Reconstruction d'images hyperspectrales à faible coût pour un imageur pilotable à double dispersion

> Ibrahim Ardi Hervé Carfantan Simon Lacroix Antoine Monmayrant



#### Who's who

#### Ibrahim Ardi: PhD student I RAP/LAAS (2016-2019)

#### Hervé Carfantan: IRAP, team SISU

Inverse problems, estimation / optimization, deconvolution...

Antoine Monmayrant: LAAS, team PHOTO Integrated photonic systems, modeling and conception

Simon Lacroix: LAAS, team RIS Autonomy of mobile robots, environment perception & modeling



Field and aerial robotics

#### **Motivations**

# Classic hyperspectral imagers fill the HS-cube slice by slice



#### Characteristics of the systems RIS and PHOTO address:

- Moving cameras
- Dynamic phenomena
- Real-time decision



 Need for real-time ("snapshot") acquisition and real-time data analysis

# Snapshot hyperspectral imagery



Hable 2012

- CASSI
- *Review of Snapshot Hyperspectral Imaging Technologies*. N. Hagen and M. Kudenov, Optical Engineering 52(9), Sept. 2013

Characteristics of these systems:

- Spatial / spectral compromise
- Often resort to heavy computations
- Tough calibration issues

### Outline

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# Outline

- Reconstruction d'images hyperspectrales à faible coût pour un imageur pilotable à double dispersion
- (Aperçu des possibilités de l'imageur)
- Reconstruction d'images hyperspectrales à faible coût pour un imageur pilotable à double dispersion
- Conclusion et perspectives

Dual-disperser architecture (inspired from [Coded Aperture Spectral Snapshot Imager, 2007])



A partial masking of the signal defines a spectral filter

Dual-disperser architecture (inspired from [Coded Aperture Spectral Snapshot Imager, 2007])



For the same mask, different spatial rays are differently spectrally filtered

**Dual-disperser architecture** 

 For a given mask, the spectral filtering depends on the objet position



Dual-disperser architecture

 For a given mask, the spectral filtering depends on the objet position



# Dual-disperser architecture

 For a given mask, the spectral filtering depends on the objet position

SLM : "Spatial Light Modulator" *e.g.* Digital Micro-mirror Device







#### Slit pattern on the DMD for a white line of pixels:



#### Slit pattern on the DMD for a whole image



Slit pattern on the DMD for a whole image: the slit acts as a "filtering cube"



 $\rightarrow$  Basis of the simple linear matrix model

 Possibility to acquire an intensity image



- Possibility to acquire an intensity image
- "Colocation" property



- Possibility to acquire an intensity image
- "Colocation" property (independence between lines)



- Possibility to acquire an intensity image
- "Colocation" property

• Simplicity of the model



$$\lambda(x_f, x_m) = \lambda_c + x_f / (\beta \alpha) - x_m / \alpha$$

- Possibility to acquire an intensity image
- "Colocation" property

• Simplicity of the model

• Programmable acquisition

# First prototype (end 2014)



# First prototype validation

Scanning slit



Imaged object: known light source through a mask





# First prototype validation

• Scanning slit



Imaged object: known light source through a mask





# Outline

- Reconstruction d'images hyperspectrales à faible coût pour un imageur pilotable à double dispersion
- (Aperçu des possibilités de l'imageur)

# A typology of use-cases

- 1. Two usual HS "products" *(i.e.* type of recovered information):
  - Full HS cube
  - Specific spectra
- 2. Two ways to control the system *(i.e.* type of DMD settings):
  - Pre-defined patterns (structured or random)
  - On-line controlled / adapted patterns
- $\rightarrow$  Four "families" of processes

Various "evaluation" criteria:

- 1. Number of acquisitions ( $\rightarrow$  transmission volume)
- 2. Computational load
- 3. Robustness wrt. noise and approximated model of the system

# Full HS cube / Predefined DMD sequence Scanning SLIT



- 1. Number of acquisitions: as much as the DMD width
- 2. Computational load: Null
- Interest / relevance: best achievable spatial/spectral resolution (to benchmark other approaches)
- No mechanical system involved

# "Full" HS cube / Predefined DMD sequence

#### Generalised Bayer mosaic



Variants: more than one acquisitions, randomized mosaic

- 1. Number of acquisitions: one or a few
- 2. Computational load: low

Note: depending on \alpha some patterns may yield some spectral mixing Relevance:

- pan-X processing readily applicable, no intrinsic registration issue
- Unmixing? (because the mixing is somehow controllable, to be further discussed)

### Full HS-Cube / Random DMD sequence

Current work of Ibrahim Ardi (see 3<sup>rd</sup> part of the talk later)

- 1. Number of acquisitions:  $\sim < 1/5^{\text{th}}$  of spectral depth
- 2. Computational load: medium (but can be parallelized and adapted to GPUs)

# Full HS-Cube / 2 DMD controlled acquisitions

"Near snapshot partitioning"

→ An *adaptive* scheme

Regularity hypothesis: presence of spectrally homogeneous regions Steps of the approach:

- 1. Acquire and segment the intensity image
- 2. Define mask pattern to recover the whole spectrum
- 3. "filtered" image acquisition and analysis



(possibility to validate the homogeneity assumption – actual algorithms yet to develop)

# Specific spectrum / Fixed DMD



Variants: multi-spectral images, spectra correlation

- 1. Number of acquisitions: "one" (rolling shutter)
- 2. Computational load: nearly null

Notes: the camera lines should be oriented normally to the dispersing direction

Relevance: random-access of mono-chromatic images (\delta \lambda controllable), possibility to define adaptive schemes (with a sequence of acquisitions)

# Specific spectra / Random DMD sequence

#### Compressed sensing

 $\rightarrow$  Analogy with the 1-pixel camera



Numerous 1-pixel spectrometers in parallel A quick unmixing approach with known end-members

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# Direct matrix model



- $I \Rightarrow \mathbf{d}$  : vecteur de taille  $RC \times 1$
- $S_0 \Rightarrow \mathbf{o}$  : vecteur de taille  $RCW \times 1$
- $T \Rightarrow H$  : matrice de taille  $RC \times RCW$

♦ H est non-inversible "W >> 1 (hyperspectral)"
♦ H est bloc-diagonale et parcimonieuse "grâce à la co-localisation"

#### Inverse problem statement

Objectif : Reconstruire l'objet d'intérêt, le plus rapidement possible avec quelques acquisitions aléatoires.

$$\mathbf{i} = \begin{pmatrix} d^{(1)} \\ \cdot \\ \cdot \\ d^{(S)} \end{pmatrix} = \begin{pmatrix} H^{(1)} \\ \cdot \\ \cdot \\ H^{(S)} \end{pmatrix} \mathbf{o} = \mathbf{Ao}$$

- i : vecteur de taille  $RCS \times 1$
- A : matrice de taille RCS × RCW

Critère quadratique pénalisé (Type Tikhnov) :

$$\hat{\mathbf{o}} = \arg\min_{\mathbf{o}}(||\mathbf{i} - \mathbf{A}\mathbf{o}||^2 + \mu_x ||\nabla_x \mathbf{o}||^2 + \mu_y ||\nabla_y \mathbf{o}||^2 + \mu_\lambda ||\nabla_\lambda \mathbf{o}||^2)$$

# Inverse problem solving

Objectif : Reconstruire l'objet d'intérêt, le plus <u>rapidement</u> possible avec quelques acquisitions aléatoires.

$$\mathbf{i} = \begin{pmatrix} d^{(1)} \\ \cdot \\ \cdot \\ d^{(S)} \end{pmatrix} = \begin{pmatrix} H^{(1)} \\ \cdot \\ \cdot \\ H^{(S)} \end{pmatrix} \mathbf{o} = \mathbf{A}\mathbf{o}$$

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Résolution direct (inversion) impossible

Résolution itérative (CGNE) : A & A<sup>t</sup>

★ Implémentation efficace grâce à la co-localisation

# Inverse problem solving

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Effet de lissage

 $\star$  Extraction de contours sur l'image panchromatique

• Input data











### Perspectives

• On the device: V2 prototype



#### Perspectives

- On the device: V2 prototype
- Model the prototype (ray transfer matrix model)
- On the Full HS-Cube reconstruction algorithm:
  - Slight improvements to the proposed approach
  - Towards *adaptive* acquisition schemes
- On other acquisition schemes
  - Engineering developments on-going
  - Analysis of earth-observation use cases

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