambda_1 + \alpha + \beta \|D_2\|^2} \right\}
\] (12)

For updating \( S \), we have

\[
S^{k+1} := \arg \min_S \frac{\lambda_1}{2} \|F - U - S\|_2^2 + \frac{\lambda_2}{2} \|S\|_1
\] (13)
The noisy Urban image and Samson image with stripes width of the stripes is 1 pixel and the direction is along Y-bands and the random locations in each selected band. The experiment, the stripes are added to the randomly selected bands and the random locations in each selected band. Firstly, we add stripes to Urban and Samson HSIs. In this experiment, the stripes are added to the randomly selected bands and the random locations in each selected band. The original size of Urban and Samson HSI data are 307 × 307 × 80 from Urban HSI and 95 × 95 × 156 from Samson HSI as the ground truth images for testing. Then we can obtain

\[ S^{k+1} = \text{shrink} \left( F - U, \frac{\lambda_3}{2 \lambda_1} \right) \]  

(14)

where \( \text{shrink} (\eta, \mu) = \frac{\eta}{|\eta|} \max (\eta - \mu, 0) \)  

(15)

For updating \( U_Z \), we have

\[ U_Z^{k+1} := \arg \min_{U_Z} \frac{\lambda_3}{2} \| U_Z \|^2 + \frac{\beta}{2} \| U_Z - D_2 U - B_2 \|^2 \]  

(16)

Then we can obtain

\[ U_Z^{k+1} = \text{shrink} \left( D_2 U + B_2, \frac{\lambda_3}{2 \beta} \right) \]  

(17)

IV. EXPERIMENTAL RESULTS

In this section, several experiments of denoising different noise from HSIs are performed. In order to verify the superiority of our model, several HSI denoising methods, such as LRTV [12], SDS [4] and MTSNMF [13] are used to denoise for comparison. In the test, the indexes, such as the mean value of peak signal-to-noise ratio (MPSNR), the mean value of structural similarity index measurement (MSSIM), and the mean value of feature similarity index measurement (MFSIM) [20], are calculated for giving a quantitative comparison.

In the following experiments, two HSIs, Urban HSI and Samson HSI, are used to test. The original size of Urban and Samson HSI data are 307 × 307 × 210 and 952 × 952 × 156, respectively. For simplicity, we just select the subimage with size of 307 × 307 × 80 from Urban HSI and 95 × 95 × 156 from Samson HSI as the ground truth images for testing. One of band images selected from Urban and Samson HSI are shown in Figs. 1 (a) and (b), respectively.

A. HSI WITH STRIPES

Fig. 2 (b) - (e) are the results of removing stripes from noisy Urban HSI data using LRTV, SDS, MTSNMF and our method, respectively. We can find that LRTV produce some degree of staircase effects, MTSNMF cannot remove the stripes completely, SDS and our method can remove stripes effectively. Fig. 3 (b) - (e) are the results of removing stripes from noisy Samson HSI data using LRTV, SDS, MTSNMF and our method, respectively. We can find that our method can remove stripes effectively, but SDS and MTSNMF can not. LRTV can remove stripes but still has some of degree of staircase effects.

Table 1 shows the mean value of quantitative indexes obtained by different methods for stripe removal. We can find that the for both Urban and Samson HSI data, our method can achieve highest indexes. It means that our method have the better performance on removing stripes than the mentioned methods.

B. HSI WITH IMPULSE NOISE

Then, we add impulse noise to Urban and Samson HSIs. In this experiment, impulse noise is added to all the bands of each HSI. The noisy Urban image and Samson image with impulse noise are show as Fig. 4 (a) and Fig. 5 (a), respectively. Then we use LRTV, SDS, MTSNMF and our method to remove the impulse noise.

Fig. 4 (b) - (e) are the results of removing impulse noise from noisy Urban HSI data and Samson HSI data using LRTV, SDS, MTSNMF and our method, respectively. We can find that LRTV produce some degree of staircase effects, SDS, MTSNMF and our method can remove the impulse noise. From Table 2 we can find that our method can achieve higher MPSNR, MSSIM and MFSIM than other methods. The results of removing impulse noise from noisy Samson HSI data using LRTV, SDS, MTSNMF and our method are shown as Fig. 5 (b) - (e), respectively, and the indexes are listed in Table 2. It can be found that our method and LRTV can get better denoising performance than SDS and MTSNMF.

C. HSI WITH STRIPES AND GAUSSIAN NOISE

In this experiment, we add stripes and Gaussian noise simultaneously to Urban and Samson HSI. Gaussian noise are added to all the bands of each HSI, and the stripes are added to randomly select bands and the random locations in each selected band. Then we use LRTV, SDS, MTSNMF and our method to remove the noise. The noise removal results are shown as Fig. 6 and Fig. 7.

Fig. 6 (a) is the noisy Urban image with stripes and Gaussian noise, Fig. 6 (b) - (e) are the results of removing noise from noisy Urban HSI data using LRTV, SDS, MTSNMF and our method, respectively. We can find that LRTV produce some degree of staircase effects, MTSNMF cannot remove the stripes completely, and our method can remove noise effectively. Fig. 7 (a) is the noisy Urban image with
FIGURE 2: Noise removal results from Noisy Urban HSI with stripe. (a) Noisy Urban image with stripe, Noise removal results using (b) LRTV, (c) SDS, (d) MTSNMF and (e) our method.

FIGURE 3: Noise removal results from Noisy Samson HSI with stripe. (a) Noisy Samson image with stripe, Noise removal results using (b) LRTV, (c) SDS, (d) MTSNMF and (e) our method.

TABLE 1: The mean value of quantitative indexes obtained by different methods for stripe removal

<table>
<thead>
<tr>
<th>Image</th>
<th>Index</th>
<th>Noisy image</th>
<th>LRTV</th>
<th>SDS</th>
<th>MTSNMF</th>
<th>Our proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban</td>
<td>MPSNR</td>
<td>21.9910</td>
<td>24.4360</td>
<td>32.3607</td>
<td>27.8584</td>
<td>35.4536</td>
</tr>
<tr>
<td></td>
<td>MSSIM</td>
<td>0.8663</td>
<td>0.8271</td>
<td>0.9482</td>
<td>0.9098</td>
<td>0.9601</td>
</tr>
<tr>
<td></td>
<td>MFSIM</td>
<td>0.9345</td>
<td>0.9336</td>
<td>0.9705</td>
<td>0.9487</td>
<td>0.9776</td>
</tr>
<tr>
<td>Samson</td>
<td>MPSNR</td>
<td>17.7893</td>
<td>34.8192</td>
<td>27.4753</td>
<td>17.8738</td>
<td>36.2844</td>
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<tr>
<td></td>
<td>MSSIM</td>
<td>0.4015</td>
<td>0.8834</td>
<td>0.7474</td>
<td>0.3400</td>
<td>0.9424</td>
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<tr>
<td></td>
<td>MF SIM</td>
<td>0.7385</td>
<td>0.9358</td>
<td>0.8915</td>
<td>0.7026</td>
<td>0.9732</td>
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</table>

FIGURE 4: Noise removal results from Noisy Urban HSI with impulse noise. (a) Noisy Urban image with impulse noise, Noise removal results using (b) LRTV, (c) SDS, (d) MTSNMF and (e) our method.

TABLE 2: The mean value of quantitative indexes obtained by different methods for impulse noise removal

<table>
<thead>
<tr>
<th>Image</th>
<th>Index</th>
<th>Noisy image</th>
<th>LRTV</th>
<th>SDS</th>
<th>MTSNMF</th>
<th>Our proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban</td>
<td>MPSNR</td>
<td>15.0447</td>
<td>20.7203</td>
<td>26.6773</td>
<td>27.0292</td>
<td>29.2614</td>
</tr>
<tr>
<td></td>
<td>MSSIM</td>
<td>0.5085</td>
<td>0.5990</td>
<td>0.9058</td>
<td>0.9094</td>
<td>0.9315</td>
</tr>
<tr>
<td></td>
<td>MF SIM</td>
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<td>0.8007</td>
<td>0.9456</td>
<td>0.9378</td>
<td>0.9613</td>
</tr>
<tr>
<td>Samson</td>
<td>MPSNR</td>
<td>15.3385</td>
<td>34.2049</td>
<td>26.7569</td>
<td>25.6796</td>
<td>31.7110</td>
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<td>MSSIM</td>
<td>0.2836</td>
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<td></td>
<td>MF SIM</td>
<td>0.6394</td>
<td>0.9264</td>
<td>0.9137</td>
<td>0.8897</td>
<td>0.9497</td>
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</table>
FIGURE 5: Noise removal results from Noisy Samson HSI with impulse noise. (a) Noisy Samson image with impulse noise, Noise removal results using (b) LRTV, (c) SDS, (d) MTSNMF and (e) our method.

FIGURE 6: Noise removal results from Noisy Urban HSI with stripe and Gaussian noise. (a) Noisy Urban image with stripe and Gaussian noise, Noise removal results using (b) LRTV, (c) SDS, (d) MTSNMF and (e) our method.

FIGURE 7: Noise removal results from Noisy Samson HSI with stripe and Gaussian noise. (a) Noisy Samson image with stripe and Gaussian noise, Noise removal results using (b) LRTV, (c) SDS, (d) MTSNMF and (e) our method.

Table 3: The mean value of quantitative indexes obtained by different methods for stripe and Gaussian noise removal

<table>
<thead>
<tr>
<th>Image</th>
<th>Index</th>
<th>Noisy image</th>
<th>LRTV</th>
<th>SDS</th>
<th>MTSNMF</th>
<th>Our proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban</td>
<td>MPSNR</td>
<td>13.6168</td>
<td>19.6979</td>
<td>22.6415</td>
<td>17.9544</td>
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<td></td>
<td>MSSIM</td>
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<td>MFSIM</td>
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<tr>
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<td>17.2445</td>
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<td>MFSIM</td>
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<td>0.7927</td>
<td>0.6183</td>
<td>0.5642</td>
<td>0.9003</td>
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</table>

Table 3 shows the mean value of quantitative indexes obtained by different methods for stripe and Gaussian noise removal. We can find that the for both Urban and Samson HSI data, our method can achieve highest indexes except MPSNR for Samson HSI data is slightly lower than LRTV method.

D. HSI WITH STRIPES AND IMPULSE NOISE

In this section, the performance of removing stripes and impulse noise simultaneous are test. Stripes and impulse noise, Fig. 7 (b) - (e) are the results of removing noise from noisy Samson HSI data using LRTV, SDS, MTSNMF and our method, respectively. We can find that our method can remove noise effectively, but LRTV, SDS and MTSNMF can not.
noise are simultaneously added to Urban and Samson HSI. Here, impulse noise are added to all the bands of each HSI, and the stripes are added to randomly select bands and the random locations in each selected band. Then we use LRTV, SDS, MTSNMF and our method to remove the noise. The results are shown as Fig. 8 and Fig. 9.

Fig. 8 (a) is the noisy Urban image with stripes and impulse noise, Fig. 8 (b) - (e) are the results of removing noise from noisy Urban HSI data using LRTV, SDS, MTSNMF and our method, respectively. Fig. 9 (a) is the noisy Urban image with stripes and impulse noise, and Fig. 9 (b) - (e) are the results of removing noise from noisy Urban HSI data using LRTV, SDS, MTSNMF and our method, respectively. We can find that we can get the similar results with case of removing stripe and Gaussian noise. The corresponding mean value of quantitative indexes are given in Table 4. We can find that our method can remove different kinds noise simultaneously, and has superiority on removing sparse noise, especially for stripes.

REFERENCES


E. HSI WITH STRIPES, IMPULSE AND GAUSSIAN NOISE

In this section, we test the performance of removing noise from noisy HSIs which exists stripes, impulse and Gaussian noise simultaneously. Firstly, the stripes, impulse and Gaussian noise are simultaneously added to Urban and Samson HSI. Then we use LRTV, SDS, MTSNMF and our method to remove the noise. The results are shown as Fig. 10 and Fig. 11. Fig. 10 (a) is the noisy Urban image, and Fig. 10 (b) - (e) are the results of removing noise from noisy Urban HSI data using LRTV, SDS, MTSNMF and our method, respectively. Fig. 11 (a) is the noisy Urban image, and Fig. 11 (b) - (e) are the results of removing noise from noisy Urban HSI data using LRTV, SDS, MTSNMF and our method, respectively. It can be found that our method can get better performance on removing different kinds of noise better than other methods. The corresponding mean value of quantitative indexes listed in Table 5 show that our can achieve the highest index values.

From all above experiments, it also can be found that for our method, the performance of denoising sparse noise is better than denoising the mixed noise of sparse and Gaussian noise, such as the results of denoising stripes, impulse and the mixed noise of stripes and impulse are better than that of denoising the mixed noise of stripes and Gaussian noise. Thus, it is concluded that our method has obvious superiority on sparse noise removal, especially on stripes removal.

V. CONCLUSION

In this paper, we propose a low-rank tensor recovery method for HSIs denoising. During the low-rank tensor recovery model formulation, the underlying low-rank tensor property of HSIs and the similarity of adjacent bands image have been used. In order to test the performance of our method, several different kinds of noise, such as stripes, impulse noise, mixed noise of stripes and Gaussian noise, mixed noise of stripes and impulse noise, mixed noise of stripes, impulse and Gaussian noise, are added to HSIs and used for testing. From the noise removal results we can find that our method.
FIGURE 8: Noise removal results from Noisy Urban HSI with stripe and impulse noise. (a) Noisy Urban image with stripe and impulse noise, Noise removal results using (b) LRTV, (c) SDS, (d) MTSNMF and (e) our method.

FIGURE 9: Noise removal results from Noisy Samson HSI with stripe and impulse noise. (a) Noisy Samson image with stripe and impulse noise, Noise removal results using (b) LRTV, (c) SDS, (d) MTSNMF and (e) our method.

TABLE 4: The mean value of quantitative indexes obtained by different methods for stripe and impulse noise removal

<table>
<thead>
<tr>
<th>Image</th>
<th>Index</th>
<th>Noisy image</th>
<th>LRTV</th>
<th>SDS</th>
<th>MTSNMF</th>
<th>Our proposed</th>
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<tr>
<td></td>
<td>MSSIM</td>
<td>0.4272</td>
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<td>MPSNR</td>
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FIGURE 10: Noise removal results from Noisy Urban HSI with stripe, impulse and Gaussian noise. (a) Noisy Urban image with stripe, impulse and Gaussian noise, Noise removal results using (b) LRTV, (c) SDS, (d) MTSNMF and (e) our method.

TABLE 5: The mean value of quantitative indexes obtained by different methods for stripe, impulse and Gaussian noise removal

<table>
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<tr>
<th>Image</th>
<th>Index</th>
<th>Noisy image</th>
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<th>SDS</th>
<th>MTSNMF</th>
<th>Our proposed</th>
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<td>10.0602</td>
<td>25.2608</td>
<td>18.0328</td>
<td>12.1381</td>
<td>25.8387</td>
</tr>
<tr>
<td></td>
<td>MSSIM</td>
<td>0.0702</td>
<td>0.6865</td>
<td>0.3035</td>
<td>0.1347</td>
<td>0.7270</td>
</tr>
<tr>
<td></td>
<td>MFSIM</td>
<td>0.4187</td>
<td>0.8027</td>
<td>0.6540</td>
<td>0.5583</td>
<td>0.9030</td>
</tr>
</tbody>
</table>
FIGURE 11: Noise removal results from Noisy Samson HSI with stripe, impulse and Gaussian noise. (a) Noisy Samson image with stripe, impulse and Gaussian noise. Noise removal results using (b) LRTV, (c) SDS, (d) MTSNMF and (e) our method.

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