



FACULTY OF ENGINEERING

Signal Processing and Machine Learning in Art Conservation

Aleksandra Pižurica

Department Telecommunications and Information Processing
Ghent University

Cambridge Image Analysis Seminars, University of Cambridge
20 November 2018

Contributors



Ljiljana Platiša



Tijana Ružić



Laurens Meeus



Shaoguang Huang



Roman Sizyakin



Hélène Dubois



Bart Devolder



Nina Žižakić



Marc De Mey



Ann Dooms



Bruno Cornelis



Max Martens



Aleksandra Pižurica



Ingrid Daubechies

Outline

- 1 Case Study: Ghent Altarpiece
 - Current conservation-restoration treatment
 - Challenges for signal processing and machine learning
- 2 Paint loss localization and crack detection
 - Sparse coding methods
 - Deep learning methods
- 3 Virtual restoration
 - Patch-based inpainting
 - Virtual restoration of the Ghent Altarpiece

Outline

- 1 Case Study: Ghent Altarpiece
 - Current conservation-restoration treatment
 - Challenges for signal processing and machine learning
- 2 Paint loss localization and crack detection
 - Sparse coding methods
 - Deep learning methods
- 3 Virtual restoration
 - Patch-based inpainting
 - Virtual restoration of the Ghent Altarpiece

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

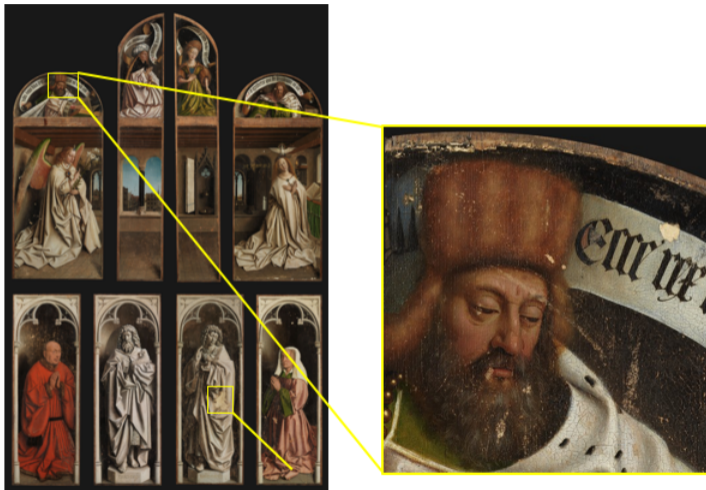


Ghent Altarpiece restoration – Phase 1



■ = Overpaint © KIK-IRPA

Ghent Altarpiece restoration – Phase 1, after cleaning: paint losses



3

Ghent Altarpiece restoration – Phase 1, after cleaning: paint losses



4

Ghent Altarpiece restoration – Phase 1, after cleaning: paint losses



Outline

- 1 Case Study: Ghent Altarpiece
 - Current conservation-restoration treatment
 - Challenges for signal processing and machine learning
- 2 Paint loss localization and crack detection
 - Sparse coding methods
 - Deep learning methods
- 3 Virtual restoration
 - Patch-based inpainting
 - Virtual restoration of the Ghent Altarpiece

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

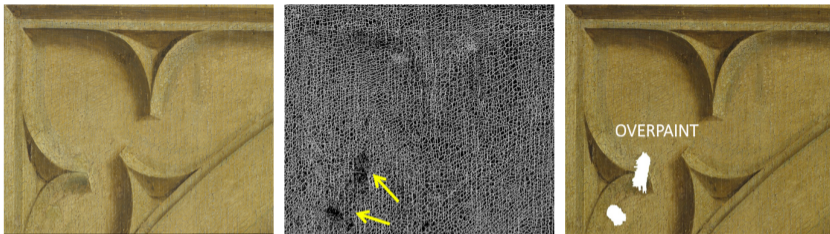
Currently done manually:

- labor intensive
- only rough indication
- prone to errors

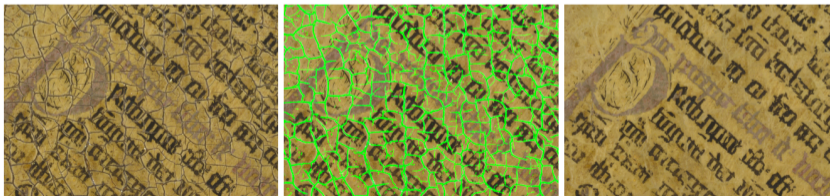


©Ghent, Kathedrale Kerkfabriek, Lukasweb

Crack detection

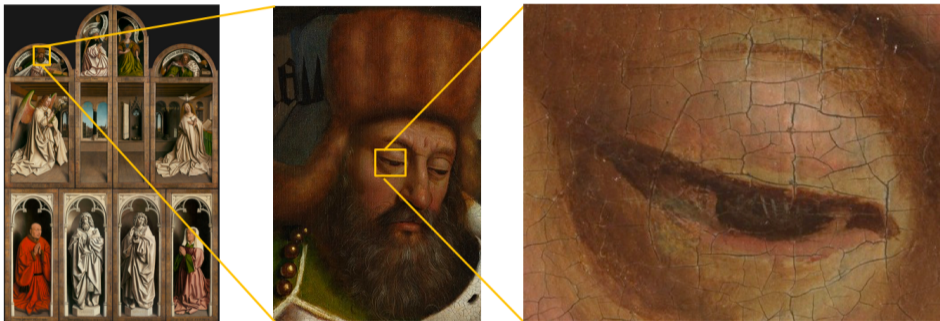


Diagnostics, overpaint detection.



Input for virtual crack filling. Improving readability of inscriptions.

Challenges: Huge data

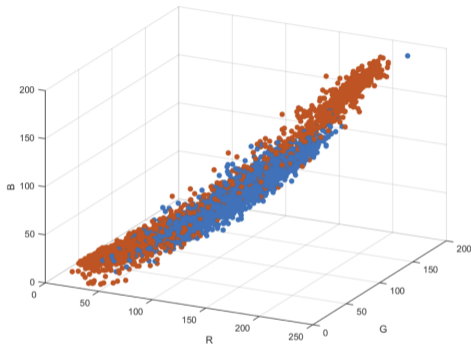


Each 15x20 cm area recorded in a separate capture with a camera fitted with a Hasselblad 120mm lens and a 50-megapixel camera back (8176 x 6132 pixels).

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



Macrophotography



X-radiography



Infrared macrophotography

Before treatment



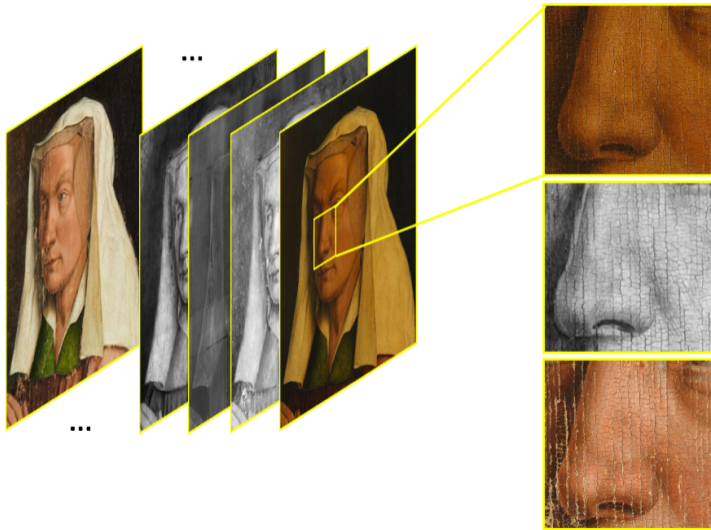
Macrophotography



Infrared reflectography

During treatment

Registration of multimodal images

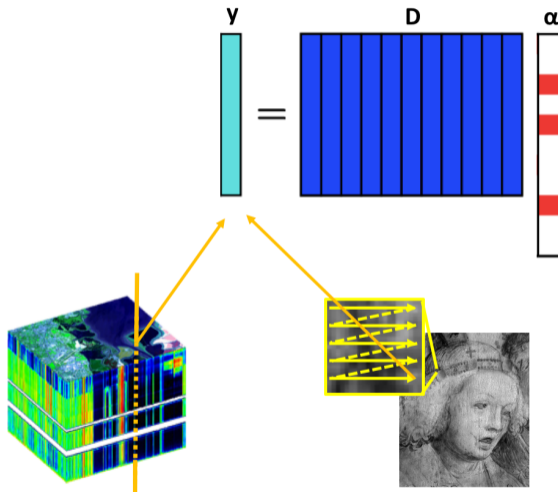


Crack patterns can be employed as landmarks.

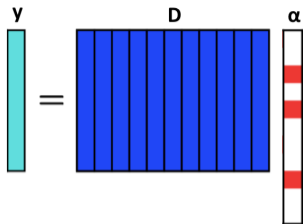
Outline

- 1 Case Study: Ghent Altarpiece
 - Current conservation-restoration treatment
 - Challenges for signal processing and machine learning
- 2 Paint loss localization and crack detection
 - Sparse coding methods
 - Deep learning methods
- 3 Virtual restoration
 - Patch-based inpainting
 - Virtual restoration of the Ghent Altarpiece

Sparse representation



Sparse coding



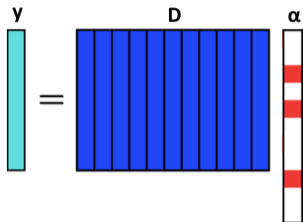
$$\hat{\alpha} = \arg \min_{\alpha} \|\mathbf{y} - \mathbf{D}\alpha\|_2^2 \quad \text{subject to} \quad \|\alpha\|_0 \leq K$$

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

Greedy algorithms

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

Sparse coding



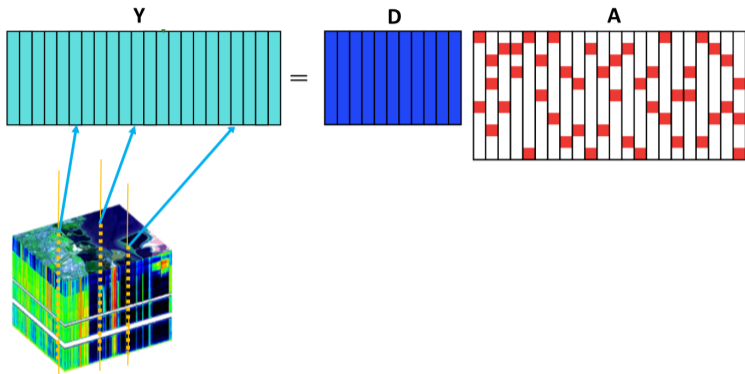
Convex relaxation:

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

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

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

Sparse coding and dictionary learning

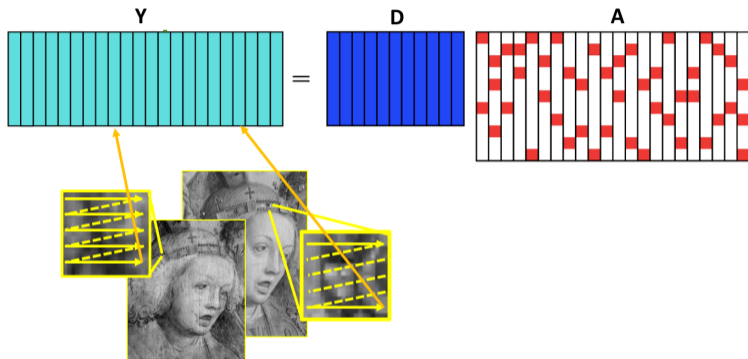


$$\{\hat{\mathbf{D}}, \hat{\mathbf{A}}\} = \arg \min_{\mathbf{D}, \mathbf{A}} \left\{ \|\mathbf{Y} - \mathbf{D}\mathbf{A}\|_F^2 \right\} \quad \text{subject to} \quad \forall i, \|\alpha_i\|_0 \leq K$$

A similar objective:

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

Sparse coding and dictionary learning

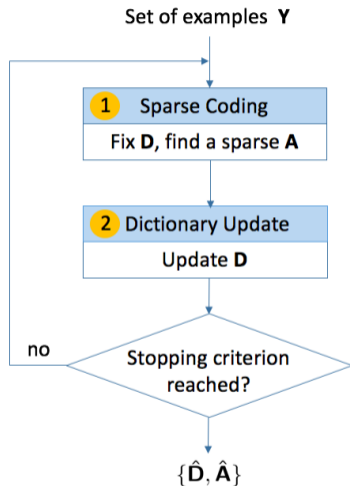


$$\{\hat{\mathbf{D}}, \hat{\mathbf{A}}\} = \arg \min_{\mathbf{D}, \mathbf{A}} \left\{ \|\mathbf{Y} - \mathbf{DA}\|_F^2 \right\} \quad \text{subject to} \quad \forall i, \|\alpha_i\|_0 \leq K$$

A similar objective:

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

Iterate Two Steps: Sparse Coding and Dictionary Update



Dictionary update:

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

Sparse Coding - A Strategy Employed by V1?

[Olshausen and Field, 1997]

Idea: **maximize the likelihood** :

$$P(\mathbf{Y}|\mathbf{D}) = \prod_i P(\mathbf{y}_i|\mathbf{D}) = \prod_i \int P(\mathbf{y}_i|\boldsymbol{\alpha}, \mathbf{D})P(\boldsymbol{\alpha})d\boldsymbol{\alpha}$$

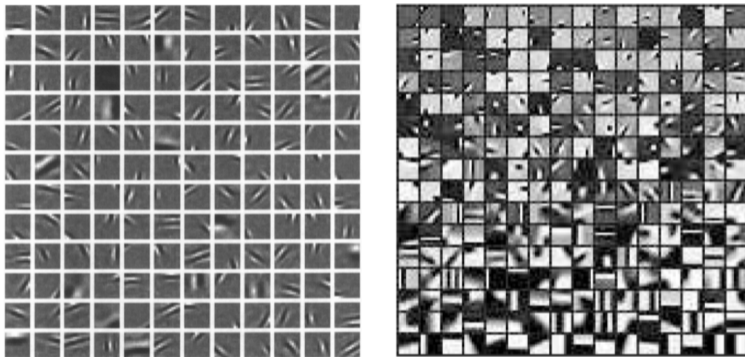
Approximate $P(\mathbf{y}_i|\mathbf{D})$ via **extremal values**. Require: $P(\boldsymbol{\alpha}) \propto e^{-\lambda|\boldsymbol{\alpha}|}$

$$\begin{aligned}\hat{\mathbf{D}} &= \arg \max_{\mathbf{D}} \sum_i \max_{\boldsymbol{\alpha}_i} \left\{ P(\mathbf{y}_i|\boldsymbol{\alpha}_i, \mathbf{D})P(\boldsymbol{\alpha}_i) \right\} \\ &= \arg \min_{\mathbf{D}} \sum_i \min_{\boldsymbol{\alpha}_i} \left\{ \|\mathbf{D}\boldsymbol{\alpha}_i - \mathbf{y}_i\|^2 + \lambda\|\boldsymbol{\alpha}_i\|_1 \right\}\end{aligned}$$

Two-step iterative procedure :

- ① Calculate $\{\boldsymbol{\alpha}_i\}_{i=1}^N$ using a **gradient descent** procedure
- ② Update the dictionary as: $\mathbf{D}^{(k+1)} = \mathbf{D}^{(k)} - \eta \sum_{i=1}^N \left(\mathbf{D}^{(k)}\boldsymbol{\alpha}_i - \mathbf{y}_i \right) \boldsymbol{\alpha}_i^T$

Learned Dictionaries of Image Atoms - Examples



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

Unsupervised vs. Supervised Dictionary Learning

- **Unsupervised** dictionary learning

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

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

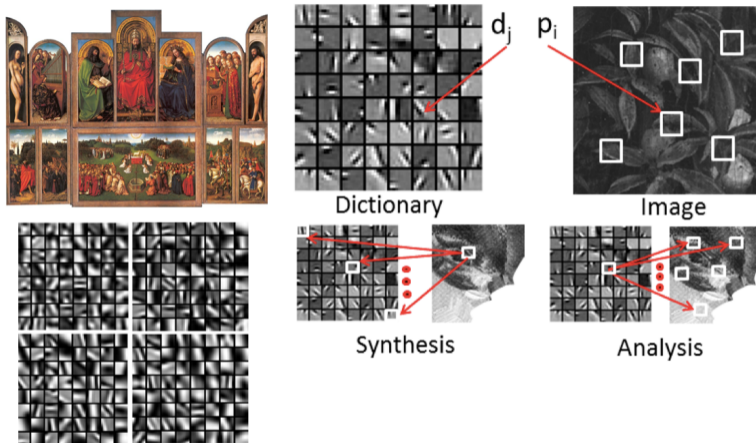
- **Supervised** (discriminative or **task-driven**)

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

subject to $\forall i, \|\alpha_i\|_0 \leq K$

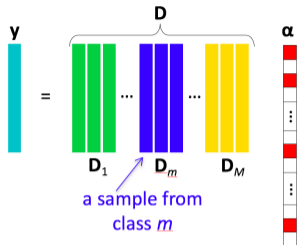
- ▶ classification problems (**H** – label inform.; **C** – classifier parameters)

Application in Painter Style Characterization



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

Sparse Representation Classification - SRC



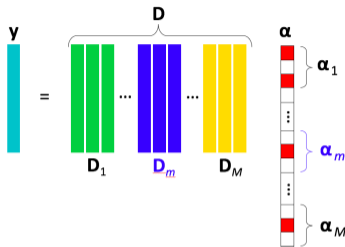
$$\hat{\alpha} = \arg \min_{\alpha} \|\mathbf{y} - \mathbf{D}\alpha\|_2^2 \quad s.t. \quad \|\alpha\|_0 \leq K$$

Let $\delta_m(\alpha)$ denote a vector whose all entries are set to zero except those associated with class m and define a class-specific residual $r_m(\mathbf{y})$

$$r_m(\mathbf{y}) = \|\mathbf{y} - \mathbf{D}\delta_m(\hat{\alpha})\|_2, \quad m = 1, \dots, M$$

and the sample class as: $identity(\mathbf{y}) = \arg \min_{m=1, \dots, M} r_m(\mathbf{y})$

Sparse Representation Classification - SRC



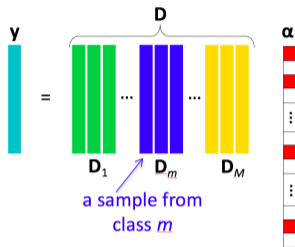
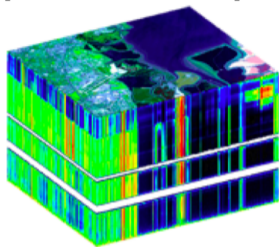
Equivalently,

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

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

SRC in Hyperspectral Image Classification

[Chen et al., 2011a]

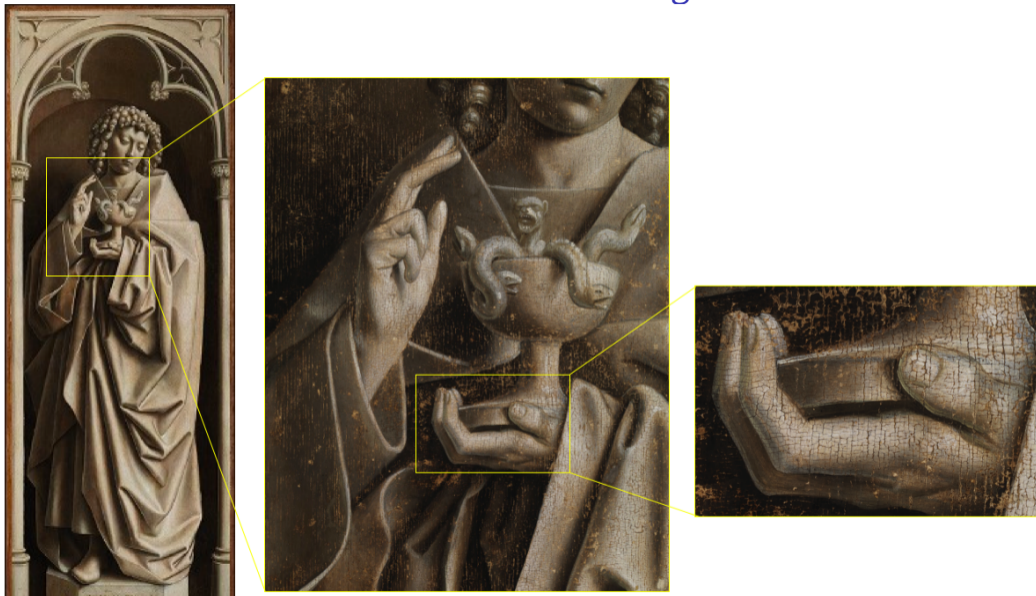


$$\hat{\boldsymbol{\alpha}} = \arg \min_{\boldsymbol{\alpha}} \|\mathbf{y} - \mathbf{D}\boldsymbol{\alpha}\|_2^2 \quad \text{subject to } \|\boldsymbol{\alpha}\|_0 \leq K$$

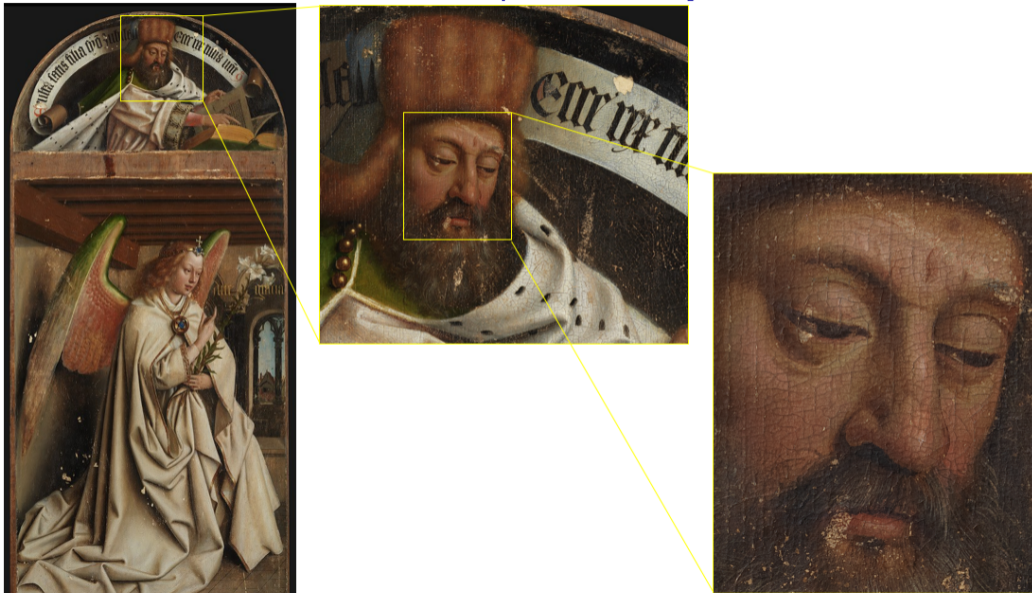
$$r_m(\mathbf{y}) = \|\mathbf{y} - \mathbf{D}_m \hat{\boldsymbol{\alpha}}_m\|_2, \quad m = 1, \dots, M$$

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

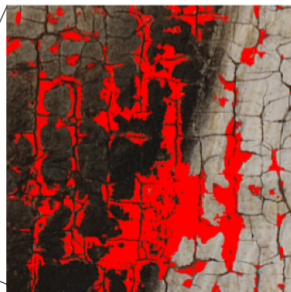
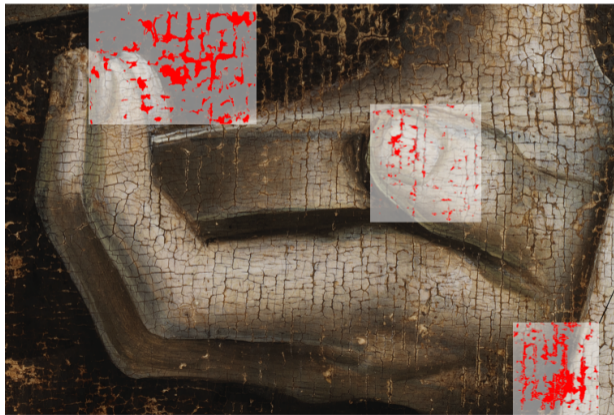
Paint loss detection data sets - *John the Evangelist*



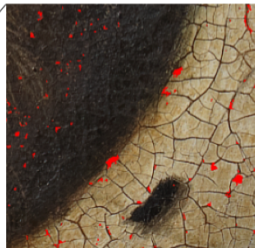
Paint loss detection data sets - *Prophet Zachary*



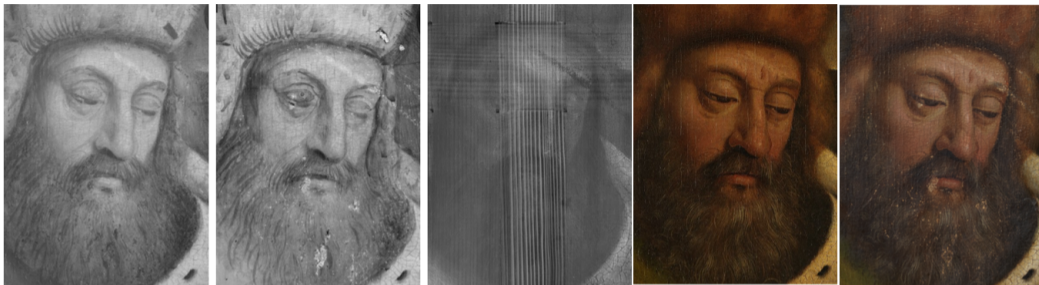
Annotations by art restorers



Annotations by art restorers



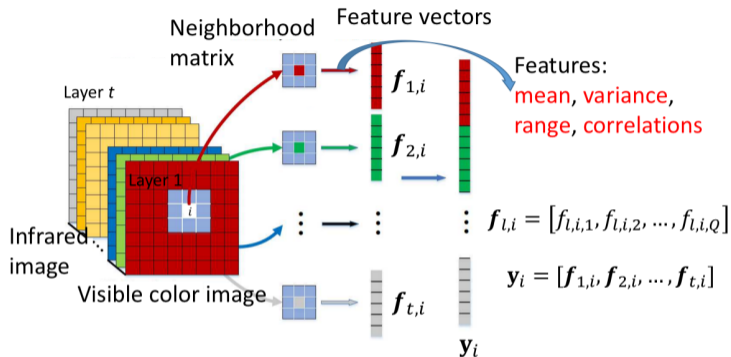
Multimodal Data



© Ghent, Kathedrale Kerkfabriek, Lukasweb

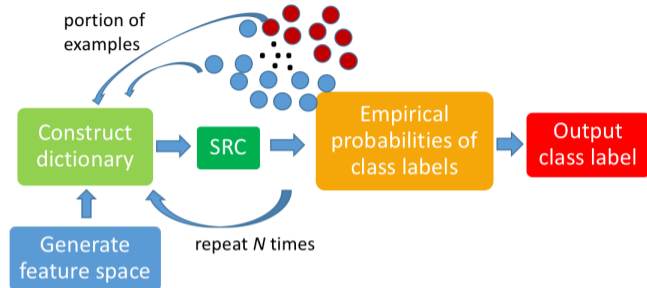
- Annotations done on macrophotographs during the treatment;
- Dictionaries for sparse representation classification constructed from the available multimodal data. The available modalities may differ from one panel to another.

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 ; $m \in \{PaintLoss, Other\}$

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

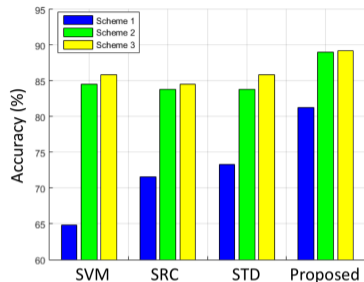
S. Huang, W. Liao, H. Zhang, and A. Pižurica (2016). Paint Loss Detection in Old Paintings by Sparse Representation Classification. iTWIST.

Paint Loss Detection Results



Image copyright: Ghent, Kathedrale Kerkfabriek, Lukasweb

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

subscriber:
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]

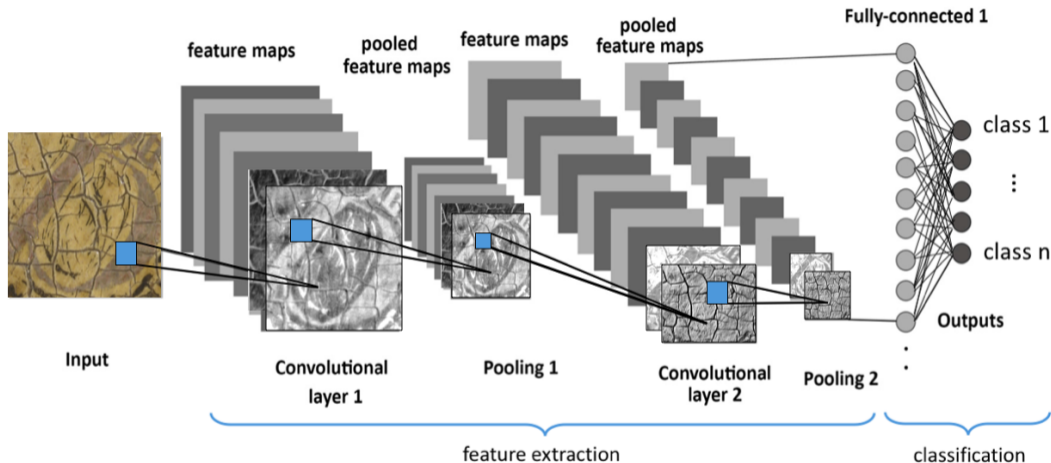
Proposed – the proposed method based on kernel-SRC [Huang et al., 2018]

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

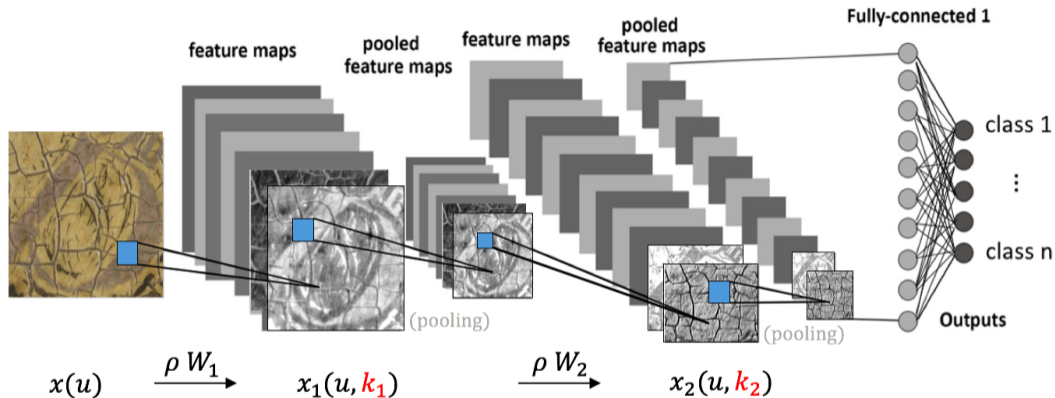
- 1 Case Study: Ghent Altarpiece
 - Current conservation-restoration treatment
 - Challenges for signal processing and machine learning
- 2 Paint loss localization and crack detection
 - Sparse coding methods
 - Deep learning methods
- 3 Virtual restoration
 - Patch-based inpainting
 - Virtual restoration of the Ghent Altarpiece

Deep learning methods



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

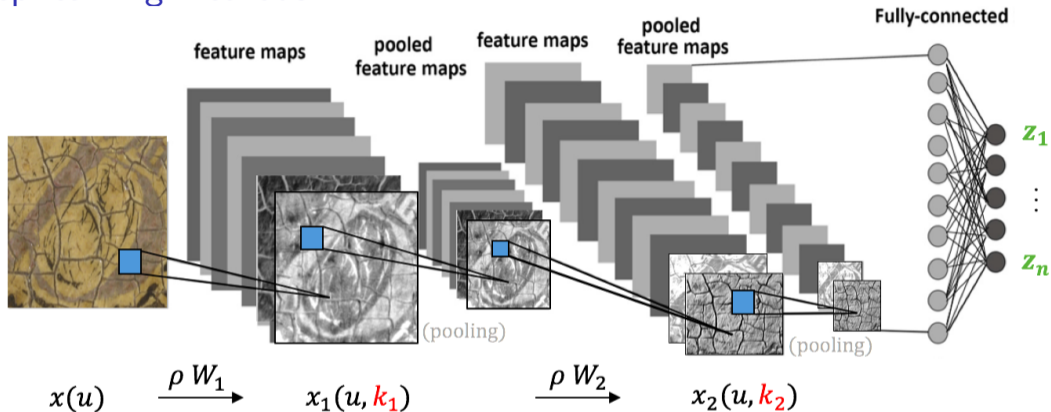
Deep learning methods



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

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

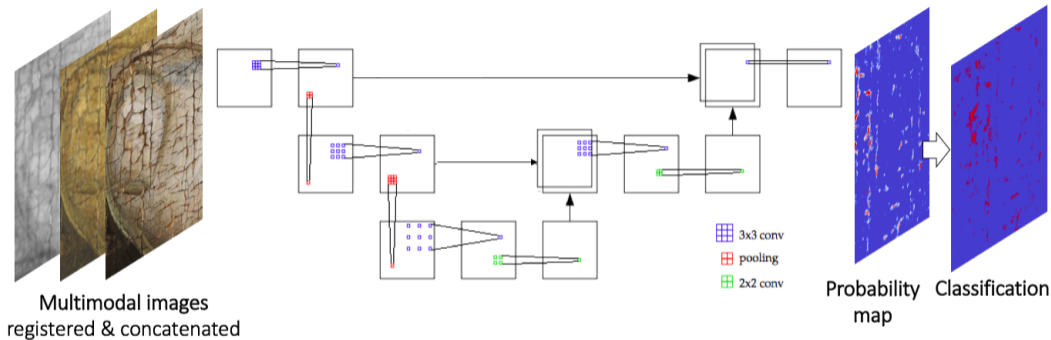
Deep learning methods



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

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

A multiscale deep learning method applied to 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 applied to paint loss detection



Size: 5954×7546 ; processed in < 1 minute

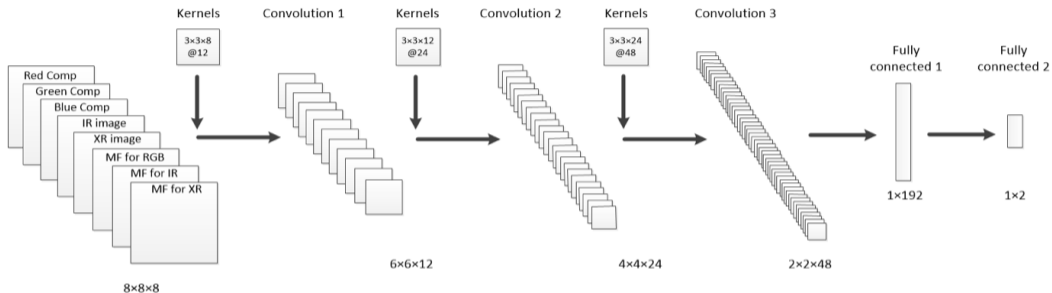
Deep learning in crack detection



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

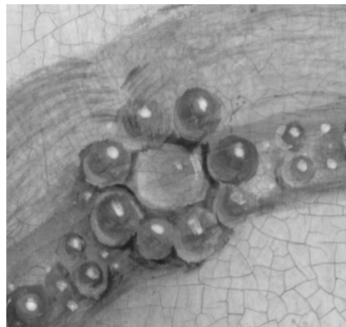


A deep learning method for crack detection in paintings

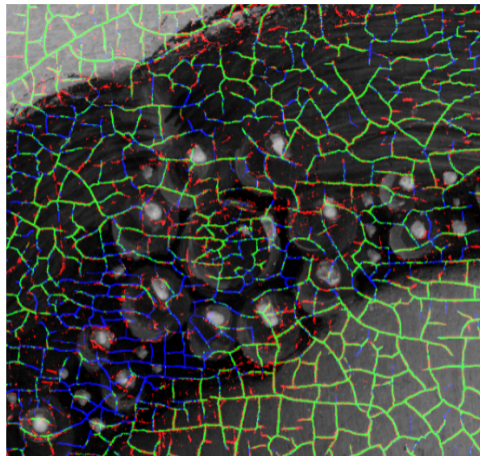
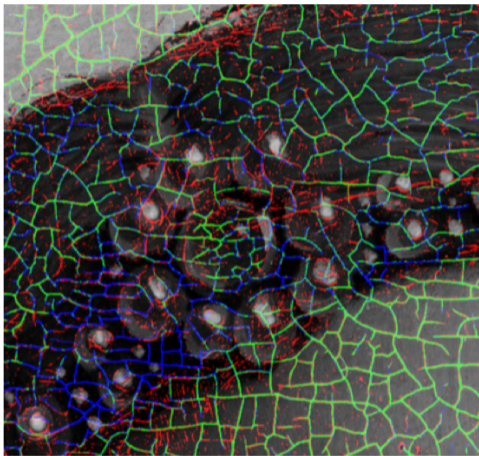


R. Sizyakin, B. Cornelis, L. Meeus, M. Martens, V. Voronin, and A. Pižurica (2018). A deep learning approach to crack detection in panel paintings. IP4AI.

Crack detection: panel *Singing Angels*



Crack detection: panel *Singing Angels*



Left: A Bayesian multimodal method (BCTF). Right: CNN-based.

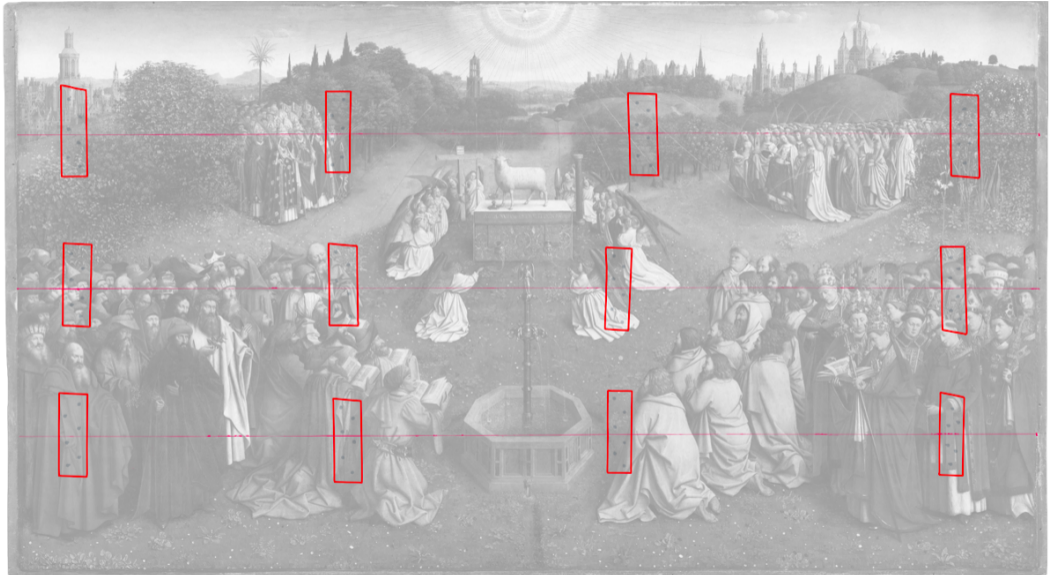
red – false detections; blue – missing cracks; green – correct.

Crack detection: Central panel

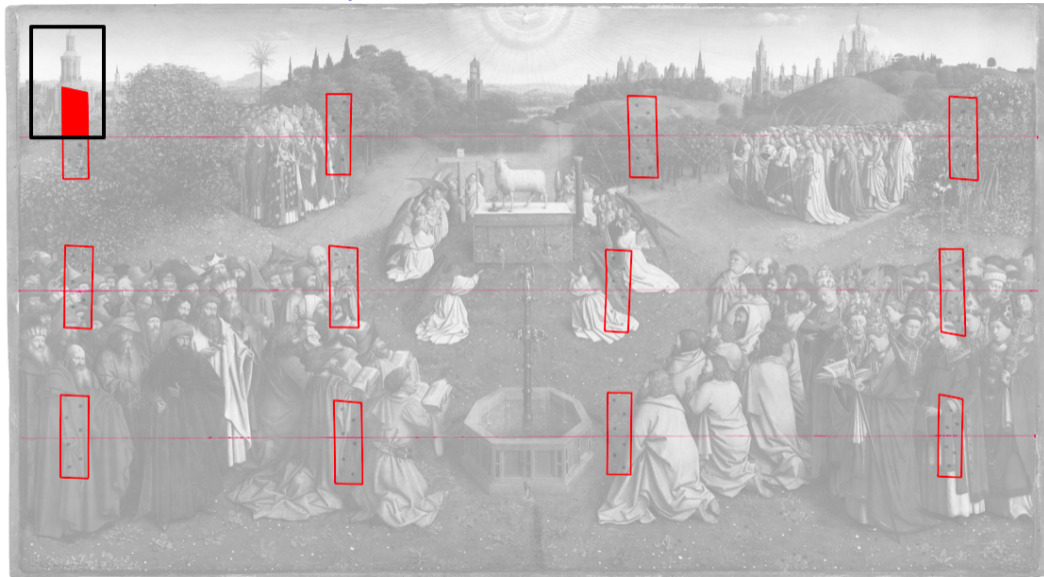


The *Mystic Lamb* – before and after the restoration.

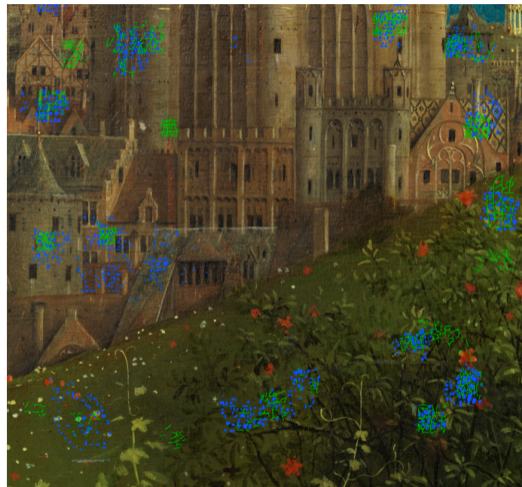
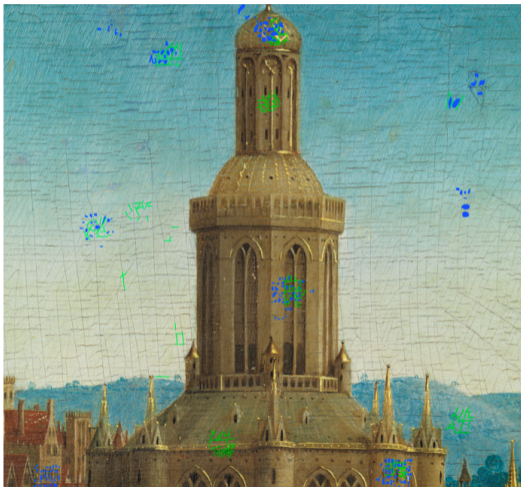
Crack detection: Central panel



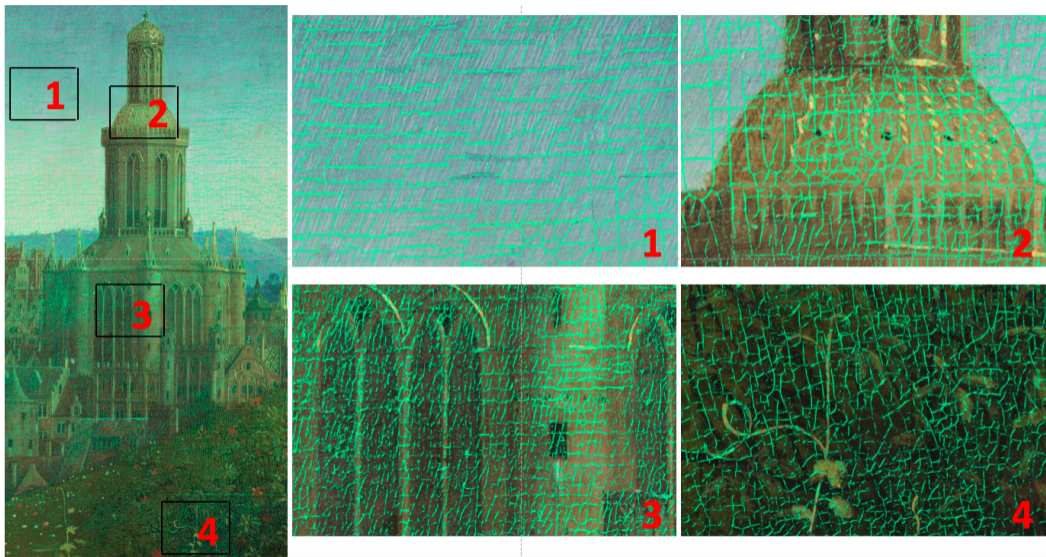
Crack detection: Central panel



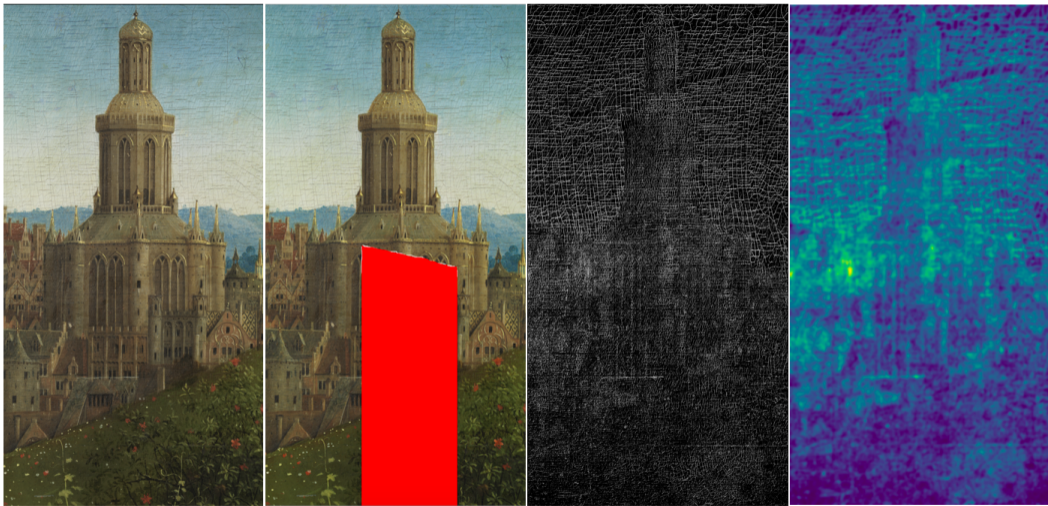
Crack detection: Central panel



Crack detection: Central panel



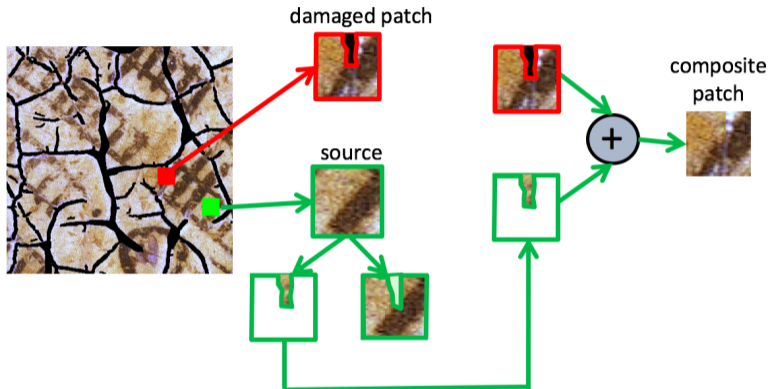
Crack detection: Central panel



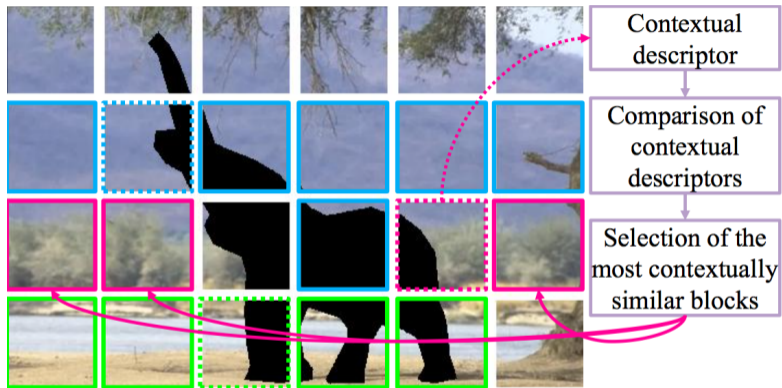
Outline

- 1 Case Study: Ghent Altarpiece
 - Current conservation-restoration treatment
 - Challenges for signal processing and machine learning
- 2 Paint loss localization and crack detection
 - Sparse coding methods
 - Deep learning methods
- 3 Virtual restoration
 - Patch-based inpainting
 - Virtual restoration of the Ghent Altarpiece

Patch-based inpainting

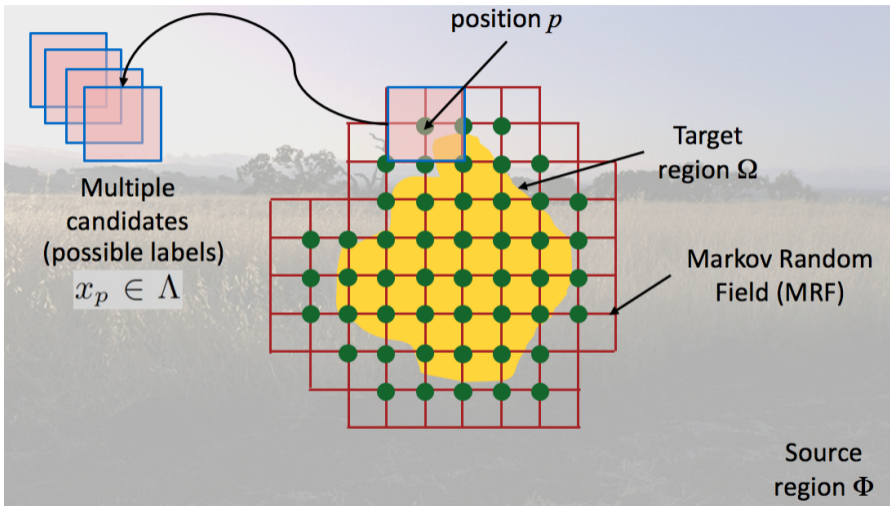


Context adaptative inpainting

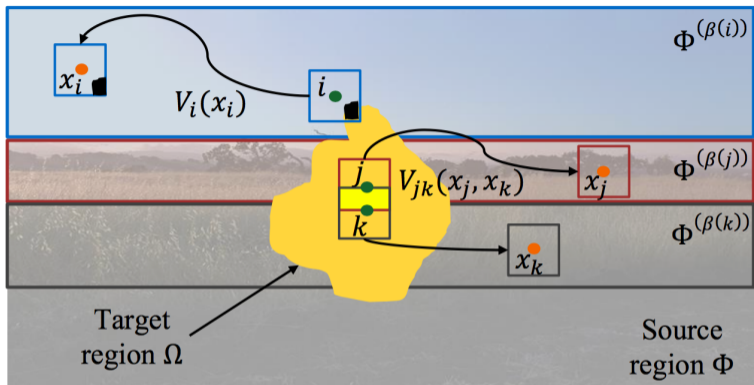


T. Ružić and A. Pižurica et al. Context-aware patch-based image inpainting using Markov random field modeling. *IEEE Transactions on Image Processing* 2015

Global inpainting



Global inpainting

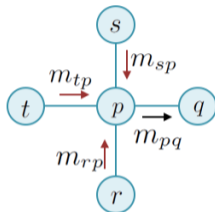


$$E(\mathbf{x}) = \sum_{i \in \nu} V_i(x_i) + \sum_{\langle i, j \rangle \in \mathcal{E}} V_{ij}(x_i, x_j), \quad (1)$$

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

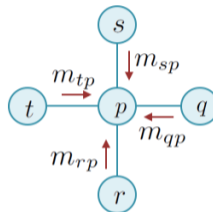
Global inpainting

Messages



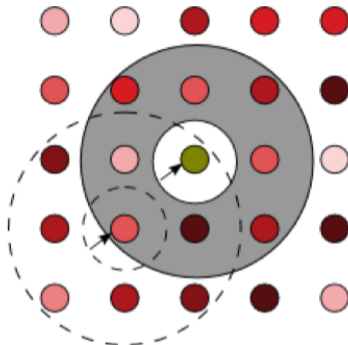
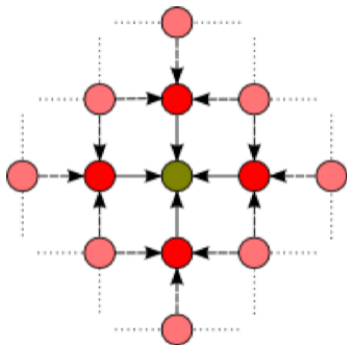
$$m_{pq}(x_q) = \min_{x_p \in \Lambda} \left\{ V_{pq}(x_p, x_q) + V_p(x_p) + \sum_{r: r \neq q, (r,p) \in \varepsilon} m_{rp}(x_p) \right\}$$

Beliefs



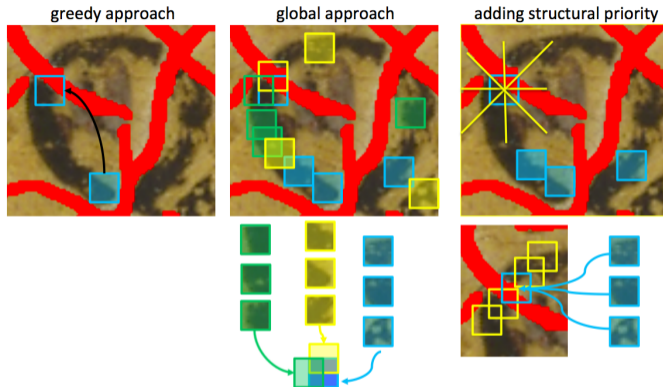
$$b_p(x_p) = -V_p(x_p) - \sum_{r: (r,p) \in \varepsilon} m_{rp}(x_p)$$

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

Outline

- 1 Case Study: Ghent Altarpiece
 - Current conservation-restoration treatment
 - Challenges for signal processing and machine learning
- 2 Paint loss localization and crack detection
 - Sparse coding methods
 - Deep learning methods
- 3 Virtual restoration
 - Patch-based inpainting
 - Virtual restoration of the Ghent Altarpiece

Crack inpainting



Crack inpainting



Virtual Restoration



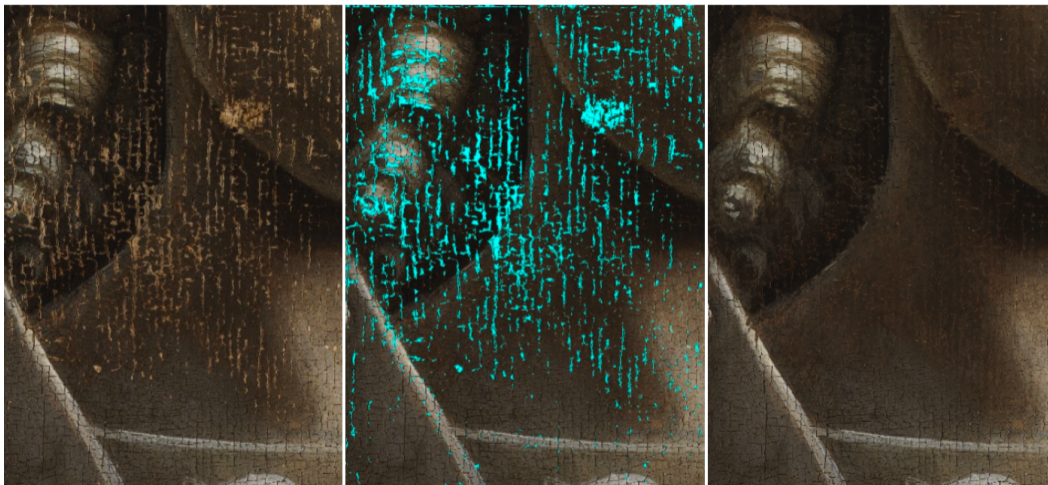
Automatic paint loss detection; inpainting method of [Ružić and Pižurica, TIP, 2015].

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: Before treatment; Middle: virtual restoration; Right: actual restoration.

Summary

- The study on the Ghent Altarpiece indicates that signal processing and machine learning techniques can provide a useful support in conservation-restoration treatments.
- Virtual restoration benefits from statistical spatial context modelling.
- Potentials of sparse coding and representation learning still to be further explored.

-  Aharon, M., Elad, M., and Bruckstein, A. (2006).
The K-SVD: An algorithm for designing of overcomplete dictionaries for sparse representation.
IEEE Trans. Signal Process., 54(11):4311–4322.
-  Chen, Y., Nasrabadi, N. M., and Tran, T. D. (2011a).
Hyperspectral image classification using dictionary-based sparse representation.
IEEE Trans. Geosci. Remote Sens., 49(10):3973–3985.
-  Chen, Y., Nasrabadi, N. M., and Tran, T. D. (2011b).
Sparse representation for target detection in hyperspectral imagery.
IEEE J. Sel. Topics Signal Process, 5(3):629640.
-  Engan, K., Aase, S. O., and Hakon-Husoy, J. H. (1999).
Method f optimal directions for frame design.
In *IEEE Int. Conf. Acoust., Speech, Signal Process. (ICASSP)*, volume 5, pages 2443–2446.

 Huang, S., Meeus, L., Cornelis, B., Devolder, B., Martens, M., and Pižurica, A. (2018).

Paint loss detection via kernel sparse representations.

In *Image Processing for Art Investigation (IP4AI)*, pages 24–26.

 Olshausen, B. A. and Field, D. J. (1997).

Sparse coding with an overcomplete basis set: A strategy employed by V1?

Vis. Res., 37(23):3311–3325.

 Ružić, T. and Pižurica, A. (2015).

Context-aware patch-based image inpainting using Markov random field modeling.

IEEE Trans. Image Process., 24(1):444–456.