Image Fusion and Reconstruction of Compressed Data: A Joint Approach

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Summary

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

Pansharpening

HIGH SPATIAL RESOLUTION

Panchromatic (PAN)

HIGH SPECTRAL DIVERSITY

Multispectral (MS)

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

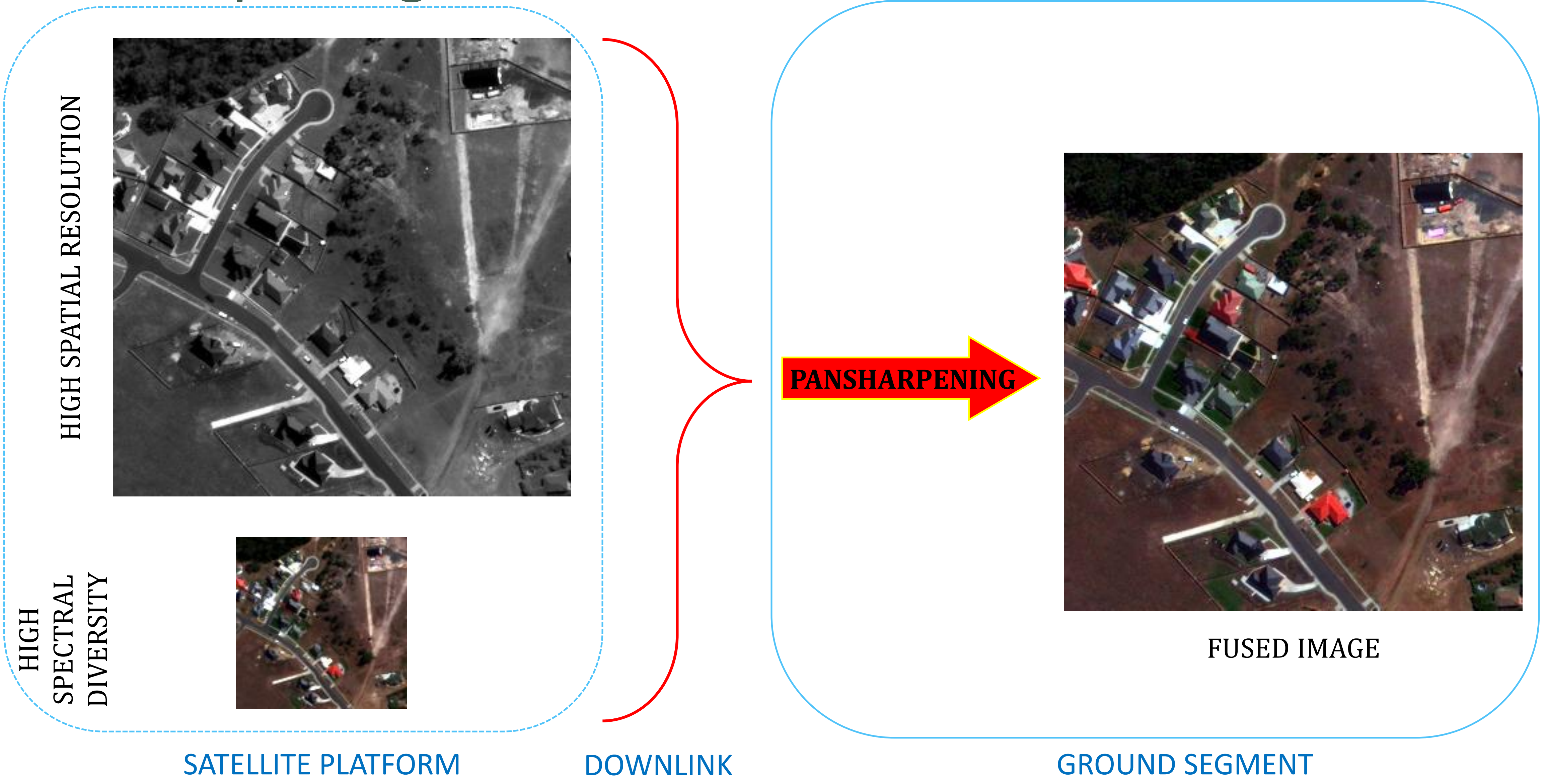
PANSHARPENING

SPECTRAL DIVERSITY: Minimum distance between two separable spectra

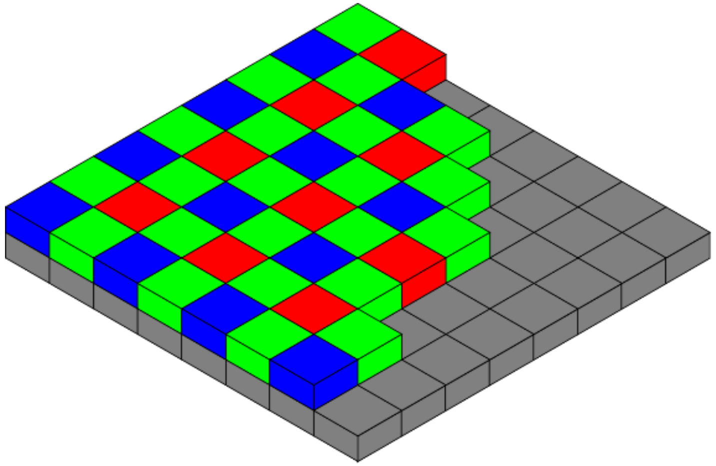
FUSED IMAGE

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

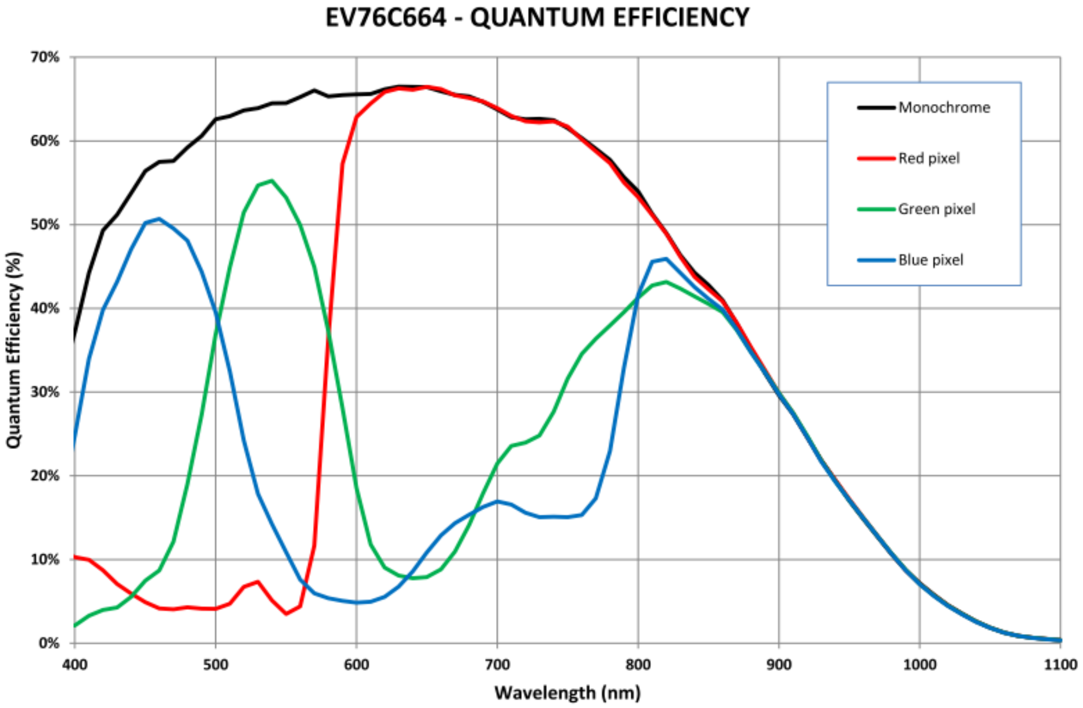
Pansharpening



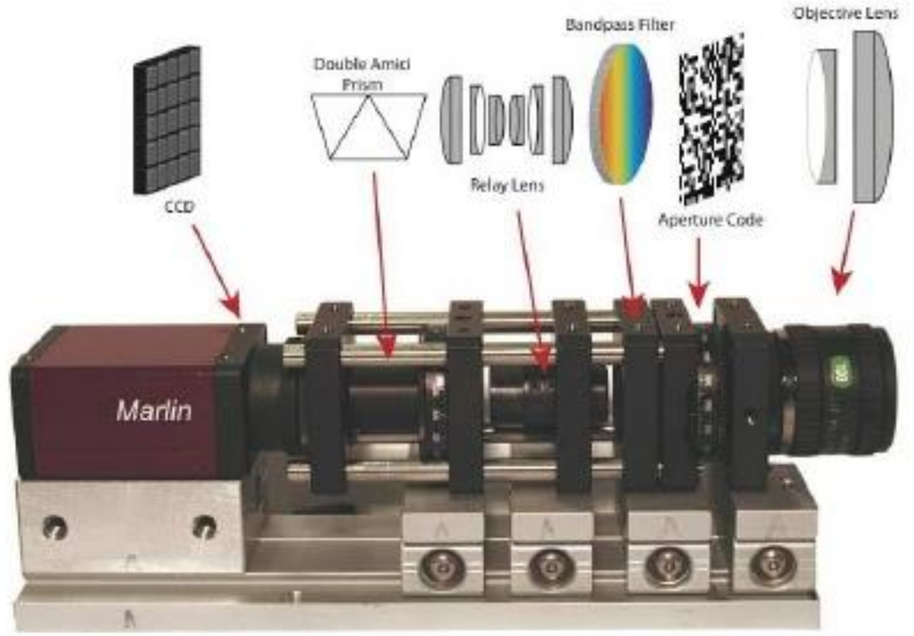
Compressed Acquisitions: Color Filter Arrays



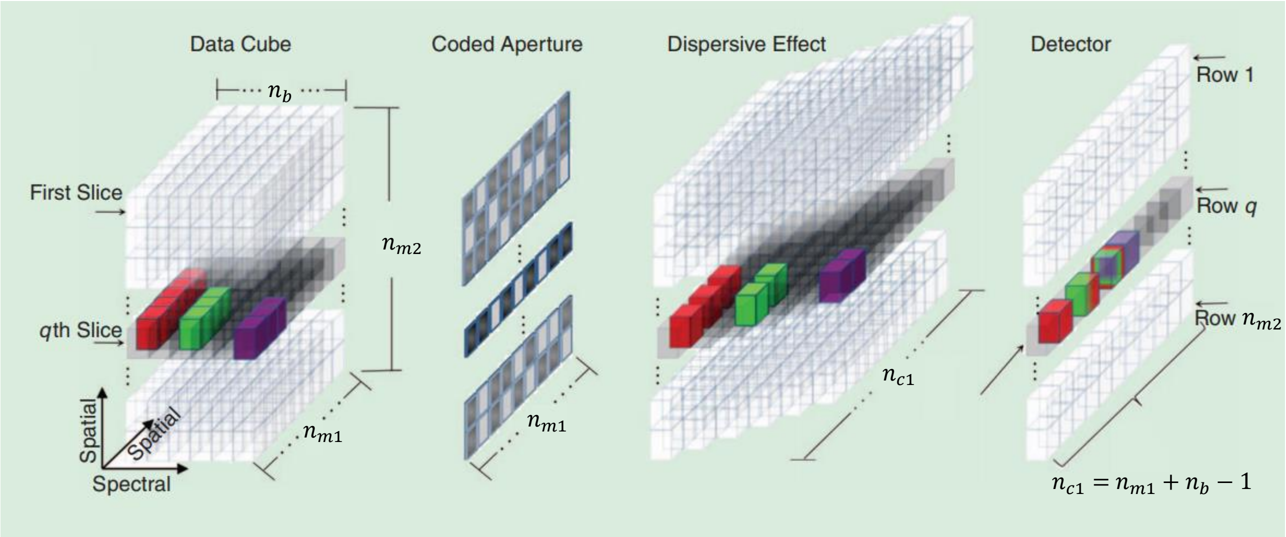
CFA (Bayer Pattern)



Compressed Acquisitions: CASSI

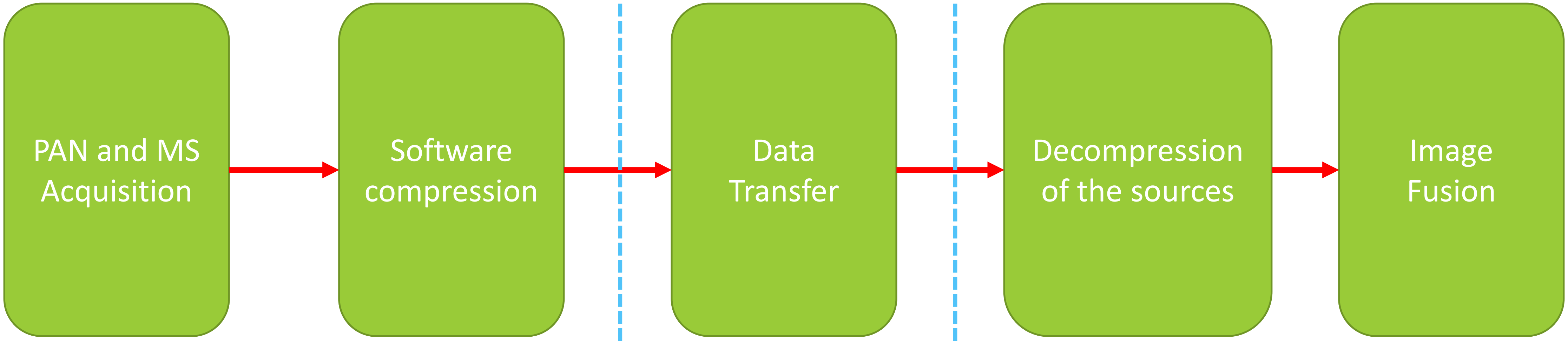


CASSI [Arce et al., 2014]

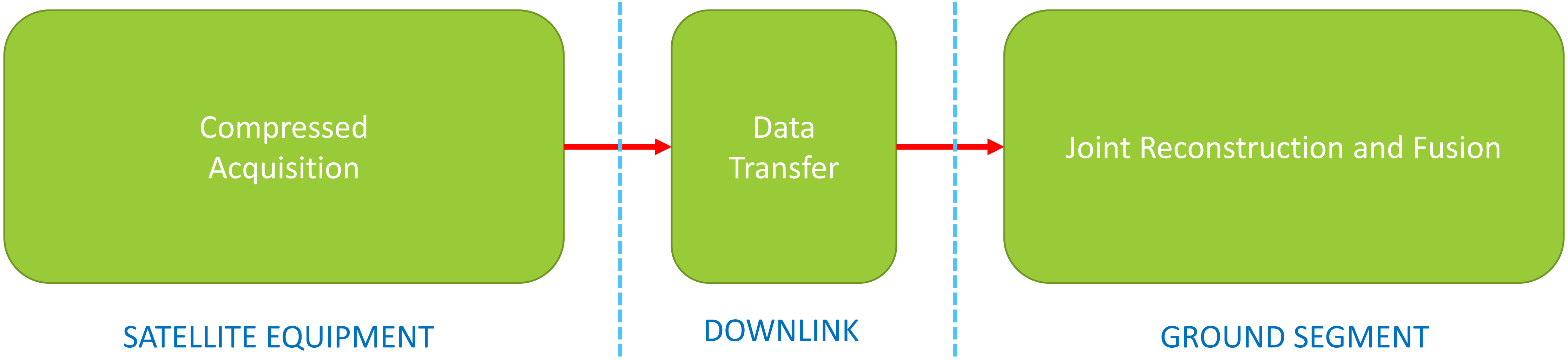


A joint model

- Classical Approach



- Proposed Model



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
  - Resolution ratio: $\rho = n_c / (n_m n_b + n_p)$
- Desired properties:

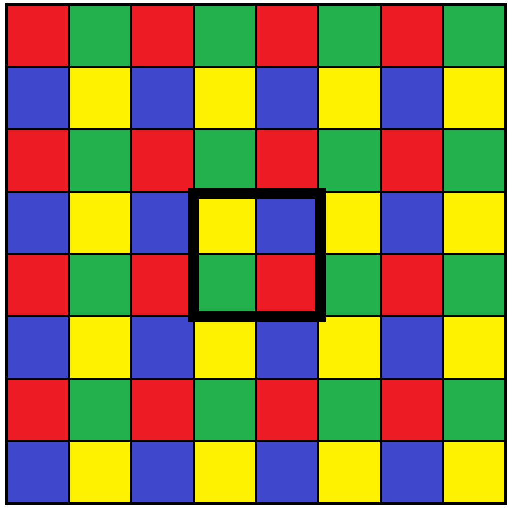
Column Concatenation

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

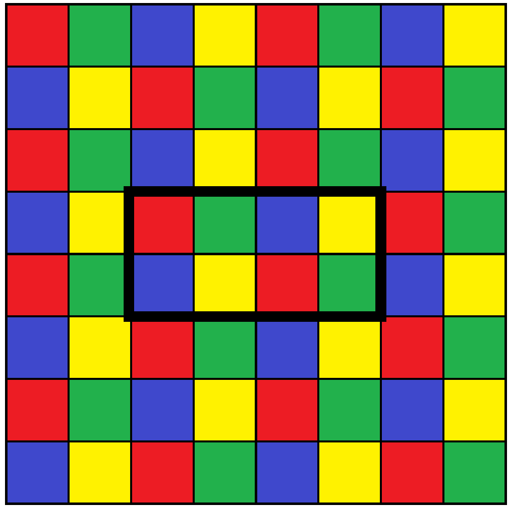
Property	Description	Mathematical model
Linearity	Optical devices are linear systems	$\boldsymbol{y} = \boldsymbol{C}[\boldsymbol{p}; \boldsymbol{m}]$
Separability	Each source is compressed indipendently	$\boldsymbol{C}$ is a block matrix
Boolean Matrix	Each output sample is a sum of input samples	$\boldsymbol{C}$ is a binary matrix
Sub-sampling	Each output sample is equal to a single input pixel	Each column of $\boldsymbol{C}$ has a single 1

Compressed acquisitions: Binary masks

RGB/NIR CAMERAS

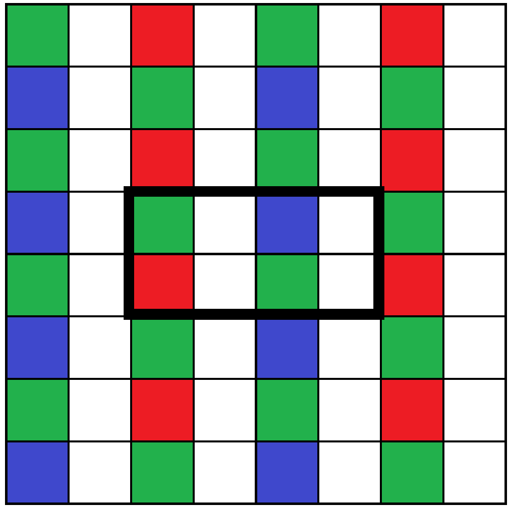


Uniform

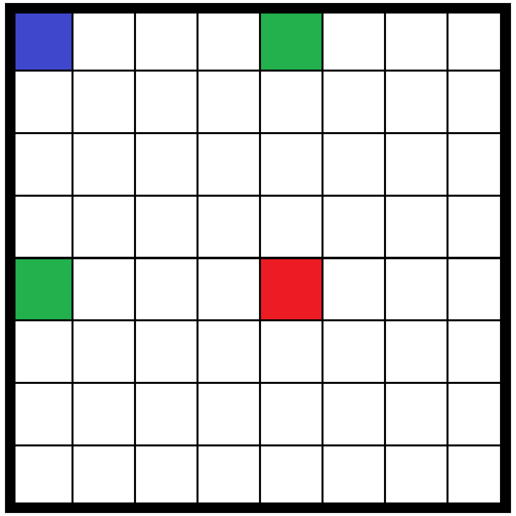


Maximum Distance
[Condat, 2009]

CAMERAS WITH DOMINANT WIDE BAND



Kodak v.3



Teledyne Onyx

Compression: Test environment

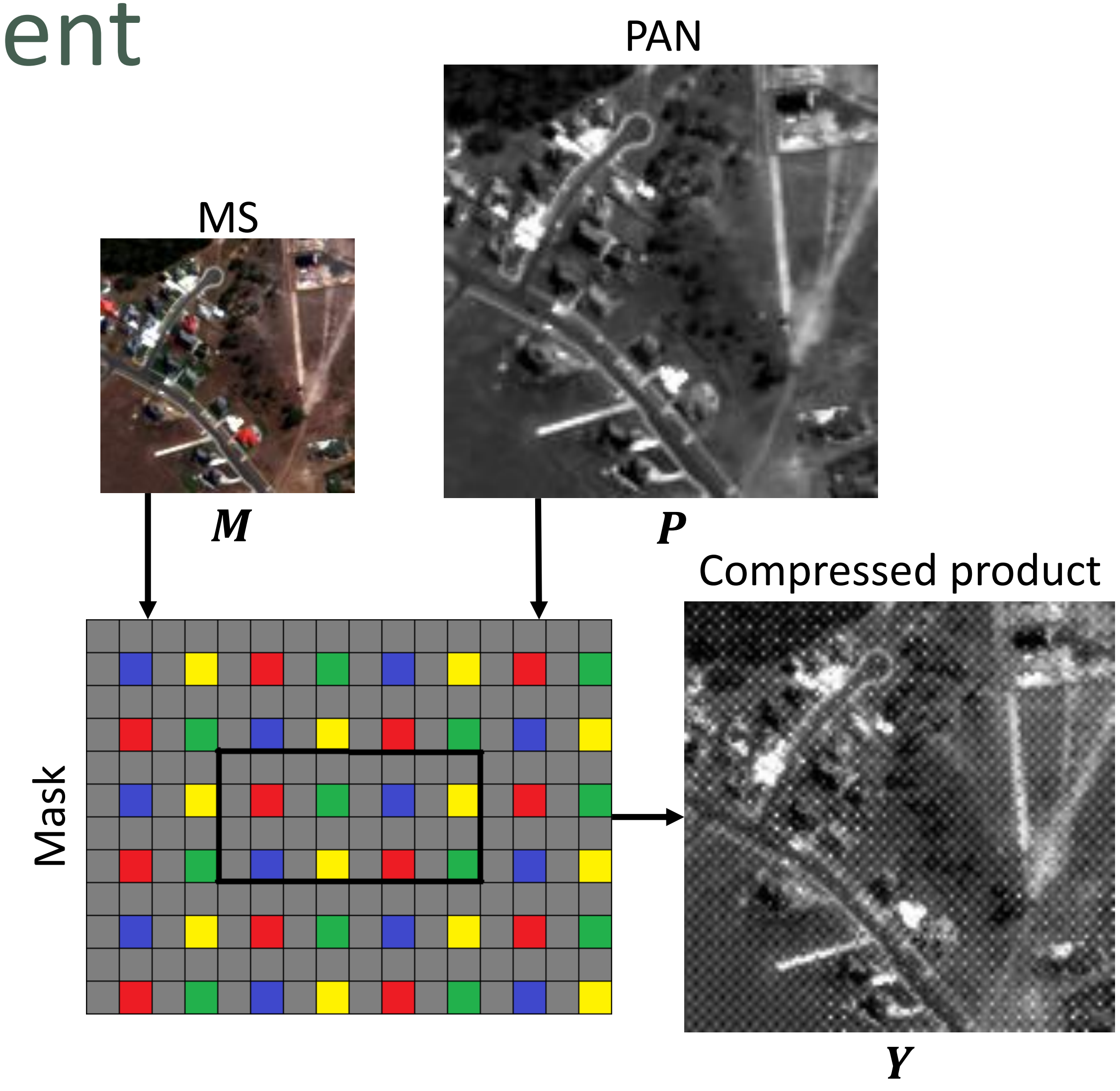
- In our experimental framework, we choose $\boldsymbol{y}$ such that n_c=n_p
- For CFA-style compression we describe each mask $\boldsymbol{H}_0$ (for the PAN) and $\boldsymbol{H}_{1,}, \dots, \boldsymbol{H}_{n_b}$ (for each band of the MS) as binary subsampling matrices
- Final compressed product is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



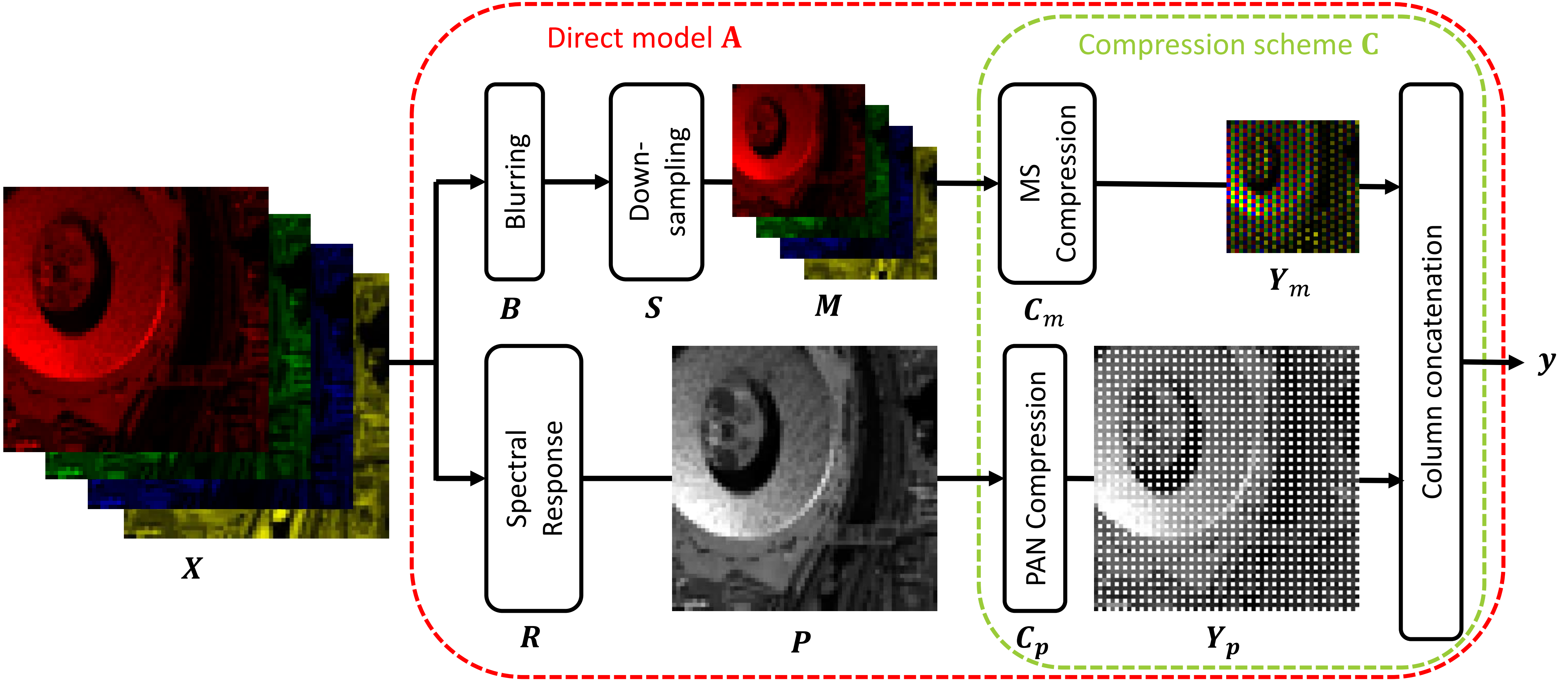
Reconstruction scheme: Direct Model

- 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 $\hat{\boldsymbol{x}} \in \mathbb{R}^{n_p n_b}$ 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: Direct Model



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)	$\hat{\boldsymbol{x}} = \text{argmin}_{\boldsymbol{x}} \left(\lVert \boldsymbol{Ax} - \boldsymbol{y} \rVert_F^2 + \lambda \varphi_{TV}(\boldsymbol{x}) \right)$ $\varphi_{TV}(\boldsymbol{x}) = \sum_{i,j} \sum_{k=1}^{n_b} \sqrt{\lvert \Delta_i \boldsymbol{X}_{i,j,k} \rvert^2 + \lvert \Delta_j \boldsymbol{X}_{i,j,k} \rvert^2}$	Primal-dual PDFP2O [Chen et al., 2013]
LASSO	$\hat{\boldsymbol{x}} = \boldsymbol{\Psi}^{-1} \left(\text{argmin}_{\boldsymbol{d}} (\lVert \boldsymbol{A\Psi}^{-1}\boldsymbol{d} - \boldsymbol{y} \rVert_2^2 + \lambda \lVert \boldsymbol{d} \rVert_1) \right)$ $\boldsymbol{d} = \boldsymbol{\Psi x}$ is a trasformation in a sparse domain	SPARSA [Wright et al., 2009]

- Where:
  - $\boldsymbol{A}$ is the linear direct model which includes compression and degradation
  - $\lVert \boldsymbol{Ax} - \boldsymbol{y} \rVert_2^2$ 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

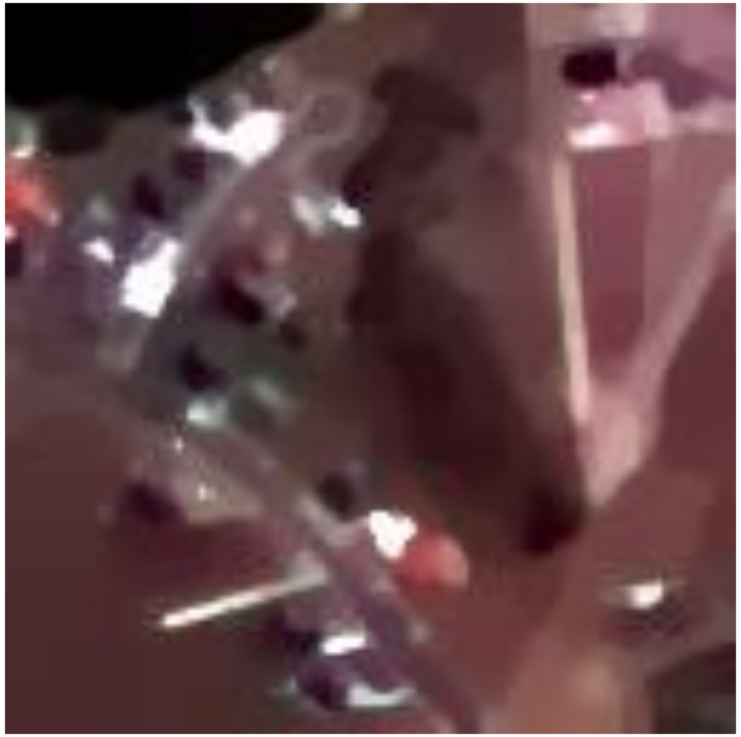
- Iteration: 0
- Iteration: 1
- Iteration: 2
- Iteration: 5
- Iteration: 10
- Iteration: 50
- Iteration: 100
- Iteration: 150
- Iteration: 250

- 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]

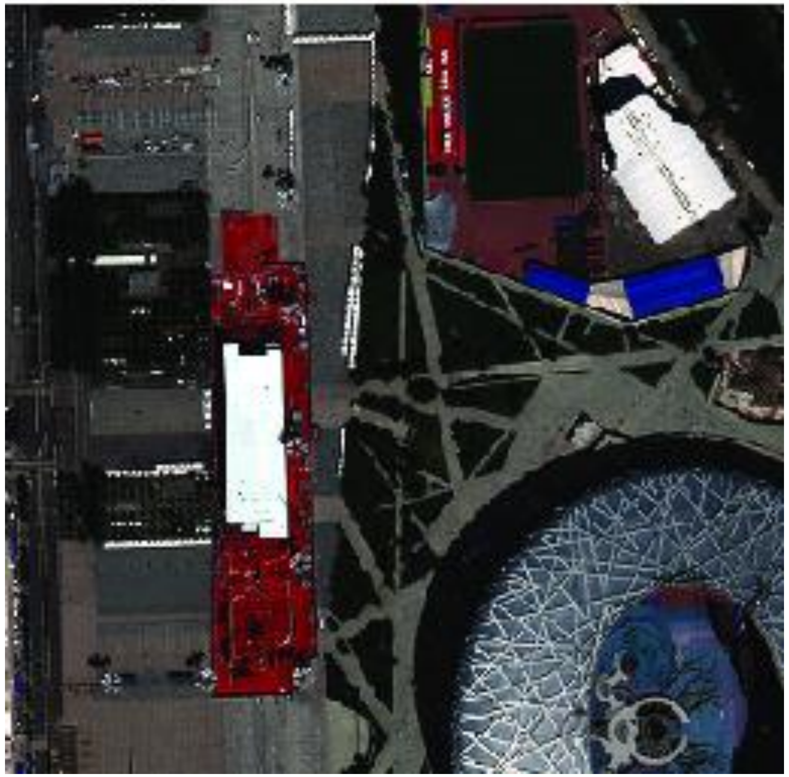
Dataset	Hobart	Beijing
Region	Canada	China
Aquisition Platform	IKONOS	Worldview-3
PAN GSD (red. res.)	2m	1,6m
PAN sizes (px)	512x512	512x512
Spatial ratio	2	2
MS bands	4	4

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

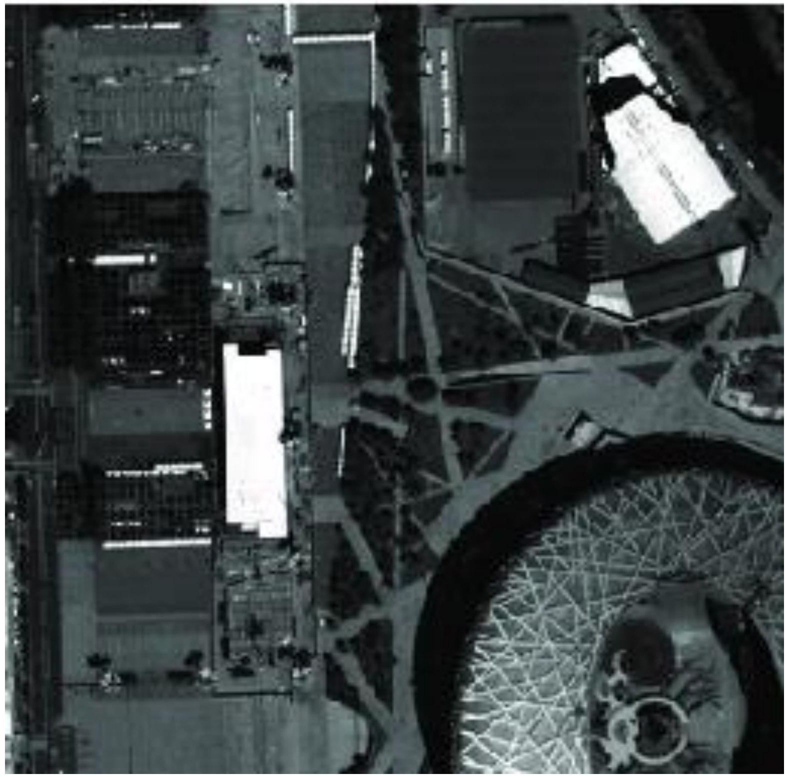
Reference fusion

Compressed fusion

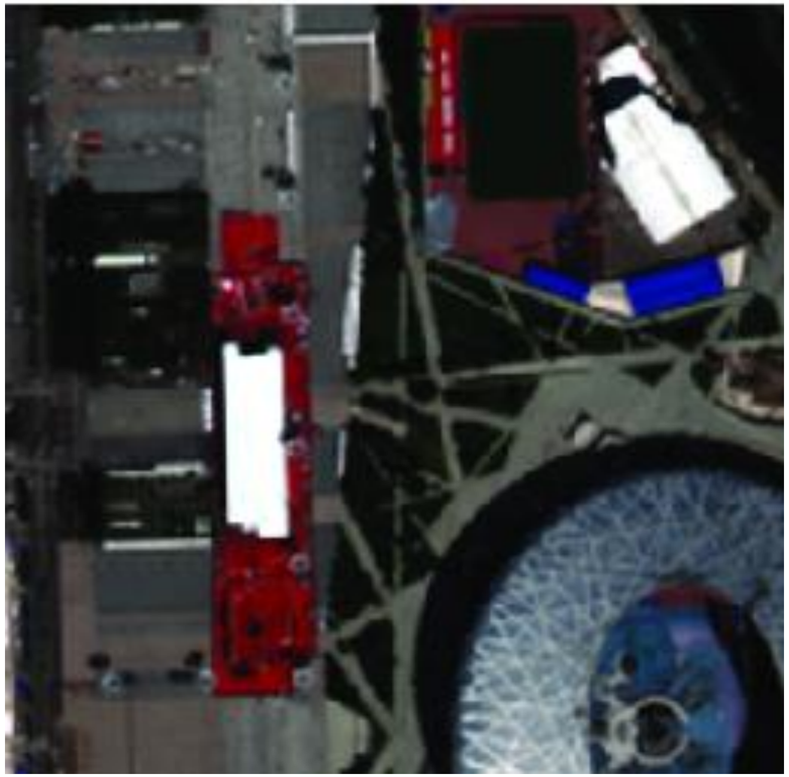
Visual analysis: Beijing dataset



GT (Ground Truth)

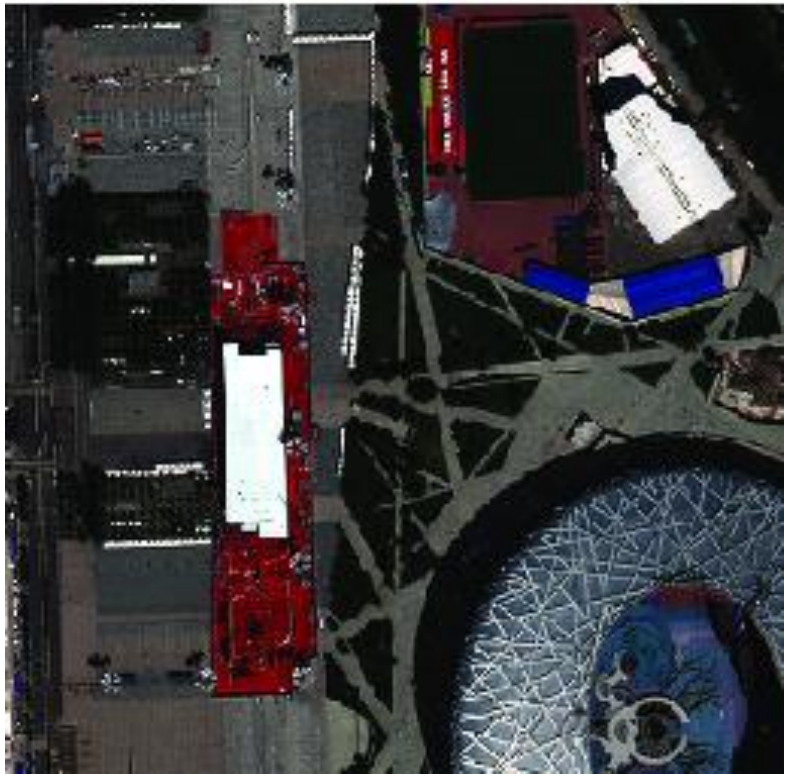


PAN

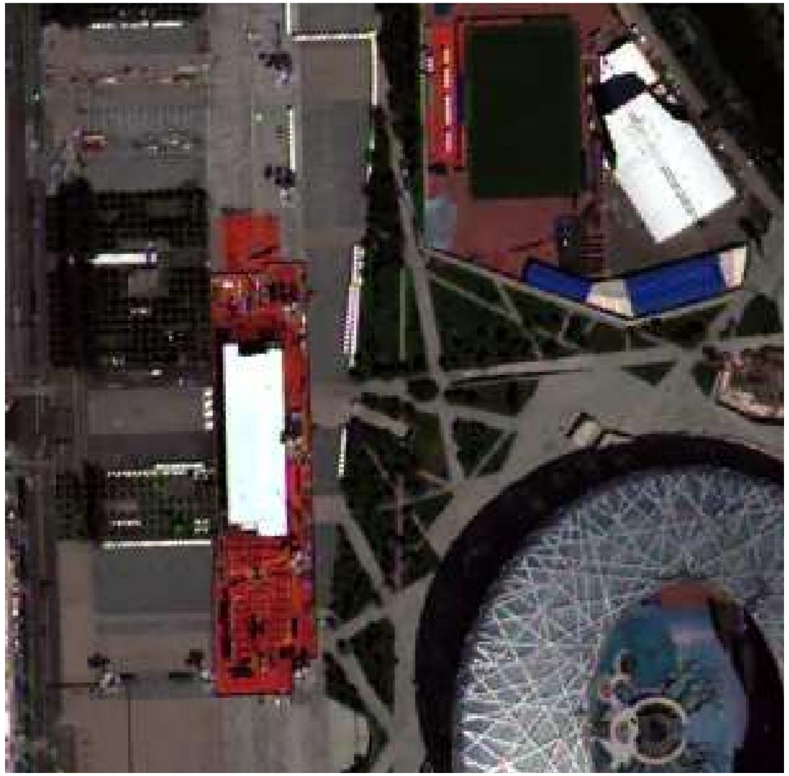


Interpolated MS

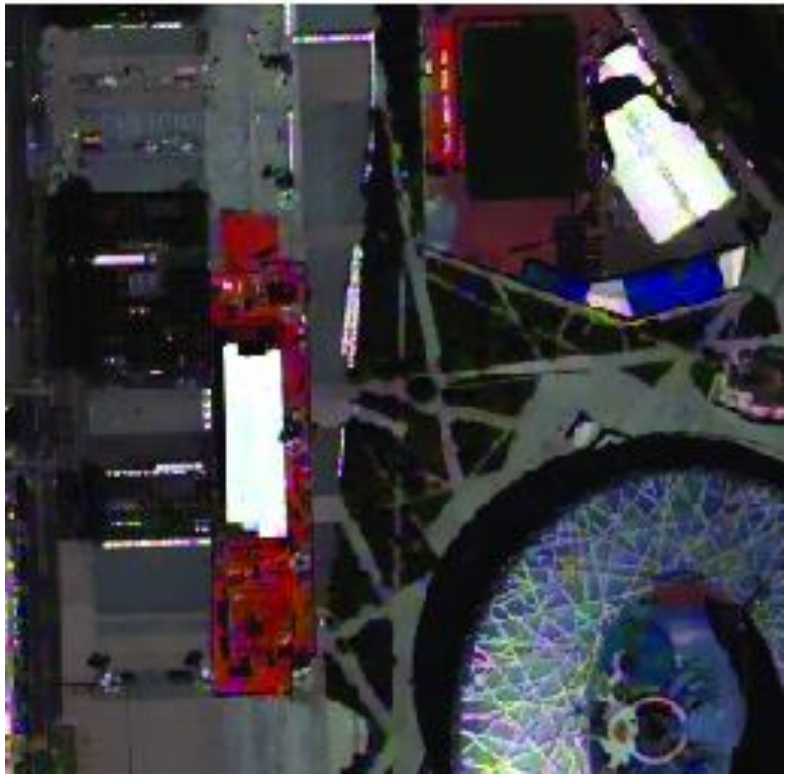
Visual analysis: Beijing dataset



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

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Thanks for the attention