AI systems for computer vision: Challenges in high-dimensional and multimodal image analysis

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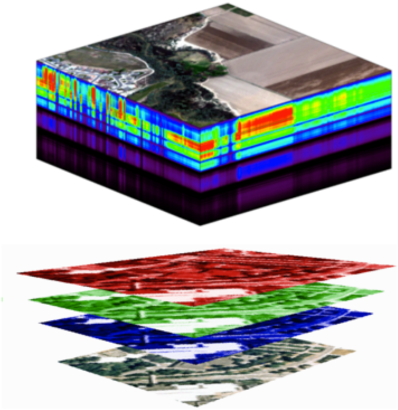
AI FOR PHOTONICS
NB Photonics Topical Meeting
February 5 2021

A Wealth of High-Dimensional Multimodal Data



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

Digitized paintings (infrared, X-Ray, visible)

Hyperspectral Imaging (HSI) in Earth observation

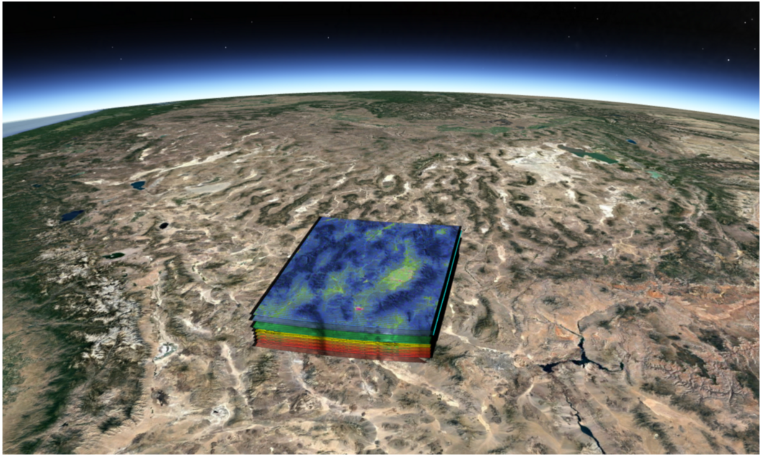
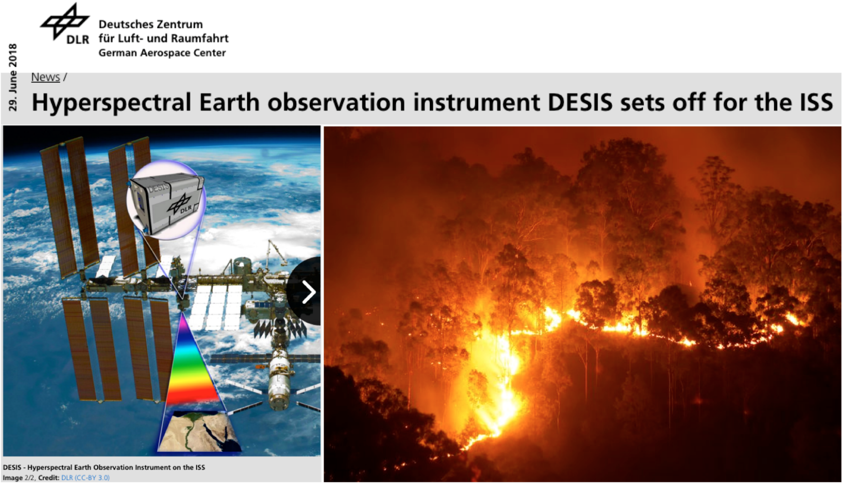


Image credit: Novus Light Technologies Today, December 2018.

HyperScout1 – the first miniaturized hyperspectral imager for space. Launched to an orbit 540km above the Earth. (ESA program, led by Cosine Measurement Systems)

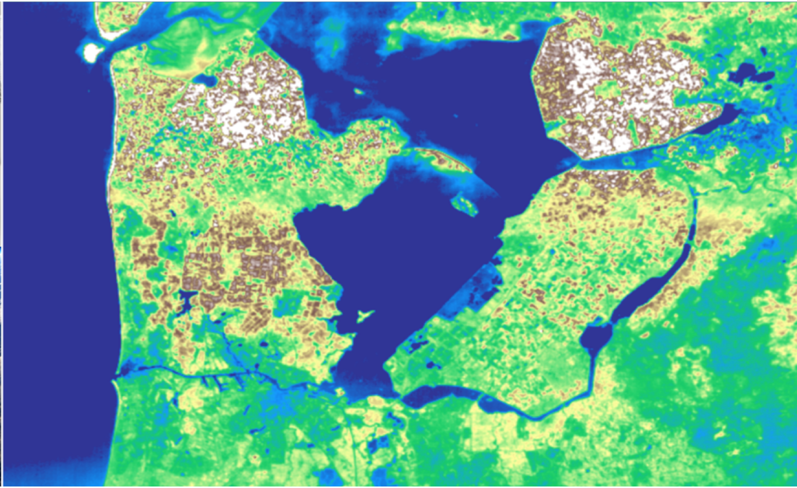
HSI space technology - game changer in environmental monitoring



DLR Earth Sensing Imaging Spectrometer (DESIS) installed on the International Space Station (ISS). Monitors environmental changes on Earth.

"Milk-carton-sized HyperScout making hyperspectral Earth views"

Space news feed, 20 May 2020

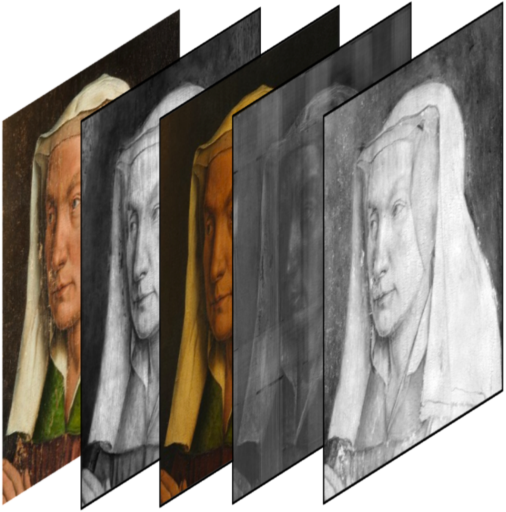


HyperScout view of Netherlands (courtesy: cosine)

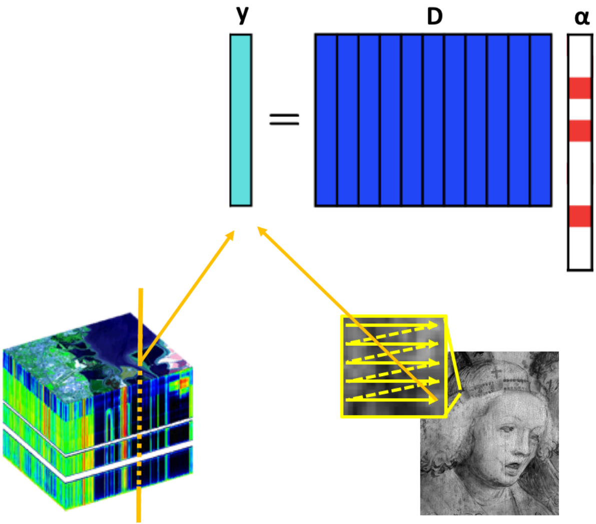
Multimodal data analysis in art investigation

Extracting useful information from multiple modalities, with

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

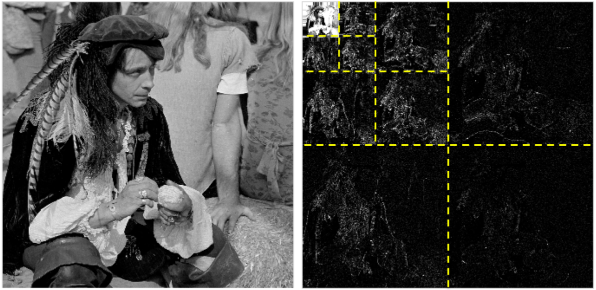


Sparse representation



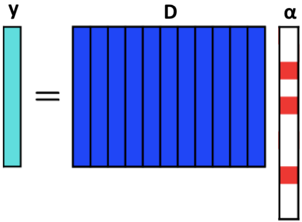
Designed vs. Learned Dictionaries

- **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

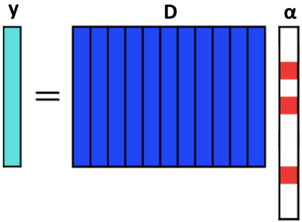
Sparse coding



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

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

Sparse coding



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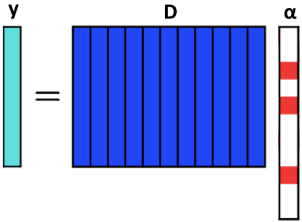
Greedy algorithms

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

Sparse coding



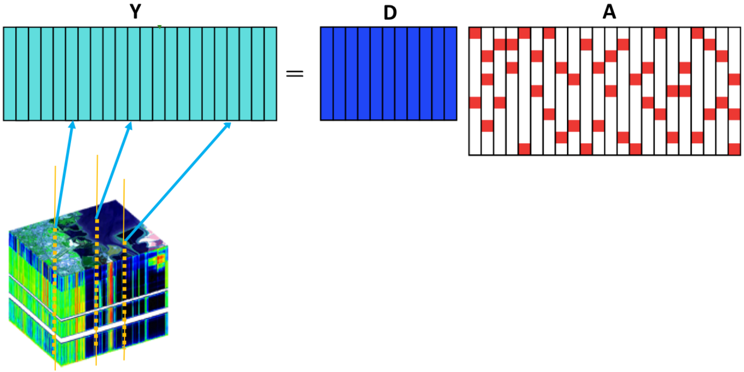
Convex relaxation:

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

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

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

Sparse coding and dictionary learning

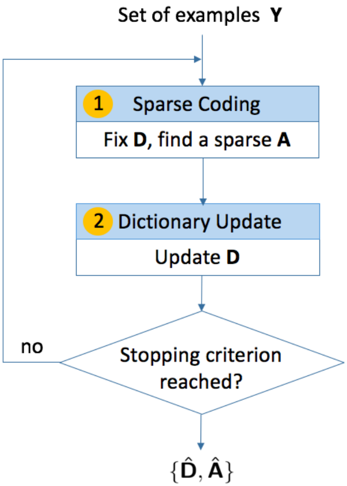


$$\{\hat{\mathrm{D}}, \hat{\mathrm{A}}\} = \arg\min_{\mathrm{D},\mathrm{A}} \left\{ \|\mathrm{Y} - \mathrm{DA}\|_F^2 \right\} \quad \text{subject to} \quad \forall i, \|\boldsymbol{\alpha}_i\|_0 \leq K$$

A similar objective:

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

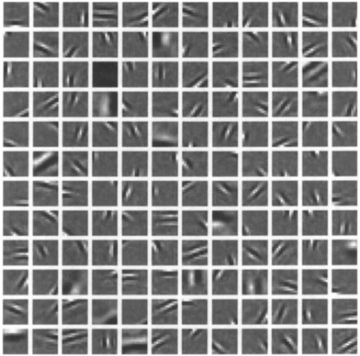
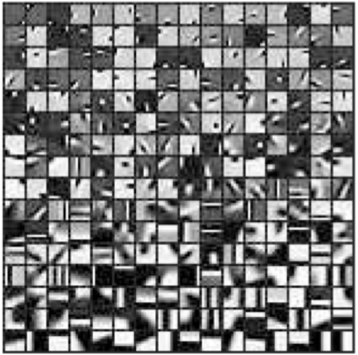
Iterate Two Steps: Sparse Coding and Dictionary Update



Dictionary update:

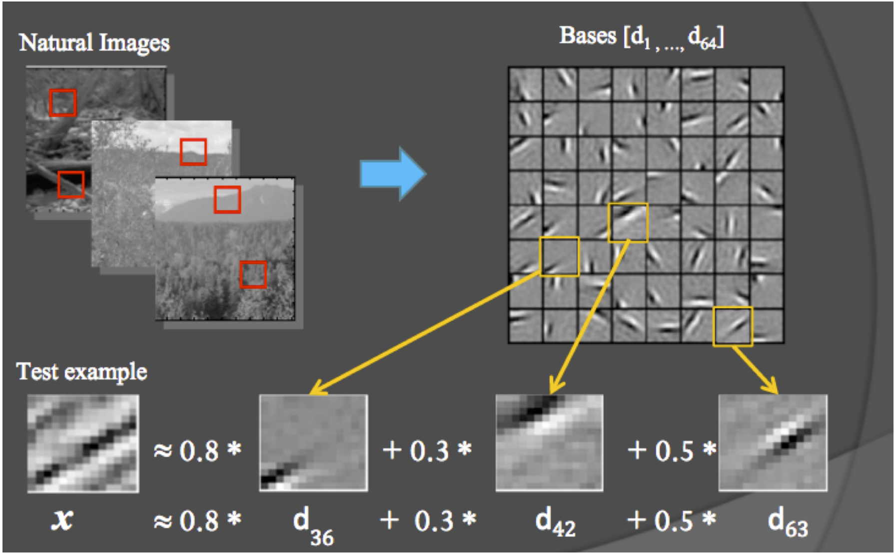
- Maximum likelihood method of [Olshausen and Field, 1997]
- MOD [Engan et al., 1999]
- K-SVD [Aharon et al., 2006]

Learned Dictionaries of Image Atoms - Examples

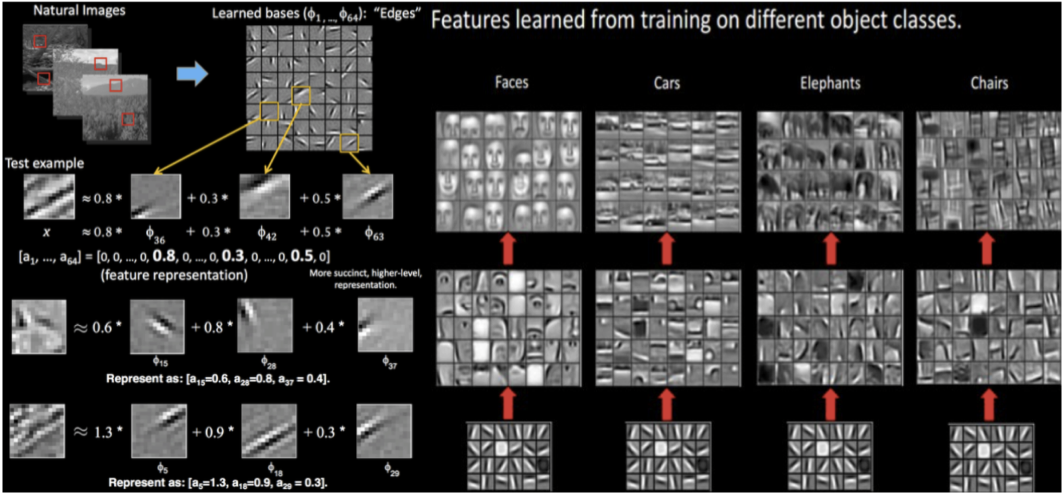
 

Examples of dictionaries trained by [Olshausen and Field, 1997] (left) and K-SVD [Aharon et al., 2006] (right)

Representation learning and sparse coding

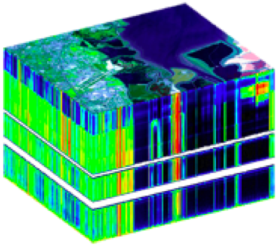


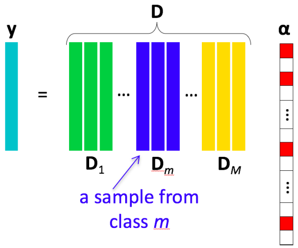
Representation learning and sparse coding



Sparse Representation Classification

[Wright et al, 2009]





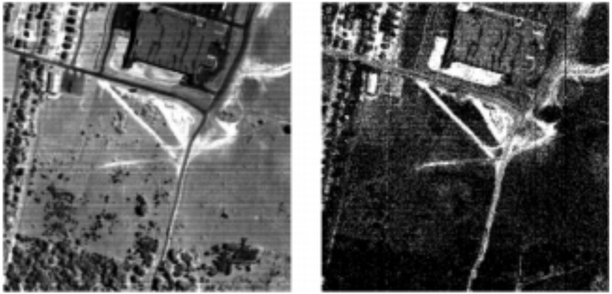
$$\hat{\alpha} = \arg\min_{\alpha} \|y - D\alpha\|_2^2 \ \text{ subject to } \|\alpha\|_0 \leq K$$

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

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

Robust SRC for Hyperspectral Image Classification

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



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

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

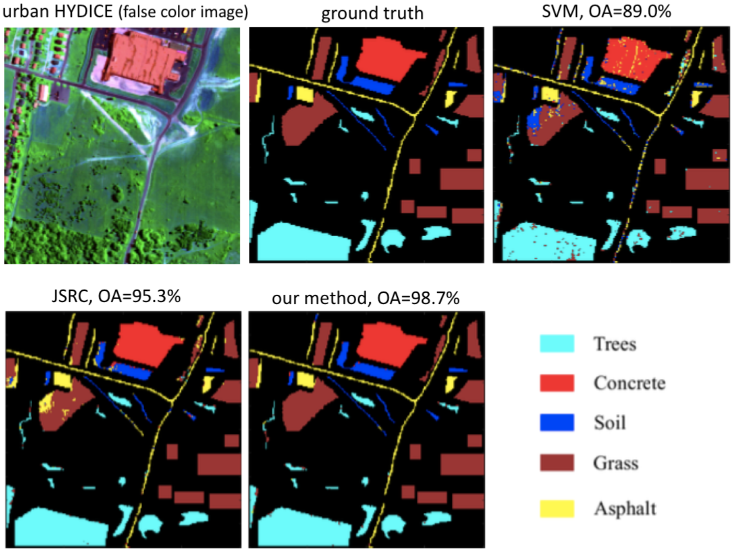
$$\{\hat{A}, \hat{S}\} = \arg\min_{A,S} \|Y - DA - S\|_F^2 + \lambda \|S\|_1 \quad \text{subject to} \quad \|A\|_{row,0} \leq K$$

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

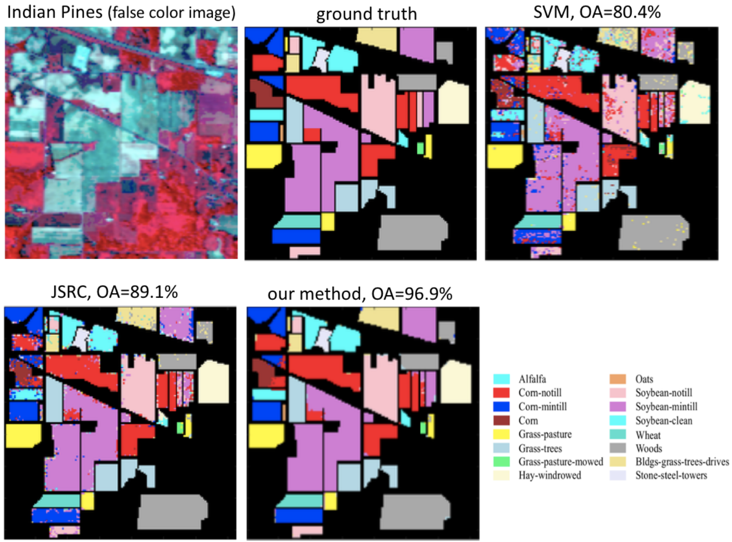
$$class(y_{central}) = \arg\min_{m=1,\ldots,M} r_m(Y)$$

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

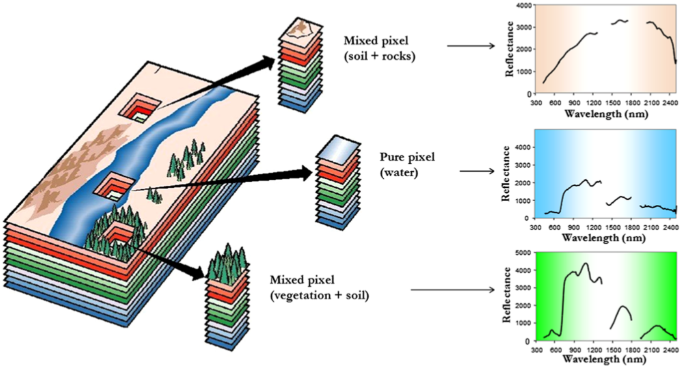
Robust SRC for Hyperspectral Image Classification



Robust SRC for Hyperspectral Image Classification

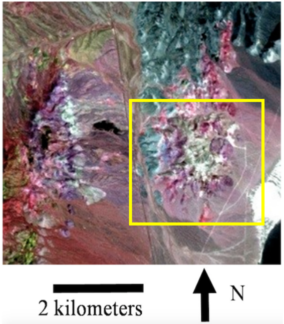


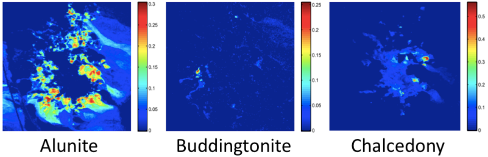
Spectral Unmixing



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



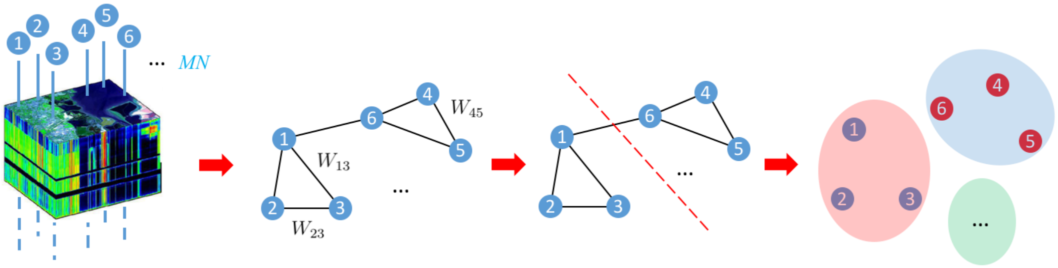


Estimated fractional abundance maps (AVIRIS Cuprite subscene, USGS library).

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.

Spectral clustering

No labelled data available → no supervised classification but instead clustering

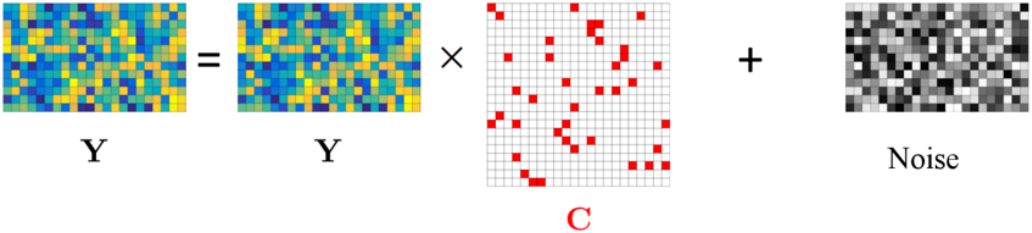


Similarity matrix: $\mathbf{W} \in \mathbb{R}^{MN \times MN}$

Sparse Subspace Clustering

[Elhamifar and Vidal, 2013]

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



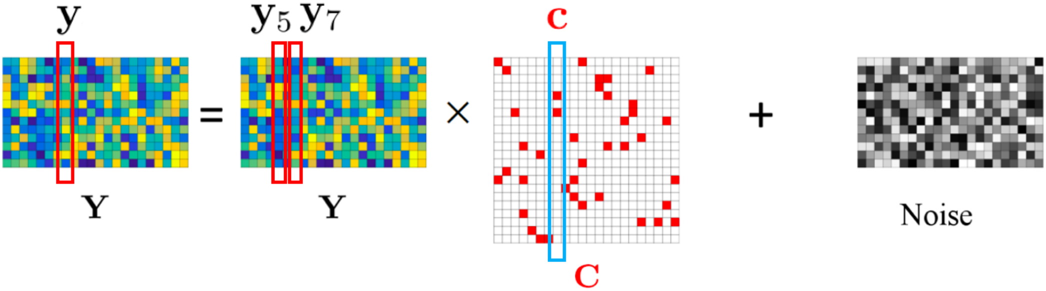
$C_{i,j} \neq 0 \rightarrow \mathrm{y}_i$ and y_j are in the same subspace.

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

Sparse Subspace Clustering

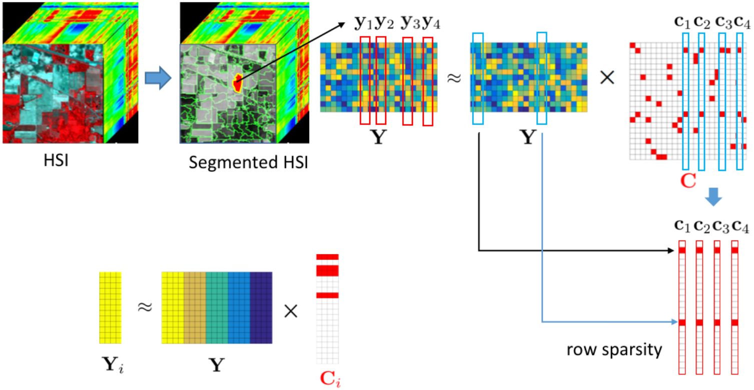
[Elhamifar and Vidal, 2013]

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



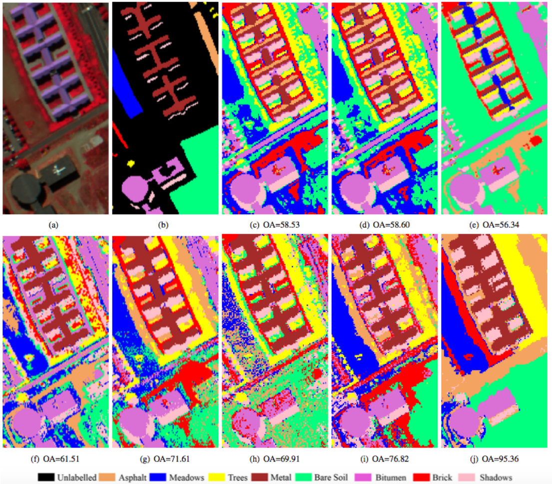
$\mathsf{y} \approx \mathsf{Y}c = \sum_i \mathsf{y}_i c_i = c_5 \mathsf{y}_5 + c_7 \mathsf{y}_7$

Joint Sparse Subspace Clustering - JSSC



S. Huang, H. Zhang and A. Pižurica (2019). 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.

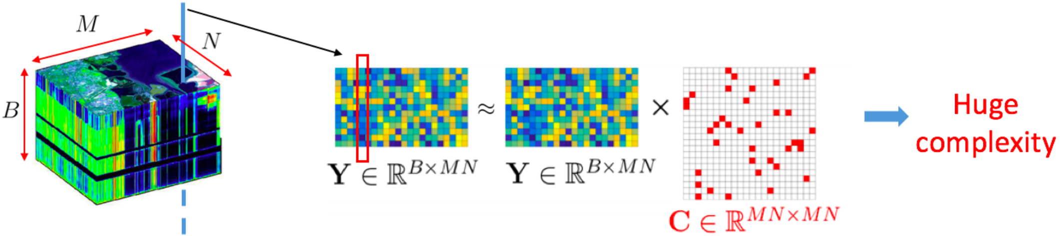
Joint Sparse Subspace Clustering - JSSC



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)

[Huang et al., 2019]

Nice, but ...

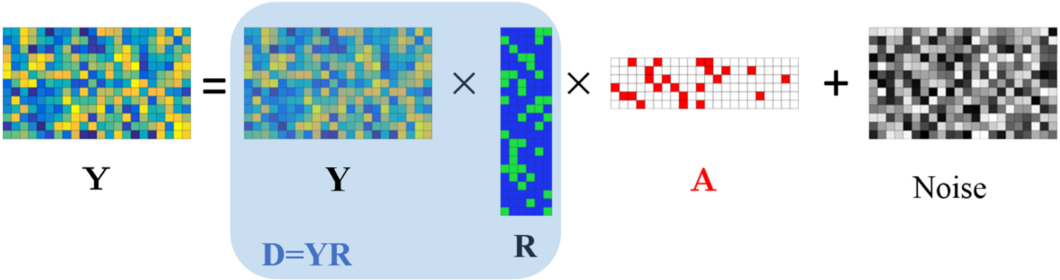


SSC becomes practically infeasible for very large scale data.

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

$\rightarrow$ 320,5 GB memory

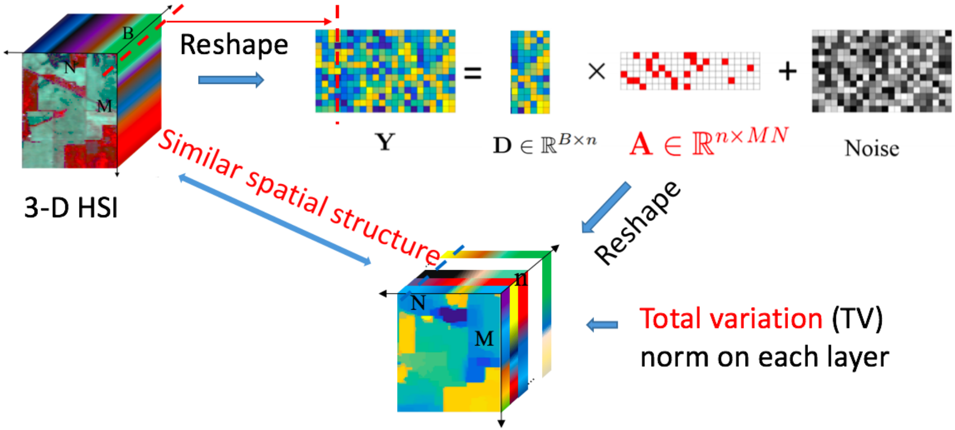
Sketching



Reduces greatly the size of the problem!

P. A. Traganitis and G. B. Giannakis (2018). Sketched subspace clustering. IEEE Trans. Signal Process. [Traganitis and Giannakis, 2018]

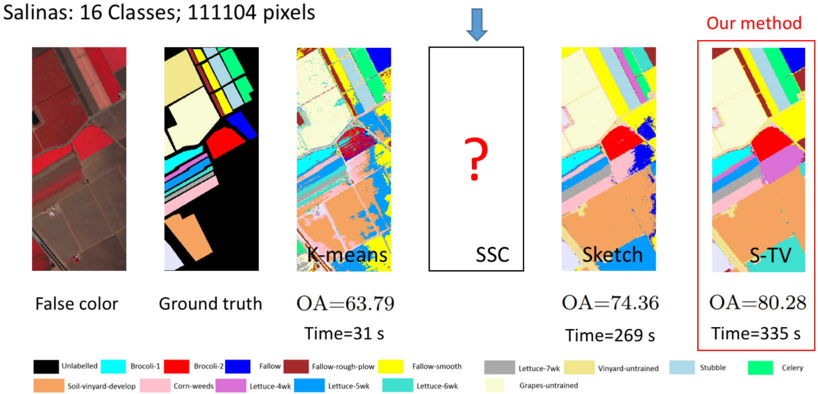
Sketched Sparse Subspace Clustering for Hyperspectral Images



S. Huang, H. Zhang and A. Pižurica (2020).
Sketch-based Subspace Clustering of Hyperspectral Images. Remote Sensing.

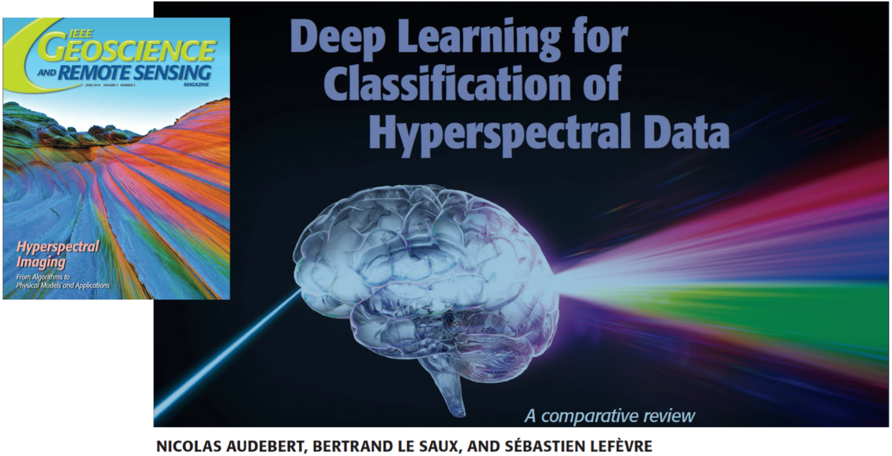
Sketched Sparse Subspace Clustering for Hyperspectral Images

$$\mathbf{Y} \in \mathbb{R}^{204\times111104} \rightarrow \mathbf{C} \in \mathbb{R}^{111104\times111104}$$



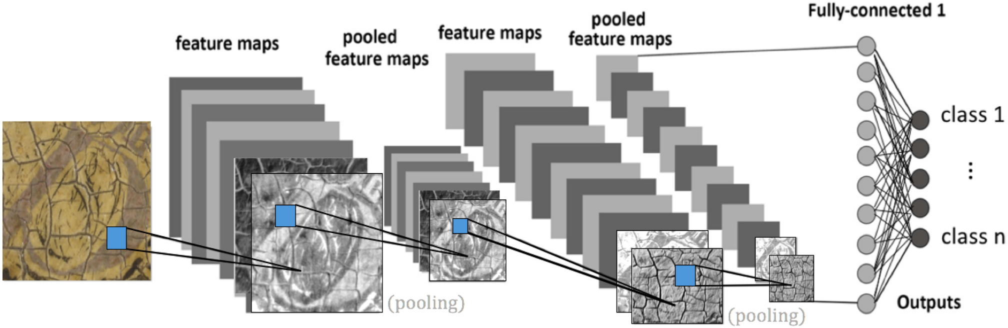
[Huang et al., 2020]

Deep learning for HSI analysis



N. Audebert, B. Le Saux, and S. Lefèvre, IEEE Geosc. Remote Sens. Mag., June 2019.

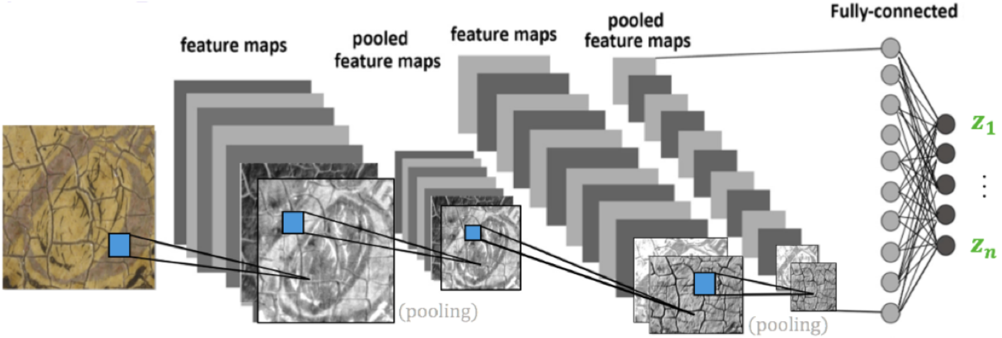
Convolutional Neural Networks (CNN)



Output at location (i, j) of the k-th feature map in the l-th layer:

$$x_{i,j}^{l,k} = \sigma\left(\sum_{m=1}^{M} \sum_{p=0}^{H_l-1} \sum_{q=0}^{W_l-1} w_{p,q}^{l,k,m} x_{(i+p),(j+q)}^{(l-1),m} + b^{l,k}\right)$$

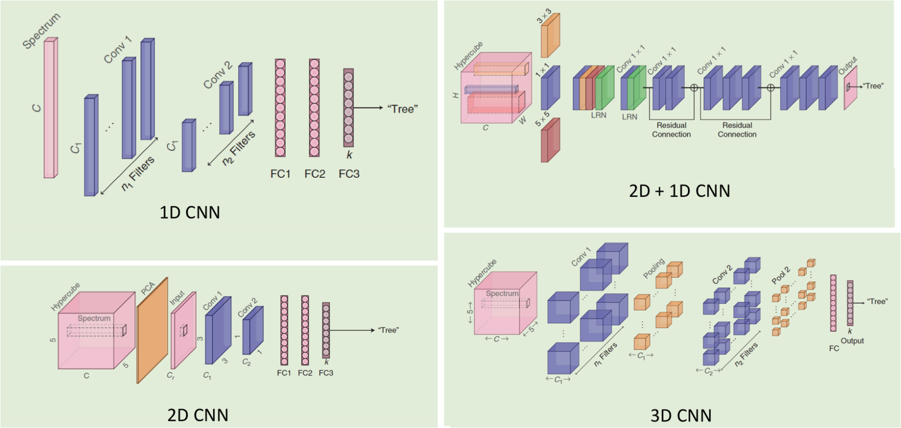
Convolutional Neural Networks (CNN)



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

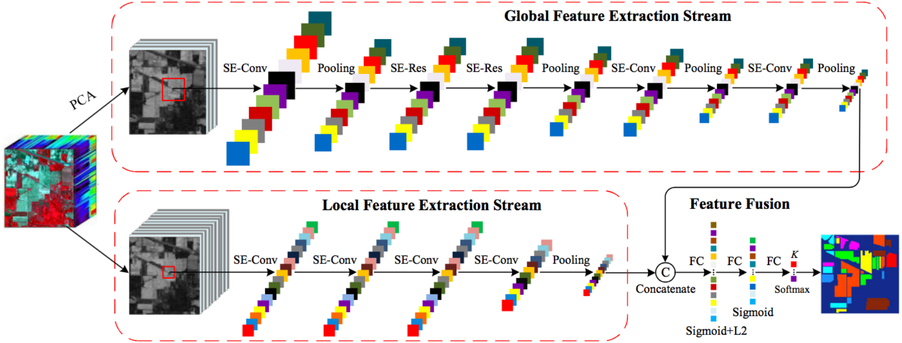
$$P(\text{class}(x_{i,j}) = c) = \frac{e^{z_c}}{\sum_k e^{z_k}}$$

Deep learning models in HSI classification



N. Audebert, B. Le Saux, and S. Lefèvre. Deep Learning for Classification of Hyperspectral Data - A comparative Review. IEEE Geosc. Remote Sens. Mag., June 2019.

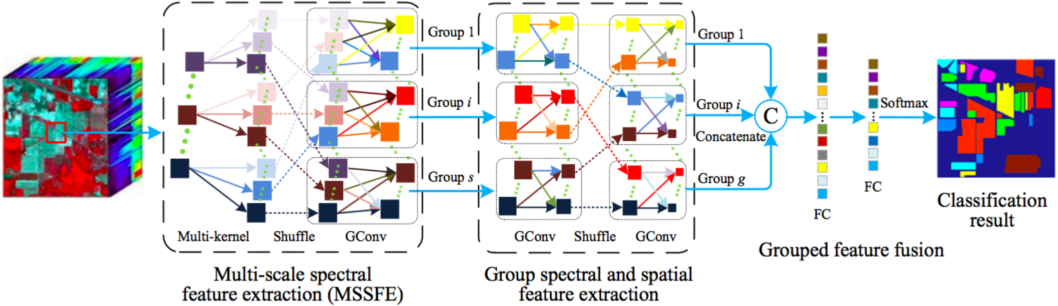
Spectral-spatial feature fusion with two-stream CNN



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, 2020. [Li et al., 2020]

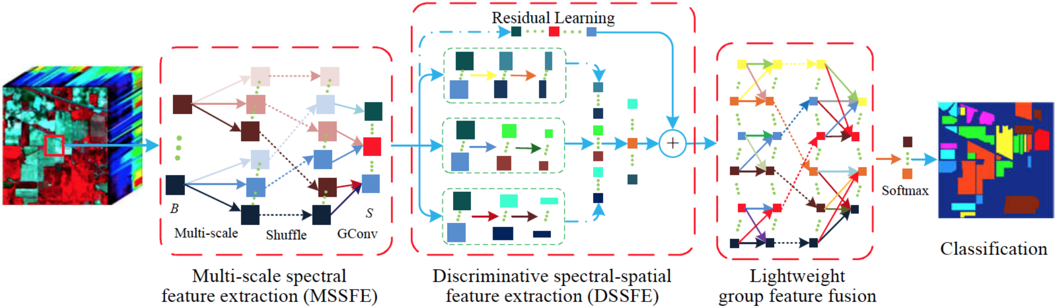
Group CNN for HSI classification



Reducing the computational complexity - applicability to large scale data.

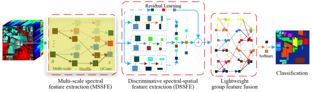
X. Li, M. Ding and A. Pižurica. Group Convolutional Neural Networks for Hyperspectral Image Classification, ICIP 2018.

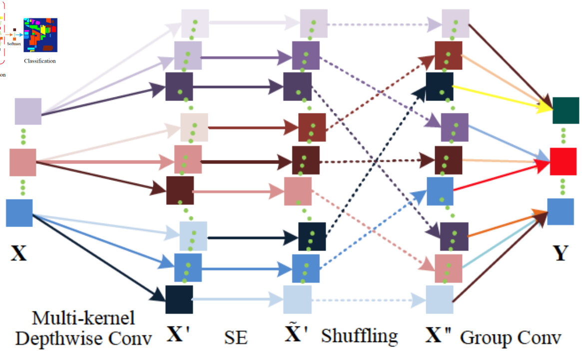
Full Group CNN (FGCNN)



X. Li, M. Ding and A. Pižurica. Full Group Convolutional Neural Networks for Robust Spectral-Spatial Feature Learning (2020). IEEE Trans. Image Process. (in review)

Full Group CNN (FGCNN)





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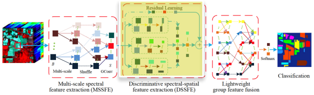

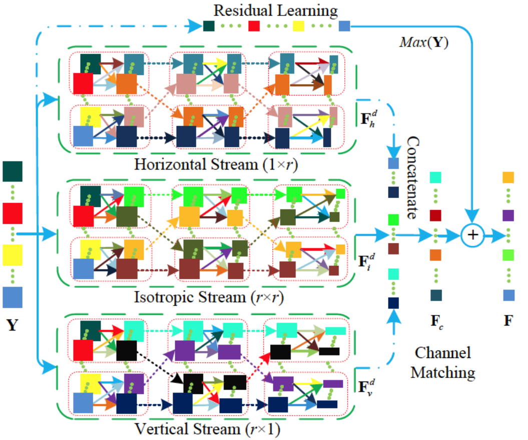

X. Li, M. Ding and A. Pižurica. Full Group Convolutional Neural Networks for Robust Spectral-Spatial Feature Learning (2020). IEEE Trans. Image Process. (in review)

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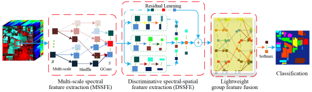
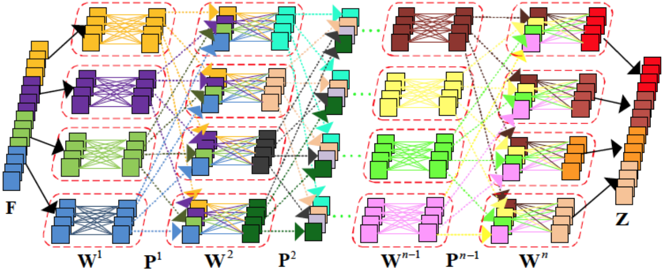




X. Li, M. Ding and A. Pižurica. Full Group Convolutional Neural Networks for Robust Spectral-Spatial Feature Learning (2020). IEEE Trans. Image Process. (in review)

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*

Ghent Altarpiece - Current Restoration Campaign

SCIENCE

The New York Times

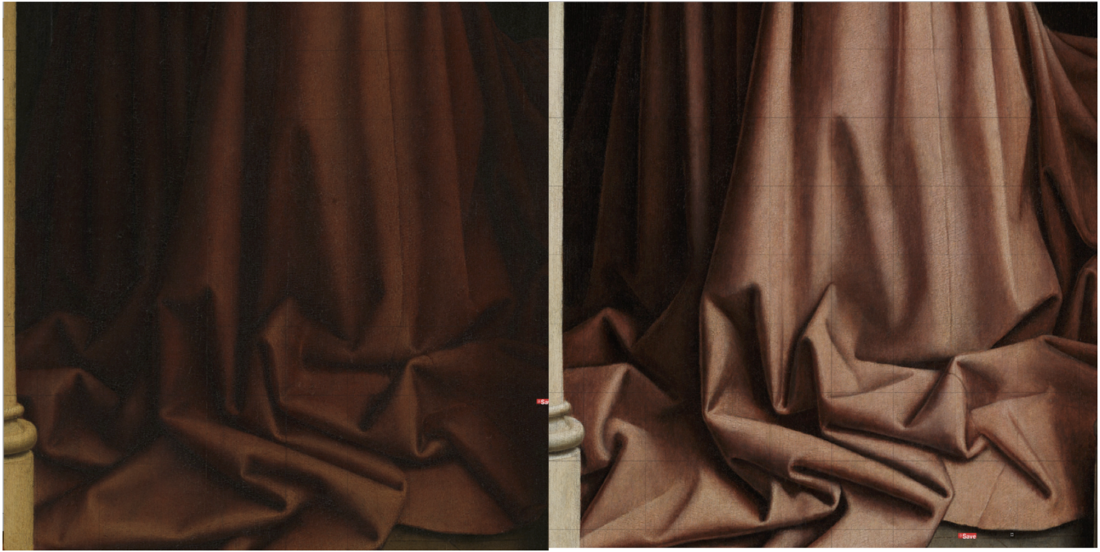
A Master Work, the Ghent Altarpiece, Reawakens Stroke by Stroke

By MILAN SCHREUER DEC. 19, 2016

Ghent Altarpiece restoration – Phase 1

= Overpaint © KIK-IRPA

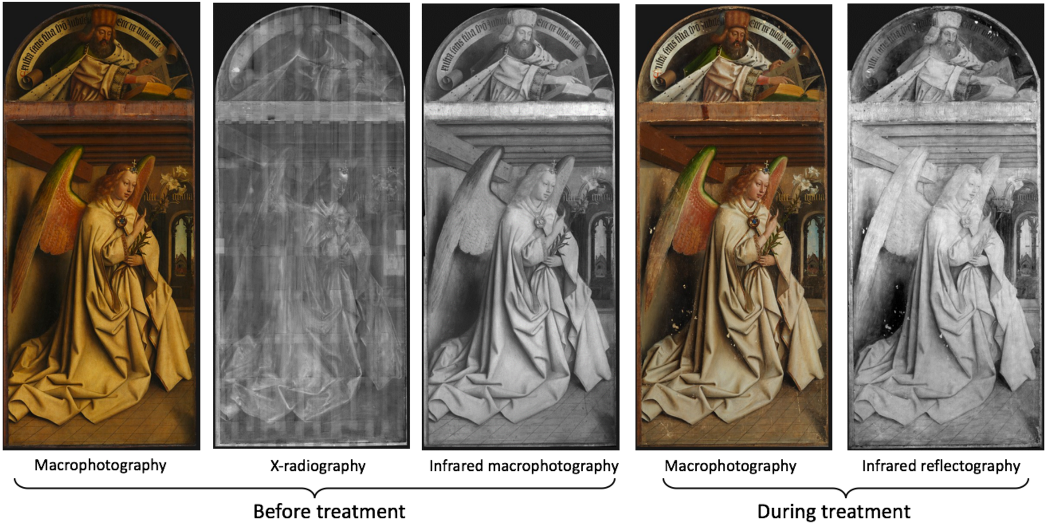
Ghent Altarpiece restoration – Phase 1



Ghent Altarpiece restoration – Phase 2 (inner panels)

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

A multimodal approach



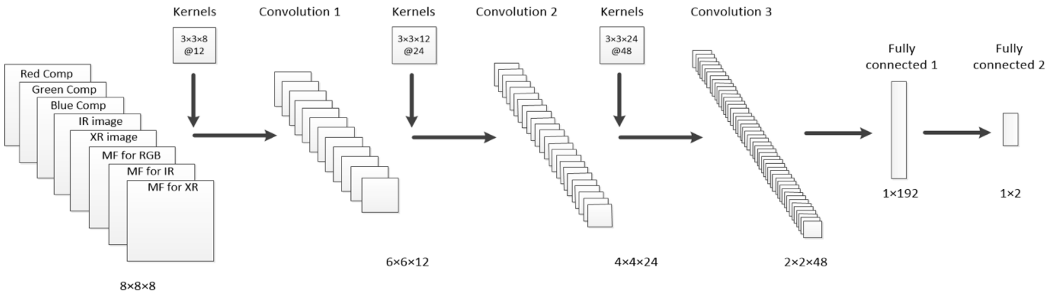
A multiscale deep learning method for paint loss detection

Size: 5954×7546; processed in < 1 minute

Deep learning in crack detection

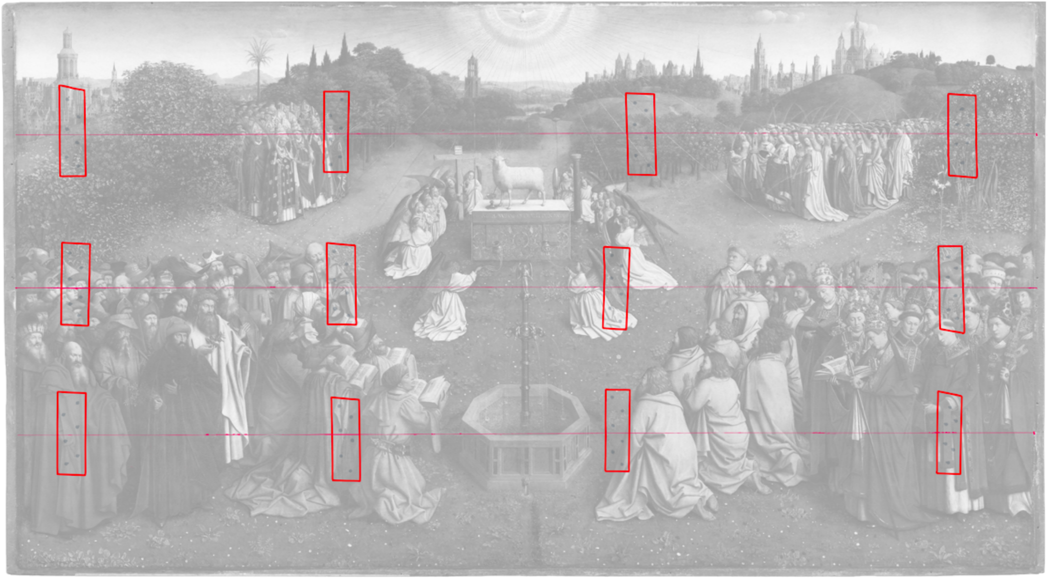
Crack detection in roads reported in [Lei et al,2016], [Cha et al, 2017].
However, crack detection in paintings is much more challenging!

A deep learning method for crack detection in paintings

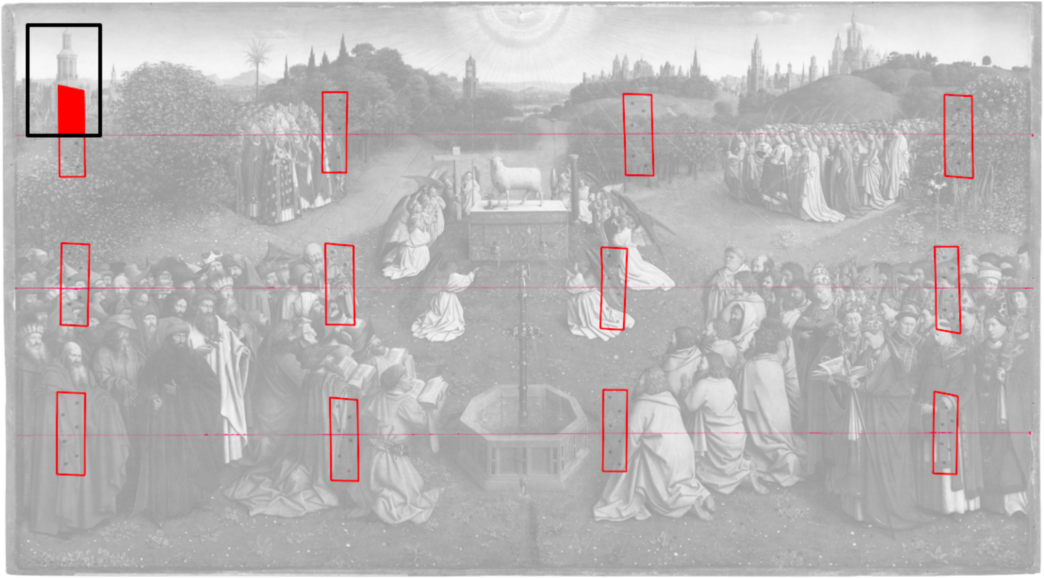


R. Sizyakin, B. Cornelis, L. Meeus, M. Martens, V. Voronin, and A. Pižurica (2018). A deep learning approach to crack detection in panel paintings. IP4AI.

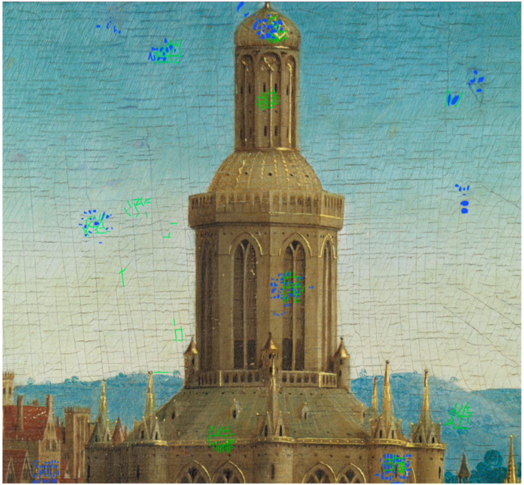
Crack detection: Central panel



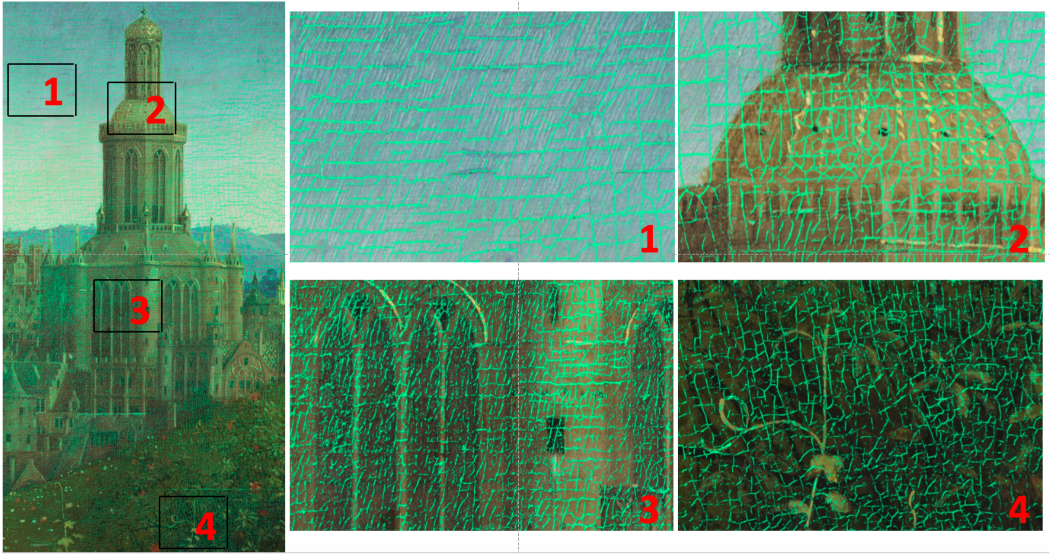
Crack detection: Central panel



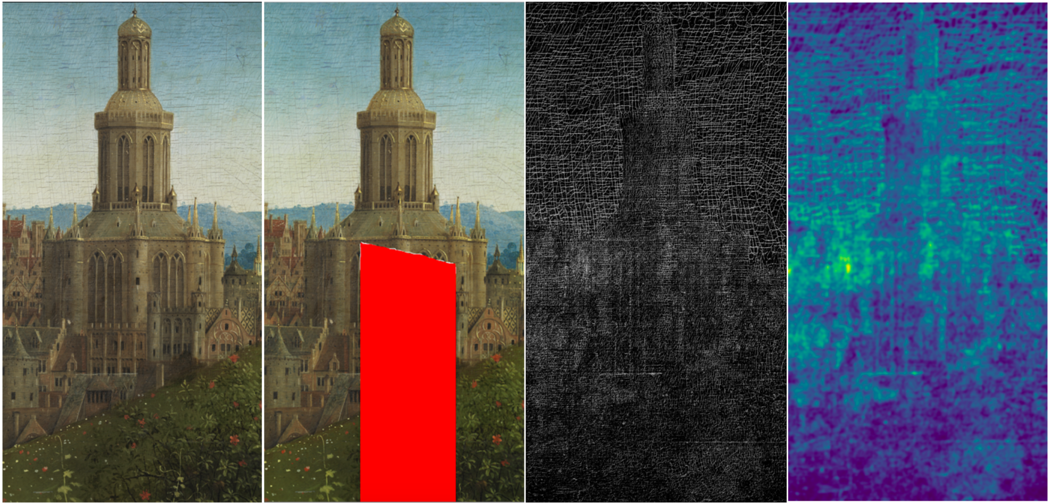
Crack detection: Central panel



Crack detection: Central panel

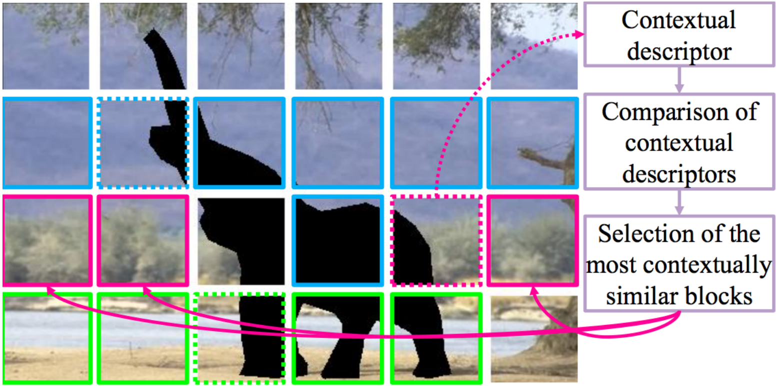


Crack detection: Central panel



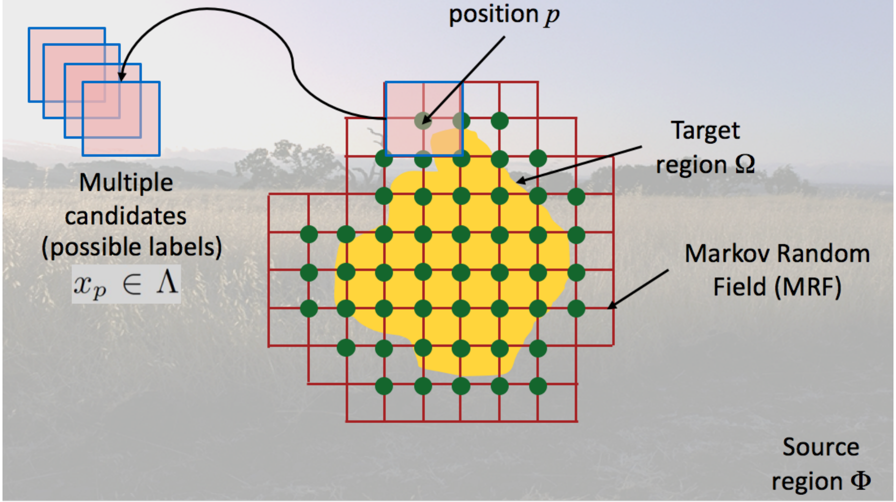
[Sizyakin et al., 2020] https://ieeexplore.ieee.org/document/9072114

Context adaptative inpainting

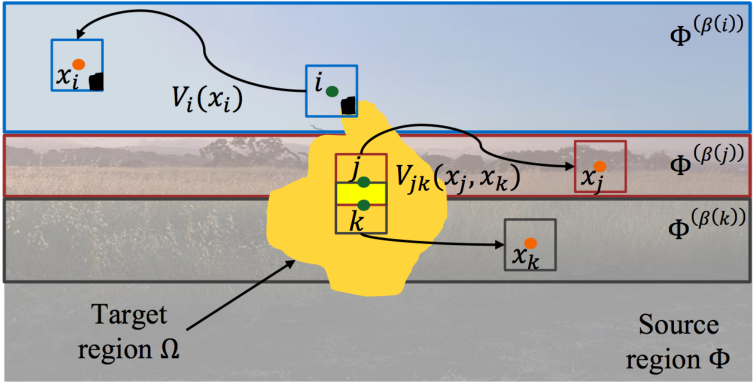


T. Ružić and A. Pižurica et al. Context-aware patch-based image inpainting using Markov random field modeling. *IEEE Transactions on Image Processing* 2015

Global inpainting



Global inpainting

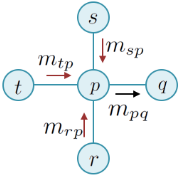


$$E(x) = \sum_{i \in \nu} V_i(x_i) + \sum_{\langle i,j \rangle \in \varepsilon} V_{ij}(x_i, x_j), \tag{1}$$

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

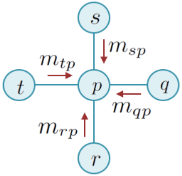
Global inpainting

Messages



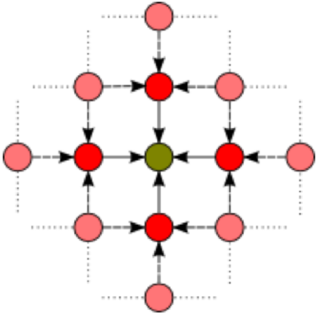
$$m_{pq}(x_q) = \min_{x_p \in \Lambda} \Big\{ V_{pq}(x_p, x_q) + V_p(x_p) + \sum_{r : r \neq q, (r,p) \in \varepsilon} m_{rp}(x_p) \Big\}$$

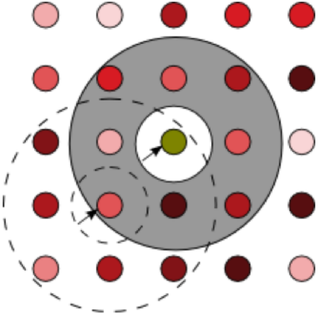
Beliefs



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

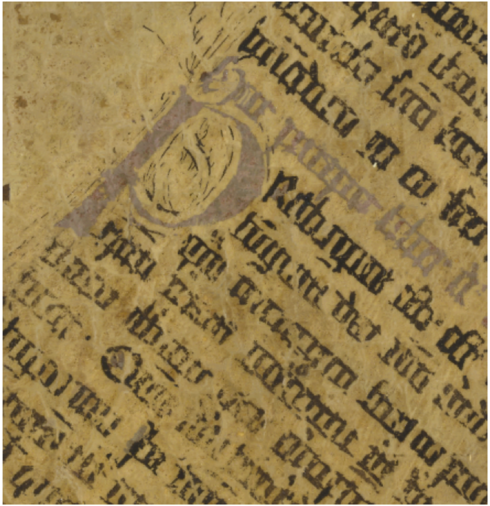
Global inpainting: efficient inference





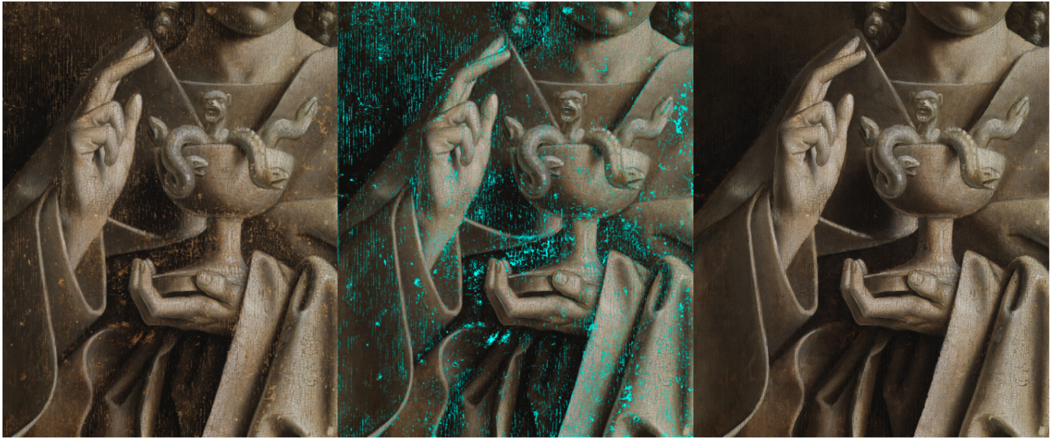
T. Ružić and A. Pižurica et al. Context-aware patch-based image inpainting using Markov random field modeling. *IEEE Transactions on Image Processing* 2015

Crack inpaiting



[Pižurica et al., 2015]

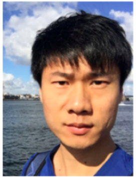
Virtual Restoration



Left: original; Middle: automatic paint loss detection method [Meeus et al., 2019]. Right: MRF-based inpainting method [Ružić and Pižurica, 2015]

Research Group for Artificial Intelligence and Sparse Modelling - GAIM


Aleksandra Pizurica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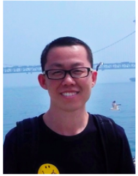
Laurens Meeus


Nina Žižakić


Xian Li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GAIM (https://gaim.ugent.be) is part of the Department Telecommunications and Information Processing at the Faculty of Engineering of Ghent Univesity.

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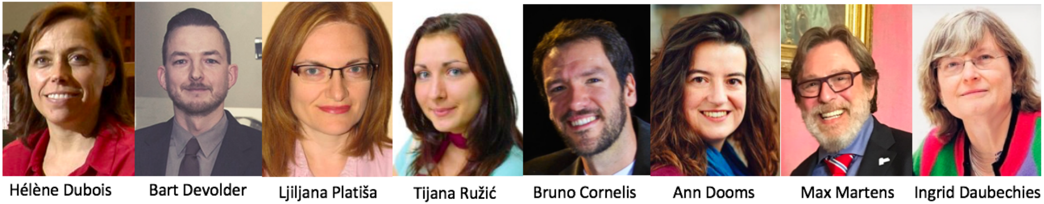

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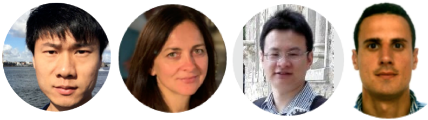

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