UNIVERSITEIT GENT

FACULTY OF **ENGINEERING**

Sparse Coding and Machine Learning in High-dimensional and Multimodal Image Processing

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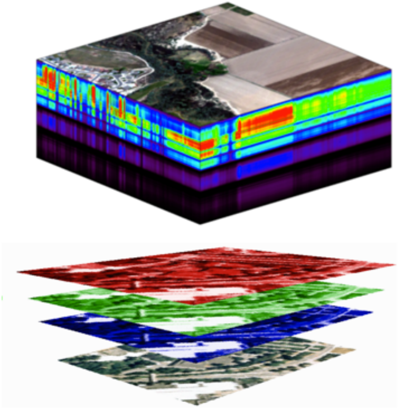
Multi-source data analysis (MSDA) workshop
Prague, 25-26 November 2019

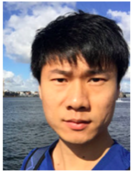
A Wealth of High-Dimensional Multimodal Data



Remote sensing data (hyperspectral, visible, LiDAR,...)

Digitized paintings (infrared, X-Ray, visible)

Collaborators


Shaoguang Huang


Hongyan Zhang


Laurens Meeus


Roman Sizyakin


Nina Žižakić


Hélène Dubois


Bart Devolder


Ljiljana Platiša


Tijana Ružić


Marc De Mey


Ann Dooms


Bruno Cornelis


Max Martens

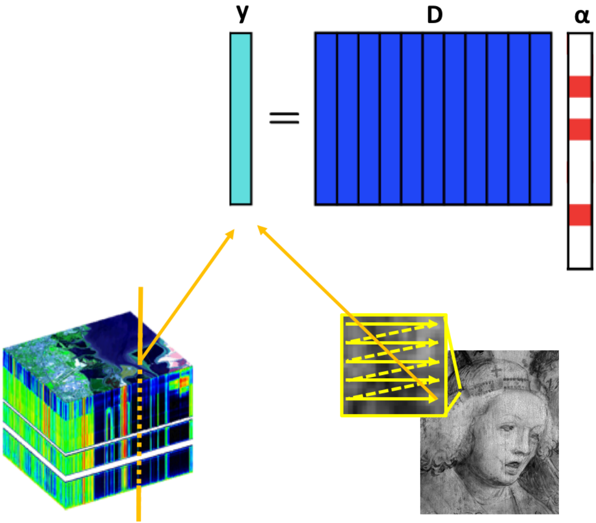

Ingrid Daubechies

Outline

1. Sparse Coding of High-Dimensional Signals
   - Sparse representation
   - Sparse Representation Classification
2. Applications in Remote Sensing
   - Robust SRC in Hyperspectral Imaging
   - Sparse Unmixing
   - Sparse Subspace Clustering
3. Applications in Art Investigation
   - The Ghent Altarpiece
   - Challenges for signal processing and machine learning
   - Paint loss detection based on sparse coding
   - Deep learning approaches
   - Virtual restoration

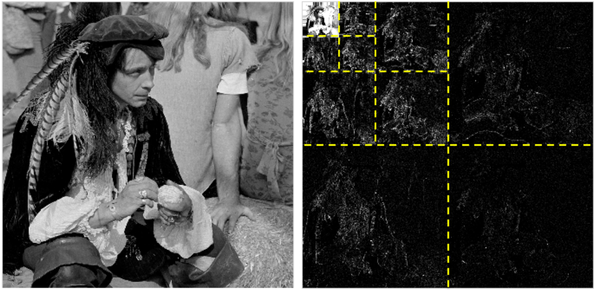
Outline

Sparse representation



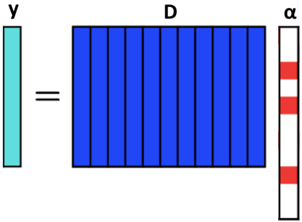
Designed vs. Learned Dictionaries

- **Designed dictionaries**: wavelets, curvelets, shearlets...
  - typically yield sparse representation of signals and images
  - advantages: generic, fast computation



- **Learned dictionaries**
  - trained on a set of representative examples
  - goal: optimally sparse representation for a given class of signals

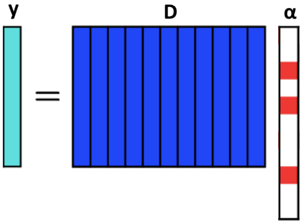
Sparse coding



$$\hat{\boldsymbol{\alpha}} = \arg\min_{\boldsymbol{\alpha}} \|\mathbf{y} - \mathbf{D}\boldsymbol{\alpha}\|_2^2 \quad \text{subject to} \quad \|\boldsymbol{\alpha}\|_0 \leq K$$

$$\hat{\boldsymbol{\alpha}} = \arg\min_{\boldsymbol{\alpha}} \|\boldsymbol{\alpha}\|_0 \quad \text{subject to} \quad \|\mathbf{y} - \mathbf{D}\boldsymbol{\alpha}\|_2^2 \leq \epsilon$$

Sparse coding



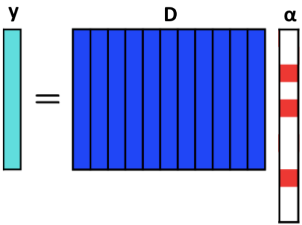
$$\hat{\boldsymbol{\alpha}} = \arg\min_{\boldsymbol{\alpha}} \|\mathbf{y} - \mathbf{D}\boldsymbol{\alpha}\|_2^2 \quad \text{subject to} \quad \|\boldsymbol{\alpha}\|_0 \leq K$$

$$\hat{\boldsymbol{\alpha}} = \arg\min_{\boldsymbol{\alpha}} \|\boldsymbol{\alpha}\|_0 \quad \text{subject to} \quad \|\mathbf{y} - \mathbf{D}\boldsymbol{\alpha}\|_2^2 \leq \epsilon$$

Greedy algorithms

- Matching Pursuit (MP) [Mallat and Zhang, '93]
- **OMP** [Tropp,'04], CoSaMP [Needell and Tropp, '09]
- IHT [Blumensath and Davies, 09]

Sparse coding



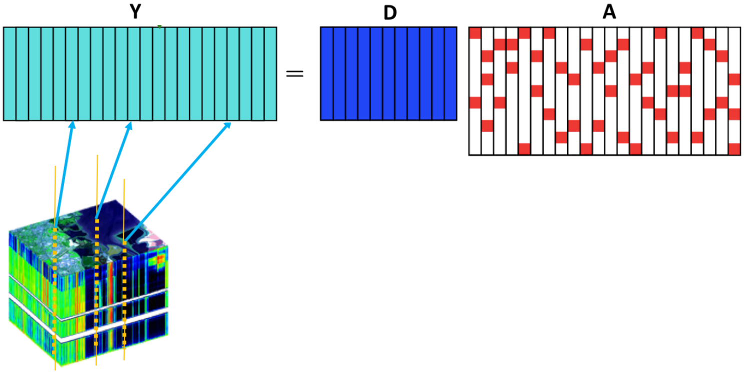
Convex relaxation:

$$\hat{\boldsymbol{\alpha}} = \arg\min_{\boldsymbol{\alpha}} \|\boldsymbol{\alpha}\|_1 \quad \text{subject to} \quad \|\mathbf{y} - \mathbf{D}\boldsymbol{\alpha}\|_2^2 \leq \epsilon$$

$$\hat{\boldsymbol{\alpha}} = \arg\min_{\boldsymbol{\alpha}} \|\mathbf{y} - \mathbf{D}\boldsymbol{\alpha}\|_2^2 + \lambda\|\boldsymbol{\alpha}\|_1$$

LASSO [Tibshirani, '96], BPDN [Chen et al, '01]

Sparse coding and dictionary learning

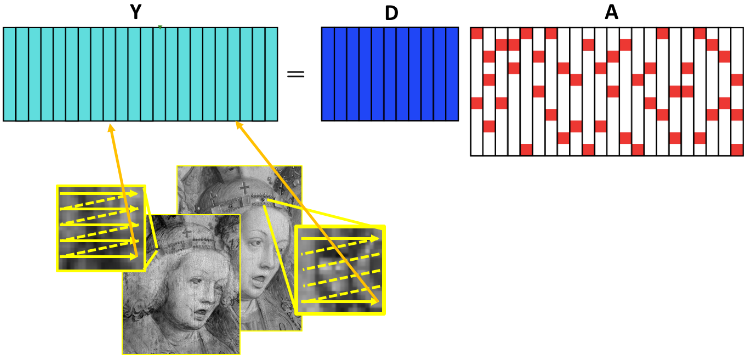


$$\{\hat{\mathbf{D}}, \hat{\mathbf{A}}\} = \arg\min_{\mathbf{D},\mathbf{A}} \left\{ \|\mathbf{Y} - \mathbf{D}\mathbf{A}\|_F^2 \right\} \quad \text{subject to} \quad \forall i, \|\boldsymbol{\alpha}_i\|_0 \leq K$$

A similar objective:

$$\{\hat{\mathbf{D}}, \hat{\mathbf{A}}\} = \arg\min_{\mathbf{D},\mathbf{A}} \sum_i \|\boldsymbol{\alpha}_i\|_0 \quad \text{subject to} \quad \|\mathbf{Y} - \mathbf{D}\mathbf{A}\|_F^2 \leq \epsilon$$

Sparse coding and dictionary learning

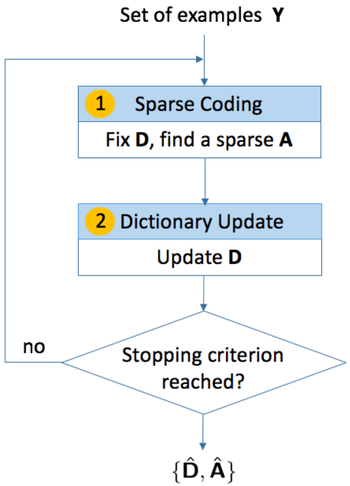


$$\{\hat{\mathbf{D}}, \hat{\mathbf{A}}\} = \arg\min_{\mathbf{D},\mathbf{A}} \left\{ \|\mathbf{Y} - \mathbf{D}\mathbf{A}\|_F^2 \right\} \quad \text{subject to} \quad \forall i, \|\alpha_i\|_0 \leq K$$

A similar objective:

$$\{\hat{\mathbf{D}}, \hat{\mathbf{A}}\} = \arg\min_{\mathbf{D},\mathbf{A}} \sum_i \|\alpha_i\|_0 \quad \text{subject to} \quad \|\mathbf{Y} - \mathbf{D}\mathbf{A}\|_F^2 \leq \epsilon$$

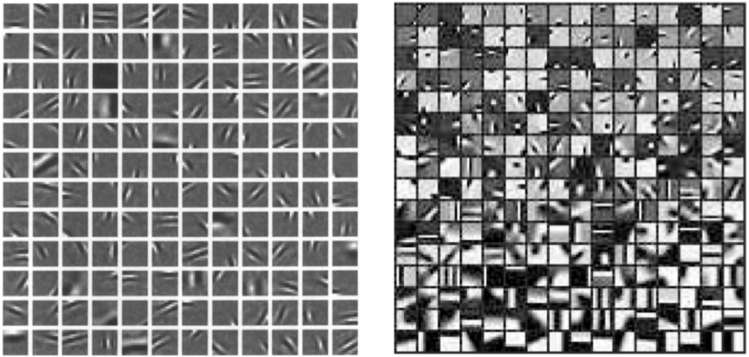
Iterate Two Steps: Sparse Coding and Dictionary Update



Dictionary update:

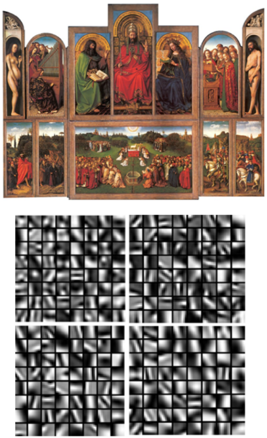
- Maximum likelihood method of [Olshausen and Field, 1997]
- MOD [Engan et al., 1999]
- K-SVD [Aharon et al., 2006]

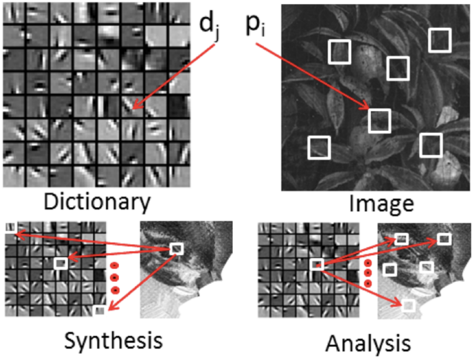
Learned Dictionaries of Image Atoms - Examples



Examples of dictionaries trained by [Olshausen and Field, 1997] (left) and K-SVD [Aharon et al., 2006] (right)

Application in Painter Style Characterization



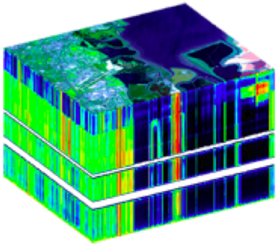


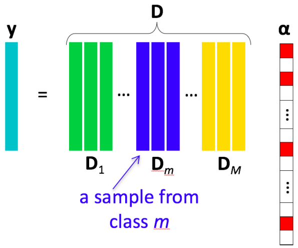
[Hughes et al, 2009], [Latić and Pižurica, 2014]

Outline

Sparse Representation Classification

[Wright et al, 2009]





$$\hat{\boldsymbol{\alpha}} = \arg\min_{\boldsymbol{\alpha}} \|\mathbf{y} - \mathbf{D}\boldsymbol{\alpha}\|_2^2 \;\; \text{subject to} \;\; \|\boldsymbol{\alpha}\|_0 \leq K$$

$$r_m(\mathbf{y}) = \|\mathbf{y} - \mathbf{D}_m \hat{\boldsymbol{\alpha}}_m\|_2, \qquad m = 1, ..., M$$

$$class(\mathbf{y}) = \arg\min_{m=1,...,M} r_m(\mathbf{y})$$

Joint Sparsity Model

Collect pixels from a small neighbourhood $\mathcal{N}_\epsilon$ into $\mathbf{Y} = [\mathbf{y}_1, ..., \mathbf{y}_T] \in \mathbb{R}^{B \times T}$

$$\mathbf{Y} = \underbrace{[\mathbf{y}_1 \ \ldots \ \mathbf{y}_T]}_{\text{pixels from } \mathcal{N}_\epsilon} = [\mathbf{D}\boldsymbol{\alpha}_1 \ \ldots \ \mathbf{D}\boldsymbol{\alpha}_T] = \mathbf{D}\underbrace{[\boldsymbol{\alpha}_1 \ \ldots \ \boldsymbol{\alpha}_T]}_{\mathbf{A}} = \mathbf{DA}$$

Sparse codes $\{\boldsymbol{\alpha}_t\}_{t=1}^T$ share the same support $\implies$ **A** is sparse with only K non-zero rows, i.e., **A** is row sparse.

JSRC method [Chen et al., 2011a]:

$$\hat{\mathbf{A}} = \arg\min_{\mathbf{A}} \|\mathbf{Y} - \mathbf{DA}\|_F^2 \ \text{ subject to } \|\mathbf{A}\|_{row,0} \leq K$$

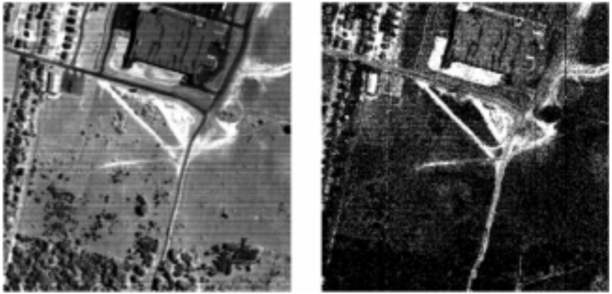
$$r_m(\mathbf{Y}) = \|\mathbf{Y} - \mathbf{D}_m\hat{\mathbf{A}}_m\|_F, \qquad m = 1, ..., M$$

$$class(\mathbf{y}_{central}) = \arg\min_{m=1,...,M} r_m(\mathbf{Y})$$

Outline

Robust SRC for Hyperspectral Image Classification

$$\mathbf{Y} = \underbrace{\mathbf{X}}_{\text{ideal image}} + \underbrace{\mathbf{N}}_{\text{Gaussian noise}} + \underbrace{\color{red}{\mathbf{S}}}_{\color{red}{\text{sparse noise}}}$$



Examples of stripe noise and mixed noise in a real hyperspectral image.

Huang, S., Zhang, H., Liao, W., and Pižurica, A. (2017). Robust joint sparsity model for hyperspectral image classification. In IEEE ICIP 2017.

Robust SRC for Hyperspectral Image Classification

$$\mathbf{Y} = \underbrace{\mathbf{X}}_{\text{ideal image}} + \underbrace{\mathbf{N}}_{\text{Gaussian noise}} + \underbrace{\mathbf{S}}_{\text{sparse noise}}$$

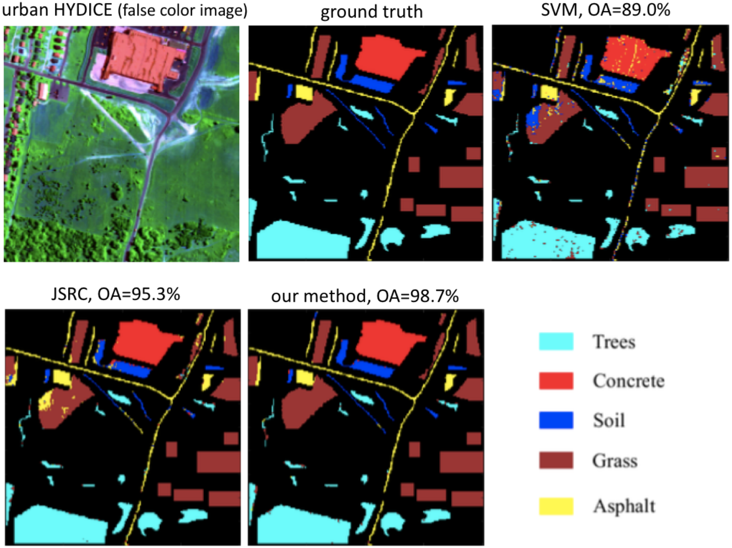
$$\{\hat{\mathbf{A}}, \hat{\mathbf{S}}\} = \arg\min_{\mathbf{A},\mathbf{S}} \|\mathbf{Y} - \mathbf{DA} - \mathbf{S}\|_F^2 + \lambda\|\mathbf{S}\|_1 \quad \text{subject to} \quad \|\mathbf{A}\|_{row,0} \leq K$$

$$r_m(\mathbf{Y}) = \|\mathbf{Y} - \mathbf{D}_m\hat{\mathbf{A}}_m - \hat{\mathbf{S}}\|_F, \qquad m = 1, \ldots, M$$

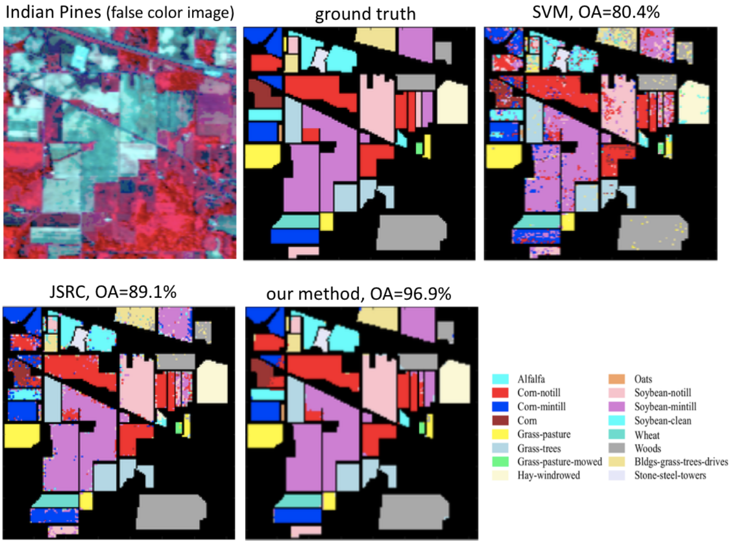
$$class(\mathbf{y}_{central}) = \arg\min_{m=1,\ldots,M} r_m(\mathbf{Y})$$

S. Huang, H. Zhang and A. Piurica (2017). A Robust Sparse Representation Model for Hyperspectral Image Classification. Sensors.

Robust SRC for Hyperspectral Image Classification

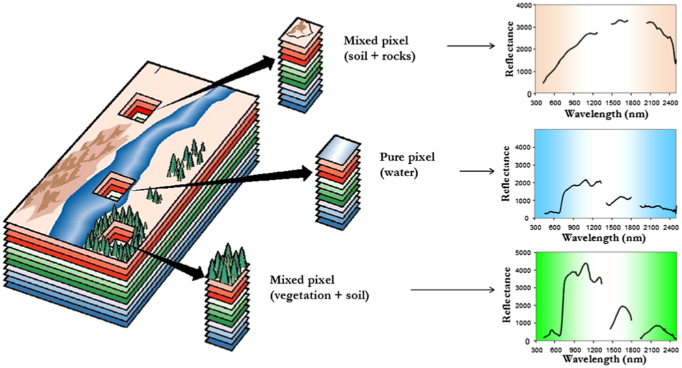


Robust SRC for Hyperspectral Image Classification



Outline

Spectral Mixing



S.R Bijitha, P. Geetha and K.P. Soman (2016). Performance Analysis and Comparative Study of Geometrical Approaches for Spectral Unmixing. International Journal of Scientific and Engineering Research.

Sparse Unmixing

Ideal hyperspectral image reordered as a matrix $\mathbf{X} \in \mathbb{R}^{B \times MN}$

Linear mixing model:

$$\mathbf{X} = \mathbf{E}\mathbf{A}$$

$\mathbf{E} \in \mathbb{R}^{B \times K}$ – library of **endmembers**; $\mathbf{A} \in \mathbb{R}^{K \times MN}$ – **abundance**

$$\mathbf{Y} = \underbrace{\mathbf{E}}_{\text{library}} \underbrace{\mathbf{A}}_{\text{abundance}} + \underbrace{\mathbf{N}}_{\text{Gaussian noise}} + \underbrace{\mathbf{S}}_{\text{sparse noise}}$$

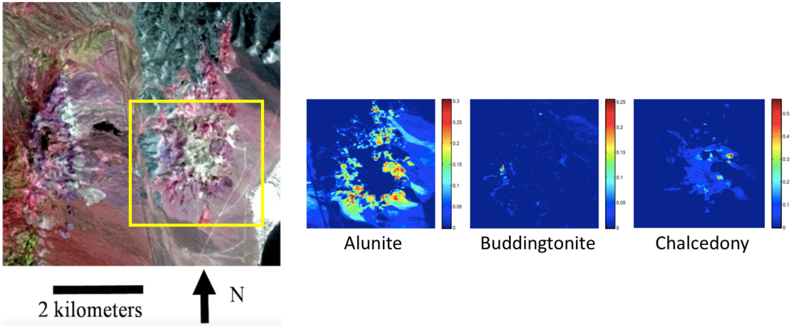
The approach of [Aggarval et al, 2016]:

$$\min_{\mathbf{A},\mathbf{S}} \|\mathbf{Y} - \mathbf{E}\mathbf{A} - \mathbf{S}\|_F^2 + \lambda_1 \|\mathbf{A}\|_{2,1} + \lambda_2 \|\mathbf{S}\|_1$$

Many similar variants exist, also making use of low-rank assumption:

$$\min_{\mathbf{A}} \operatorname{rank}\{\mathbf{A}\} \quad \text{subject to} \quad \|\mathbf{Y} - \mathbf{E}\mathbf{A} - \mathbf{S}\|_F^2 \leq \epsilon$$

Sparse Unmixing



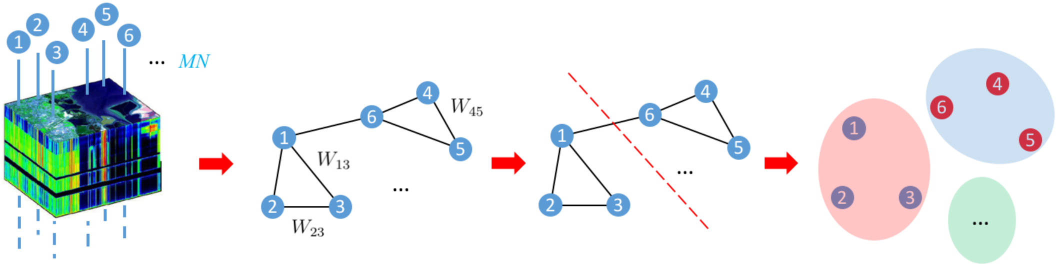
Estimated fractional abundance maps (AVIRIS Cuprite subscene, USGS library).

R. Wang, H.-C. Li, A. Pižurica, J. Li, A. Plaza, and W. J. Emery (2017). Hyperspectral Unmixing Using Double Reweighted Sparse Regression and Total Variation. IEEE Geoscience and Remote Sensing Letters.

Outline

Spectral clustering

No labelled data available $\rightarrow$ no supervised classification but instead clustering

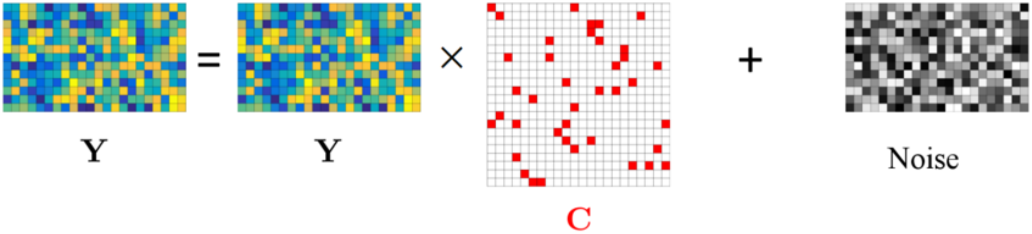


Similarity matrix: $\mathbf{W} \in \mathbb{R}^{MN \times MN}$

Sparse Subspace Clustering

[Elhamifar and Vidal, 2013]

Self-representation model: $\mathbf{Y} = \mathbf{Y}\mathbf{C} + \mathbf{N}$; $\qquad \mathbf{Y} = [\mathbf{y}_1 ... \mathbf{y}_N] \in \mathbb{R}^{m \times N}$



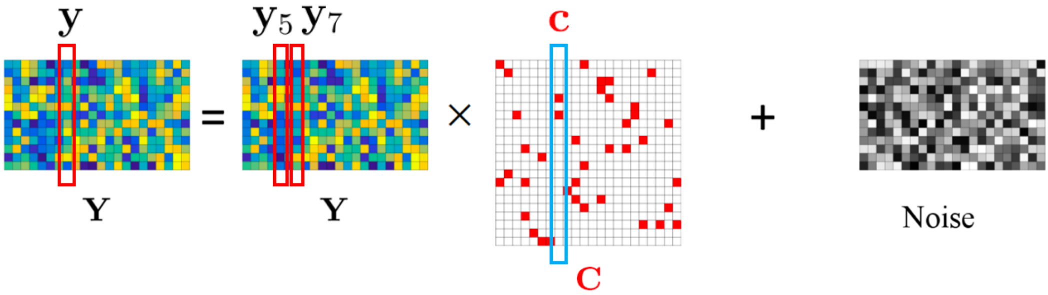
$C_{i,j} \neq 0 \rightarrow \mathbf{y}_i$ and $\mathbf{y}_j$ are in the same subspace.

Similarity matrix: $W = |C| + |C|^T$

Sparse Subspace Clustering

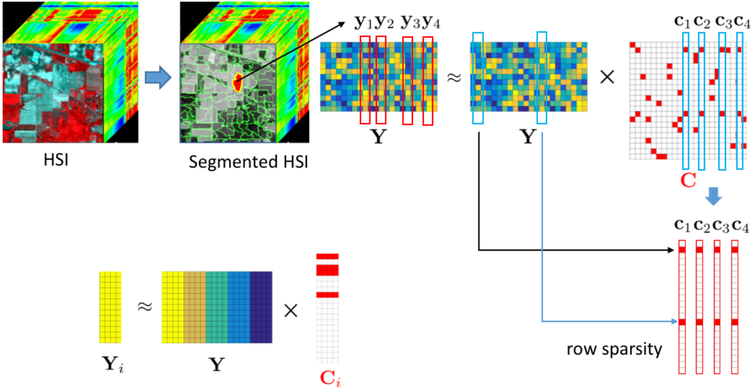
[Elhamifar and Vidal, 2013]

Self-representation model: $\mathbf{Y} = \mathbf{Y}\mathbf{C} + \mathbf{N}$; $\mathbf{Y} = [\mathbf{y}_1 \ldots \mathbf{y}_N] \in \mathbb{R}^{m \times N}$



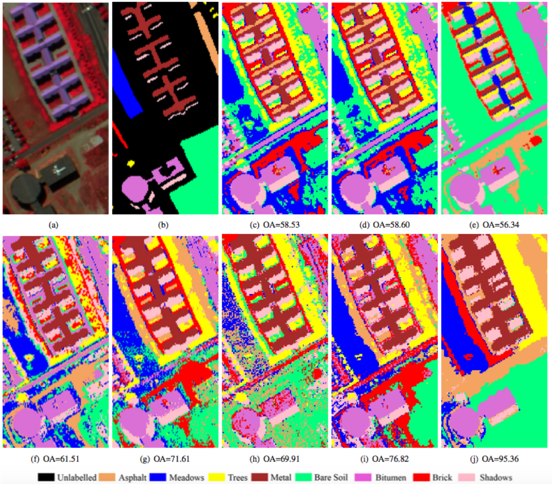
$\mathbf{y} \approx \mathbf{Y}\mathbf{c} = \sum_i \mathbf{y}_i c_i = c_5 \mathbf{y}_5 + c_7 \mathbf{y}_7$

Joint Sparse Subspace Clustering - JSSC



S. Huang, H. Zhang and A. Pižurica (2018). Semi-supervised Sparse Subspace Clustering Method With a Joint Sparsity Constraint for Hyperspectral Remote Sensing Images. IEEE J. Sel. Topics in Earth Observation and Remote Sens.

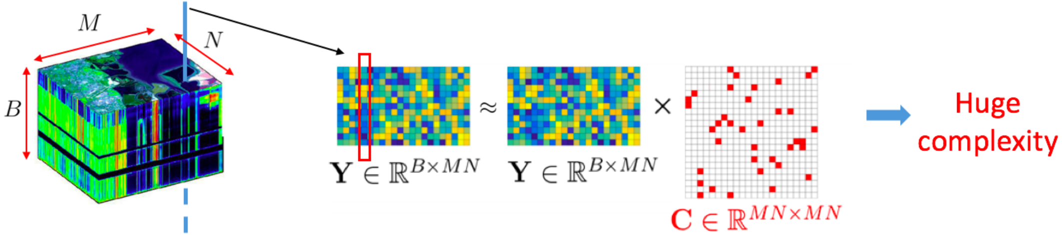
Joint Sparse Subspace Clustering - JSSC



Pavia University image. (a) False color image, (b) Ground truth (c) FCM, (d) k-means, (e) CFSFDP, (f) SSC, (g) L2-SSC, (h) CPPSSC (1 % labelled samples), (i) JSSC and (j) JSSC-L (1% labelled samples)

S. Huang, H. Zhang and A. Pižurica (2018). IEEE JSTARS

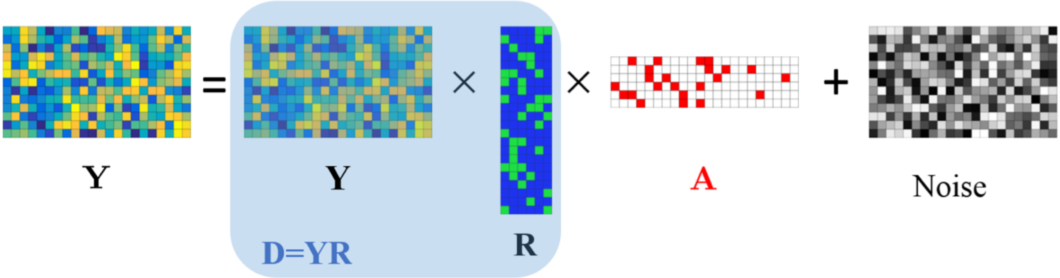
Nice, but ...



SSC becomes practically infeasible for very large scale data.

E.g. for the full *Pavia University* image 610 $\times$ 340, the size of **C** is 207400 $\times$ 207400
$\rightarrow$ 320,5 GB memory

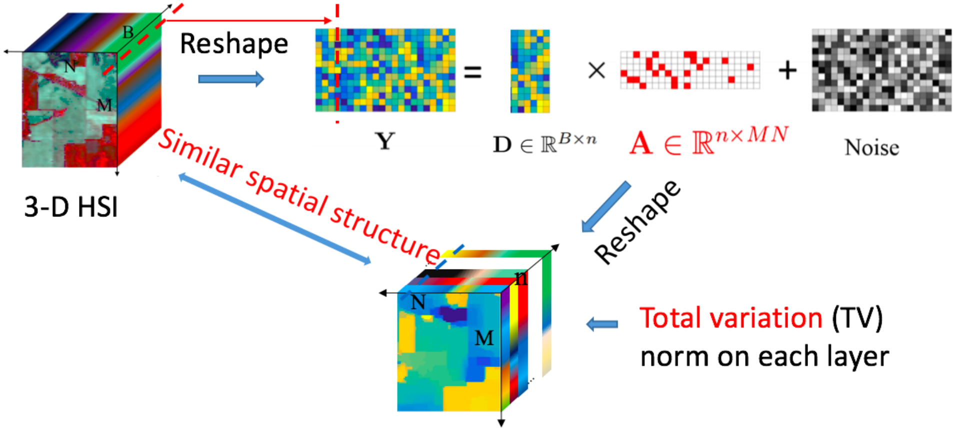
Sketching



Reduces greatly the size of the problem!

P. A. Traganitis and G. B. Giannakis. Sketched subspace clustering. IEEE Trans. Signal Process., vol. 66, no. 7, pp. 16631675, 2018.

Sketched Sparse Subspace Clustering for Hyperspectral Images

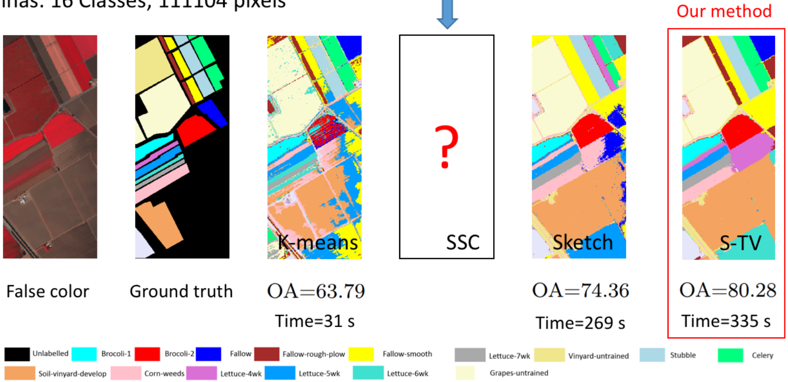


S. Huang, H. Zhang and A. Pižurica Sketched Sparse Subspace Clustering with Total Variation Constraint for Hyperspectral Images, submitted to Information Sciences (2019).

Sketched Sparse Subspace Clustering for Hyperspectral Images

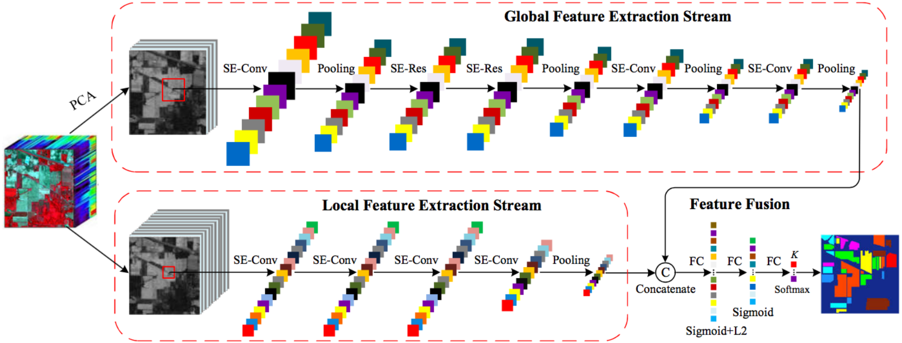
$\mathbf{Y} \in \mathbb{R}^{204 \times 111104} \rightarrow \mathbf{C} \in \mathbb{R}^{111104 \times 111104}$

Salinas: 16 Classes; 111104 pixels



S. Huang, H. Zhang and A. Pižurica Sketched Sparse Subspace Clustering with Total Variation Constraint for Hyperspectral Images, submitted to Information Sciences (2019).

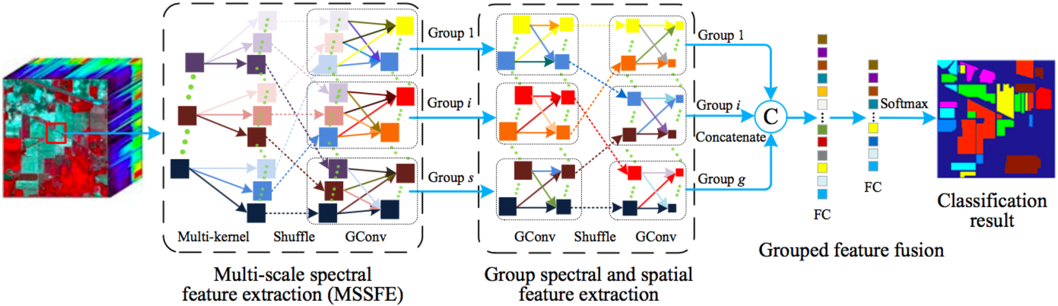
Deep learning in HSI classification



Improving the performance in the case of limited labelled data.

X. Li, M. Ding and A. Pižurica. Deep Feature Fusion via Two-Stream Convolutional Neural Network for Hyperspectral Image Classification, IEEE Transactions on Geoscience and Remote Sensing, in press (2019).

Deep learning in HSI classification



Reducing the computational complexity - applicability to large scale data.

X. Li, M. Ding and A. Pižurica. Group Convolutional Neural Networks for Hyperspectral Image Classification, ICIP 2018.

Outline

The *Ghent Altarpiece*

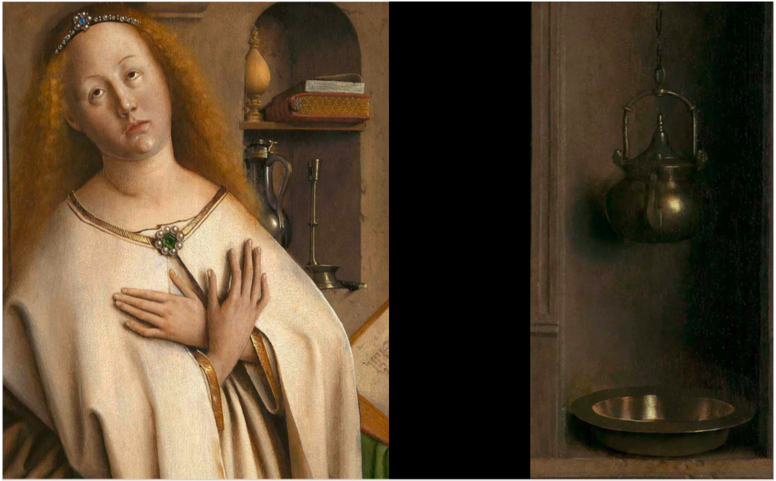
Hubert and Jan Van Eyck, completed in 1432.

The *Ghent Altarpiece*

Hubert and Jan Van Eyck, completed in 1432.

The *Ghent Altarpiece* - Some details

The *Ghent Altarpiece* - Some details



The *Ghent Altarpiece* - Some details

The current restoration of the *Ghent Altarpiece*

Ghent Altarpiece - Current Restoration Campaign

SCIENCE

The New York Times

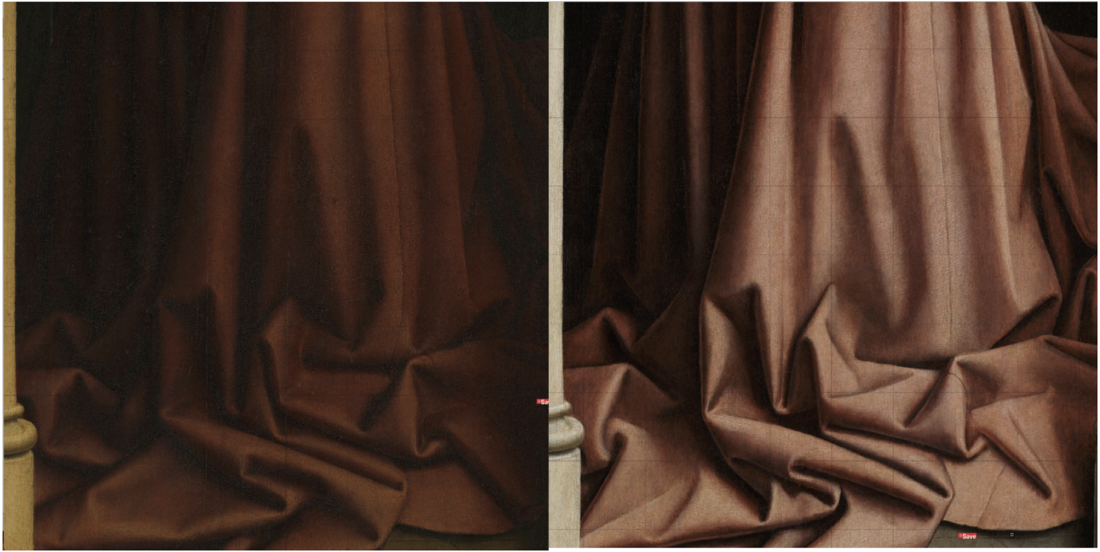
A Master Work, the Ghent Altarpiece, Reawakens Stroke by Stroke

By MILAN SCHREUER DEC. 19, 2016

Ghent Altarpiece restoration – Phase 1

= Overpaint © KIK-IRPA

Ghent Altarpiece restoration – Phase 1

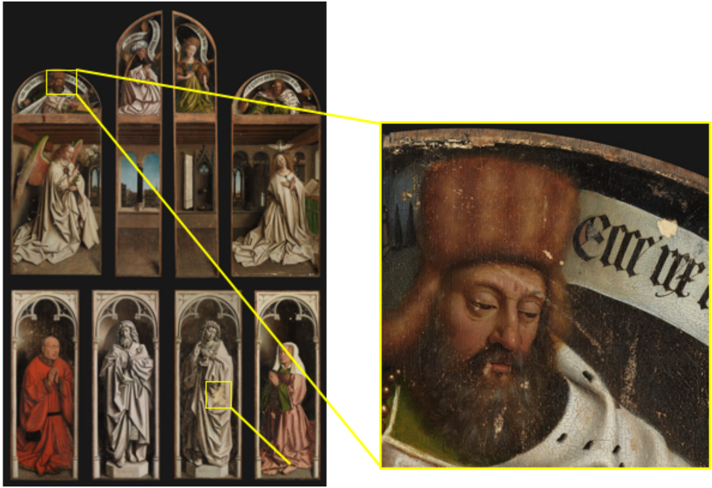


Ghent Altarpiece restoration – Phase 2 (inner panels)

The *Mystic Lamb* – before and after the restoration.

Central panel

Restoration – Phase 1, after cleaning: paint losses



3

Restoration – Phase 1, after cleaning: paint losses

Outline

Why do we need automatic paint loss detection?

Paint loss detection is crucial for

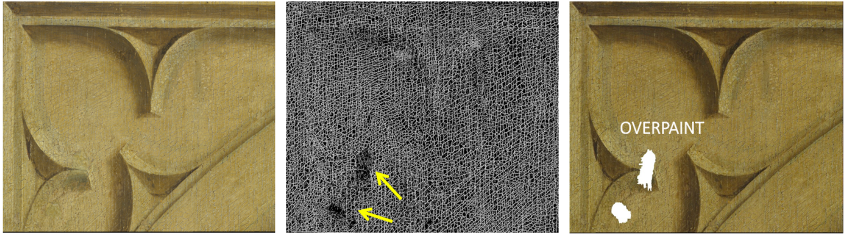
- documenting purpose
- virtual restoration
- decision making in the actual restoration process

Currently done manually:

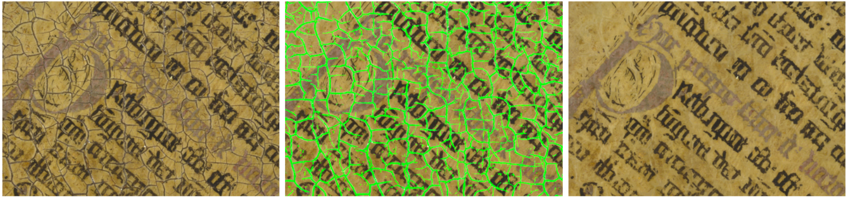
- labor intensive
- only rough indication
- prone to errors

©Ghent, Kathedrale Kerkfabriek, Lukasweb

Crack detection



Diagnostics, overpaint detection.

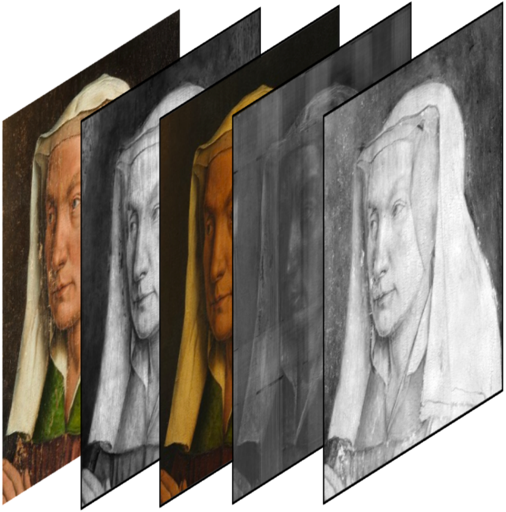


Input for virtual crack filling. Improving readability of inscriptions.

Challenges: Information extraction from multimodal data

Extracting useful information from multiple modalities, with

- huge data
- imperfect alignment
- scarce annotations
- erroneous annotations



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Paint loss detection problem - difficulties

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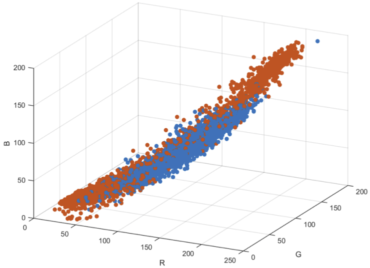
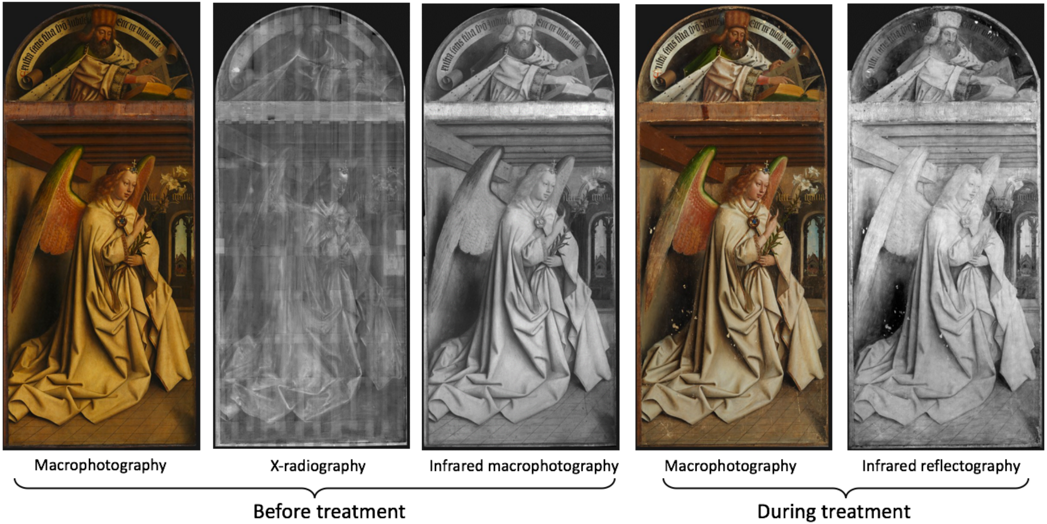
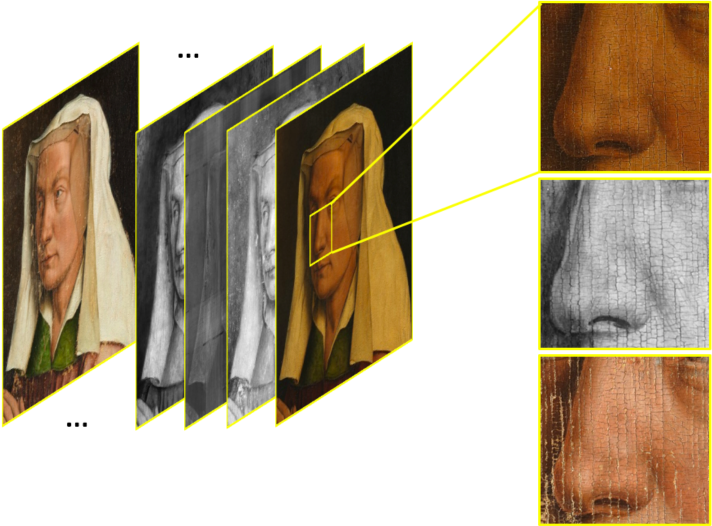


A scatter plot of RGB values for randomly selected paint loss and background pixels in the macrophotography after cleaning (red: paint loss; blue: background).

A multimodal approach



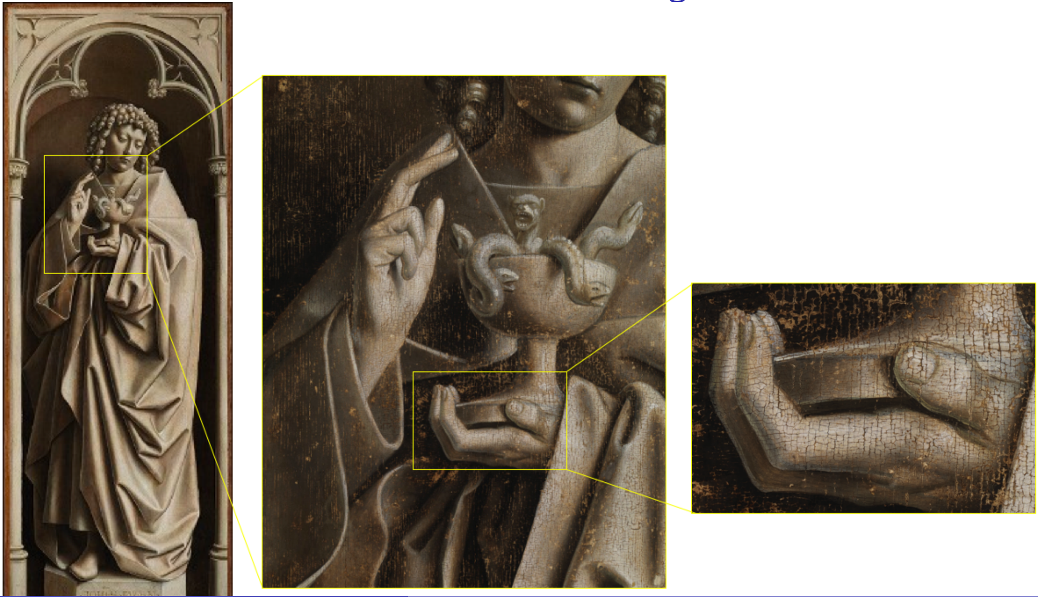
Registration of multimodal images



Crack patterns can be employed as landmarks.

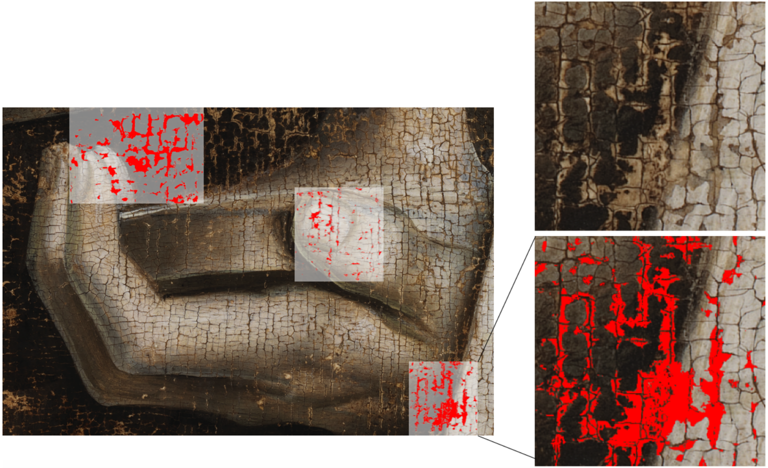
Outline

Paint loss detection data sets - *John the Evangelist*

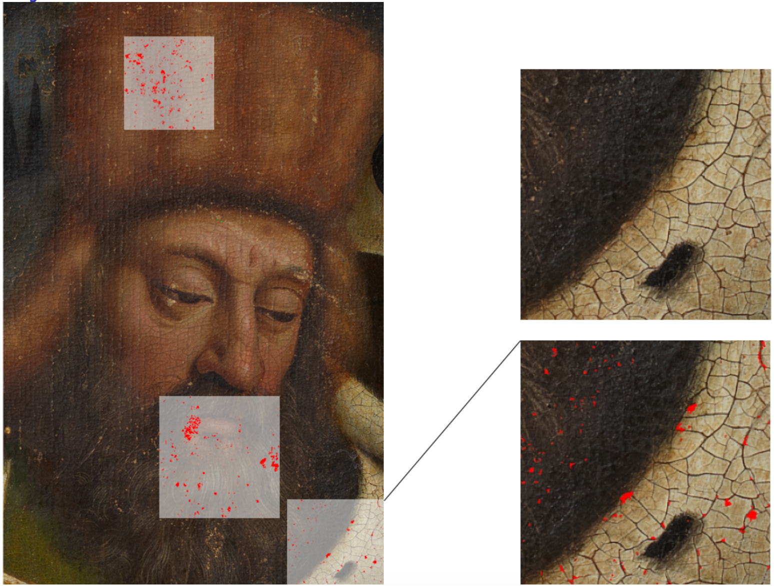


Paint loss detection data sets - *prophet Zachary*

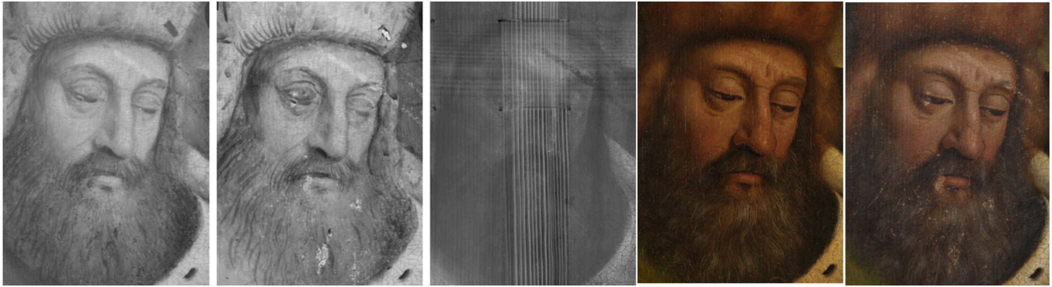
Annotations by art restorers



Annotations by art restorers



Multimodal Data



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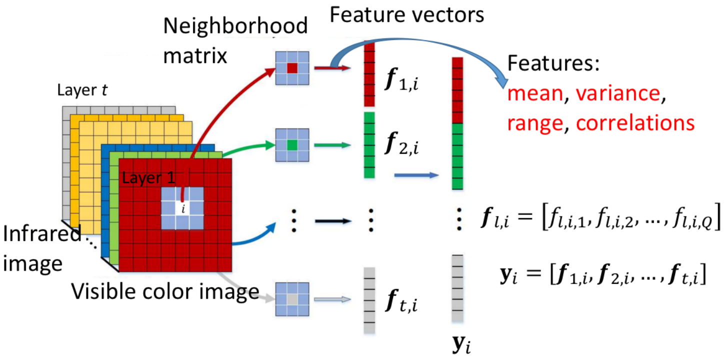
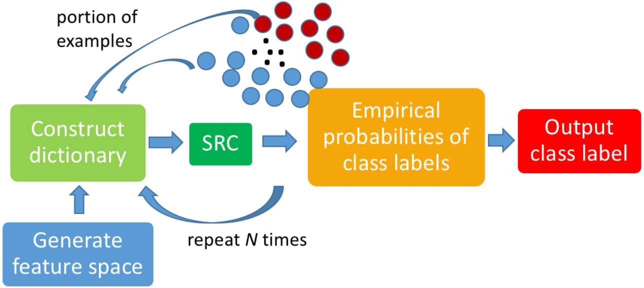
- Annotations done on macrophotographs during the treatment;
- Dictionaries for sparse representation classification constructed from the available multimodal data. The available modalities may differ from one panel to another.

Features for SRC



S. Huang, W. Liao, H. Zhang, and A. Pižurica (2016). Paint Loss Detection in Old Paintings by Sparse Representation Classification. iTWIST.

SRC-based Paint Loss Detection Method

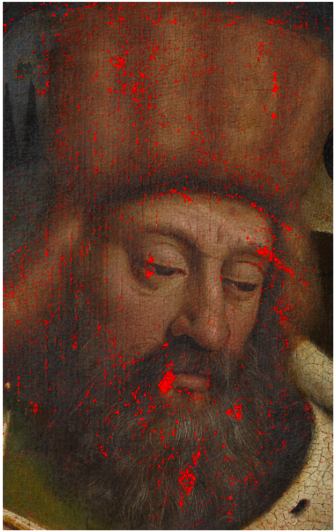


N_j^m - number of trials in which $\mathbf{y}_j$ was labelled as class m; $m \in \{PaintLoss, Other\}$

$$class(\mathbf{y}_j) = \arg\max_m p_j(m) = \underbrace{\arg\max_m (N_j^m/N)}_{\text{empirical prob. of class } m}$$

S. Huang, W. Liao, H. Zhang, and A. Pižurica (2016). Paint Loss Detection in Old Paintings by Sparse Representation Classification. iTWIST.

Paint Loss Detection Results



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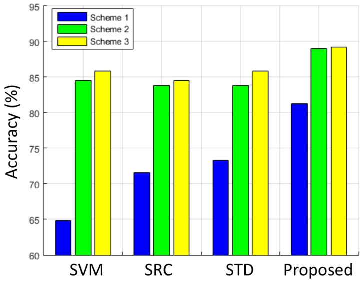
Paint Loss Detection - Numerical results



Schemes	Number of modalities	Imaging modalities
1	1	M_{AC}
2	3	M_{AC}, M_{BC}, IR_{BC}
3	5	M_{AC}, M_{BC}, IR_{BC}, IRR_{BC}, X-ray$_{BC}$

M – macrophotography
IR – infrared macrophotography
IRR – infrared reflectography
X-ray – radiography

subscript:
AC – after cleaning
BC – before cleaning

SVM – Support Vector Machines
SRC – Direct application of SRC (Sparse Representation Classification)
STD – Sparse Representation for Target Detection [Chen et al., 2011b]
Proposed – the proposed method based on kernel-SRC [Huang et al., 2018]

S. Huang, L. Meeus, B. Cornelis, B. Devolder, M. Martens, and A. Pižurica, (2018). Paint loss detection via kernel sparse representations. In Image Processing for Art Investigation (IP4AI).

Outline

1. Sparse Coding of High-Dimensional Signals
   - Sparse representation
   - Sparse Representation Classification
2. Applications in Remote Sensing
   - Robust SRC in Hyperspectral Imaging
   - Sparse Unmixing
   - Sparse Subspace Clustering
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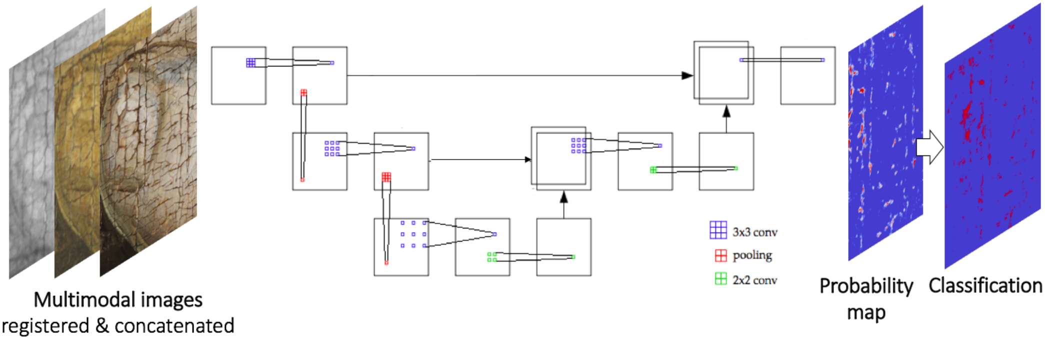
A multiscale deep learning method for paint loss detection

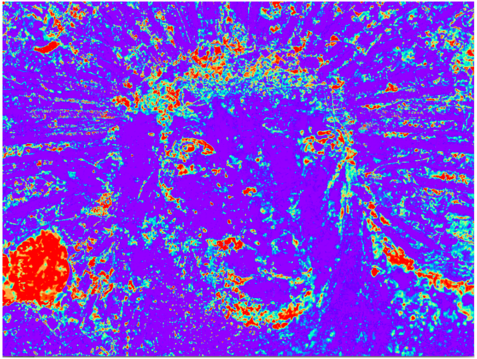


L. Meeus, S. Huang, B. Devolder, M.Martens, and A. Pižurica (2018).
Deep Learning for Paint Loss Detection: A Case Study on the Ghent Altarpiece. IP4AI.

A multiscale deep learning method for paint loss detection

Size: 5954×7546; processed in < 1 minute

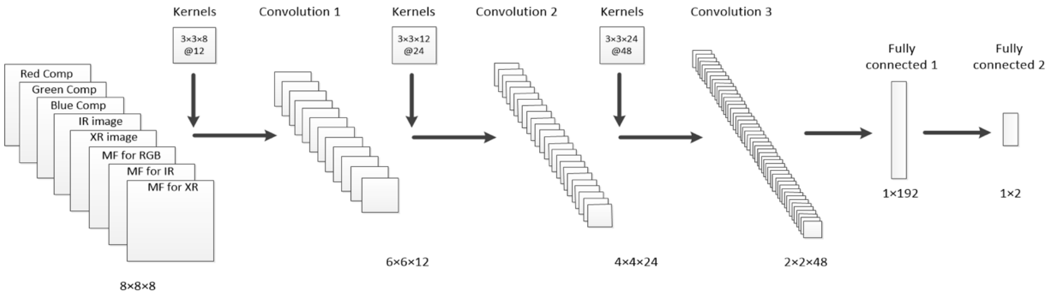
A multiscale deep learning method for paint loss detection



Deep learning in crack detection

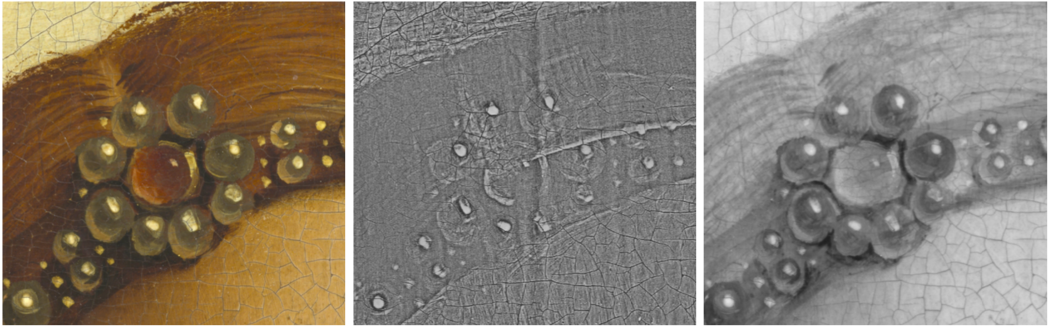
Crack detection in roads reported in [Lei et al,2016], [Cha et al, 2017].
However, crack detection in paintings is much more challenging!

A deep learning method for crack detection in paintings

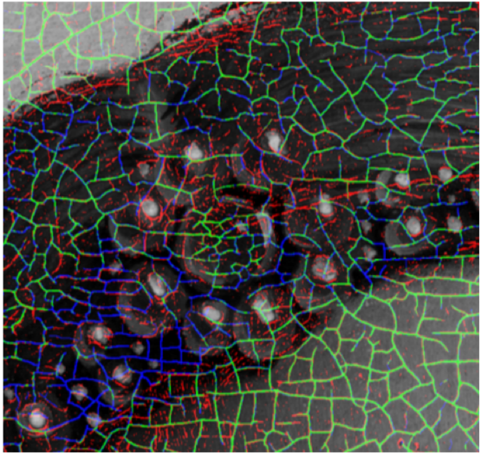


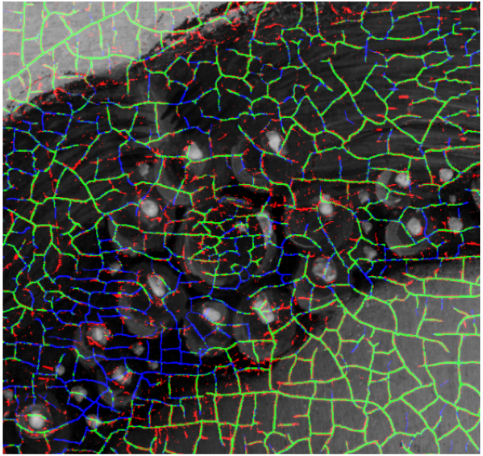
R. Sizyakin, B. Cornelis, L. Meeus, M. Martens, V. Voronin, and A. Pižurica (2018). A deep learning approach to crack detection in panel paintings. IP4AI.

Crack detection: panel *Singing Angels*



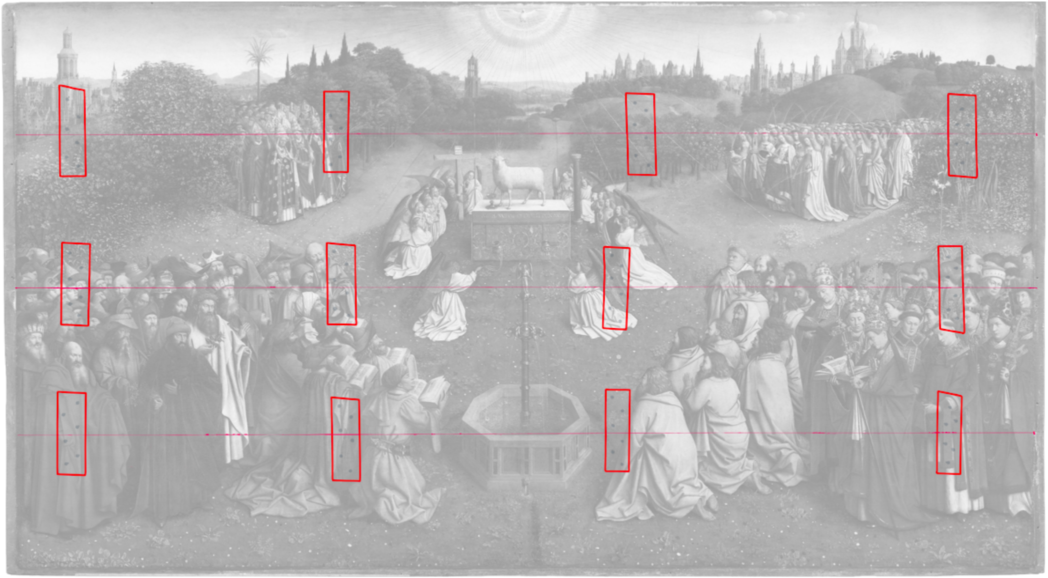
Crack detection: panel *Singing Angels*



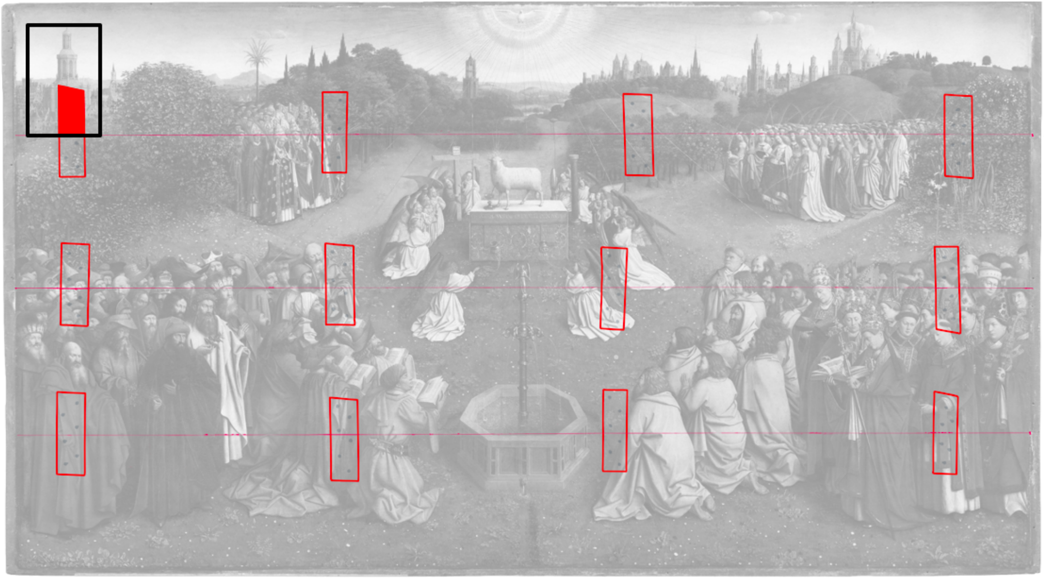


Left: A Bayesian multimodal method (BCTF). Right: CNN-based.
red – false detections; blue – missing cracks; green - -correct.

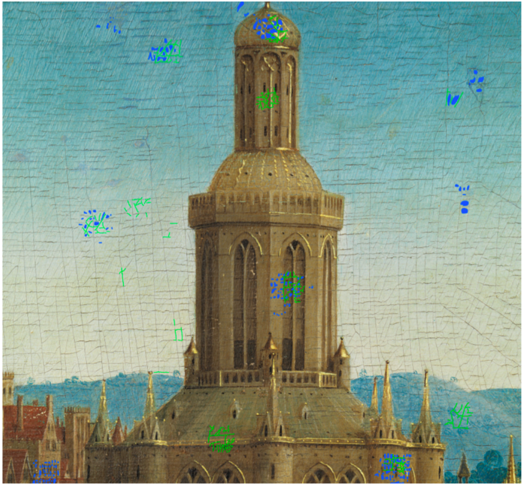
Crack detection: Central panel



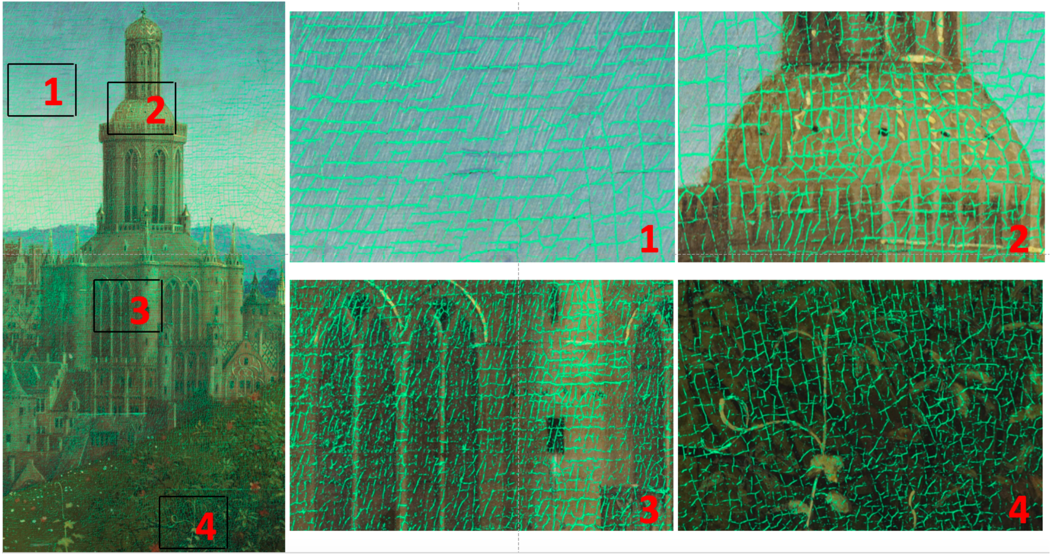
Crack detection: Central panel



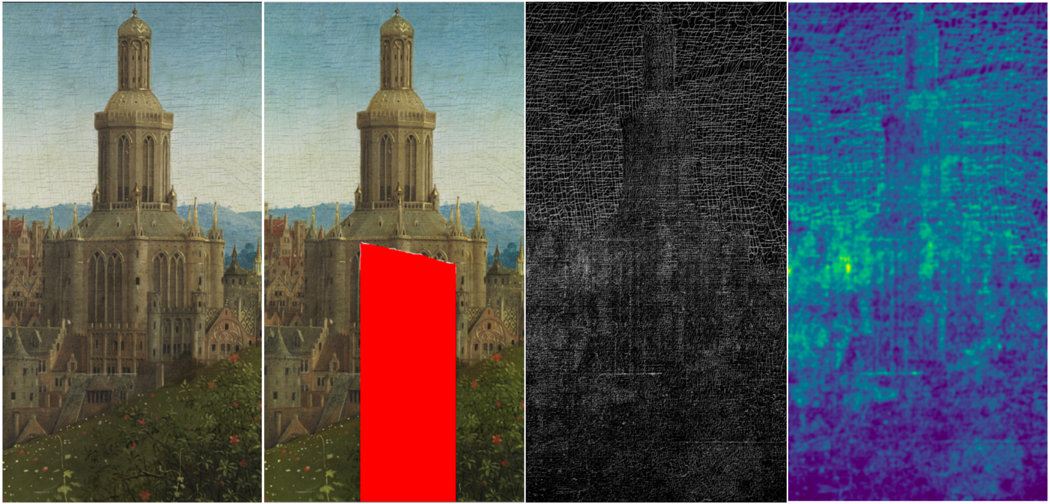
Crack detection: Central panel



Crack detection: Central panel



Crack detection: Central panel



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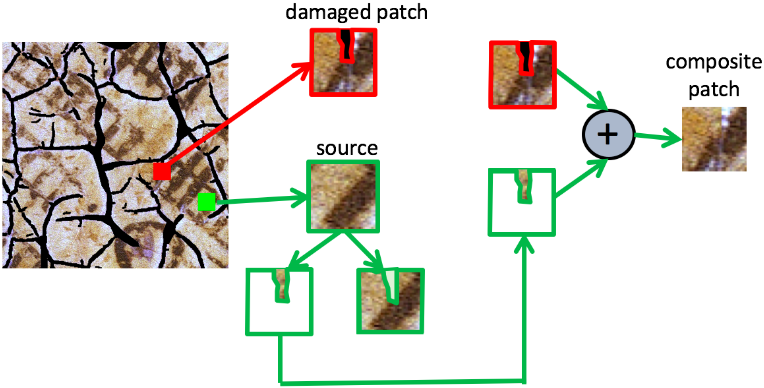
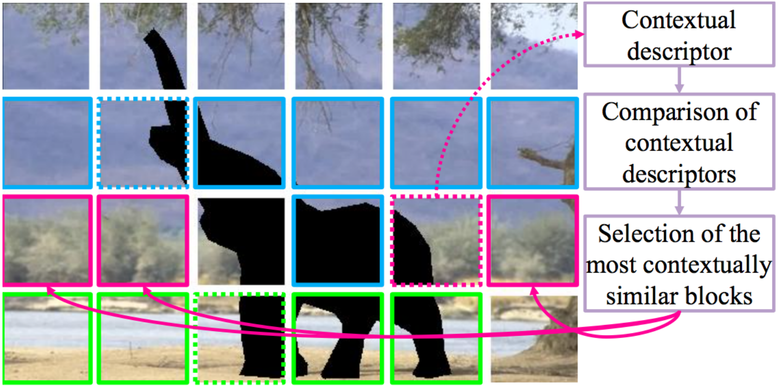
Patch-based inpainting

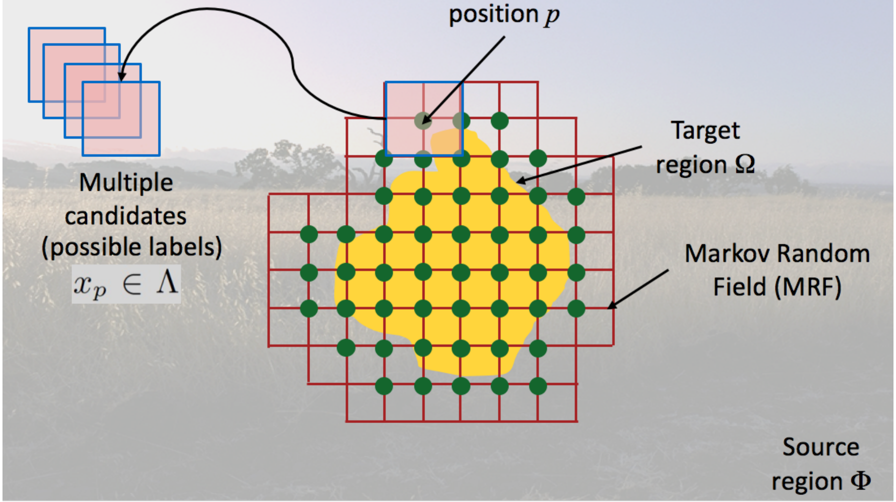


Context adaptative inpainting

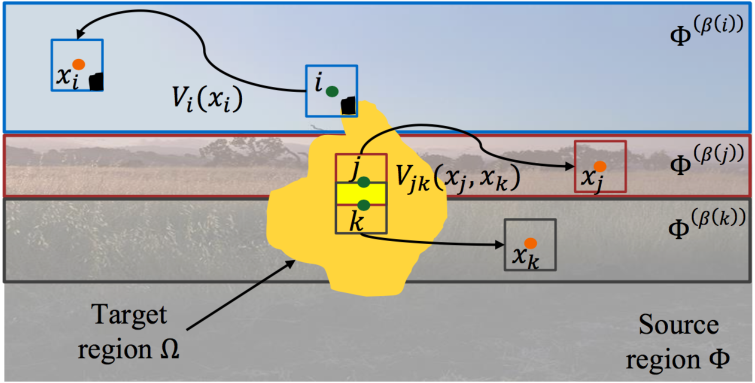


T. Ružić and A. Pižurica et al. Context-aware patch-based image inpainting using Markov random field modeling. *IEEE Transactions on Image Processing* 2015

Global inpainting



Global inpainting

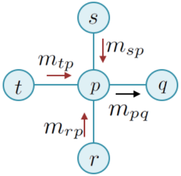


$$E(\mathbf{x}) = \sum_{i \in \nu} V_i(x_i) + \sum_{\langle i,j \rangle \in \varepsilon} V_{ij}(x_i, x_j), \qquad (1)$$

[Komodakis and Tziritas, 2007], [Ružić and Pižurica, 2015]

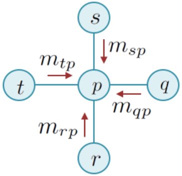
Global inpainting

Messages



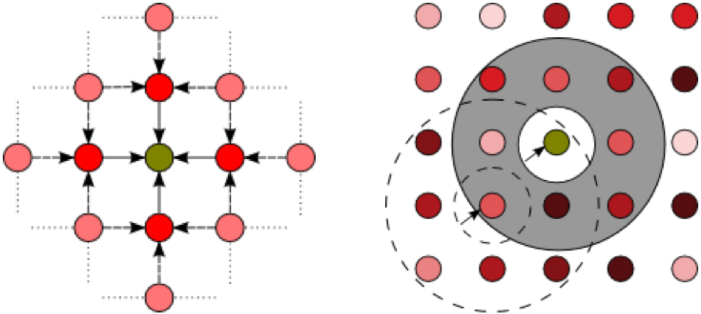
$$m_{pq}(x_q) = \min_{x_p \in \Lambda} \left\{ V_{pq}(x_p, x_q) + V_p(x_p) + \sum_{r: r \neq q, (r,p) \in \varepsilon} m_{rp}(x_p) \right\}$$

Beliefs



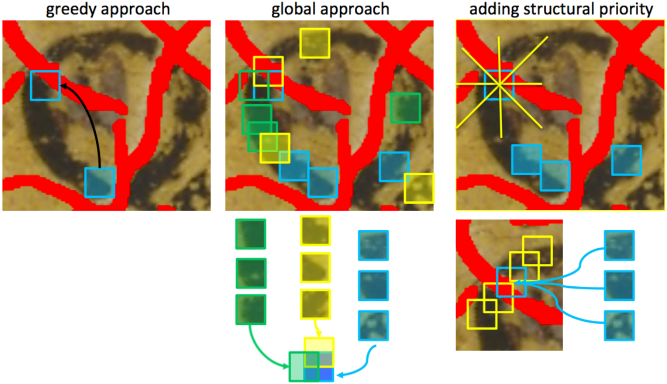
$$b_p(x_p) = -V_p(x_p) - \sum_{r:(r,p) \in \varepsilon} m_{rp}(x_p)$$

Global inpainting: efficient inference



T. Ružić and A. Pižurica et al. Context-aware patch-based image inpainting using Markov random field modeling. *IEEE Transactions on Image Processing* 2015

A summary of patch based inpainting



$$P_{i,j} = \mathcal{S}(\phi_i, \phi_j) + \max_k \sum_{l \in N_{j,k}} \mathcal{S}(\phi_i, \phi_l)$$

A. Pižurica et al. Digital Image Processing of the Ghent Altarpiece. *Signal Process. Mag.* 2015

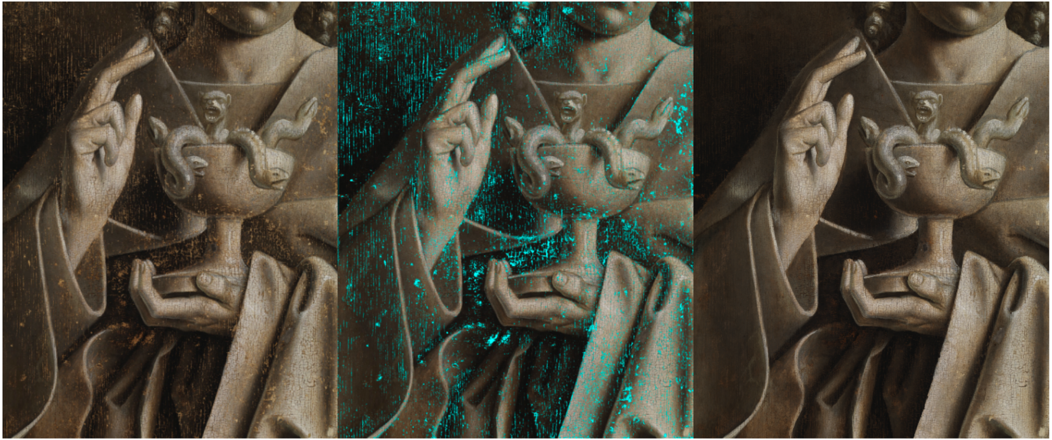
Crack inpaiting

Crack inpaiting

Virtual Restoration

Automatic paint loss detection;
inpainting method of [Ružić and Pižurica, TIP, 2015].

Virtual Restoration



Automatic paint loss detection;
inpainting method of [Ružić and Pižurica, TIP, 2015].

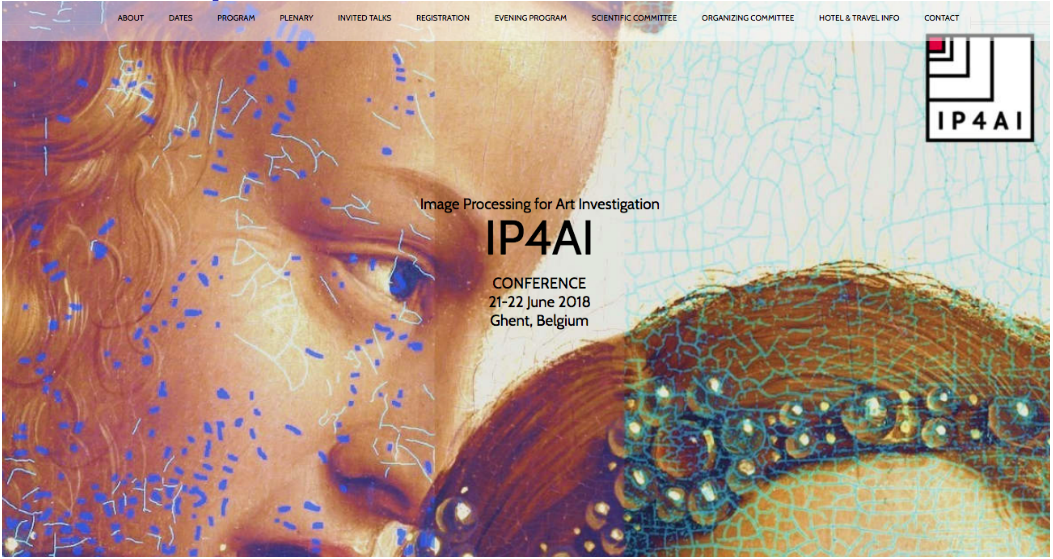
Virtual Restoration

Automatic paint loss detection;
inpainting method of [Ružić and Pižurica, TIP, 2015].

Virtual Restoration

Left: Input; Middle: virtual restoration; Right: actual restoration.

IP4AI Community



Special Session at ISIT 2019

ISIT 2019 Special Session on Applications in Fine Arts

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