Groupe hyperspectral

Part 3.2 - Hyperspectral sharpening

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Hyperspectral sharpening

Observation model ($\mathbf{A}$ is separable)

$$\mathbf{Y}_h = \mathbf{X}\mathbf{A}_x\mathbf{M} + \mathbf{N}_y, \qquad \mathbf{Y}_m = \mathbf{A}_\lambda\mathbf{X} + \mathbf{N}_m$$

- $\mathbf{X} \in \mathbb{R}^{R\times N}$
- $\mathbf{Y}_h \in \mathbb{R}^{R\times M}$ - observed hyperspectral image
  ($M = N/d^2$ - d is the downsampling factor)
- $\mathbf{Y}_m \in \mathbb{R}^{L\times N}$ - observed multispectral image
- $\mathbf{A}_x \in \mathbb{R}^{N\times N}$ - (usually a convolution)
- $\mathbf{A}_\lambda \in \mathbb{R}^{L\times R}$ - (spectral responses of the MS sensor)
- $\mathbf{M} \in \mathbb{R}^{N\times N}$ - (downsampling matrix)
- $\mathbf{N}_h \sim \mathcal{MN}(\mathbf{0}_{R\times M}, \mathbf{C}_h, \mathbf{I}_M)$
- $\mathbf{N}_m \sim \mathcal{MN}(\mathbf{0}_{L\times N}, \mathbf{C}_m, \mathbf{I}_N)$

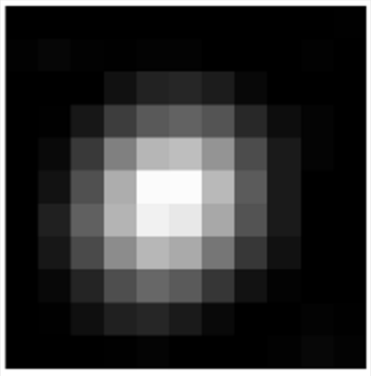
Hyperspectral sharpening

Hyperspectral sharpening contains a number of HSI subproblems:

- Denoising: $\mathbf{A}_x = \mathbf{I}_N$, $\mathbf{M} = \mathbf{I}_N$, observation: $\mathbf{Y}_h$
- Inpainting: $\mathbf{A}_x = \mathbf{I}_N$, $\mathbf{M}$ is diagonal (a mask), observation: $\mathbf{Y}_h$
- Superresolution: $\mathbf{A}_x$ is a lowpass filer, $\mathbf{M}$ is a dowsampling operator; observation: $\mathbf{Y}_h$
- HS pansharpening: $\mathbf{A}_x$ is a lowpass filer, $\mathbf{M}$ is a dowsampling operator, observation $\mathbf{Y}_h$ and $\mathbf{Y}_m \in \mathbb{R}^{1\times N}$ (a pancromatic image)
- HS MSharpening: $\mathbf{A}_x$ ia a lowpass filer, $\mathbf{M}$ is a dowsampling operator, observation $\mathbf{Y}_h$ and $\mathbf{Y}_m \in \mathbb{R}^{L\times N}$ (an MS image)

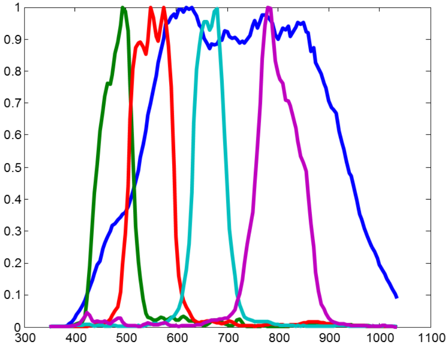
Illustrative example of blurring operators

Estimated PSF of the Hyperion instrument (GSD = 10 m)



Hyperion spatial resolution: 30 m

Spectral responses of the IKONOS sensor



MS channels: green, red, cyan, magenta
Pan Channel: blue

Hyperspectral sharpening variational formulation

What about the conditioning of the Hyperspectral sharpening (HSharp) problem?

Number of optimization variables: $R \times N$

Number of measurements: $R \times M + L \times N = (R/d^2 + L)N$

Hsharpening is ill-posed if $L/R < 1 - 1/d^2$, which is always the case (example: HYPERION/IKONOS, $L/R \simeq 0.02$, $1 - 1/d^2 \simeq 0.9$)

Typical variational formulation

$$\min_{\mathbf{X}} (1/2)\left\|\mathbf{Y}_h - \mathbf{X}\mathbf{A}_x\mathbf{M}\right\|_{Q_h}^2 + (1/2)\left\|\mathbf{Y}_m - \mathbf{A}_\lambda\mathbf{X}\right\|_{Q_m}^2 + \phi_S(\mathbf{X}) + \phi_{LR}(\mathbf{X})$$

where

$$\|\cdot\|_{Q_h}^2 := \left\|\mathbf{C}_h^{-1/2}(\cdot)\right\|_F^2, \qquad \|\cdot\|_{Q_m}^2 := \left\|\mathbf{C}_m^{-1/2}(\cdot)\right\|_F^2$$

$\phi_S(\cdot)$ is a spatial-spectral regularizer

$\phi_{LR}(\cdot)$ is a low rank regularizer

Hyperspectral sharpening with low rank hard constraint

HSIs spectral vectors live systematically in a low dimensional subspace

$$\mathbf{X} = \mathbf{E}\mathbf{Z}, \qquad \mathbf{E} \in \mathbb{R}^{R \times p}, (p \ll R), \qquad \mathbf{Z} \in \mathbb{R}^{p \times N}$$

$\mathbf{E}$ may be learned from $\mathbf{Y}_h$ [B-D & Nascimento, 12]

Variational formulation with hard low rank constraint

$$\min_{\mathbf{Z}} (1/2) \|\mathbf{Y}_h - \mathbf{E}\mathbf{Z}\mathbf{A}_x\mathbf{M}\|^2_{Q_h} + (1/2)\|\mathbf{Y}_m - \mathbf{A}_\lambda \mathbf{E}\mathbf{Z}\|^2_{Q_m} + \phi_S(\mathbf{Z})$$

Advantages:

- The number of optimization variable reduces often by more than one order of magnitude
- there is no need for low rank regularization

Hyperspectral sharpening algorithms: HySure

HySure (Hyperspectral Superesolution) [Simoes, B-D, &, Almeida, 14] solves the optimization

$$\min_{\mathbf{Z}} (1/2)\left\|\mathbf{Y}_h - \mathbf{E}\mathbf{Z}\mathbf{A}_x\mathbf{M}\right\|_{Q_h}^2 + (1/2)\left\|\mathbf{Y}_m - \mathbf{A}_\lambda\mathbf{E}\mathbf{Z}\right\|_{Q_m}^2 + \phi_{\mathsf{VTV}}(\mathbf{Z})$$

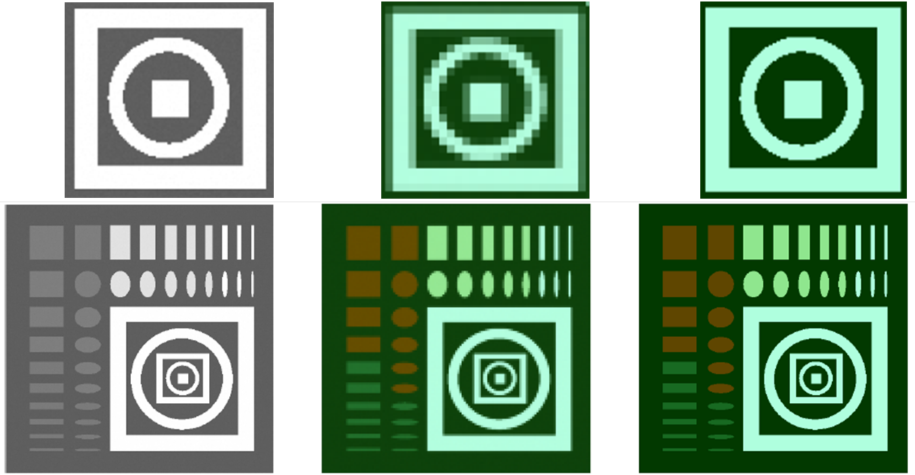
where

- $\mathbf{E}$, $\mathbf{A}_x$, and $\mathbf{A}_\lambda$ are learned from $\mathbf{Y}_h$ and $\mathbf{Y}_m$ prior to the estimation of $\mathbf{Z}$
- ϕ_{VTV} is the structured tensor TV for $q = 2$
- The optimization is solved with SALSA by using the template:

$$\begin{aligned}
g_1(\cdot) &= (1/2)\left\|\mathbf{Y}_h - \mathbf{E}(\cdot)\mathbf{M}\right\|_{Q_h}^2 & \mathbf{U}_1 &= \mathbf{Z}\mathbf{A}_x \\
g_2(\cdot) &= (1/2)\left\|\mathbf{Y}_m - \mathbf{A}_\lambda\mathbf{E}(\cdot)\right\|_{Q_h}^2 & \mathbf{U}_2 &= \mathbf{Z} \\
g_3(\cdot) &= \phi_{\mathsf{VTV}}(\cdot) & \mathbf{U}_3 &= \mathbf{Z}
\end{aligned}$$

Results: HySure in a HS+PAN simulated data set

Simulated HSI and PAN: $\mathbf{X} \in \mathbb{R}^{103\times(512\times512)}$, $d = 4$, $p = 10$, spatial PSF: Gaussian 5×5, $\sigma = 2$, iid noise, $\mathrm{SNR}_h = 30\,\mathrm{dB}$, $\mathrm{SNR}_m = 40\,\mathrm{dB}$



(a) Panchromatic image. (b) Hyperspectral image (false (c) HySure's result (false color).

Results: HySure in a HS+PAN synthetic data set

RESULTS FOR DATASET A (HSI+PAN FUSION).

	ERGAS	SAM	UIQI
GS	1.330	1.136	0.868
GSA	1.268	1.156	0.870
FIHS	1.788	1.456	0.863
PCA	1.451	1.149	0.865
BT	1.832	1.427	0.875
HPF	3.277	1.688	0.845
HySure	**0.717**	**0.524**	**0.895**

$$\mathrm{ERGAS}(\mathbf{Z}, \widehat{\mathbf{Z}}) \stackrel{\text{def}}{=} 100\frac{1}{S}\sqrt{\frac{1}{L_h}\sum_{l=1}^{L_h}\frac{\mathrm{MSE}(\mathbf{Z}_{l:}, \widehat{\mathbf{Z}}_{l:})}{\mu^2_{\widehat{\mathbf{Z}}_{l:}}}}$$

$$\mathrm{SAM}(\mathbf{Z}, \widehat{\mathbf{Z}}) \stackrel{\text{def}}{=} \frac{1}{n_m}\sum_{j=1}^{n_m}\arccos\left(\frac{\mathbf{Z}_{:j}^T\widehat{\mathbf{Z}}_{:j}}{\|\mathbf{Z}_{:j}\|_2\|\widehat{\mathbf{Z}}_{:j}\|_2}\right)$$

UIQI [Wang & Bovik, 03] combines Loss of correlation, constrast distortion, and luminance distrotion

Results: HySure in a HS+PAN semi-synthetic data set

Simulated HSI and PAN: $\mathbf{X} \in \mathbb{R}^{640\times 340}$, $d = 4$, $p = 10$, spatial PSF: Gaussian 5×5, $\sigma = 2$, iid noise, $\text{SNR}_h = 30\,\text{dB}$, $\text{SNR}_m = 40\,\text{dB}$

(a) Observed HSI (false

(b) Observed panchromatic

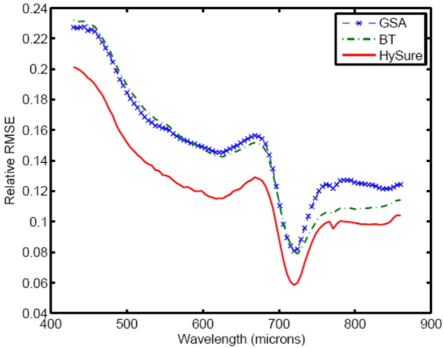
(c) HySure's result (false

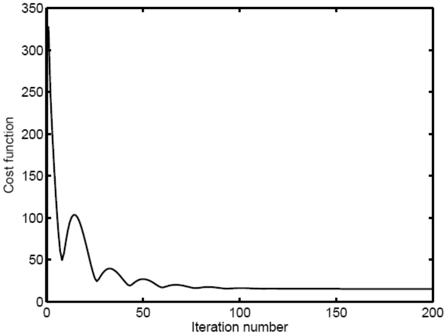
(d) BT's result (false color).

BT - Brovey Transform method [Huang et al. 04]

Results: HySure in a HS+PAN semi-synthetic data set

Simulated HSI and PAN: $\mathbf{X} \in \mathbb{R}^{640\times 340}$, $d = 4$, $p = 10$, spatial PSF: Gaussian 5×5, $\sigma = 2$, iid noise, $\text{SNR}_h = 30\,\text{dB}$, $\text{SNR}_m = 40\,\text{dB}$



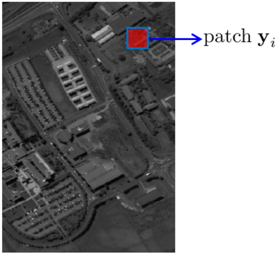


GSA - Gram-Schmidt adaptive [Aiazzi et al. 07]

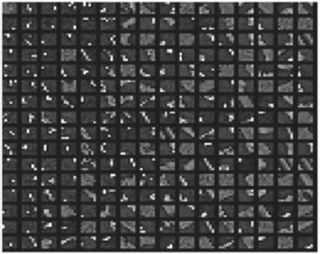
Hyperspectral sharpening: dictionary-based regularization

Motivation: patch-based dictionaries learned from the (high spatial resolution) MS bands fit very well the HS bands

MS band



DL $\longrightarrow$



$$\mathbf{D} = [\mathbf{d}_1, \ldots, \mathbf{d}_K]$$

$$\mathbf{y}_i \simeq \sum_{i \in S_i} \alpha_i \mathbf{d}_i$$

A path $\mathbf{x}_i$ of the a HS band is well approximated by the dictionary atoms $\mathbf{d}_i$ for $i \in \mathcal{S}_i$

$$\mathbf{x}_i \simeq \sum_{i \in \mathcal{S}_i} a_i \mathbf{d}_i \qquad \Rightarrow \qquad \mathbf{X} \simeq \mathcal{L}(\mathbf{D}, \mathbf{A}, \mathcal{S})$$

Hyperspectral sharpening: dictionary based regularization

HS-MS image fusion based on a sparse representation (HFSR) [Wei et al., 15]

$$\min_{\mathbf{Z},\mathbf{A}} (1/2)\big\|\mathbf{Y}_h - \mathbf{E}\mathbf{Z}\mathbf{A}_x\mathbf{M}\big\|^2_{Q_h} + (1/2)\big\|\mathbf{Y}_m - \mathbf{A}_\lambda\mathbf{E}\mathbf{Z}\big\|^2_{Q_m} + \tau\phi_{\mathsf{DL}}(\mathbf{Z},\mathbf{A})$$

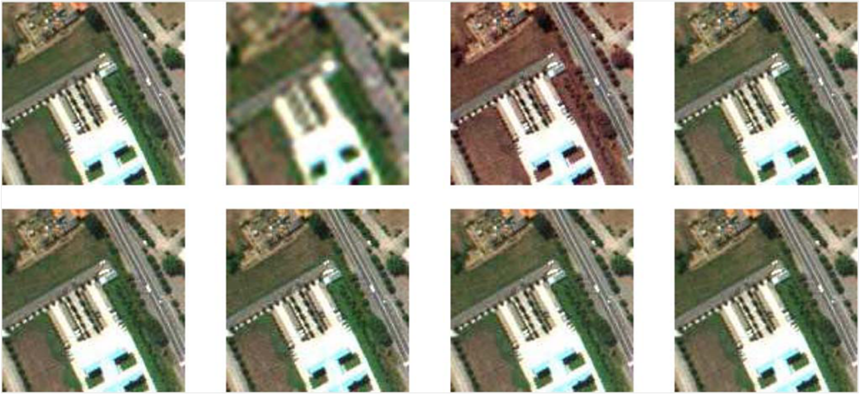
where $\mathbf{Z}$ are representation coefficients of $\mathbf{X}$ with respect to $\mathbf{E}$, $\mathbf{A}$ is the code for $\mathbf{X}$ with respect to the dictionary $\mathbf{D}$, and

$$\phi_{\mathsf{DL}}(\mathbf{Z},\mathbf{A}) := \big\|\mathbf{E}\mathbf{Z} - \mathcal{L}(\mathbf{D},\mathbf{A},\mathcal{S})\big\|^2_F$$

Algorithm 1: HFSR

Learn the dictionary using online learning [Mairal et al., 09]
Compute the support $\mathcal{S}$
for $k = 0, 1, \ldots$ **do**
  optimize wrt $\mathbf{Z}$ using SALSA
  use gradient descent wrt $\mathbf{A}$

HS+MS fusion (subset of Pavia data set, $\mathbf{X} \in \mathbb{R}^{93\times(128\times128)}$, $d = 4$, $p = 5$



From left to right and top to bottom: Reference; observed HS; observed MS; MAP, wavelet MAP; coupled nonnegative matrix factorization (CNMF); MMSE estimator; proposed method.

MAP - [Hardie et al., 04]
wavelet MAP- [Zhang et al., 09]
CNMF - [Yokoya et al., 12]
MMSE - [Qi et al., 12]

Results: HFSR in the a Pavia subcene

HS+MS fusion

Methods	RMSE	UIQI	SAM	ERGAS	DD	Time
MAP [14]	1.148	0.9875	1.962	1.029	8.666	**3**
Wavelet MAP [17]	1.099	0.9885	1.849	0.994	8.349	75
CNMF [18]	1.119	0.9857	2.039	1.089	9.007	14
HMC [16]	1.011	0.9903	1.653	0.911	7.598	6003
Rough $\tilde{\text{U}}$	1.136	0.9878	1.939	1.019	8.586	\
Proposed	**0.947**	**0.9913**	**1.492**	**0.850**	**7.010**	282

[Hardie et al., 04]
[Zhang et al., 09]
[Yokoya et al., 12]
[Qi et al., 12]

HS+PAN fusion

Methods	RMSE	UIQI	SAM	ERGAS	DD	Time
MAP [14]	1.857	0.9690	4.162	2.380	1.356	**2**
Wavelet MAP [17]	1.848	0.9697	4.191	2.354	1.360	55
CNMF [18]	1.964	0.9669	4.569	2.467	1.450	5
HMC [16]	1.748	0.9730	3.996	2.234	1.288	7828
Rough $\tilde{\text{U}}$	1.853	0.9691	4.158	2.375	1.355	\
Proposed	**1.745**	**0.9731**	**3.948**	**2.231**	**1.281**	252

HS fusion by sparse regression in the spectral domain

Rationale:

1. Suppose that we have access to a dictionary $\mathbf{D} = [\mathbf{d}_1, \ldots, \mathbf{d}_K]$ with respect to which the spectral vectors $\mathbf{x}_i$ may be represented (e.g., mixing matrix, overcomplete dictionary):
$$\mathbf{x}_i = \mathbf{D}\boldsymbol{\alpha}_i^*$$
2. Use the MS image recover the code $\boldsymbol{\alpha}_i$, $i = 1, \ldots, n$
$$\widehat{\boldsymbol{\alpha}}_i = \arg\min_{\boldsymbol{\alpha}} \left\|\mathbf{y}_{m,i} - \mathbf{A}_\lambda \mathbf{D}\boldsymbol{\alpha}\right\|_2^2 + \phi(\boldsymbol{\alpha})$$
3. Recover the HS vectors
$$\widehat{\mathbf{x}}_i = \mathbf{D}\widehat{\boldsymbol{\alpha}_i} \quad i = 1, \ldots, n$$
4. (necessary condition) $\boldsymbol{\alpha}_i^*$ can not be recovered if $\|\boldsymbol{\alpha}_i\|_0^* > L$ (L is number of MS bands)

HS fusion by sparse regression in the spectral domain

Dictionary learning methodologies:

- sparse code in the spectral domain [Charles et al., 11]
- linear unmixing [Zurita-Milla et. al, 06], [Kawakami et al.,11], [Licciardi et al.,14]
- locally low rank [Veganzones et al. 14. 15]

Couple matrix factorization. A related approach
[Yokoya, et al., 12], [Huang et al., 14]

Aims at solving the couple pair of factorization problem:

$$\min_{\mathbf{E}} \|\mathbf{Y}_h - \mathbf{E}\mathbf{Z}_h\|_F^2 \qquad \text{s.t.:} \quad \mathbf{Z}_h = \mathbf{Z}\mathbf{A}_x$$

$$\min_{\mathbf{Z}} \|\mathbf{Y}_h - \mathbf{E}_m\mathbf{Z}\|_F^2 \qquad \text{s.t.:} \quad \mathbf{E}_m = \mathbf{A}_\lambda\mathbf{E}$$

with alternating optimization.

Hyperspectral pansharpening: a review ([Loncan et al. , 15])

A comparison of eleven methods

Methods originally designed for MS pansharpening

Component substitution

CS, PCA, Gram-Schmidt (GS), GS Adaptive (GSA)

Multiresolution analysis

Smoothing Filter-based Intensity Modulation (SFIM)

Generalized Laplacian Pyramid (MTF-GLP)

MTF-GLP with High Pass Modulation (MTF-GLP-HPM)

Hybrid methods

Guided filter in the PCA domain (GFPCA)

Methods originally designed for MS pansharpening

Bayesian Methods

Naive Gaussian prior

Sparsity promoting prior

HySure

Matrix Factorization

(CNMF) Coupled Non-negative Matrix Factorization

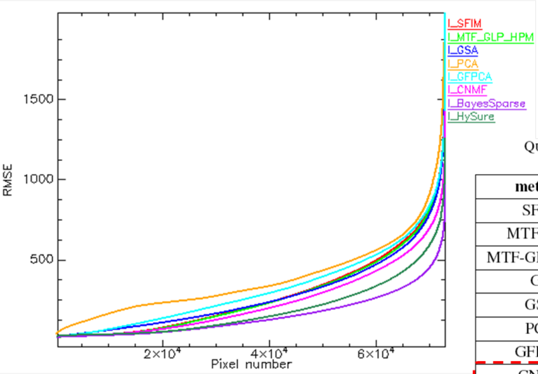
Hyperspectral pansharpening: a review ([Loncan et al. , 15])

CARACTERISTIC OF THE THREE DATASETS

dataset	dimensions	spatial res	N	instrument
Moffett	PAN 185×395 HS 37×79	20m 100m	224	AVIRIS
Camargue	PAN 500×500 HS 100×100	4m 20m	125	HyMap
Garons	PAN 400×400 HS 80×80	4m 20m	125	HyMap

Mosfet performance indexes ([Loncan et al. , 15])

Mosfet data set

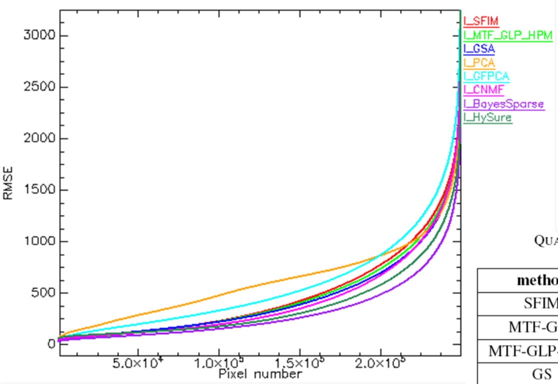


QUALITY MEASURES FOR THE MOFFETT FIELD DATASET

method	CC	SAM	RMSE	ERGAS
SFIM	0.92955	9.5271	365.2577	6.5429
MTF-GLP	0.93919	9.4599	352.1290	6.0491
MTF-GLP-HPM	0.93817	9.3567	354.8167	6.1992
GS	0.90521	14.1636	443.4351	7.5952
GSA	0.93857	11.2758	363.7090	6.2359
PCA	0.89580	14.6132	463.2204	7.9283
GFPCA	0.91614	11.3363	404.2979	7.0619
CNMF	0.95496	9.4177	314.4632	5.4200
Bayesian Naive	0.97785	7.1308	220.0310	3.7807
Bayesian Sparse	**0.98168**	**6.6392**	**200.3365**	**3.4281**
HySure	0.97059	7.6351	254.2005	4.3582

Camargue performance indexes ([Loncan et al. , 15])

Camargue data set

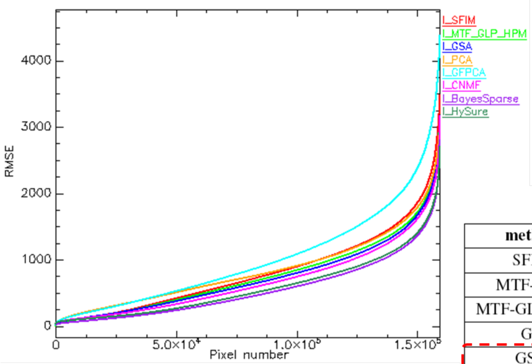


QUALITY MEASURES FOR THE CAMARGUE DATASET

method	CC	SAM	RMSE	ERGAS
SFIM	0.91886	4.2895	637.1451	3.4159
MTF-GLP	0.92397	4.3378	622.4711	3.2666
MTF-GLP-HPM	0.92599	4.2821	611.9161	3.2497
GS	0.91262	4.4982	665.0173	3.5490
GSA	0.92826	4.1950	587.1322	3.1940
PCA	0.90350	5.1637	710.3275	3.8680
GFPCA	0.89042	4.8472	745.6006	4.0001
CNMF	0.9300	4.4187	591.3190	3.1762
Bayesian Naive	0.95195	3.6428	489.5634	2.6286
Bayesian Sparse	**0.95882**	**3.3345**	**448.1721**	**2.4712**
HySure	0.9465	3.8767	511.8525	2.8181

Garons performance indexes ([Loncan et al. , 15])

Garons data set



QUALITY MEASURES FOR THE GARONS DATASET

method	CC	SAM	RMSE	ERGAS
SFIM	0.77052	6.7356	1036.4695	5.1702
MTF-GLP	0.80124	6.6155	956.3047	4.8245
MTF-GLP-HPM	0.79989	6.6905	962.1076	4.8280
GS	0.80347	6.6627	1037.6446	5.1373
GSA	0.80717	6.7719	928.6229	4.7076
PCA	0.81452	6.6343	1021.8547	5.0166
GFPCA	0.63390	7.4415	1312.0373	6.3416
CNMF	0.82993	6.9522	893.9194	4.4927
Bayesian Naive	0.86857	5.8749	784.1298	3.9147
Bayesian Sparse	**0.87834**	**5.6377**	**750.3510**	**3.7629**
HySure	0.86080	6.0224	778.1051	4.0454

Original and fused images ([Loncan et al. , 15])

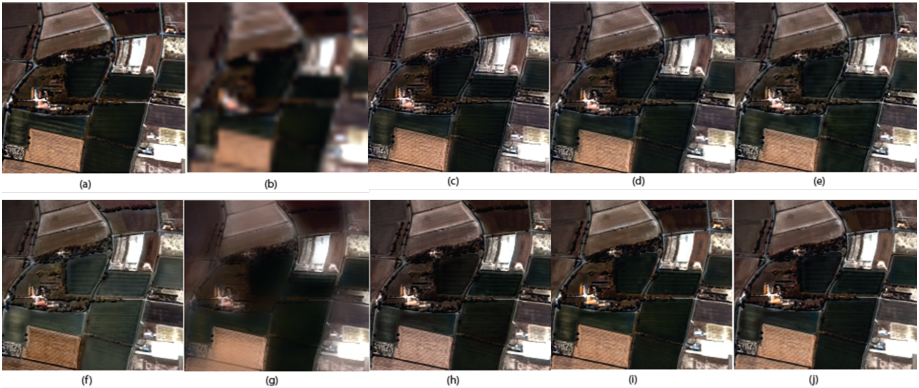


Fig. 6. Details of original and fused Camargue dataset HS image in the visible domain. (a) reference image, (b) interpolated HS image, (c) SFIM, (d) MTF-GLP-HPM, (e) GSA, (f) PCA, (g) GFPCA, (h) CNMF, (i) Bayesian Sparse, (j) HySure