UNIVERSITEIT GENT

FACULTY OF ENGINEERING

Multimodal Image Processing and Machine Learning in Computer Vision

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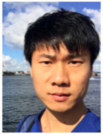
21 December 2018

Contributors



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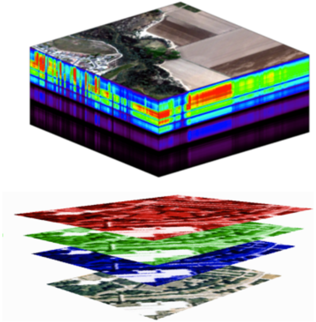
Outline

1. Sparse Coding of High-Dimensional Signals
   - Sparse representation
   - Unsupervised vs. Supervised Dictionary Learning
   - 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

A Wealth of High-Dimensional Multimodal Data

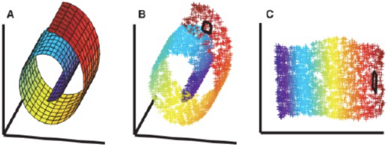


Remote sensing data (hyperspectral, visible, LiDAR,...)

Digitized paintings (infrared, X-Ray, visible)

Capturing Intrinsic Structure of the Data

- High-dimensional data often exhibits **low-dimensional structure**
- Early models (PCA): find a linear subspace in which data resides
- Recent methods
  - Capture more complex low-dimensional structures (manifolds or unions of multiple linear subspaces)



P. V. Dinh: Review on Manifold Learning, 2009

  - Data has a sufficiently **sparse representation** with respect to some basis or a dictionary

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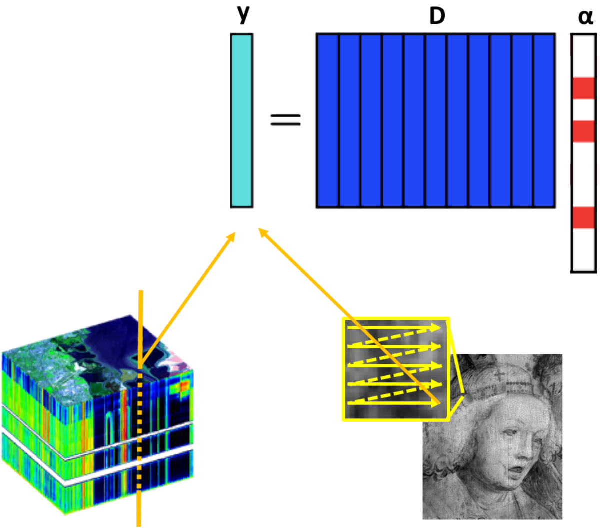
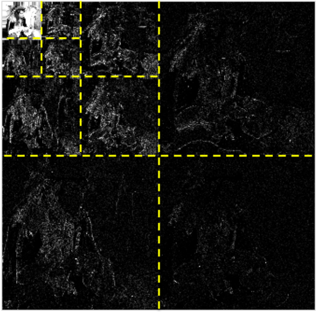
Sparse representation



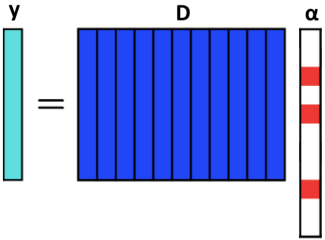
Designed vs. Learned Dictionaries

- **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

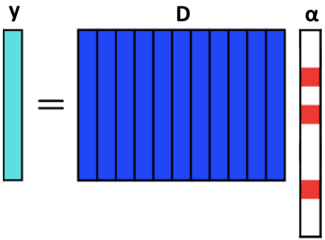
Sparse coding



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

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

Sparse coding



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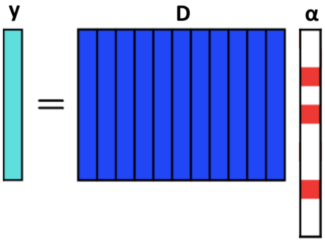
Greedy algorithms

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

Sparse coding



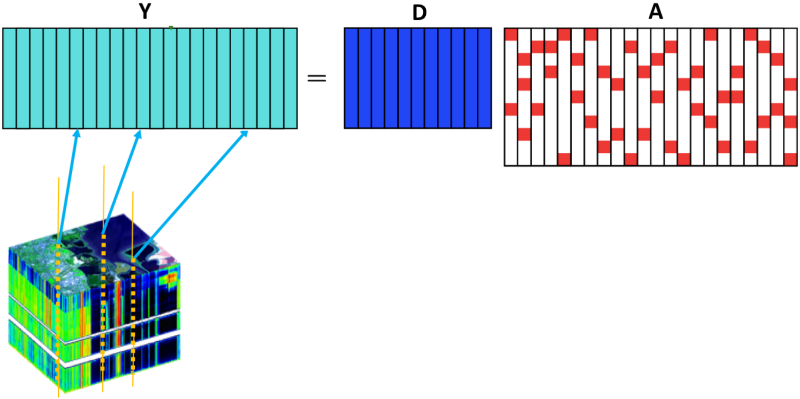
Convex relaxation:

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

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

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

Sparse coding and dictionary learning

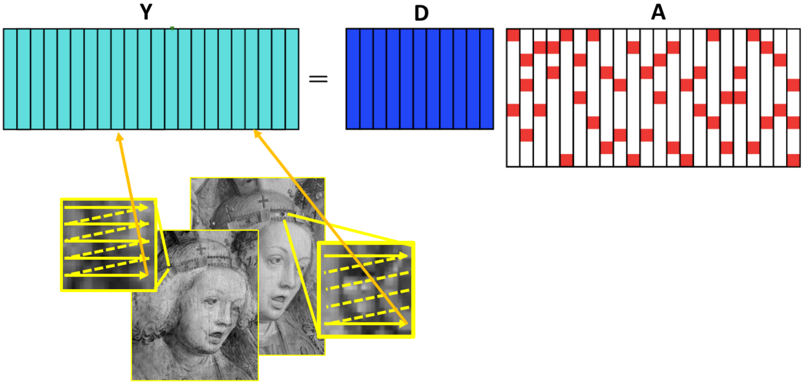


$$\{\hat{\mathbf{D}}, \hat{\mathbf{A}}\} = \arg\min_{\mathbf{D},\mathbf{A}} \left\{ \|\mathbf{Y} - \mathbf{DA}\|_F^2 \right\} \quad \text{subject to} \quad \forall i, \|\boldsymbol{\alpha}_i\|_0 \leq K$$

A similar objective:

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

Sparse coding and dictionary learning



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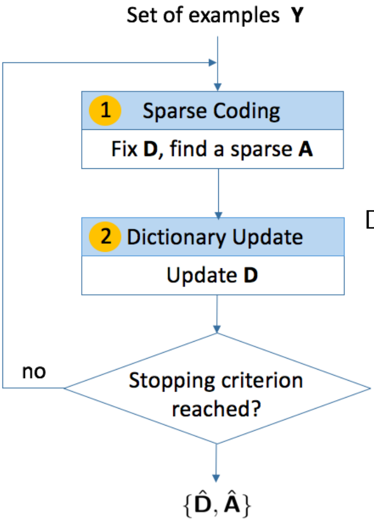
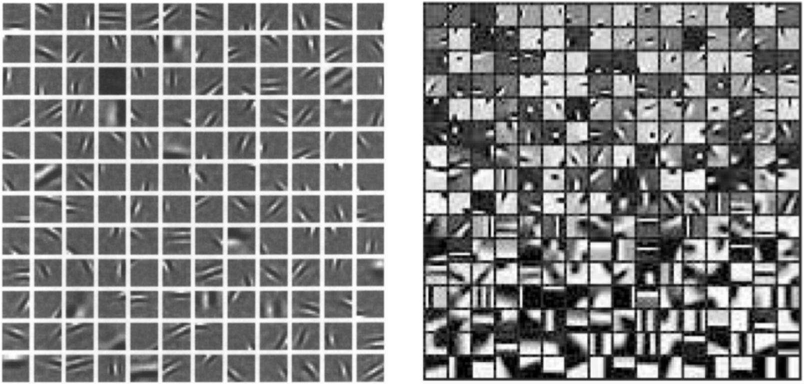
Iterate Two Steps: Sparse Coding and Dictionary Update



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)

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Unsupervised vs. Supervised Dictionary Learning

- **Unsupervised** dictionary learning

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

  - minimizes the reconstruction error
  - inverse problems (restoration, inpainting,...)

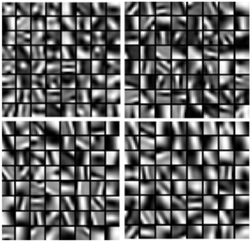
- **Supervised** (discriminative or **task-driven**)

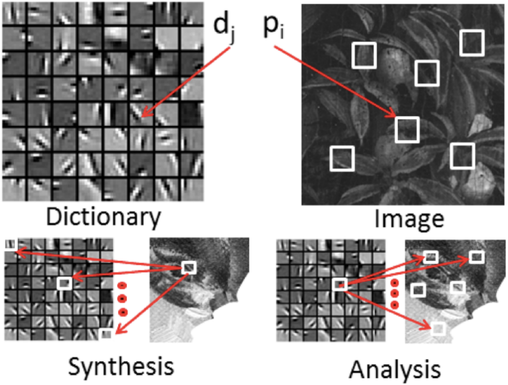
$$\{\hat{\mathbf{D}}, \underbrace{\hat{\mathbf{C}}}_{\text{class. par.}}, \hat{\mathbf{A}}\} = \arg\min_{\mathbf{D},\mathbf{C},\mathbf{A}} \left\{ \|\mathbf{Y} - \mathbf{D}\mathbf{A}\|_F^2 + \mu\| \underbrace{\mathbf{H}}_{\text{labels}} - \mathbf{C}\mathbf{A}\|_F^2 + \eta\|\mathbf{C}\|_F^2 \right\}$$

$$\text{subject to} \quad \forall i, \|\boldsymbol{\alpha}_i\|_0 \leq K$$

  - classification problems (**H** – label inform.; **C** – classifier parameters)

Application in Painter Style Characterization





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

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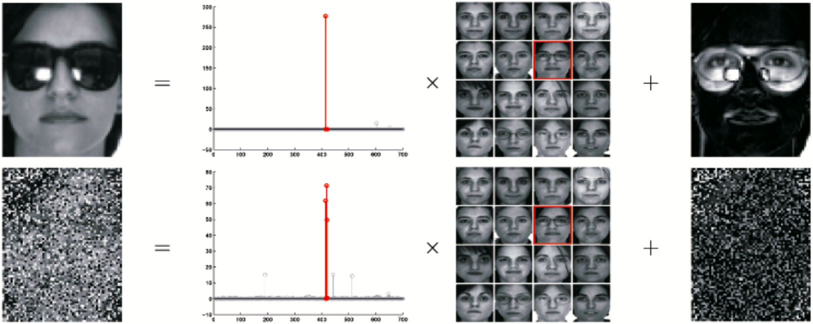
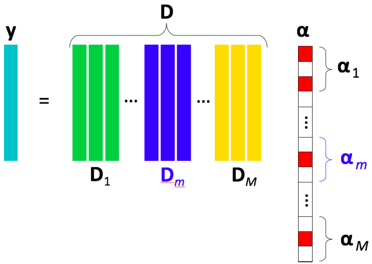
Sparse Representation Classification - SRC



Wright, J., Yang, A. Y., Ganesh, A., Sastry, S. S., and Ma, Y. (2009). Robust face recognition via sparse representation. IEEE PAMI.

Sparse Representation Classification - SRC



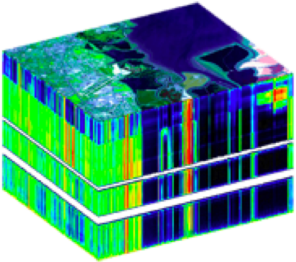
Equivalently,

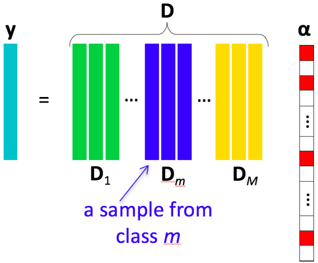
$$r_m(\mathbf{y}) = \|\mathbf{y} - \mathbf{D}_m \hat{\alpha}_m\|_2, \qquad m = 1, ..., M$$

$$identity(\mathbf{y}) = \underset{m=1,\ldots,M}{\arg\min}\; r_m(\mathbf{y})$$

SRC in Hyperspectral Image Classification

[Chen et al., 2011a]





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

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

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

Joint Sparsity Model

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

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

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]:

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

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

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

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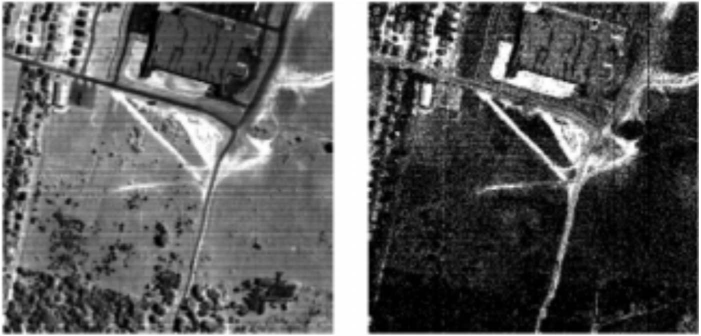
Robust SRC for Hyperspectral Image Classification

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



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

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

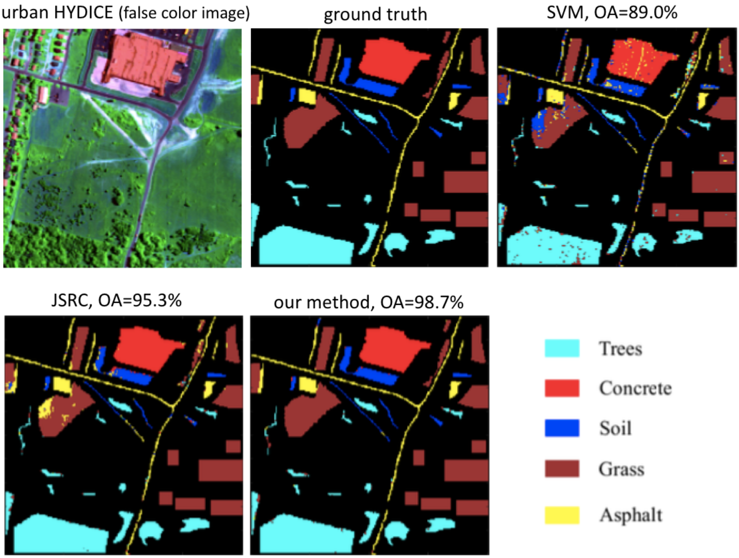
$$\{\hat{\mathbf{A}}, \hat{\mathbf{S}}\} = \arg\min_{\mathbf{A},\mathbf{S}} \|\mathbf{Y} - \mathbf{D}\mathbf{A} - \mathbf{S}\|_F^2 + \lambda\|\mathbf{S}\|_1 \quad \text{subject to} \quad \|\mathbf{A}\|_{row,0} \leq K$$

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

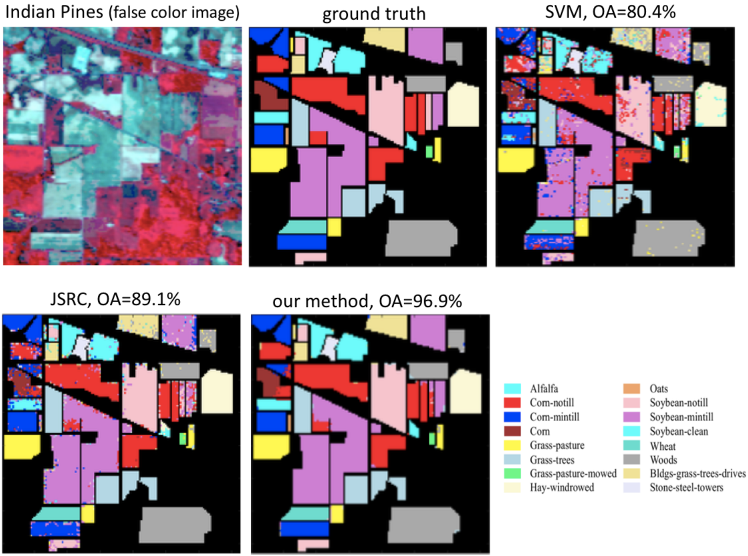
$$class(\mathbf{y}_{central}) = \arg\min_{m=1,\dots,M} r_m(\mathbf{Y})$$

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



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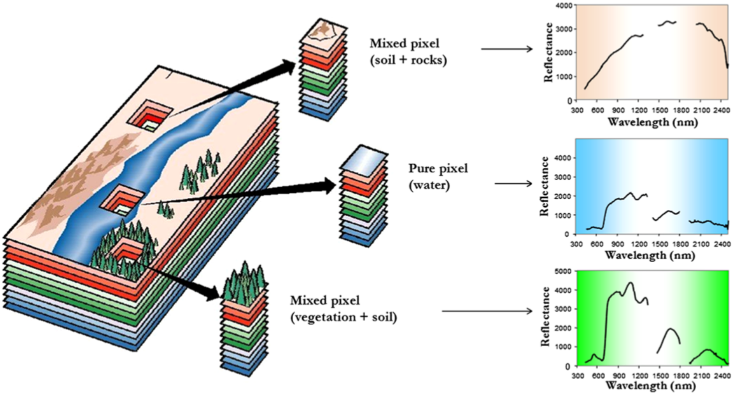
Spectral Mixing



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**

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

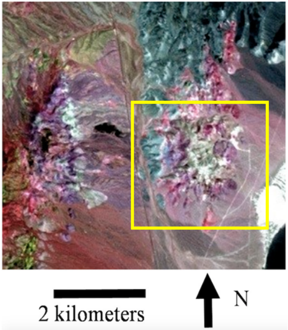
The approach of [Aggarval et al, 2016]:

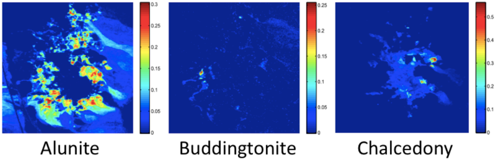
$$\min_{\mathbf{A},\mathbf{S}} \|\mathbf{Y} - \mathbf{E}\mathbf{A} - \mathbf{S}\|_F^2 + \lambda_1 \|\mathbf{A}\|_{2,1} + \lambda_2 \|\mathbf{S}\|_1$$

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





Fractional abundance maps estimated for the AVIRIS Cuprite subscene with the 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.

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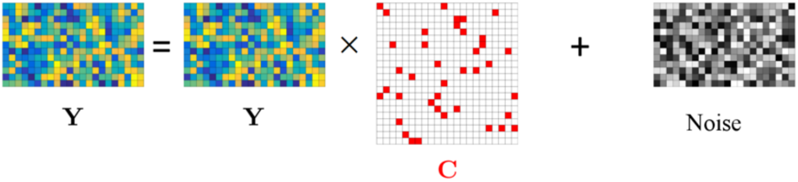
Sparse Subspace Clustering

[Elhamifar and Vidal, 2013]

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



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

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

Sparse Subspace Clustering

[Elhamifar and Vidal, 2013]

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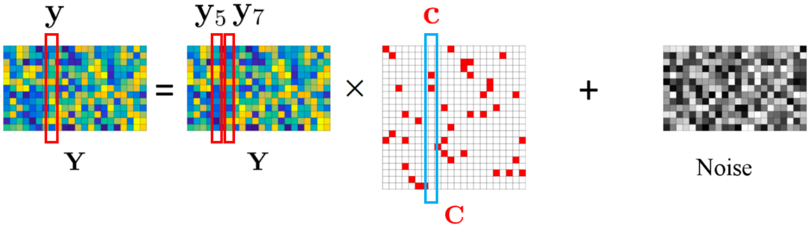
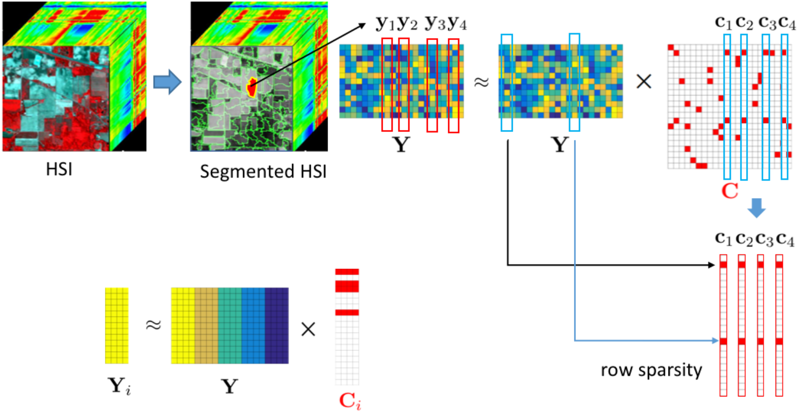


$\mathbf{y} \approx \mathbf{Y}\mathbf{c} = \sum_i \mathbf{y}_i c_i = c_5 \mathbf{y}_5 + c_7 \mathbf{y}_7$

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

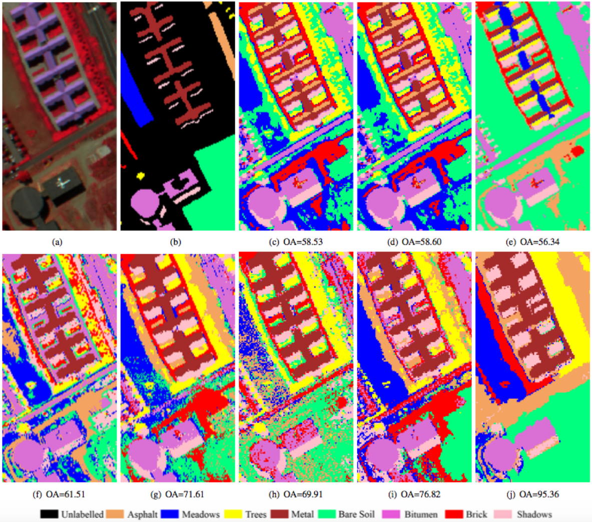
Similarity matrix: $W = |C| + |C|^T$

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

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The *Ghent Altarpiece*

Hubert and Jan Van Eyck, completed in 1432.

The *Ghent Altarpiece*

Hubert and Jan Van Eyck, completed in 1432.

The current restoration of the *Ghent Altarpiece*

Ongoing conservation-restoration treatment (started in 2012).

Ghent Altarpiece - Current Restoration Campaign

SCIENCE

The New York Times

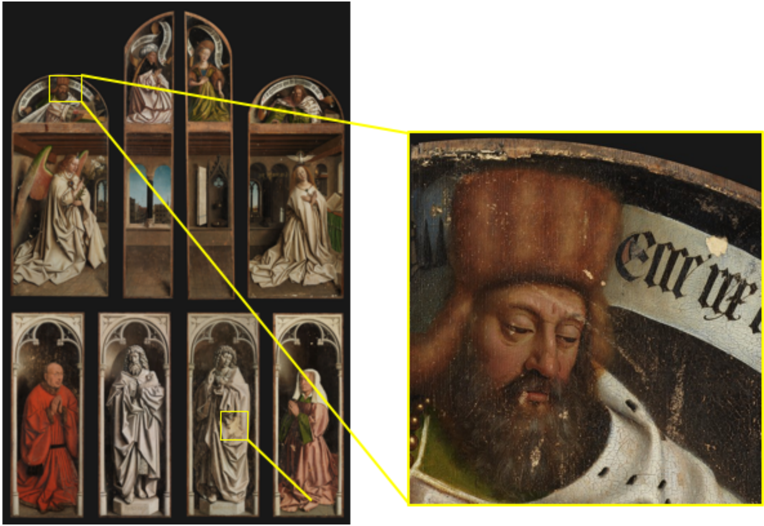
A Master Work, the Ghent Altarpiece, Reawakens Stroke by Stroke

By MILAN SCHREUER DEC. 19, 2016

Ghent Altarpiece restoration – Phase 1

= Overpaint © KIK-IRPA

Restoration – Phase 1, after cleaning: paint losses



3

Restoration – Phase 1, after cleaning: paint losses

Restoration – Phase 1, after cleaning: paint losses

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Why do we need automatic paint loss detection?

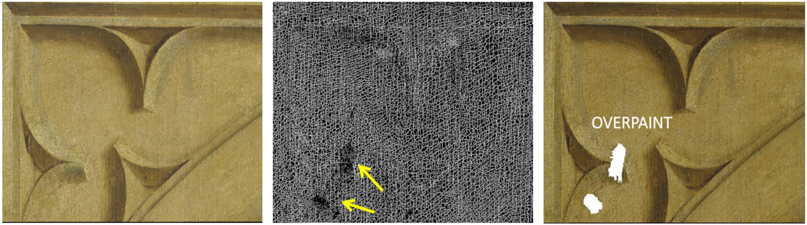
Paint loss detection is crucial for

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

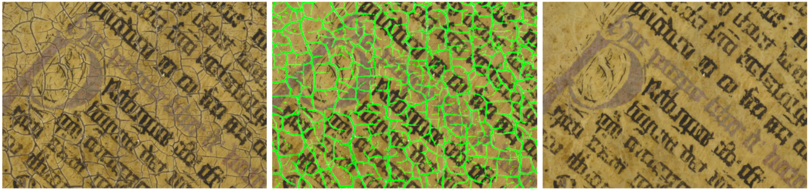
Currently done manually:

- labor intensive
- only rough indication
- prone to errors

Crack detection

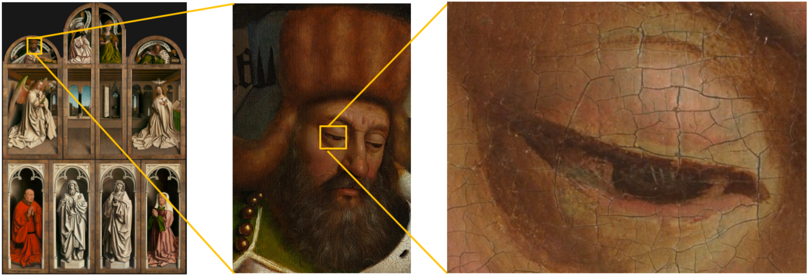


Diagnostics, overpaint detection.



Input for virtual crack filling. Improving readability of inscriptions.

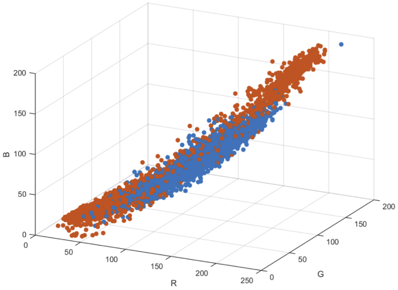
Challenges: Huge data



Each 15x20 cm area recorded in a separate capture with a camera fitted with a Hasselblad 120mm lens and a 50-megapixel camera back (8176 x 6132 pixels).

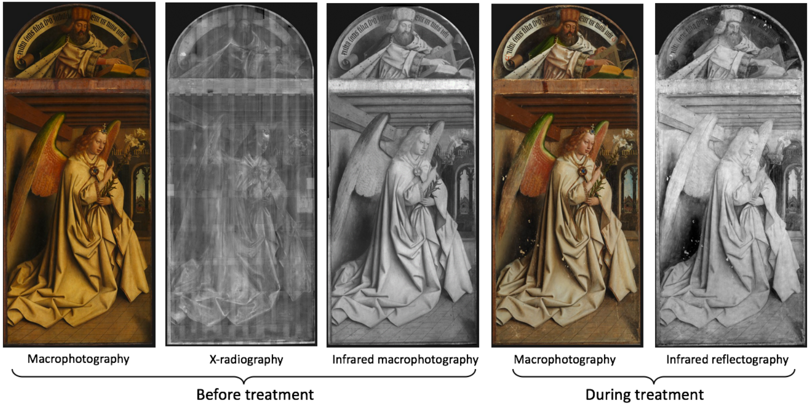
Paint loss detection problem - difficulties

©Ghent, Kathedrale Kerkfabriek, Lukasweb



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



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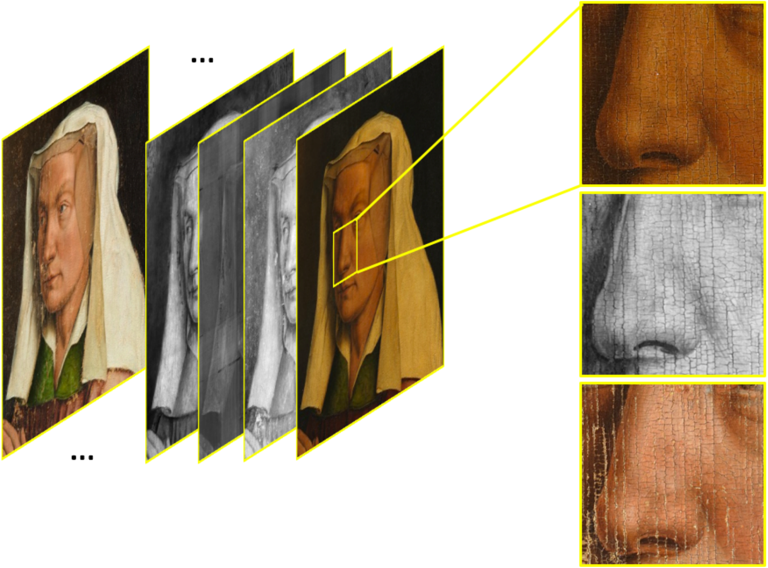
Registration of multimodal images



Crack patterns can be employed as landmarks.

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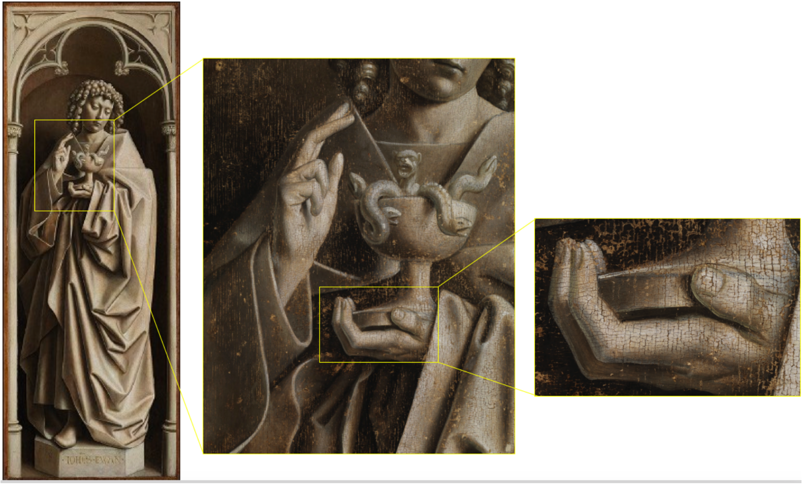
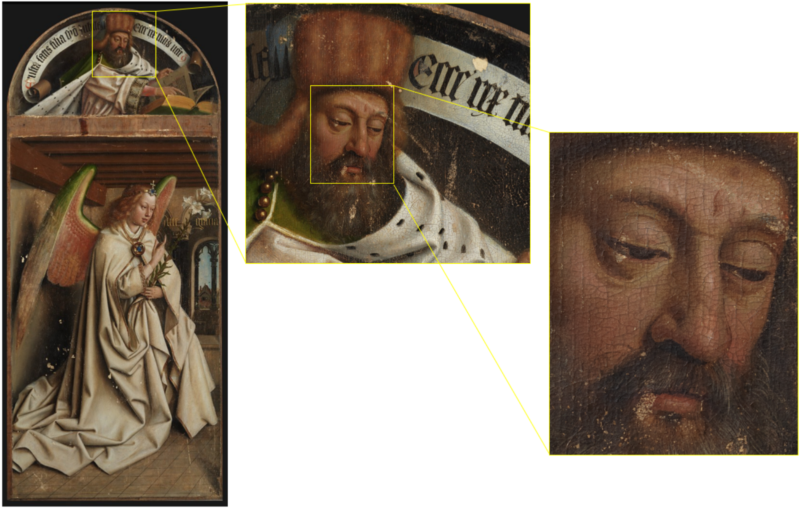
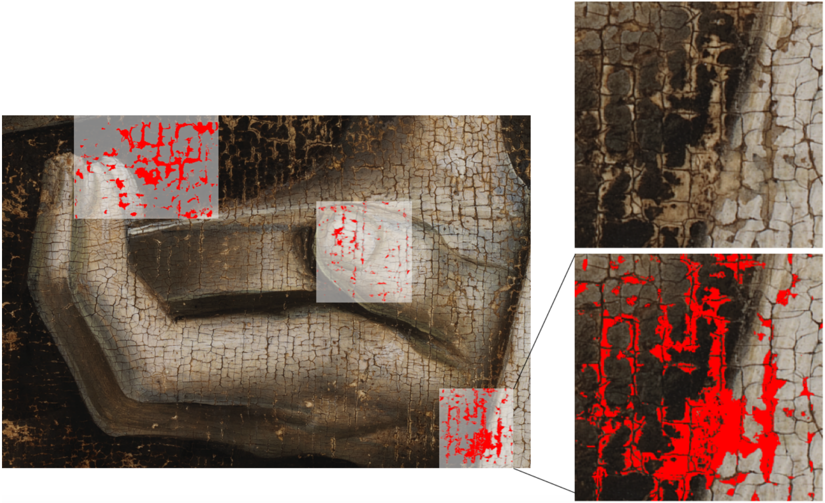
Paint loss detection data sets - *John the Evangelist*



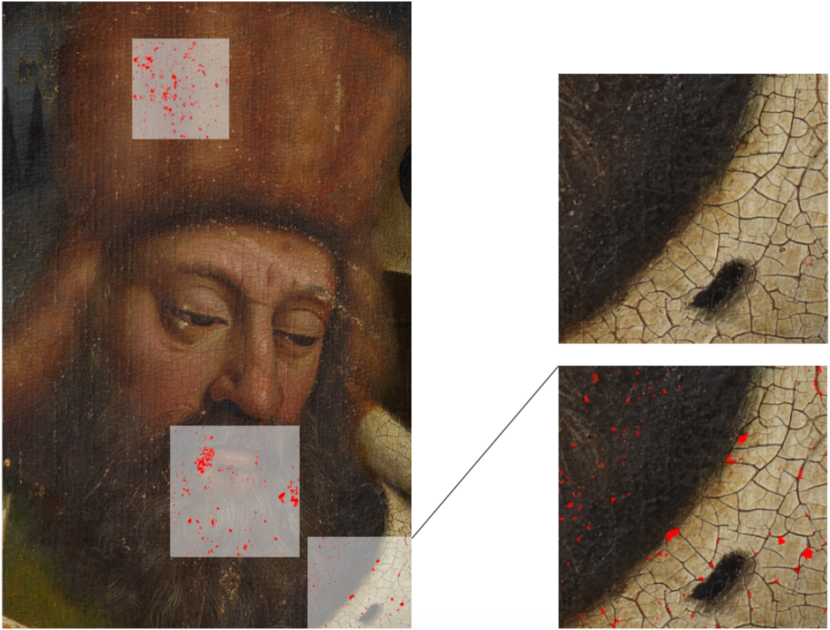
Paint loss detection data sets - *prophet Zachary*



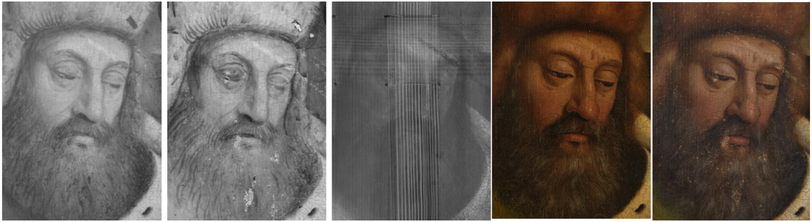
Annotations by art restorers



Annotations by art restorers



Multimodal Data



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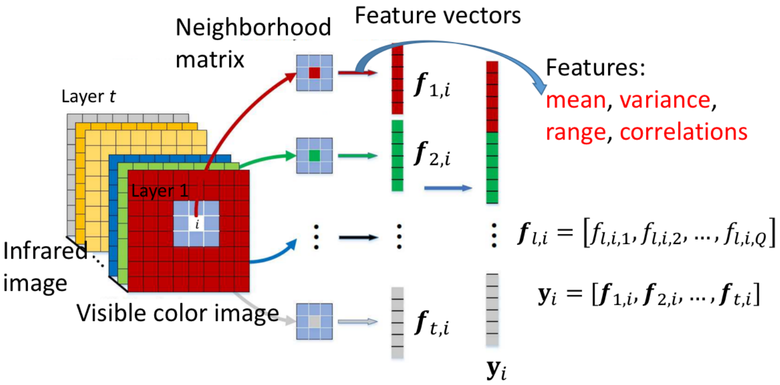
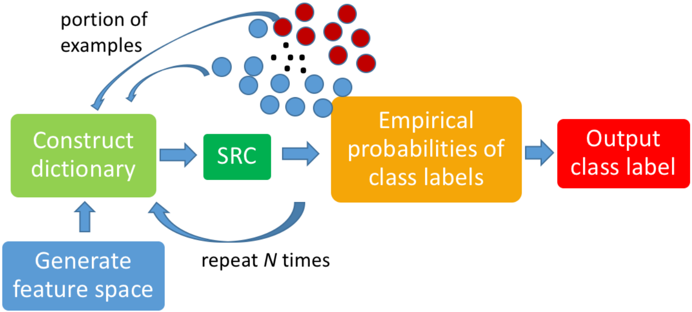
- Annotations done on macrophotographs during the treatment;
- Dictionaries for sparse representation classification constructed from the available multimodal data. The available modalities may differ from one panel to another.

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

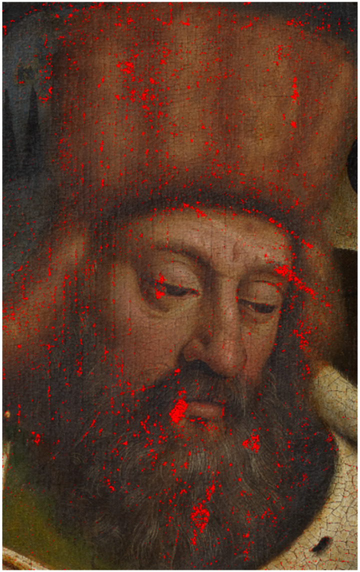


N_j^m - number of trials in which $\mathbf{y}_j$ was labelled as class m;
$m \in \{PaintLoss, Other\}$

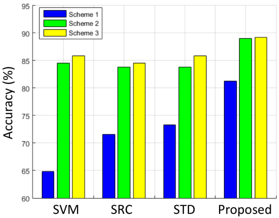
$$class(\mathbf{y}_j) = \arg\max_m p_j(m) = \underbrace{\arg\max_m \,(N_j^m/N)}_{\text{empirical prob. of class } m}$$

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



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).

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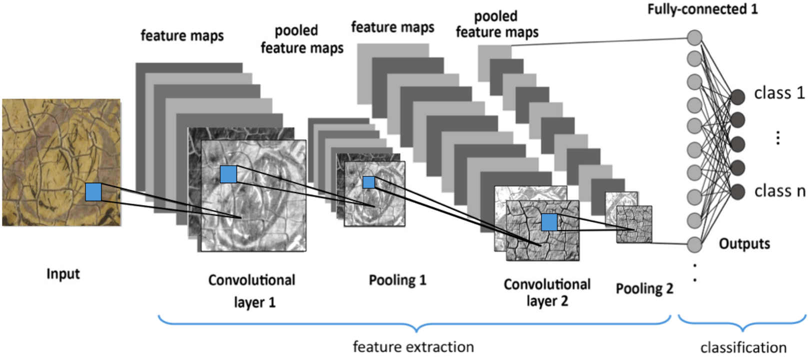
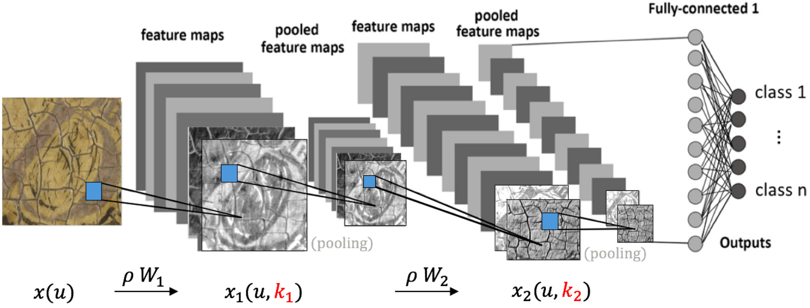
Deep learning methods



A generic concept of a classifier based on a convolutional neural network (CNN).

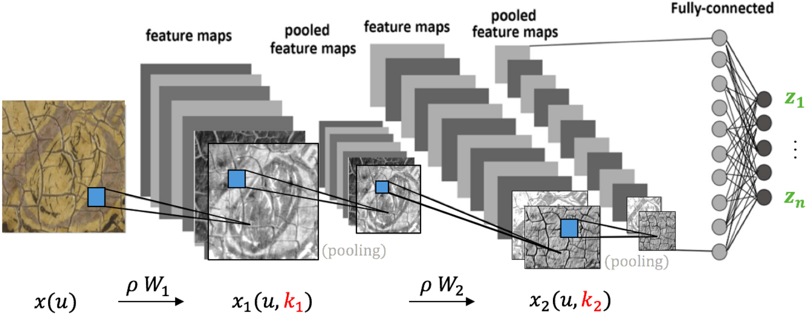
Deep learning methods



ρ – **pointwise nonlinearity** (e.g., ReLU); W_i – **linear operator** (convolution);

$$W_j x_{j-1}(u, k_j) = \sum_k \sum_v x_{j-1}(v, k) w_{j,k_j}(u - v, k) = \sum_k (x_{j-1}(., k) \star w_{j,k_j}(., k))(u)$$

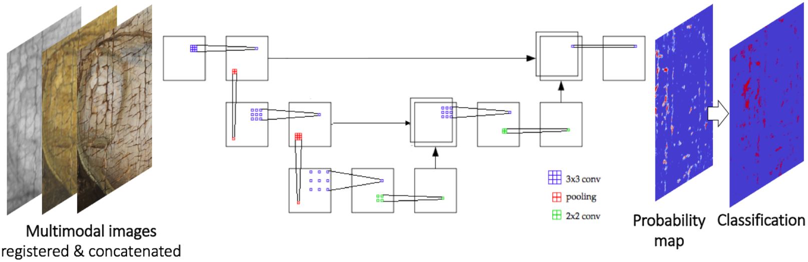
Deep learning methods



Predicted probabilities of class labels using the **softmax** rule:

$$P(class(x(u) = j | z_j) = \frac{e^{z_j}}{\sum_l e^{z_l}}$$

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.

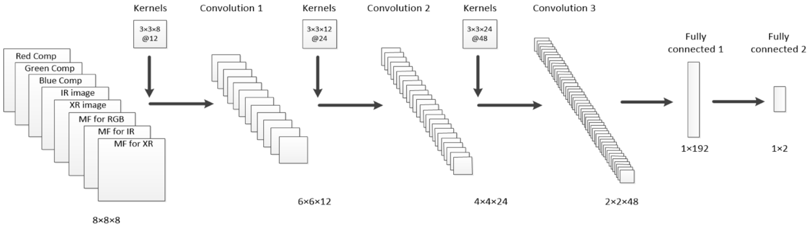
A multiscale deep learning method for paint loss detection

Size: 5954×7546; processed in < 1 minute

Deep learning in crack detection

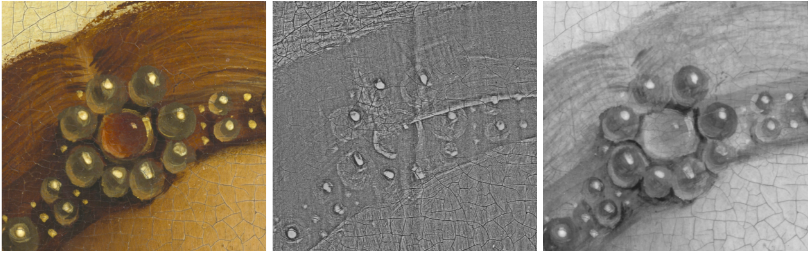
Crack detection in roads reported in [Lei et al,2016], [Cha et al, 2017].
However, crack detection in paintings is much more challenging!

A deep learning method for crack detection in paintings

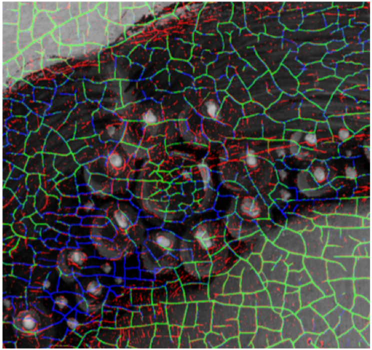


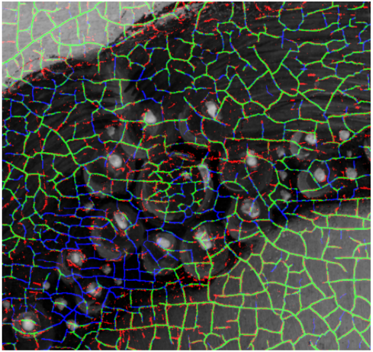
R. Sizyakin, B. Cornelis, L. Meeus, M. Martens, V. Voronin, and A. Pižurica (2018). A deep learning approach to crack detection in panel paintings. IP4AI.

Crack detection: panel *Singing Angels*



Crack detection: panel *Singing Angels*





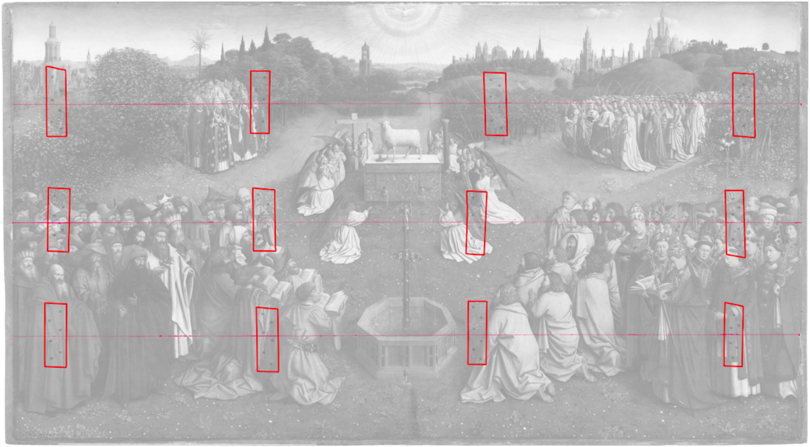
Left: A Bayesian multimodal method (BCTF). Right: CNN-based.
red – false detections; blue – missing cracks; green - -correct.

Crack detection: Central panel

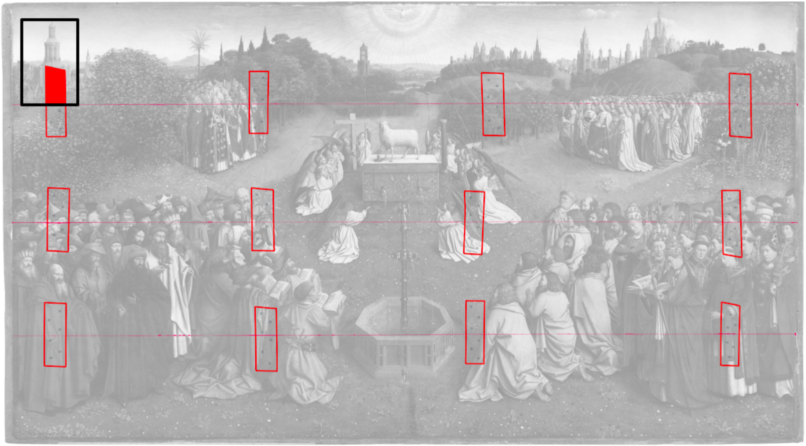
The *Mystic Lamb* – before and after the restoration.

Crack detection: Central panel

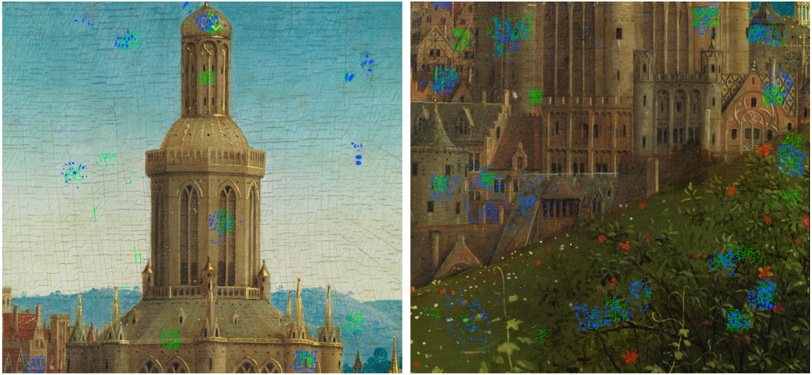
Crack detection: Central panel



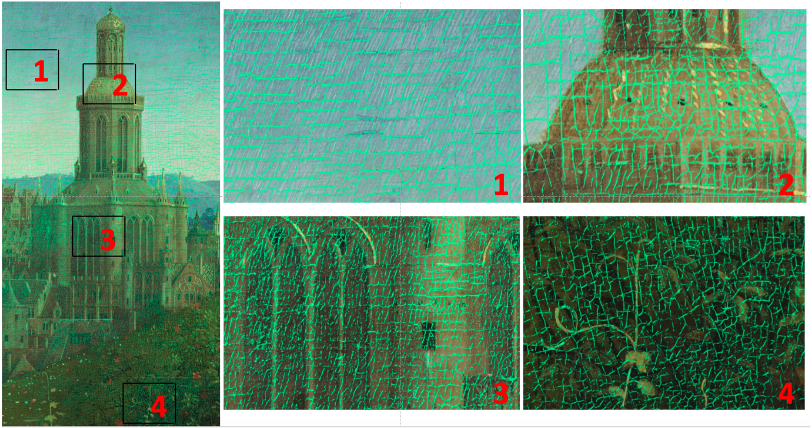
Crack detection: Central panel



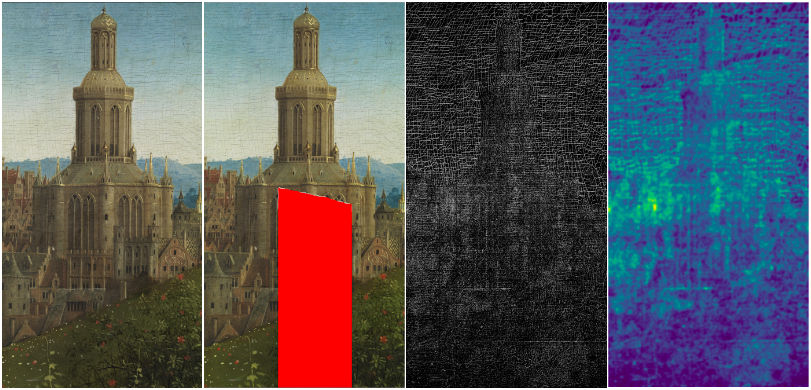
Crack detection: Central panel



Crack detection: Central panel



Crack detection: Central panel



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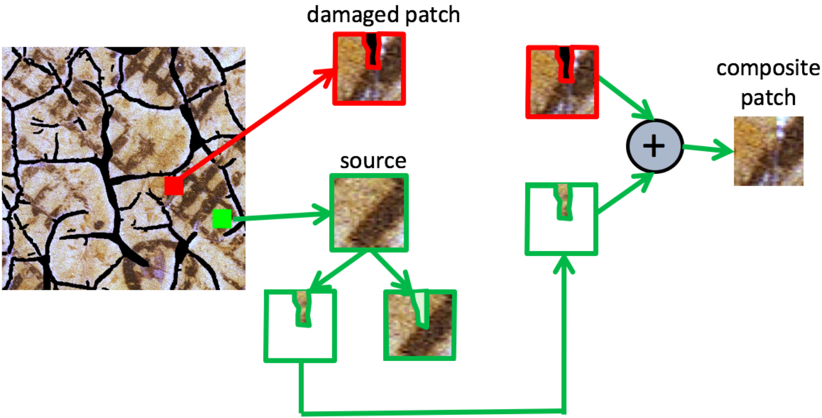
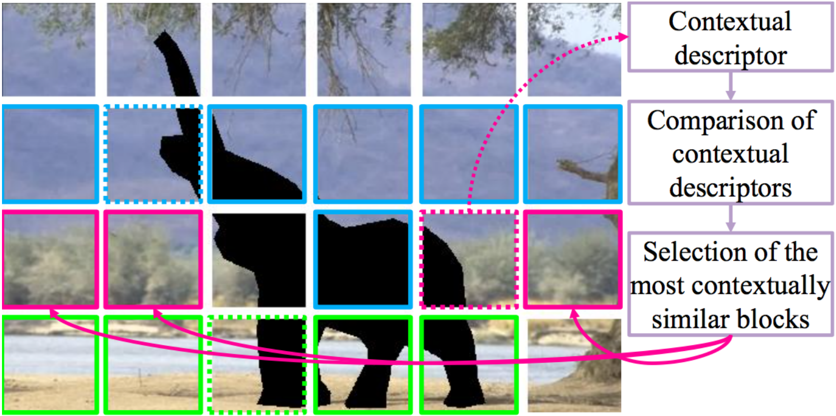
Patch-based inpainting

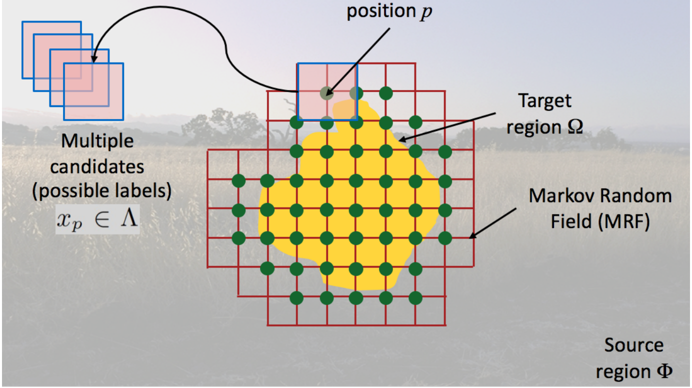


Context adaptative inpainting

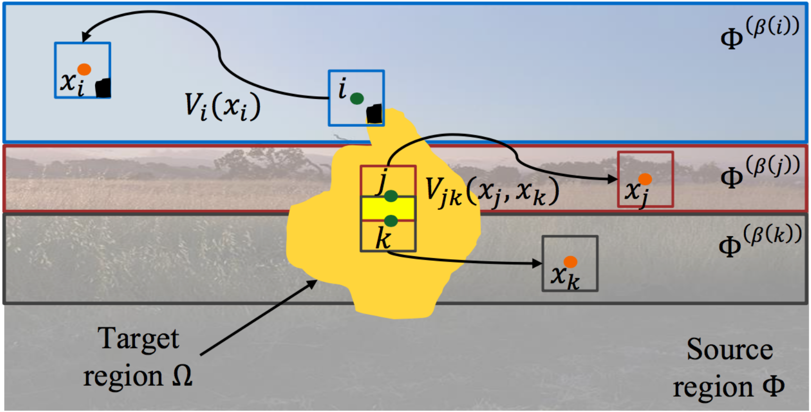


T. Ružić and A. Pižurica et al. Context-aware patch-based image inpainting using Markov random field modeling. *IEEE Transactions on Image Processing* 2015

Global inpainting



Global inpainting

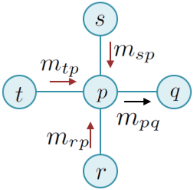


$$E(\mathbf{x}) = \sum_{i \in \nu} V_i(x_i) + \sum_{\langle i,j \rangle \in \varepsilon} V_{ij}(x_i, x_j), \tag{1}$$

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

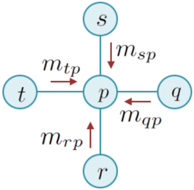
Global inpainting

Messages



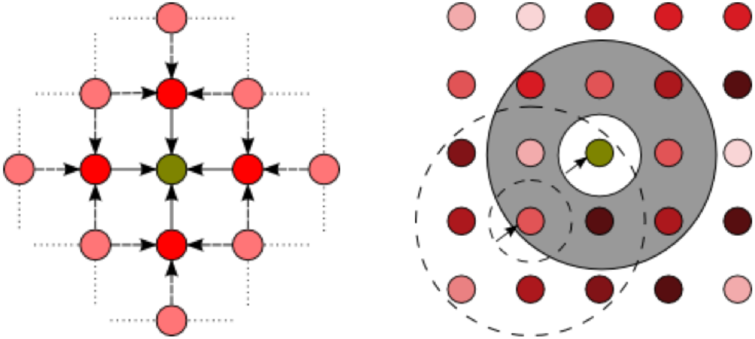
$$m_{pq}(x_q) = \min_{x_p \in \Lambda} \Big\{ V_{pq}(x_p, x_q) + V_p(x_p) + \sum_{r: r \neq q, (r,p) \in \varepsilon} m_{rp}(x_p) \Big\}$$

Beliefs



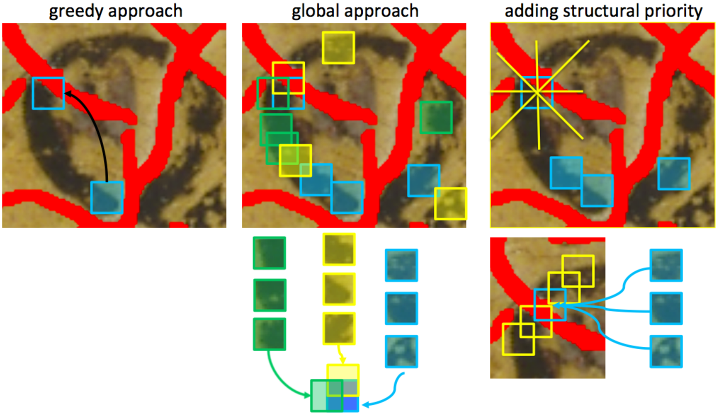
$$b_p(x_p) = -V_p(x_p) - \sum_{r:(r,p) \in \varepsilon} m_{rp}(x_p)$$

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

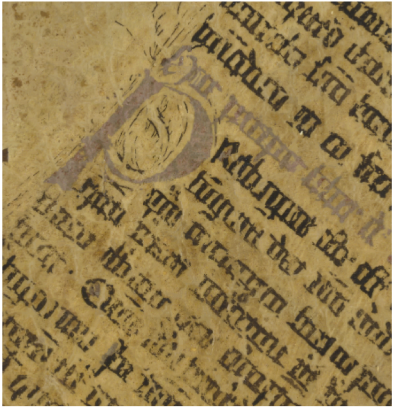


$$P_{i,j} = \mathcal{S}(\phi_i, \phi_j) + \max_k \sum_{l \in N_{j,k}} \mathcal{S}(\phi_i, \phi_l)$$

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

Crack inpaiting

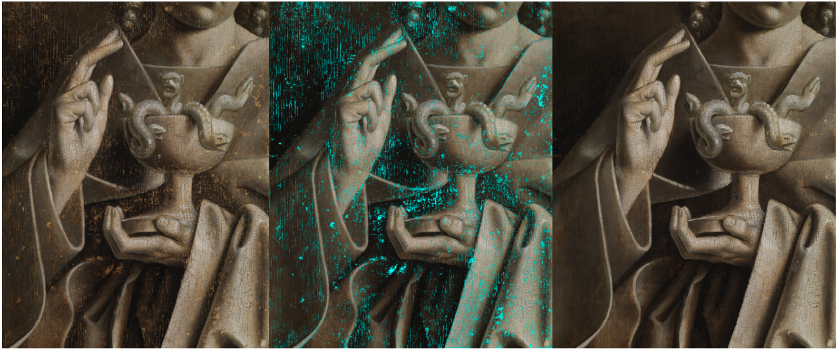
Crack inpaiting



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].

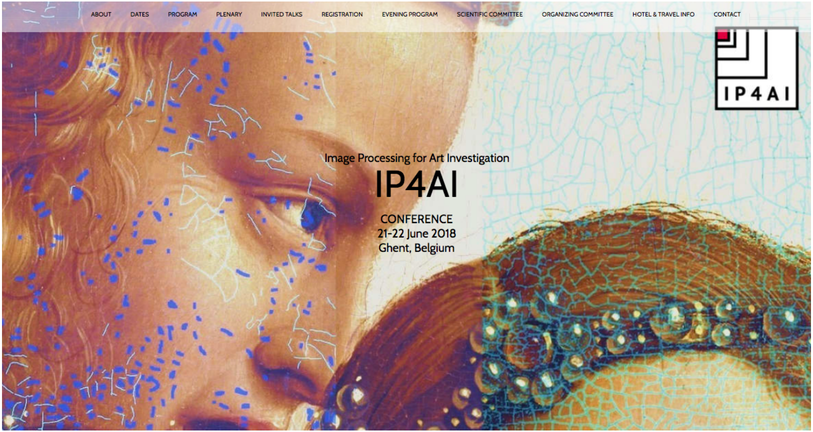
Virtual Restoration

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

Virtual Restoration

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

IP4AI Community



IP4AI - Image Processing for Art Investigation

IP4AI 2018 proceedings: https://ip4ai.ugent.be/

Special Session at ISIT 2019

ISIT 2019 Special Session on Applications in Fine Arts

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