Super-Resolution: a pre-processing step for Hyperspectral Pansharpening

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Directeurs de thèse
Sophie FABRE (ONERA/DOTA)
Jocelyn CHANUSSOT (GIPSA-LAB)
Encadrant:
Xavier BRIOTTET (ONERA/DOTA)
I) Context

II) State of the art

III) Proposed approach: Super-resolution PAN

IV) Conclusion & perspectives
I) What is pansharpening?

Context: Preparation of the spatial Earth’s observatory mission, HYPXIM
I) What is pansharpening?

**Context:** Preparation of the spatial Earth’s observatory mission, HYPXIM

- Panchromatique camera: High **spatial** resolution image (1.8 m)

**Panchromatique image (PAN)**

- High **spatial** resolution
- Poor **spectral** resolution
- Give information on the geometry of the scene
Context: Preparation of the spatial Earth’s observatory mission, HYPXIM

- Panchromatique camera: High spatial resolution image (1.8 m)
- Hyperspectral sensor: High spectral resolution image (8 m)

Hyperspectral image (HS)

- Low spatial resolution
- High spectral resolution
- Give information on the composition of the scene
I) What is pansharpening?

**Context:** Preparation of the spatial Earth’s observatory mission, HYPXIM

→ **Targeted application** classification of urban area (< 5 m)
I) What is pansharpening?

**Context:** Preparation of the spatial Earth’s observatory mission, HYPXIM

† **Targeted application** classification of urban area (< 5 m)

![Panchromatic image (PAN) 1.8m](image1)

![Hyperspectral image (HS) 8m](image2)

**Fusion**
I) What is pansharpening?

**Context:** Preparation of the spatial Earth’s observatory mission, HYPXIM

→ **Targeted application** classification of urban area (< 5 m)

Panchromatique image (PAN) 1,8m + Hyperspectral image (HS) 8m

<table>
<thead>
<tr>
<th>Ideal result of the fusion 1,8m</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Good spatial and spectral resolutions</td>
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<tr>
<td>- Give information on both the geometry and the nature of the scene</td>
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</table>
I) Context

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II) State of the art

5 main families of methods:
II) State of the art

5 main families of methods:

- **Component Substitution (CS)**

Method originally designed for MS + PAN fusion
→ Spatial information is well preserved
→ Can create spectral distortion

Example of methods:
- Principal Component Analysis (PCA) [Chavez1989]
- Gram Schmidt adaptive (GSA) [Laben2000]
II) Component Substitution (CS)
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II) Component Substitution (CS)

Transformation

HS

HS upscaled

Intensity Component

PAN Image

Other components
II) Component Substitution (CS)

For PCA: Intensity Component = First Principal Component
II) Component Substitution (CS)

Transformation

HS

HS upscaled

Substitution

Intensity Component

PAN Image

Other components
II) Component Substitution (CS)

1. Transformation
2. Substitution
3. Inverse Transformation

- HS
- HS upscaled
- Intensity Component
- PAN Image
- Fused Image
- Other components
II) State of the art

5 main families of methods:

- Component Substitution (CS)
- **Multi-Resolution Analysis (MRA)**

Method originally designed for MS + PAN fusion
Similar to CS method, main difference → use spatial filter

→ Spectral information is well preserved
→ Can create some spatial blur

Example of methods:

- Modulation transfert function Generalized Laplacian Pyramid with High Pass Modulation (MTF-GLP-HPM) [Vivone2014] → Laplacian Pyramid
- Smoothing filter-based intensity modulation (SFIM) [Liu2000] → single linear time invariant low pass filter
II) Component Substitution (CS)

PAN Image

HS

HS upscaled
II) Component Substitution (CS)

- HS
- HS upscaled
- PAN Image
- Spatial details
- Details extraction
II) Component Substitution (CS)

- HS
- PAN Image
- Details extraction
- Spatial details
- HS upscaled
- Injection model
- Fused Image
II) MultiResolution Analysis (MRA)

Details extraction and injection model using Laplacian Pyramid method
II) State of the art

5 main families of methods:

- Component Substitution (CS)
- Multi-Resolution Analysis (MRA)
- Hybrid

Combine elements from different families

Example: Guided Filter PCA (GFPCA) [LiaoSubmitted]
II) State of the art

5 main families of methods:

- Component Substitution (CS)
- Multi-Resolution Analysis (MRA)
- Hybrid
- **Matrix Factorization**

Originally designed for MS + HS
Use unmixing to write MS and HS image as a product of two matrices: abundance and endmembers

Example: Coupled Non-negative Matrix Factorization (CNMF) [Yokoya2012]
II) State of the art

5 main families of methods:

• Component Substitution (CS)
• Multi-Resolution Analysis (MRA)
• Hybrid
• Matrix Factorization
• **Bayesian Method**

Originally designed for MS + HS
Use bayesian method to modelise the fusion process
Sensor characteristic is needed

Methods: [Wei2015] [Simoes2015]
II) State of the art

5 main families of methods:

- Component Substitution (CS)
- Multi-Resolution Analysis (MRA)
- Hybrid
- Matrix Factorization
- Bayesian Method

A review paper has been written on this topic:

**Review paper on Hyperspectral Pansharpening:**
II) Dataset and evaluation

Dataset information

- Rural area from Camargue (France)
- Source data: Airbone HS data acquired with Hymap
- Simulated dataset
- Spatial resolution: PAN: 2 m, HS: 8 m (ratio 4)
II) Dataset and evaluation

Criteria for the evaluation of the results: Wald’s protocole + Visual spatial analysis + Visual spectral analysis

- Spatial → CC: cross correlation (ideal value 1)
- Spectral → SAM: spectral Angle Mapper (ideal value 0)
- Global → RMSE: root mean squared error & ERGAS*: Dimensionless Global Error (ideal value 0)

* « Erreur relative globale adimensionnelle de synthèse »
II) Results: Visual analysis (0.4 – 0.8 μm domain)
II) Results: Visual analysis (0.4 – 0.8 μm domain)
II) Results: Visual spectral analysis

Good performance on homogenous area but some problem with transition area

→ Case of mixed pixels is generally ignored
Summary

I) Context

II) State of the art

III) Proposed approach: Super-resolution PAN

IV) Conclusion & perspectives
Currently, most of the methods do not modify the spectral information of HS.

→ Mixed pixels will stay mixed, which creates halo around small objects.
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Solution:
→ Adding a pre-processing step to unmix these pixels
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Original HS image

Endmember extraction and abundance estimation

Mixed pixel → Rearrangement of the subpixels

Improved HS
III) Step 1: Endmembers Extraction

- HS
- PAN
- BPT construction

Endmembers Extraction

Local endmember $\rightarrow$ to take into account spectral variability

Endmembers extraction step done by using VCA
III) Step 2: detection of pure/mixed pixels

**Hypothesis:** Homogeneous area in PAN → pure HS pixel

Local endmember → Pure pixels close to mixed pixels
III) Step 3: Unmixing of mixed pixels

Principle:

Each candidate endmember -> converted in PAN domain

Spatially arrange the converted endmembers to mimic PAN information with respect to the abundance information
III) Step 4: Addition of spatial information

Simple method based on a gain to add spatial information without modifying spectral information
III) Evaluation of the super-resolution step on a synthetic image

(a) PAN image                           (b) Reference image
(c) Enlarged HS                     (d) Super-resolution PAN

Endmembers used for the synthetic image

<table>
<thead>
<tr>
<th>method</th>
<th>Rate of reconstruction error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Super-resolution PAN</td>
<td>0.0001%</td>
</tr>
</tbody>
</table>
III) Evaluation of the full method on real dataset (extract)

Presentation of the real dataset

![Images showing PAN image, Ref image, and HS enlarged image](image)

Results of the fusion

![Images showing MTF-GLP-HPM, GSA, Super-resolution, CNMF, Bayesian sparse](image)

<table>
<thead>
<tr>
<th>method</th>
<th>CC</th>
<th>SAM</th>
<th>RMSE</th>
<th>ERGAS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Super-Res</td>
<td>0.95</td>
<td>2.65</td>
<td>3.53</td>
<td>3.21</td>
</tr>
<tr>
<td>GSA</td>
<td>0.93</td>
<td>3.51</td>
<td>4.12</td>
<td>4.07</td>
</tr>
<tr>
<td>MTF GLP HPM</td>
<td>0.91</td>
<td>3.71</td>
<td>4.53</td>
<td>4.57</td>
</tr>
<tr>
<td>CNMF</td>
<td>0.95</td>
<td>3.30</td>
<td>3.42</td>
<td>3.48</td>
</tr>
<tr>
<td>Bayesian Sparse</td>
<td>0.89</td>
<td>3.88</td>
<td>4.85</td>
<td>5.41</td>
</tr>
</tbody>
</table>
III) Evaluation of the full method on real dataset -> Toulouse (urban)
• Most of the methods from the State of the Art have the same limitation
  ➔ Transition area (mixed pixels)
• To address this issue some preliminary work has been presented
  ➔ Preliminary unmixing step to improve result at subpixel level in transition area

• More tests need to be done to evaluate this approach:
  ➔ Test on different landscape (particularly urban area: ANR HYPEP)
  ➔ Test with different ratio
Review paper on Hyperspectral Pansharpening:

Codes for the toolbox are available at: http://OpenRemoteSensing.net/
References


