Unifying Image Fusion and Compression: A Variational Approach

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Pansharpening

HIGH SPATIAL RESOLUTION

Panchromatic (PAN)

HIGH SPECTRAL DIVERSITY

Multispectral (MS)

SPATIAL RESOLUTION: Minimum spatial distance required to distinguish two objects on the scene

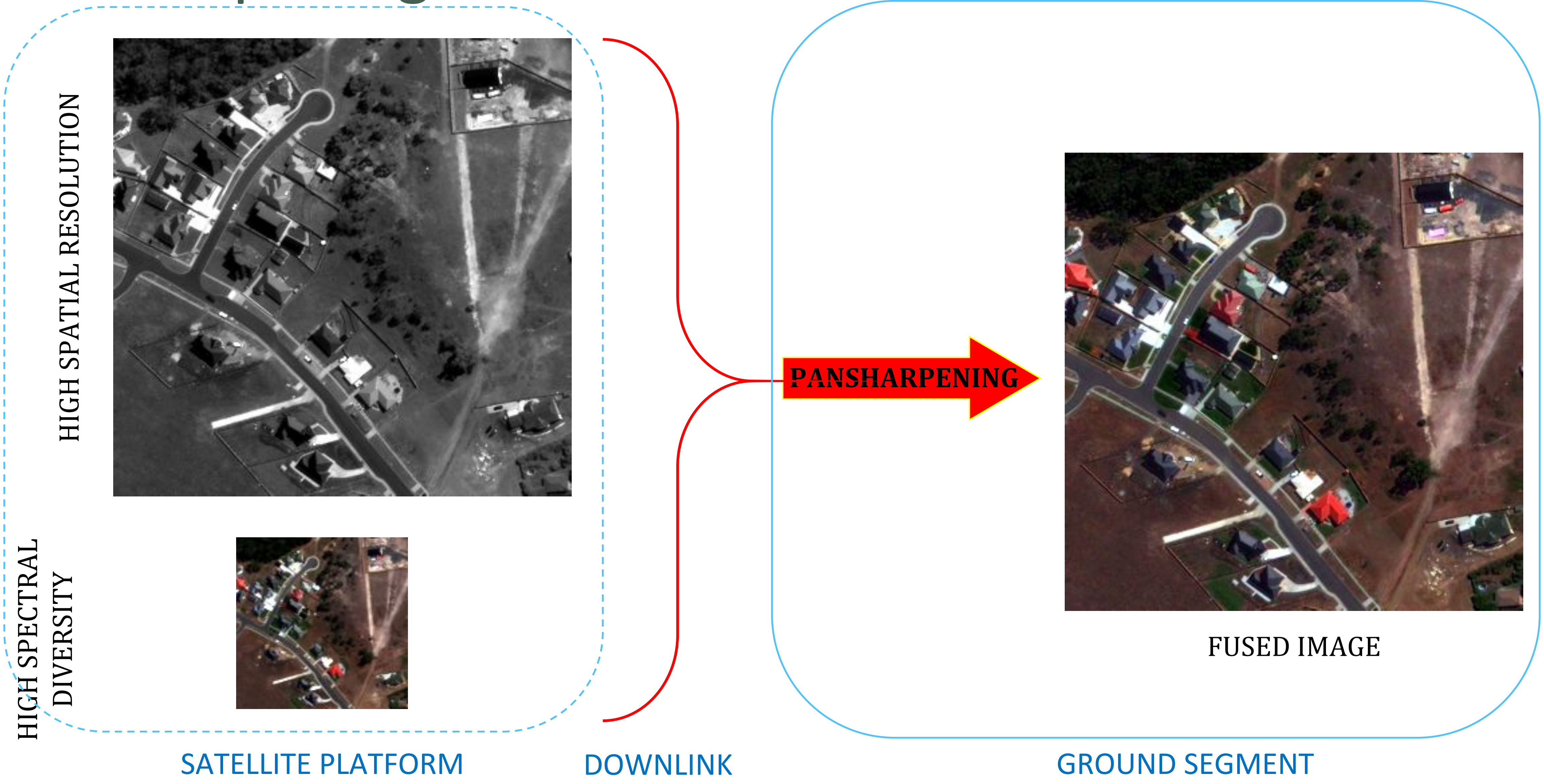
PANSHARPENING

SPECTRAL DIVERSITY: Minimum distance between two separable spectra

FUSED IMAGE

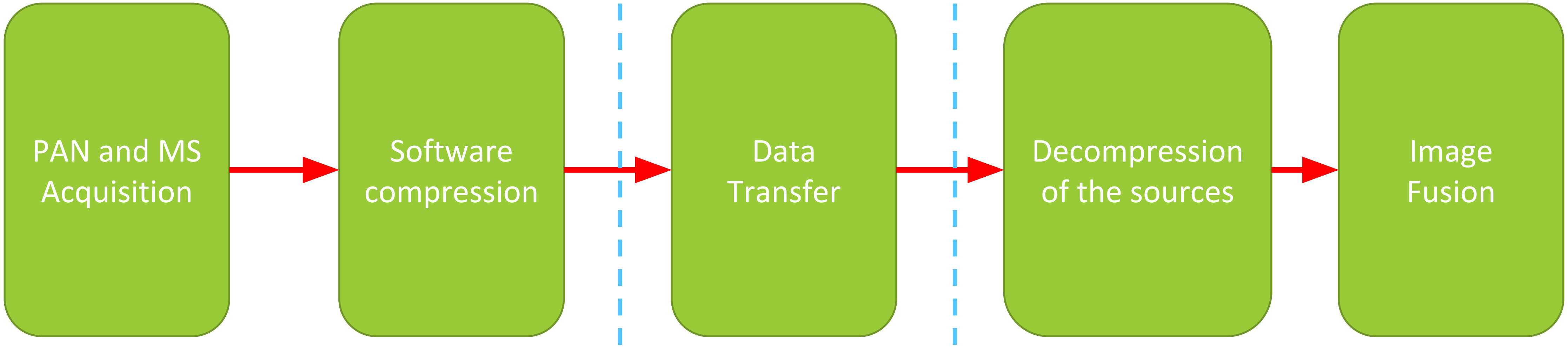
Definition: Sharpening (i/e: enhanching) a multispectral image with a panchromatic one [Vivone et al., 2015, Loncan et al., 2016]

Pansharpening

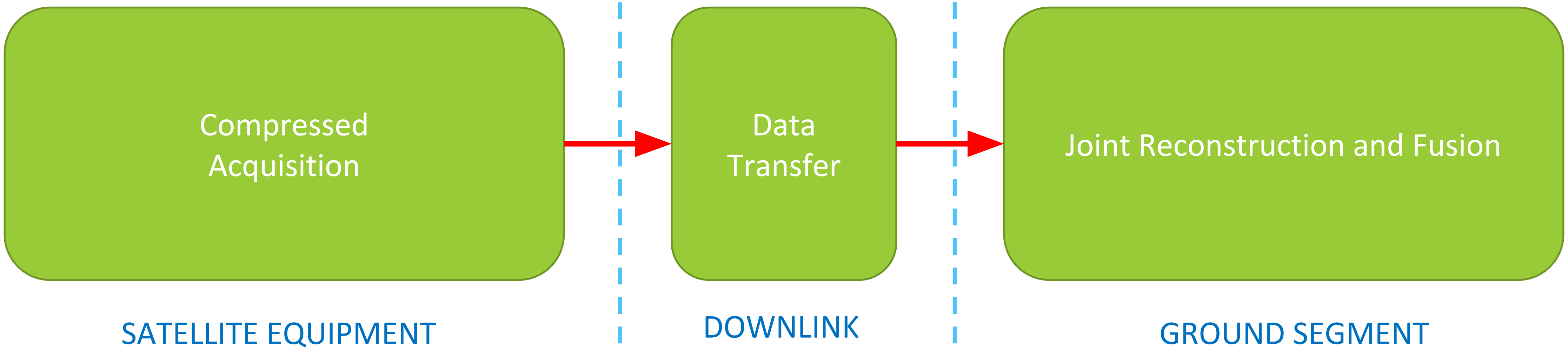


A joint model

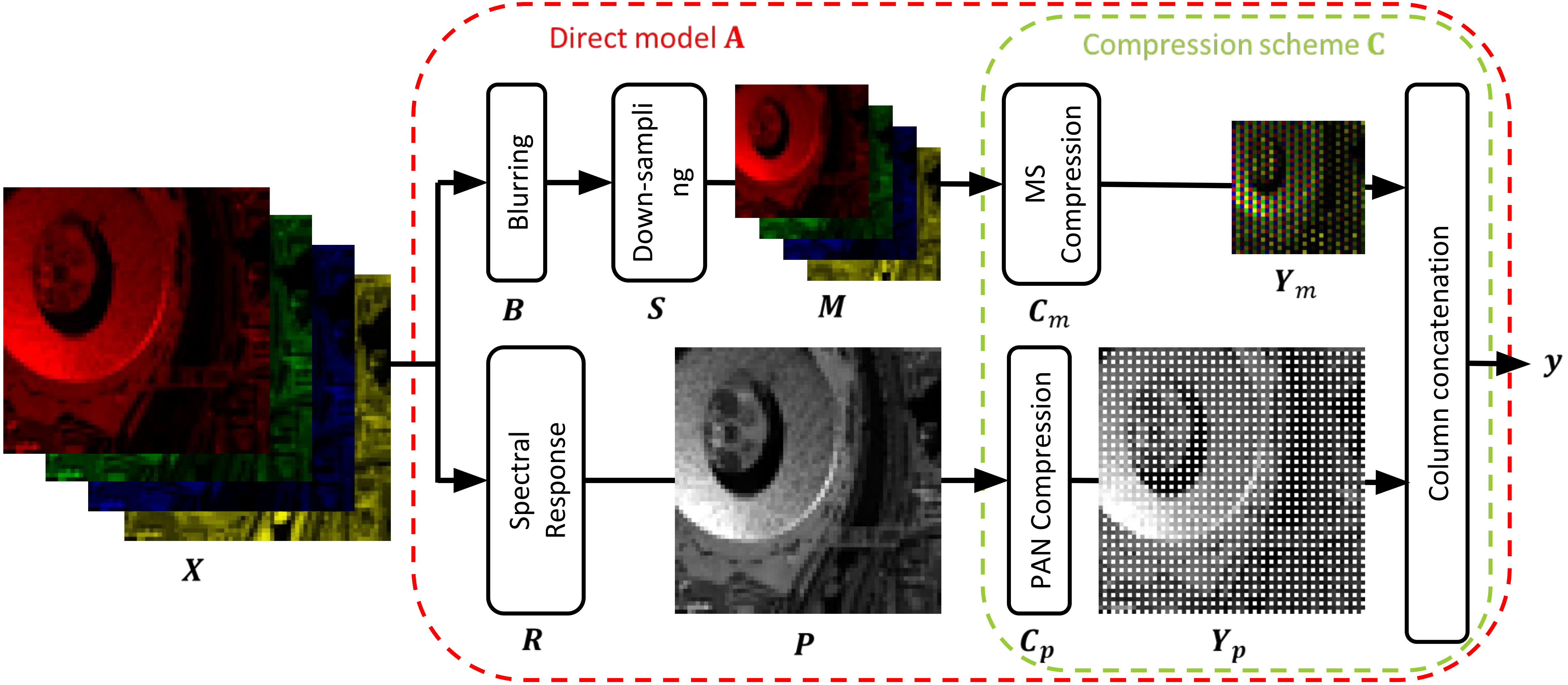
- Classical Approach



- Proposed Model



Reconstruction scheme: Direct Model

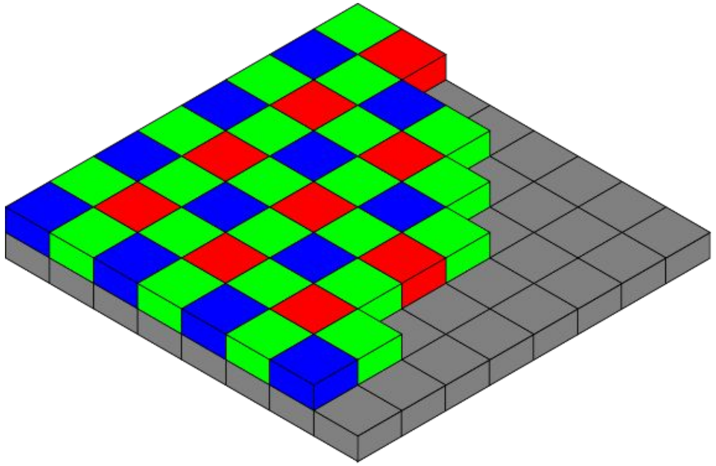


See you at the poster

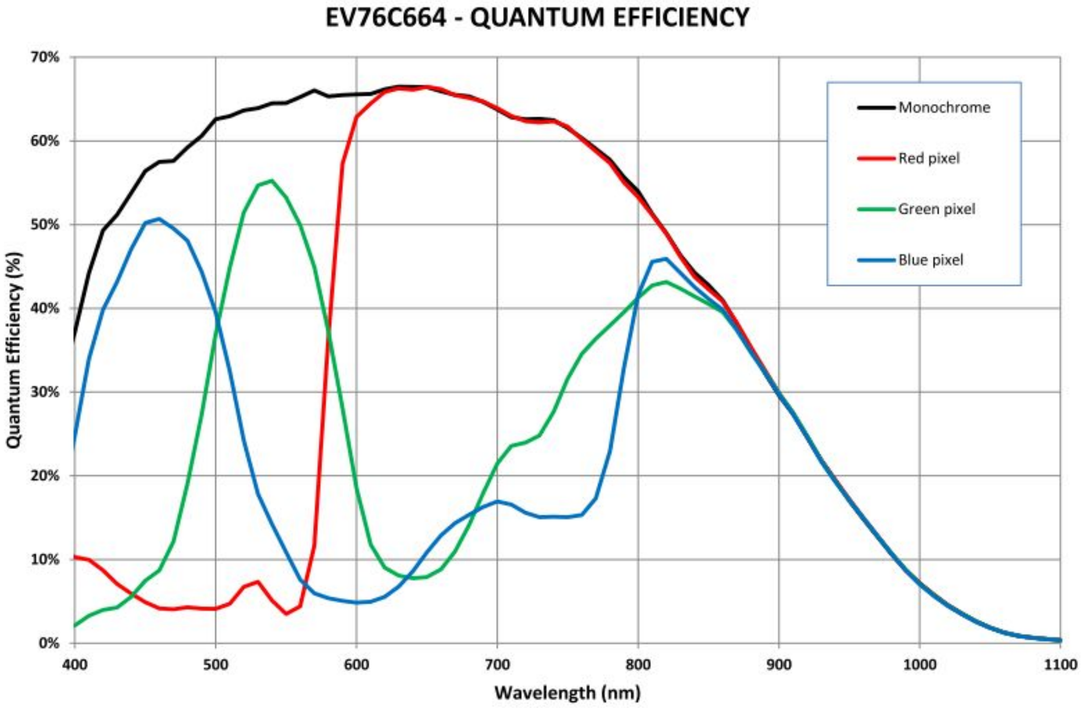
Summary

- Background
  - Pansharpening
  - Compressed Acquisitions
- Contribution
  - Joint model of compression and fusion
  - Employed Regularizers
- Experimental results
- Conclusion

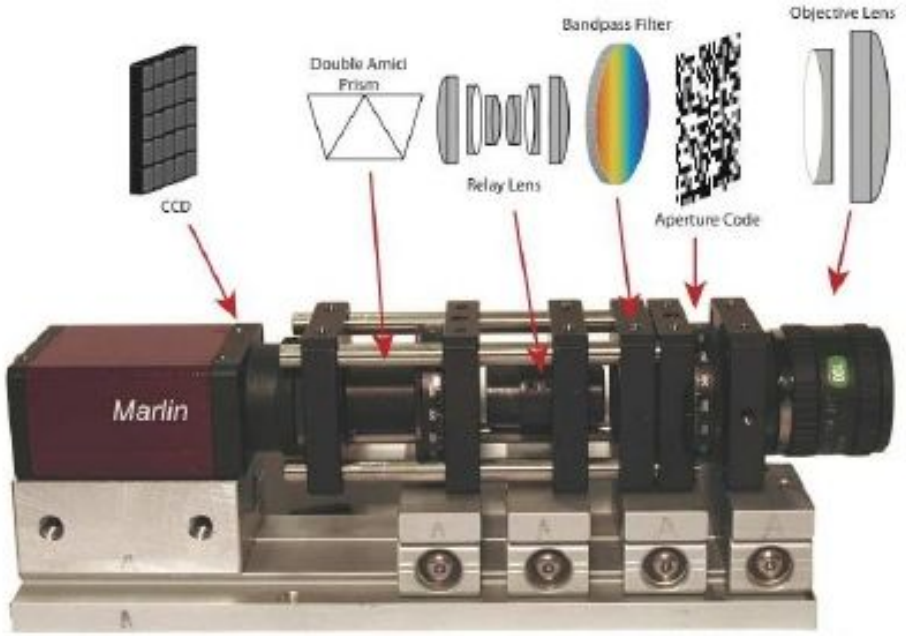
Compressed Acquisitions: Color Filter Arrays



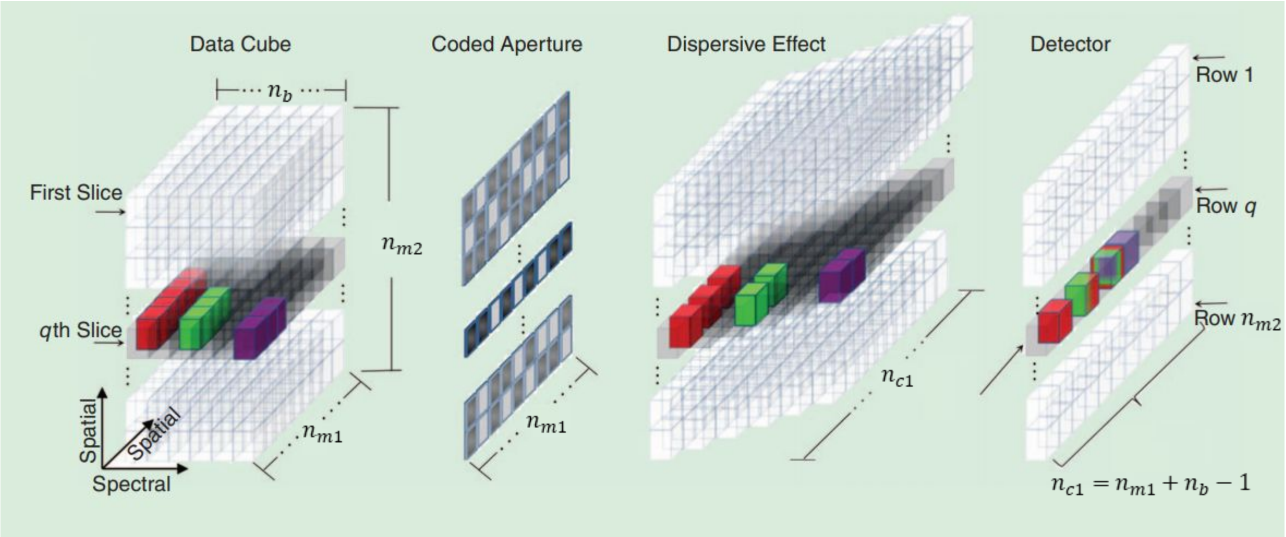
CFA (Bayer Pattern)



Compressed Acquisitions: CASSI



CASSI [Arce et al., 2014]



Compressed Acquisition: Model

- Given:
  - A PAN signal $\boldsymbol{p} \in \mathbb{R}^{n_p}$
  - A MS signal $\boldsymbol{m} \in \mathbb{R}^{n_m n_b}$
- Target: Generate an easy model for the optical compressed acquisition $\boldsymbol{y} \in \mathbb{R}^{n_c}$ of multimodal sources
  - Compression ratio: $\rho = n_c / (n_m n_b + n_p)$

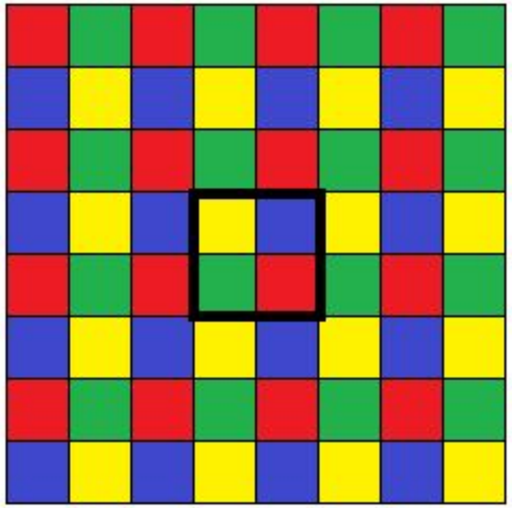
Column Concatenation

n_m=#pixels MS
n_b=#bands MS
n_p=#pixels PAN
n_c=#output samples

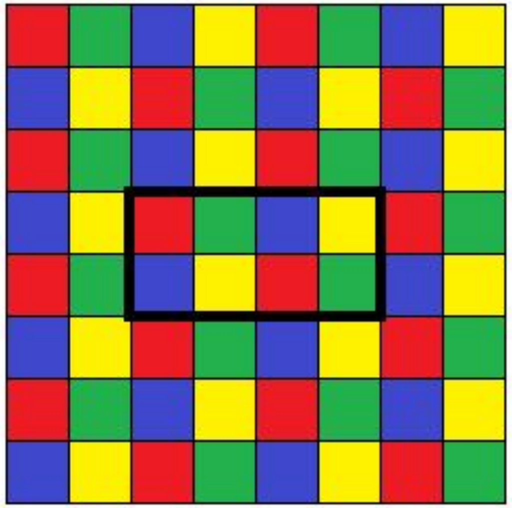
Property	Description	Mathematical model
Linearity	Optical devices are linear systems	
Separability	Each source is compressed indipendently	
Boolean Matrix	Each output sample is a sum of input samples	
Sub-sampling	Each output sample is equal to a single input pixel	

Compressed acquisitions: Binary masks

RGB/NIR CAMERAS

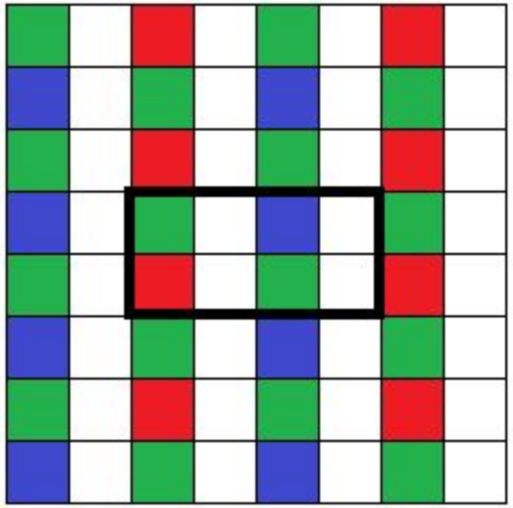


Uniform

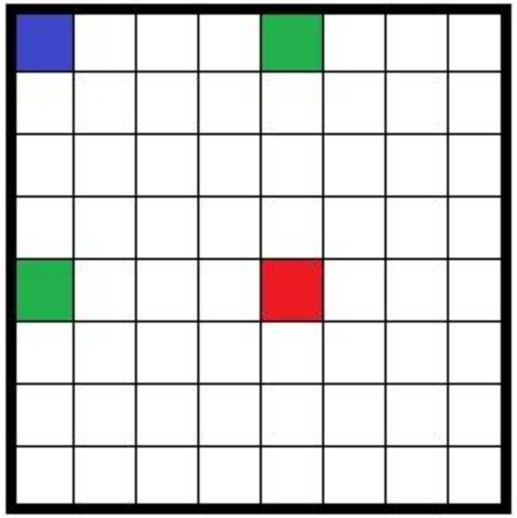


Maximum Distance
[Condat, 2009]

CAMERAS WITH DOMINANT WIDE BAND



Kodak v.3



Teledyne Onyx

Compression: Test environment

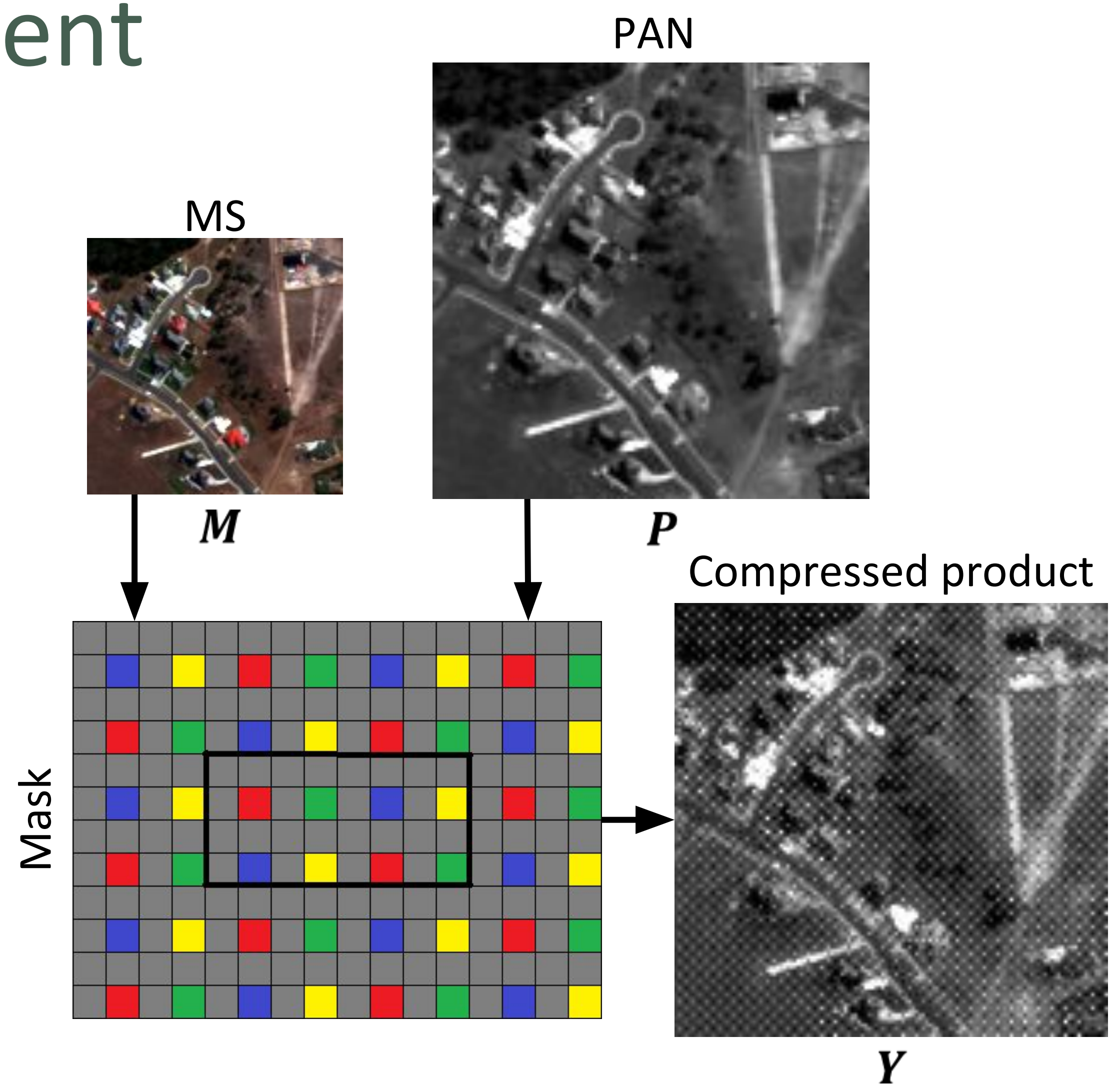
- In our experimental framework, we choose $\boldsymbol{y}$ such that n_c=n_p
- For CFA-style compression we describe each mask $\boldsymbol{H}_0$ (for the PAN) and $\boldsymbol{H}_{1,}, \dots, \boldsymbol{H}_{n_b}$ (for each band of the MS) as binary subsampling matrices
- Final compressed product is hence:

$$\boldsymbol{Y} = \boldsymbol{P} \otimes \boldsymbol{H}_0 + \boldsymbol{U}\left(\sum_{k=1}^{n_b} \boldsymbol{M}_k \otimes \boldsymbol{H}_k\right)$$

Where

- $\otimes$ stands for element-wise product
- $\boldsymbol{M}_k$ is the k-th band of the MS source
- $\boldsymbol{U}$ is a zero-padding (upsampling) oparator

- For CASSI-style compression, the equation can be easily modified by introducing a shift within parenthesis and taking random masks.



Reconstruction scheme: Direct Model

- We propose to solve this problem with a variational approach:
  - We suppose $\boldsymbol{x} \in \mathbb{R}^{n_p n_b}$ is the unknown ideal vector image to reconstruct (written in lexicographic order) and we want to find an estimation $\widehat{\boldsymbol{x}} \in \mathbb{R}^{n_p n_b}$ of such signal
- The PAN and MS sources are supposed to be generated according to this model:

$$\begin{cases} \boldsymbol{p} = \boldsymbol{R}\boldsymbol{x} + \boldsymbol{e}_P \\ \boldsymbol{m} = \boldsymbol{S}\boldsymbol{B}\boldsymbol{x} + \boldsymbol{e}_M \end{cases}$$

- Where:
  - $\boldsymbol{R} \in \mathbb{R}^{n_p \times n_p n_b}$ is a matrix related to the how the spectral response of the MS covers the one of the PAN
  - $\boldsymbol{B} \in \mathbb{R}^{n_p n_b \times n_p n_b}$ is a blurring matrix
  - $\boldsymbol{S} \in \mathbb{R}^{n_m n_b \times n_p n_b}$ is a subsampling matrix
  - $\boldsymbol{e}_P$ and $\boldsymbol{e}_M$ are instances of i.i.d. AWGN with zero mean and an unknown variance

Reconstruction scheme: Inverse Model

- The inversion is achieved by minimizing a cost function, for which we consider two approaches:

Regularization	Cost function	Solver
Vector Total Variation (VTV)		Primal-dual PDFP2O [Chen et al., 2013]
LASSO		SPARSA [Wright et al., 2009]

- Where:
  - $\boldsymbol{A}$ is the linear direct model which includes compression and degradation
  - $||\boldsymbol{Ax}-\boldsymbol{y}||_2^2$ is the maximum likelihood estimator
  - The remaining term is a regularization function
  - λ weights the two contributes
  - Δ_i and Δ_j indicate discrete gradient in the horizontal and vertical direction

Reconstruction scheme: Iterations

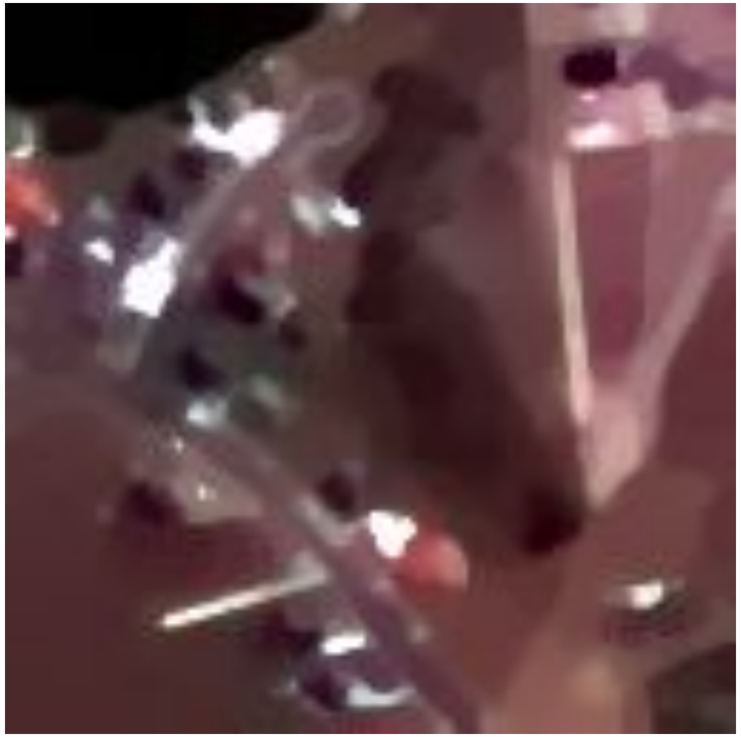
- Iteration: 0
- Iteration: 1
- Iteration: 2
- Iteration: 5
- Iteration: 10
- Iteration: 50
- Iteration: 100
- Iteration: 150
- Iteration: 250

- Dataset specifics:
  - Region: Hobart, Canada
  - Acquisition platform: IKONOS
  - PAN GSD: 2m
  - PAN sizes: 512x512 px
  - Spatial ratio: 2
  - MS bands: 4

Reconstruction scheme: Effect of λ parameter

$\lambda = 0.0001$

$\lambda = 0.0015\ (optimal)$



- $\lambda = 0.0040$

Reduced Resolution validation

- Objective quality assessment was performed according to the Wald's protocol [Wald et al., 1997]

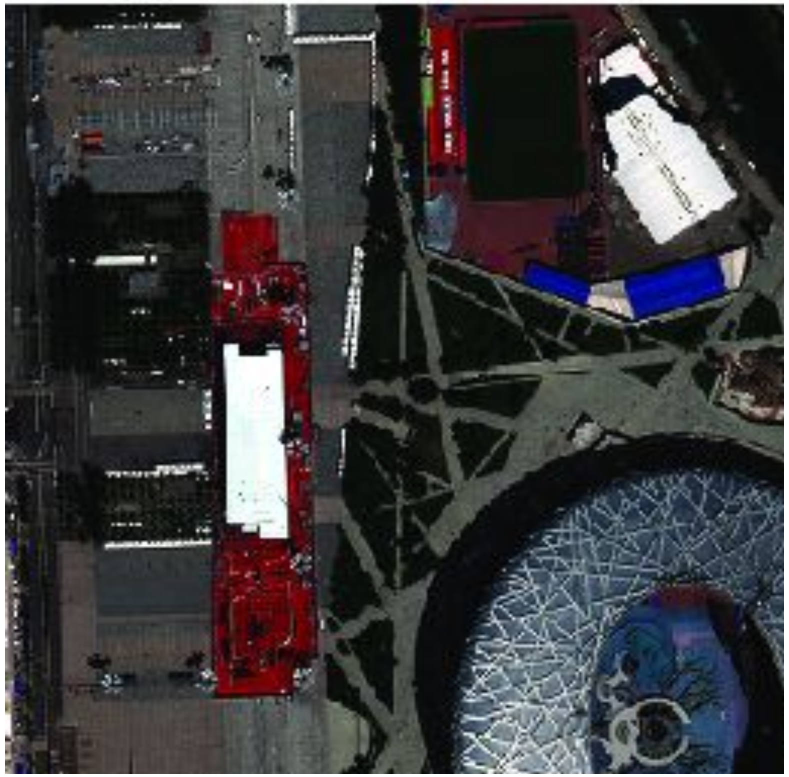
		ERGAS	SAM	Q4	sCC
	Ideal value	0	0	1	1
Hobart	Interpolated MS	6.5	3.0	0.88	0.52
Hobart	MTF-GLP-CBD	3.4	3.0	0.96	0.82
Hobart	CASSI+LASSO	8.2	6.5	0.82	0.53
Hobart	CASSI+VTV	7.0	5.3	0.88	0.62
Hobart	CFA+LASSO	6.3	4.8	0.89	0.57
Hobart	CFA+VTV	**5.2**	**4.0**	**0.93**	**0.65**
Beijing	Interpolated MS	12.5	4.4	0.78	0.30
Beijing	MTF-GLP-CBD	8.3	4.5	0.91	0.74
Beijing	CASSI+LASSO	13.2	9.5	0.77	0.53
Beijing	CASSI+VTV	11.5	6.5	0.82	0.59
Beijing	CFA+LASSO	11.4	6.9	0.83	0.56
Beijing	CFA+VTV	**10.5**	**5.6**	**0.85**	**0.60**

Reference fusion

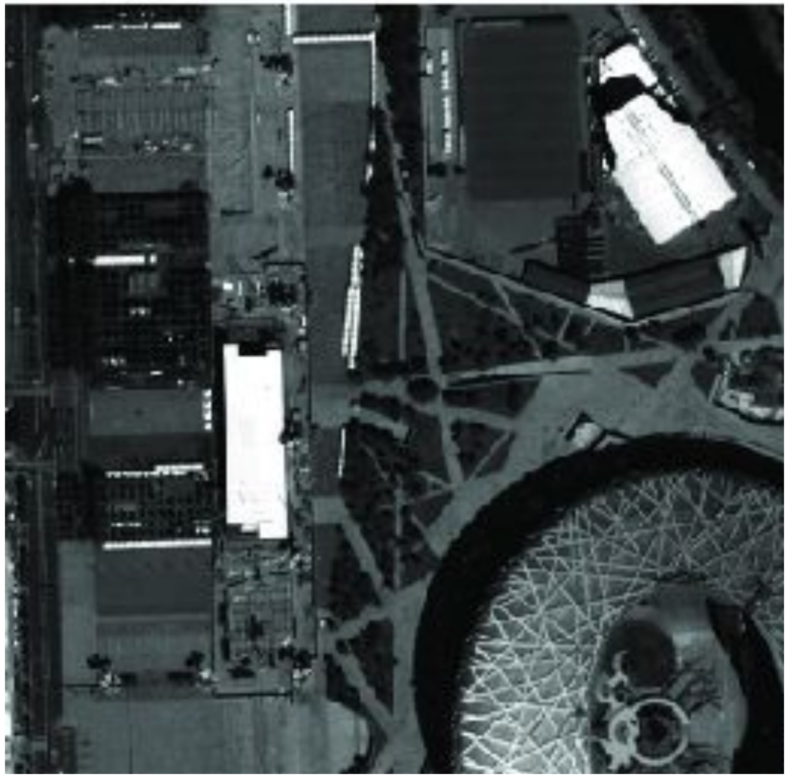
Compressed fusion

Dataset	Hobart	Beijing
Region	Canada	China
Aquisition Platform	IKONOS	Worldview-3
PAN GSD (red. res.)	2m	1,6m
PAN sizes (px)	512x512	512x512
Spatial ratio	2	2
MS bands	4	4

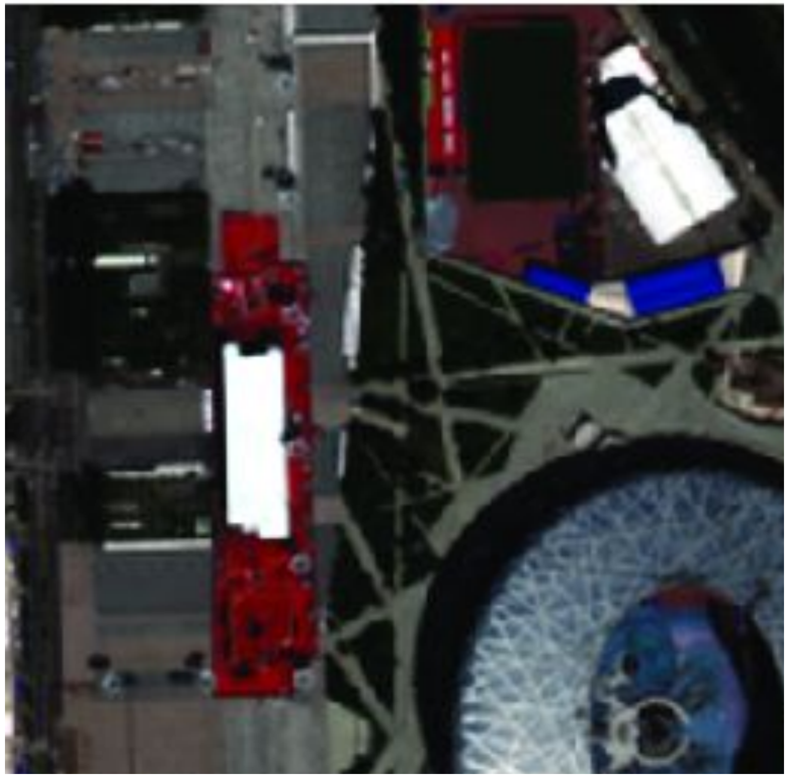
Visual analysis: Beijing dataset



GT (Ground Truth)

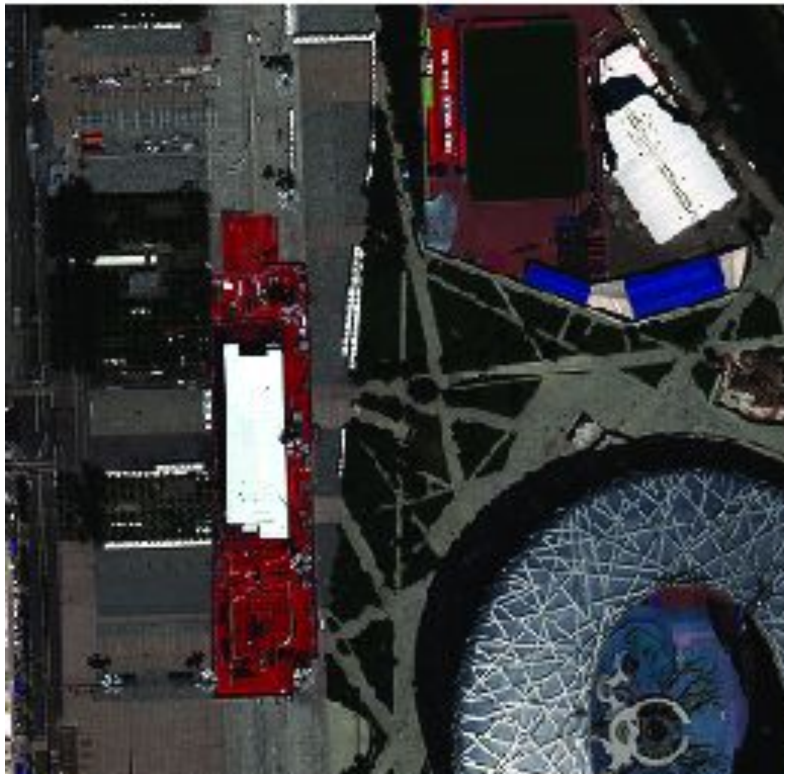


PAN



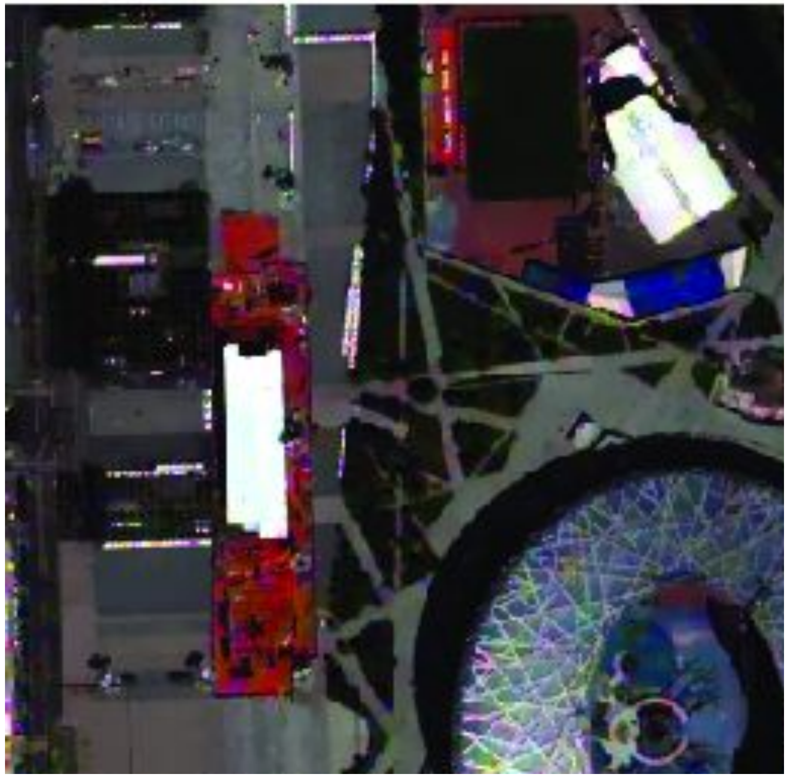
Interpolated MS

Visual analysis: Beijing dataset



GT (Ground Truth)

CFA+VTV



CASSI+VTV

Visual analysis: Hobart dataset

GT (Ground Truth)

PAN

Interpolated MS

Visual analysis: Hobart dataset

GT (Ground Truth)

CFA+VTV

CASSI+LASSO

Conclusions and future perspectives

- We presented a flexible model for joint approach of fusion and reconstruction of compressed images
- Compression can be tailored for optical hardware implementation
- Preliminary tests show potential for the reconstruction with total variation based regularization
- Future perspectives:
  - Comparison with software compression (e.g. JPEG2000)
  - Investigate mathematical conditions which link compression with loss of quality on the fused image
  - Expansion of the framework to hyperspectral images

References

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Pansharpening (1/2)

- Particular instance of data fusion between satellite acquired images
- Sources:
  - An image with high spatial resolution, such as a panchromatic (PAN)
    - Spectral resolution: Minimum spatial distance required to distinguish two objects on the scene
  - An image with high spectral diversity, such as a multispectral (MS)
    - Spectral diversity: Minimum distance between two separable spectra
- Target: Generate a fused image that features both characteristics at the same time

Pansharpening (2/2)

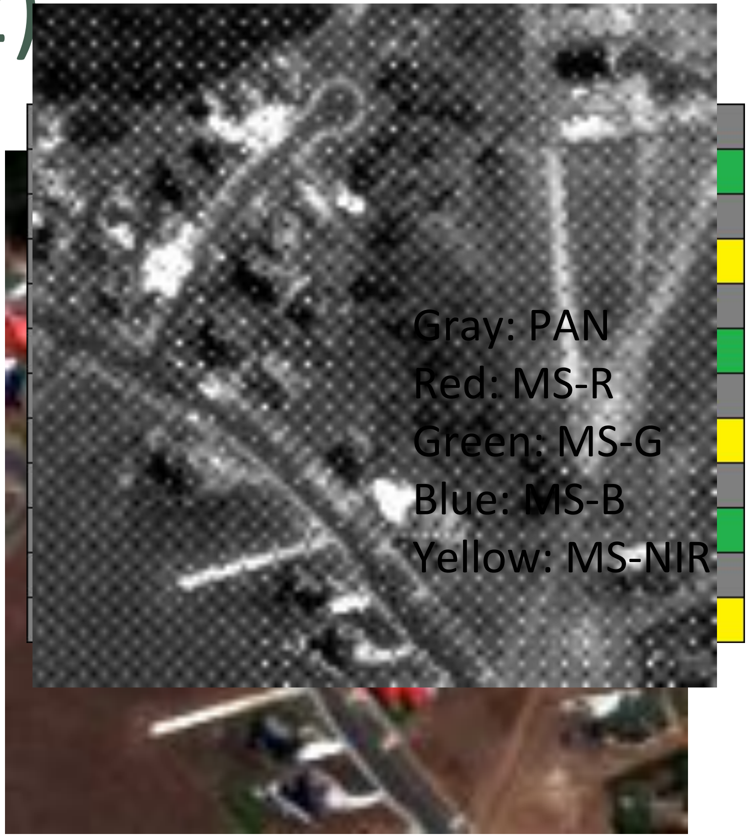
- PAN and MS are acquired by many commercial satellites (Worldview, Geo-eye, QuickBird, IKONOS, etc.)
- Physical and technology constraints don’t allow sensors to acquire an image which jointly features the highest available spatial resolution and spectral diversity
- There is a high commercial demand of fused products (eg: Google Earth)
- Various scientific application: change detection, object recognition, scene interpretation [Dalla Mura et al., 2015]

Compressed Acquisition: Introduction

- Compression allows to save storage resources on board and trasmission bandwidth
- Large amount of image data acquired by satellite platforms
  - Increase of image sizes are expected due to technological improvements (better spatial resolution and larger swaths)
- Allows a plan for a constellation of low-cost satellites
- Example of TOPSAT (a low-cost data satellite [Yu et al., 2009])
  - PAN images of 8000 pixels at 2.5m GSD
  - MS images of three bands of 2100 pixels each at 5m GSD
  - Each snapshot acquisition is around 70 Mbits and the satellite can’t store more than four of those packets

Compression: Proposed approach (1/2)

- Assumption: we want to generate a compression by generating a synthetic P which embeds information from both so
- Sources:
  - A PAN image $\boldsymbol{P} \in \mathbb{R}^{n_p}$
  - A MS image $\boldsymbol{M}$; it will be cal $\widetilde{\boldsymbol{M}}$ when scale e GSD of the (for simplicity
- Method: For each pixel coordinate, each source is masked and then overlayed
- Target: A compressed image $\boldsymbol{Y} \in \mathbb{R}^{n_p}$, reaching a compression rate $n_p/(n_p + n_m n_b)$

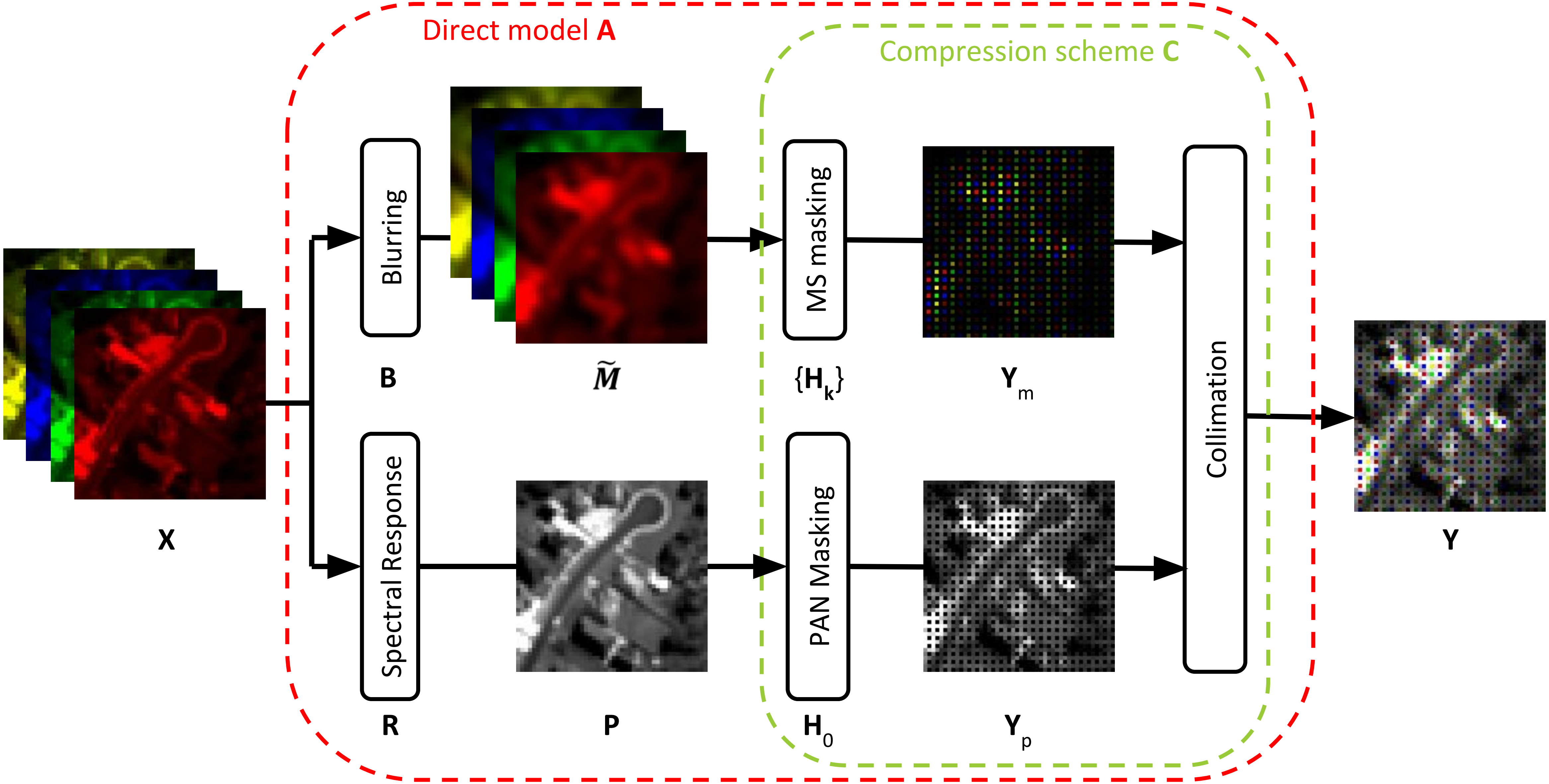


Compressed product
Interpolated MS

Reconstruction scheme

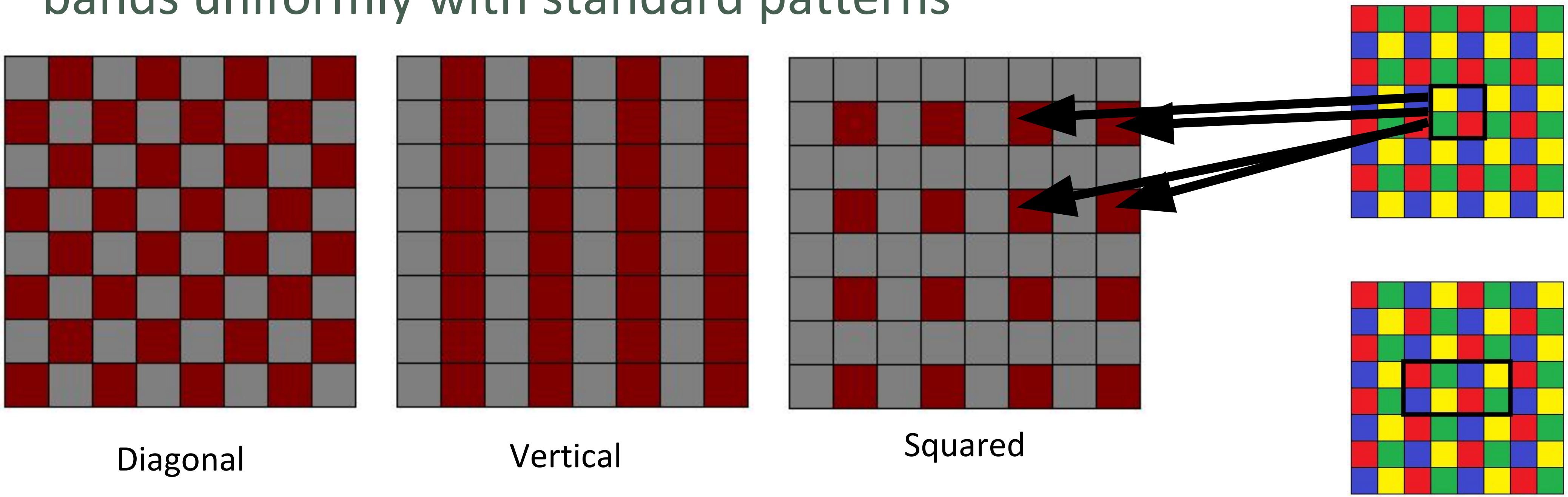
- Deconstruction/demosaicing is done by the ground segment
- It's a joint approach:
  - Not simply a fusion, as we just have a compressed signal
  - Not simply a decompression, as the target is to recover the fused image and not the original sources
- We propose to solve this problem with a variational approach:
  - We suppose $\boldsymbol{X} \in \mathbb{R}^{n_p \times n_b}$ is the unknown ideal image to reconstruct
  - We want to find an estimation $\widehat{\boldsymbol{X}} \in \mathbb{R}^{n_p \times n_b}$ of such signal

RECOSTRUCTION SCHEME: DIRECT MODEL



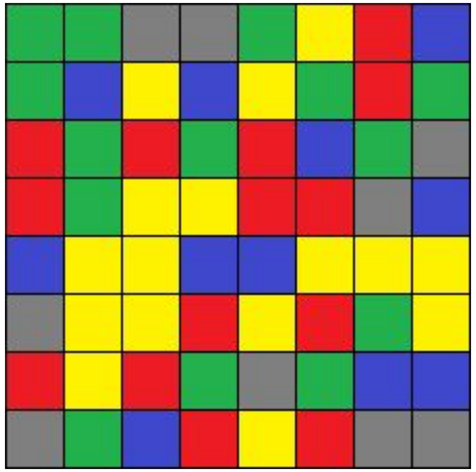
Testbed: Uniform masks

- We use the PAN as dominant pattern and we fill the holes with the MS bands uniformly with standard patterns

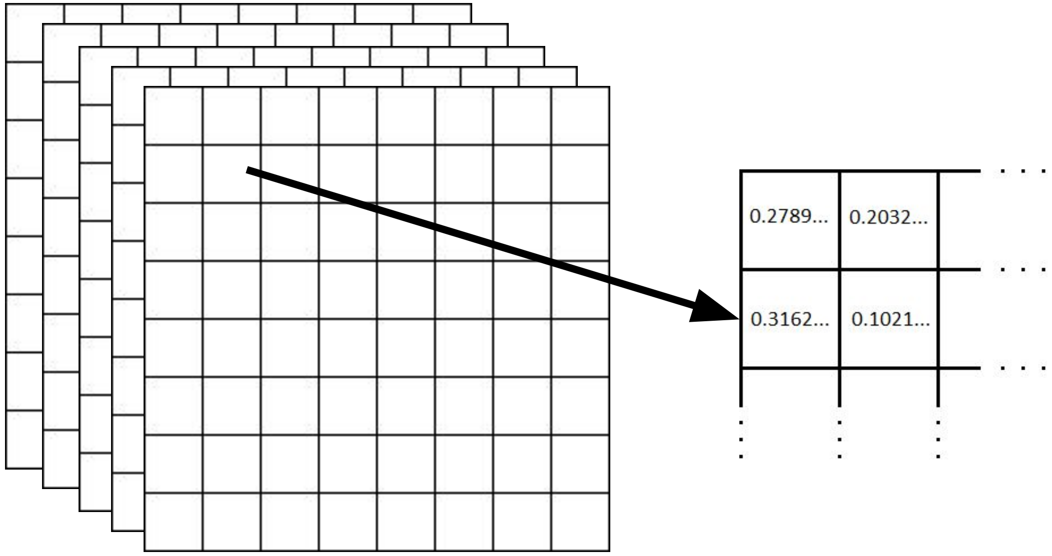


Testbed: Random masks

- We propose a new approach for masks based on matrices with random coefficients

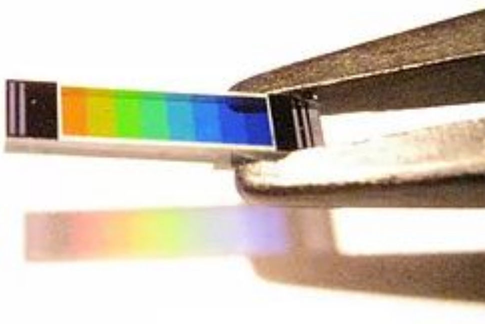


Random pattern
[Amba et al.,2016]



Proposed

Color Shades™



A comparison

- We have made 2 comparison to test the viabililty of the approach

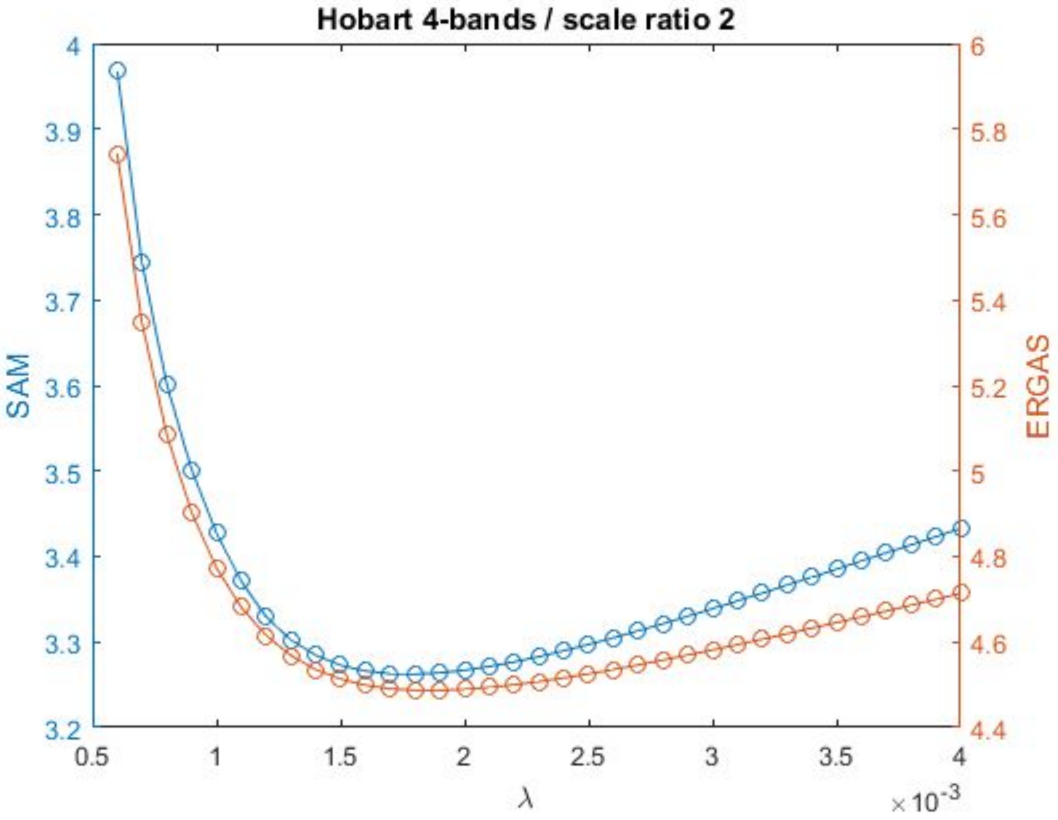
1. We check the most performing classical approach to pansharpening, without any compression, to assess the ideal performance of the fusion; it turns out to be the MTF-GLP-CBD [Alparone et al., 2007]
2. We test all the proposed combinations of masks with our proposed reconstruction framework, including our proposed mask

Quality assessment is performed with the Wald's protocol [Wald et al., 1997]

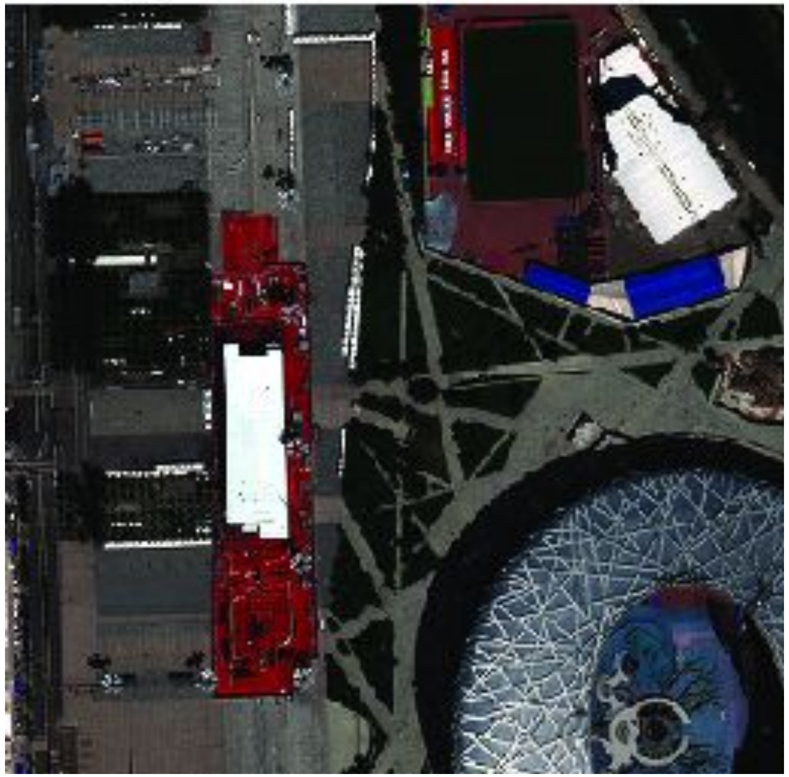
- Dataset specifics:
  - Region: San Francisco, USA
  - Acquisition platform: QuickBird
  - PAN GSD: 2.4m
  - PAN sizes: 128x128 px
  - Spatial ratio: 2
  - MS bands: 4

Reconstruction scheme: Effect of lambda parameter (2/2)

- Tradeoff between imposing a smoothness on the final product and remotion of the texturing effect (overfitting)
- Results are consistent between different quality indices used for the Wald protocol's test [Wald et al., 1997]

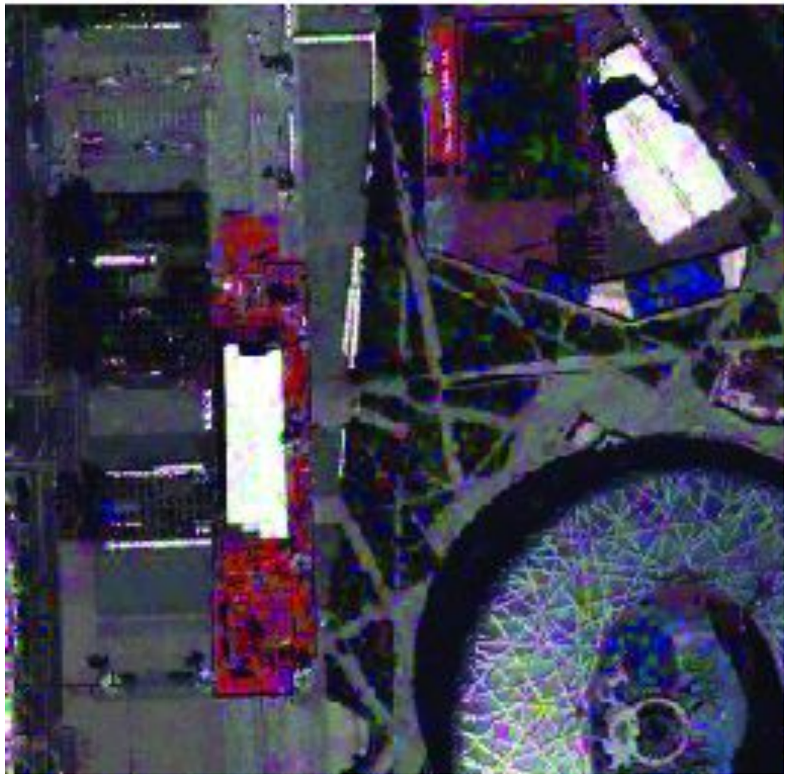


Mask comparison: Visual analysis



GT (Ground Truth)

CFA+TVT



CASSI+LASSO

A comparison: Visual analysis

GT (Ground Truth)

Proposed

PAN

Diagonal+Uniform

MS

References

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