

Repeated Pattern Detection using Convolutional Neural Network Activations

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Introduction – Motivation

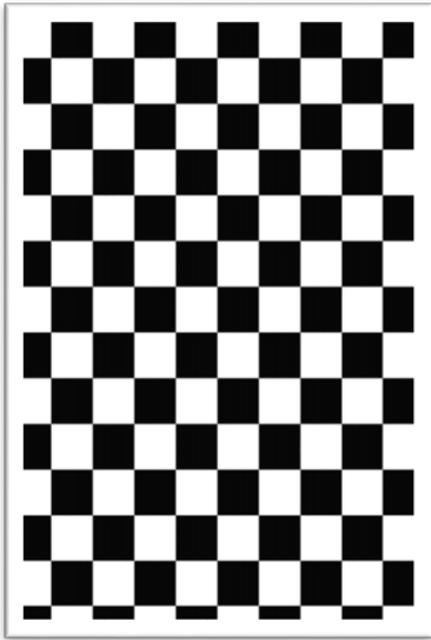
- Repeated patterns are everywhere
 - Varying from perfect to imperfect (irregular, varying visual aspect)
 - Why detect them?
 - Insights on scene structure, perspective
 - Object segmentation [Schindler et al., CVPR 2008]
 - Image retrieval
 - Ambiguities for pairwise image matching
 - 3D reconstruction w/ SfM [Wu et al., CVPR 2011]



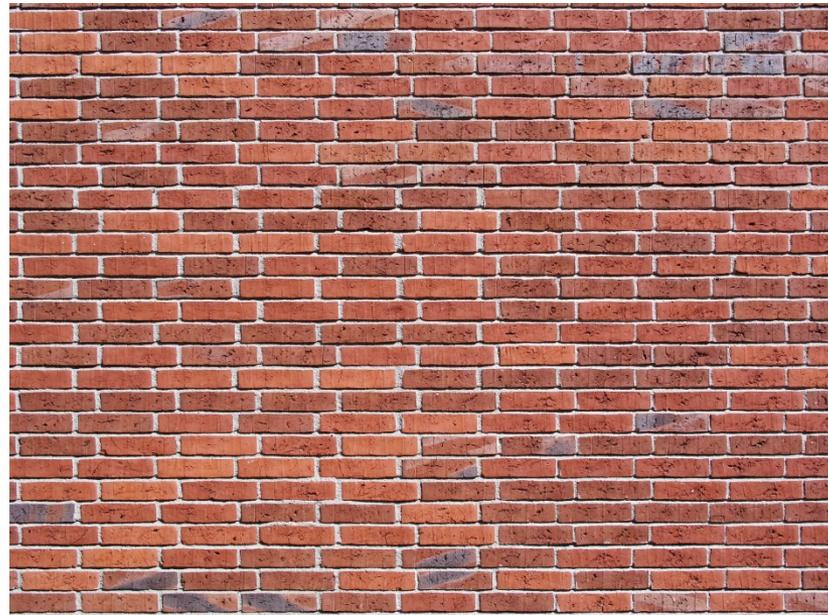


Introduction – Problem statement

- Detect patterns from a single view
 - Human: relatively easy task
 - Machine: can be hard



Easy



Doable



Hard



Introduction – key of our algorithm

- Deep convolutional representations can learn semantics



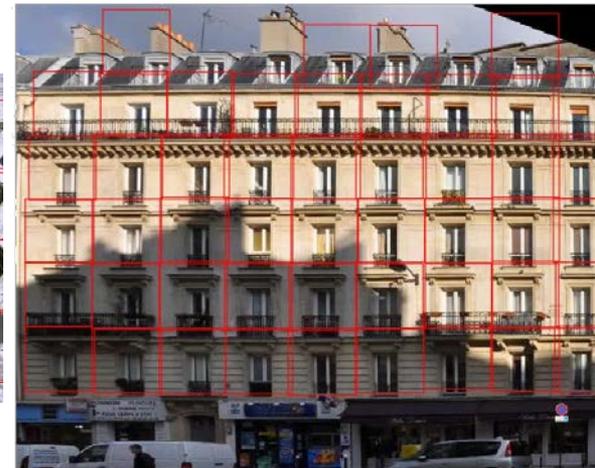
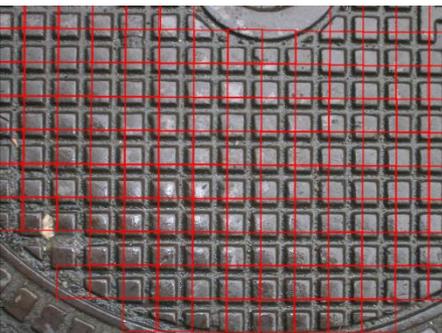
Semantic segmentation

<http://www.robots.ox.ac.uk/~szheng/crfasrmdemo>



Introduction – our objective

- Leverage this deep understanding to **gain robustness w.r.t. visual appearance** in repetition detection
- Present an original algorithm that **infers a grid** representing the underlying repetition





Introduction – outline

- Related work & positioning
- Convolutional Neural Networks
 - How they work
 - What can they bring on our task
 - Hint: robustness to content variety
- Our method: technical explanation
- Results
- Conclusions & future work



Related work – overview

- Open question: what defines a repeated pattern ?
 - No unique definition / no easy benchmarking
- By content (as repetitive clustered local features):
 - Keypoints [Torii et al. 13, Park et al. 11a]
 - Regions [Pritts et al 14]
 - Tiles [Proesmans et al. 99, Liu et al. 04]
 - *Feature constellations for complex patterns* [Liu et al. 13]
- By scene structure (regularity, lattice, projection)
 - Fronto-parallel [Zhao et al.11]
 - 2D Lattice [Doubek et al. 10, Park et al. 11a]
 - *Thin plate spline warped lattice* [Park et al. 11b]
 - Unstructured “stamps” on a plane [Pritts et al 14, Liu et al. 13]

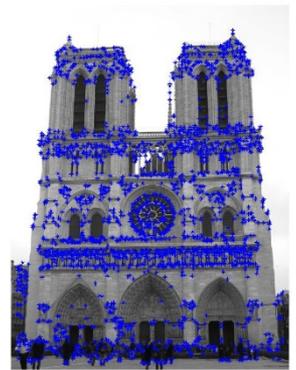


Image courtesy: P. Sangkloy (CS Brown)

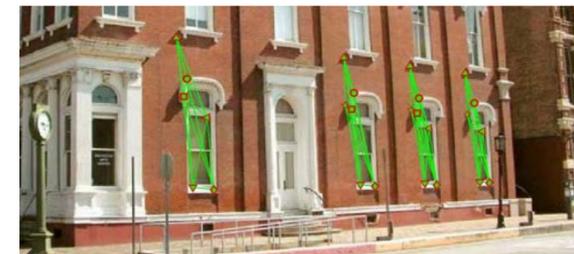


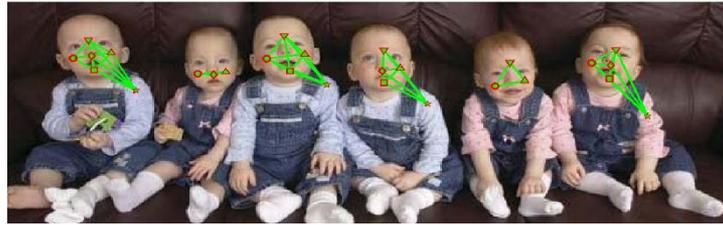
Image courtesy: Liu et al. 13

Related work – state of the art

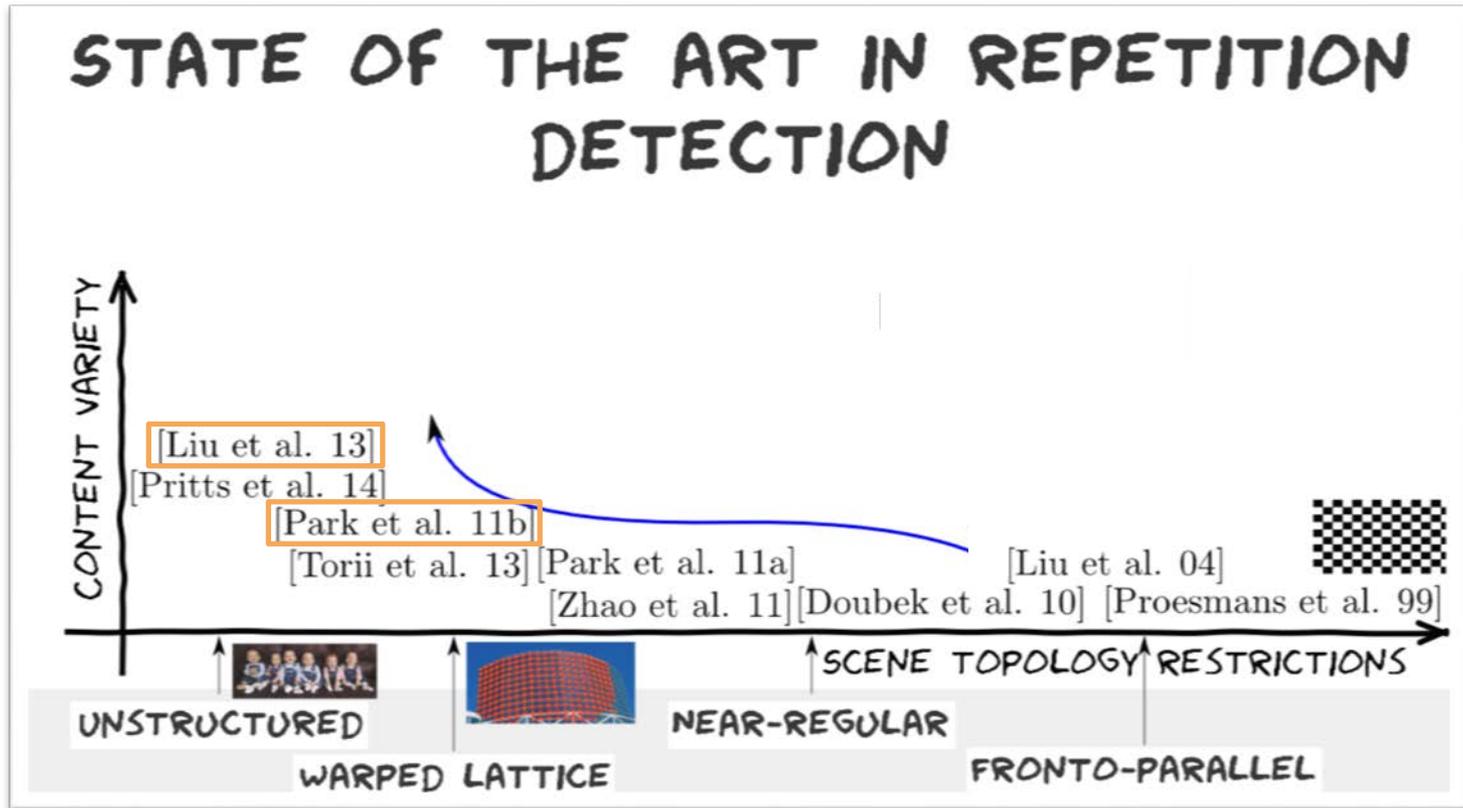
- Park et al. 11b
 - Deformed regular lattice



- GRASP (Liu et al. 13)
 - Unstructured
 - Perspective



Related work – our positioning



- We fixed scene assumptions: near-regular, near-fronto-parallel
- Gained robustness w.r.t. variety of detected content

Convolutional Neural Networks: crash course

- What's a CNN ?
 - Base brick: convolution



*

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

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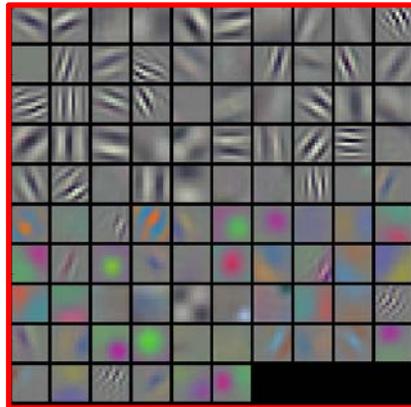
Image courtesy: Andrej Karpathy (Stanford course)

Convolutional Neural Networks: crash course

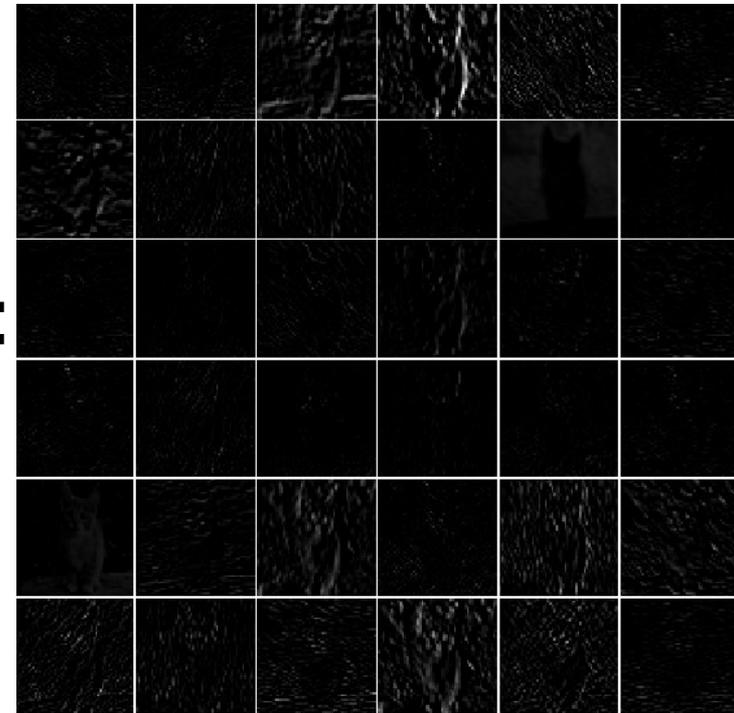
- What's a CNN ?
 - Base layer: K convolutions



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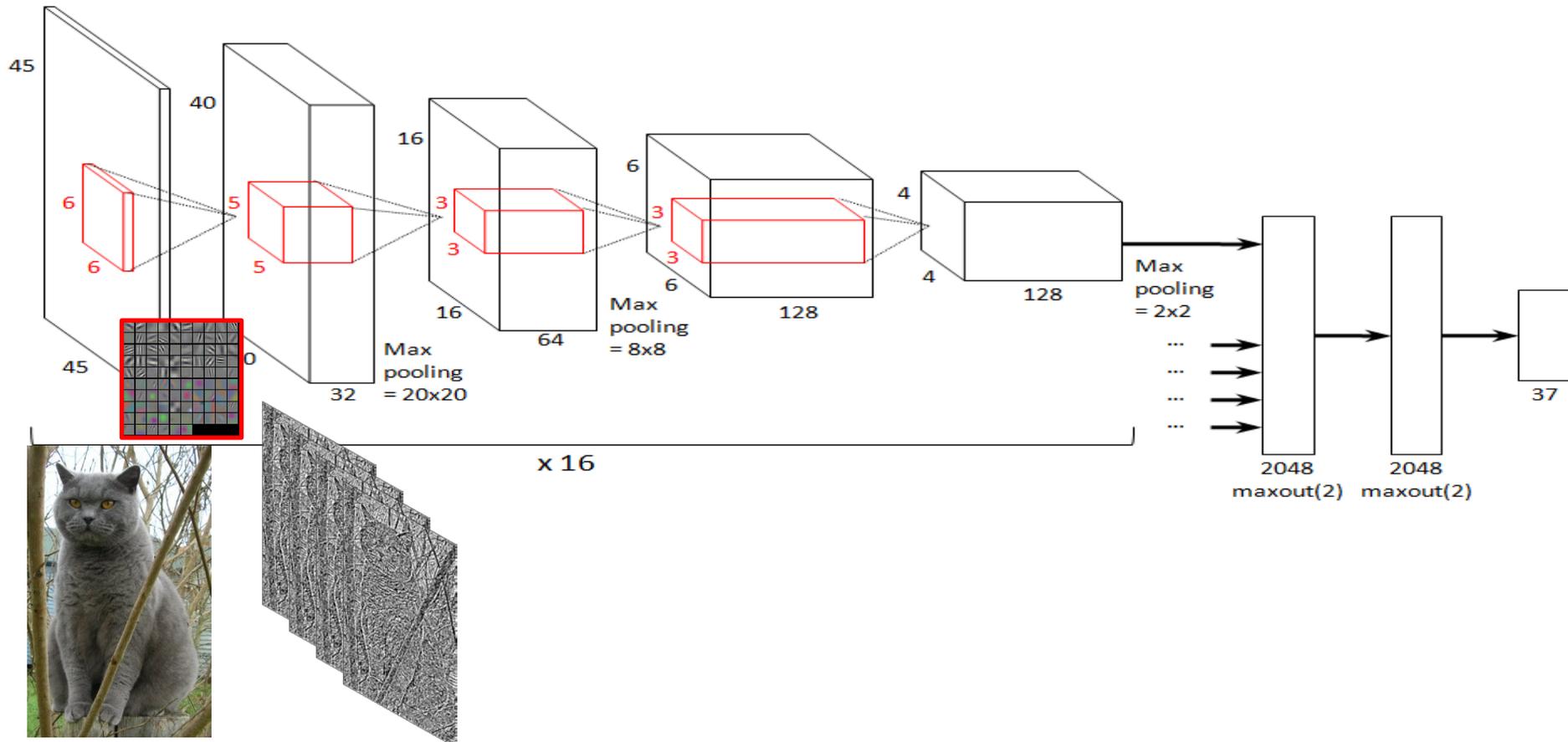
K filters

K activations



Convolutional Neural Networks: crash course

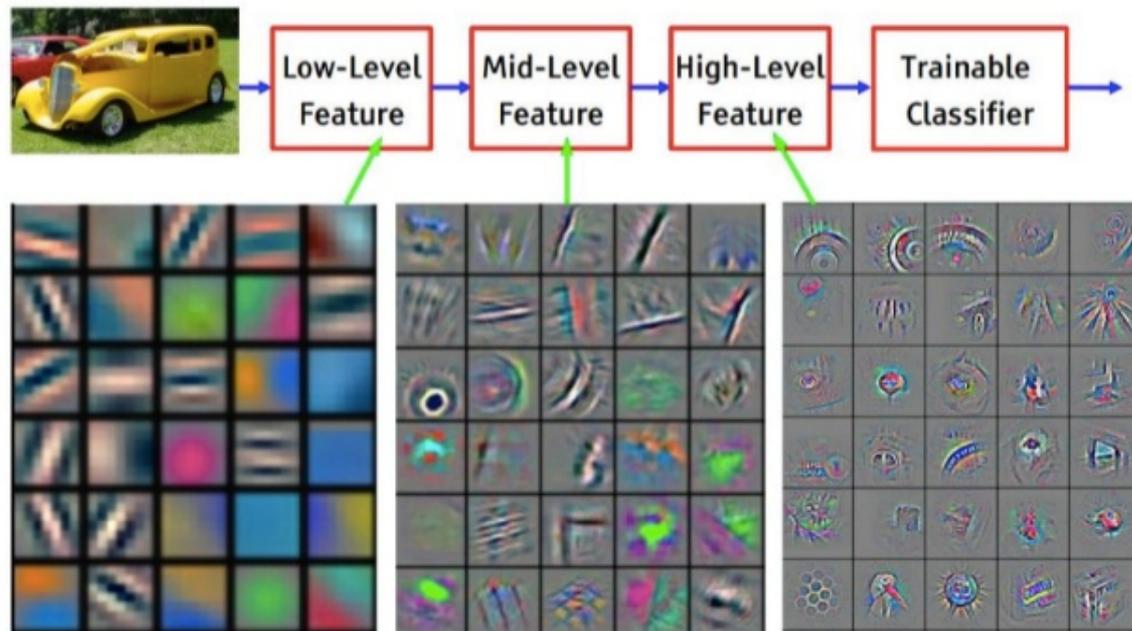
- What's a CNN ?
 - Base CNN: L stacked layers + non-linearities





Convolutional Neural Networks: crash course

- What's a CNN ?
 - Deeper = more abstraction / more semantic meaning

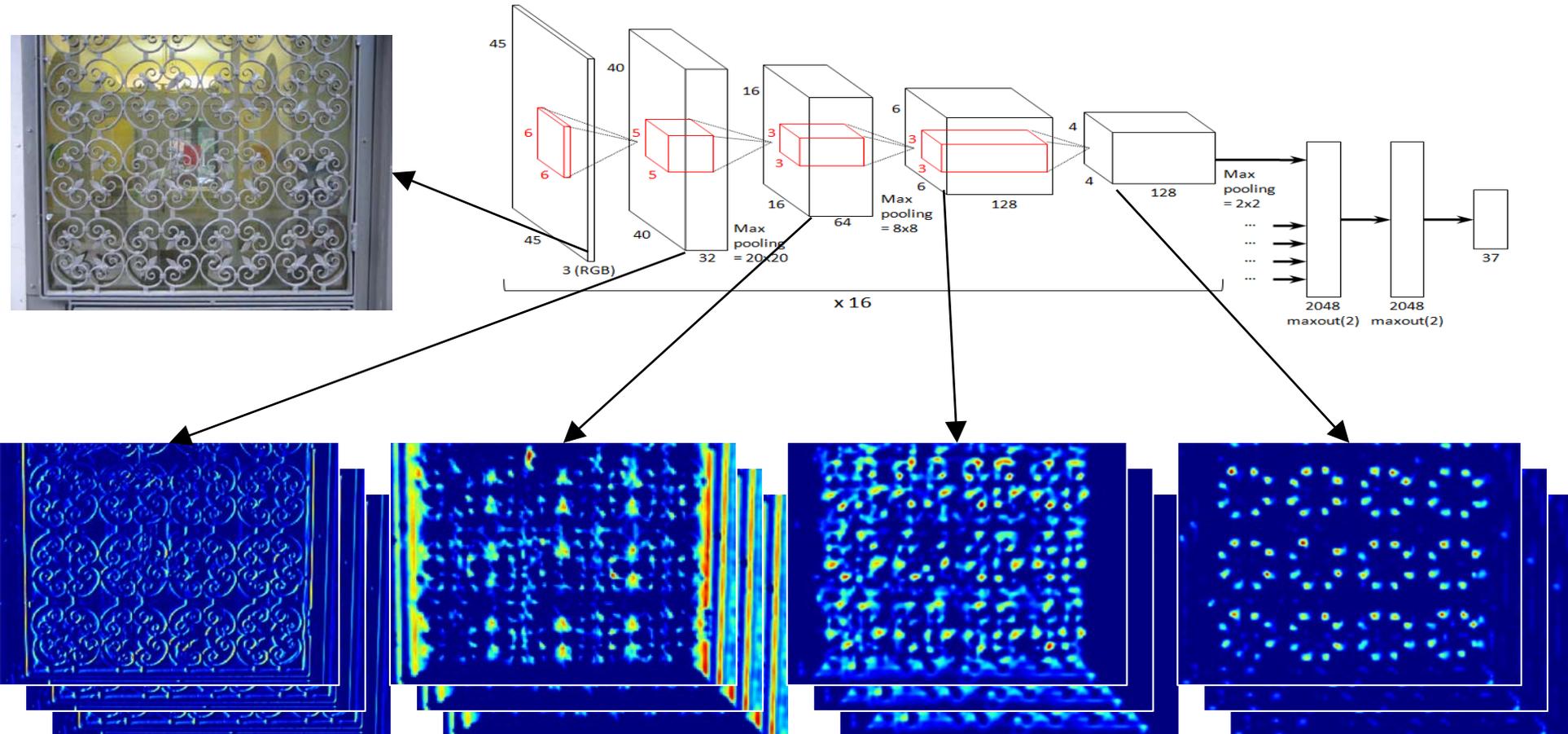


Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]



Our method

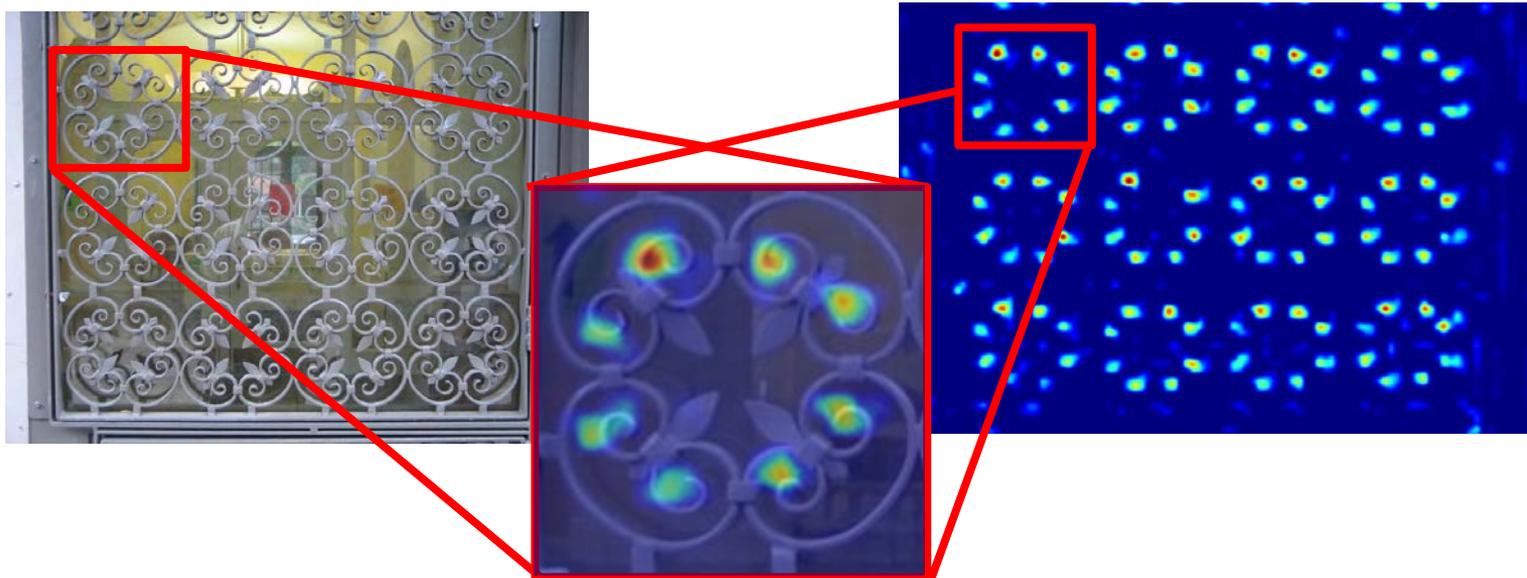
- CNN filter activations on repetitive patterns





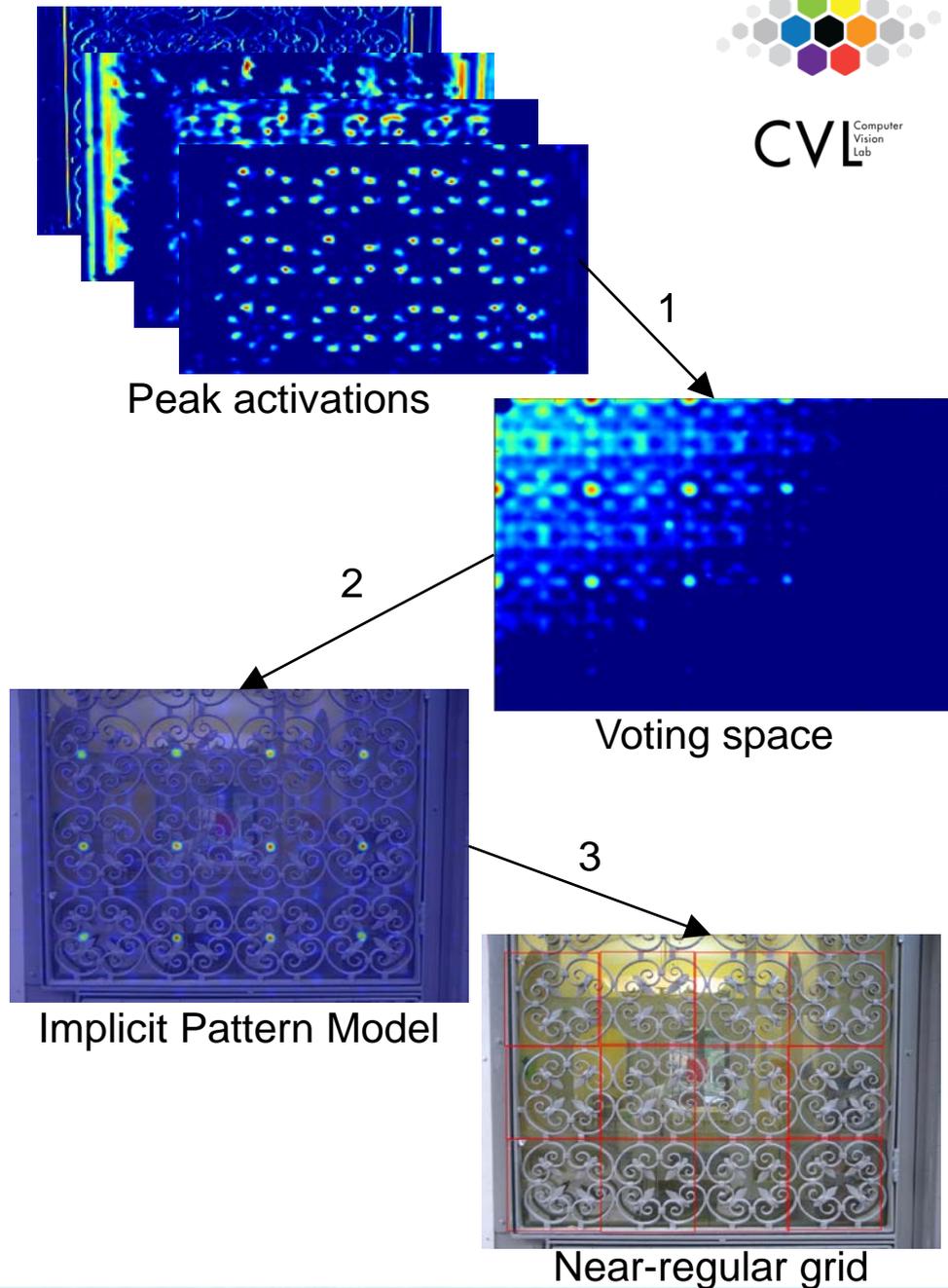
Our method

- CNN filter activations on repetitive patterns
 - Are expressive
 - Are strong on repetitive elements
 - Are robust: consistent throughout visual appearance variations



Our method – algorithm

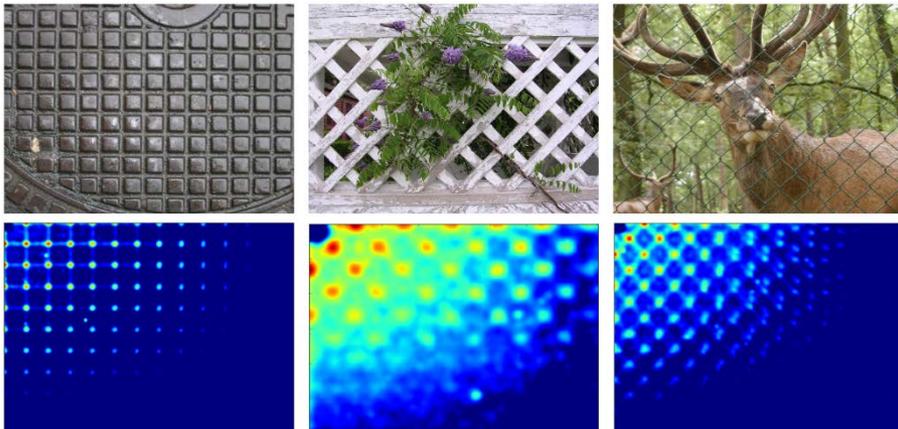
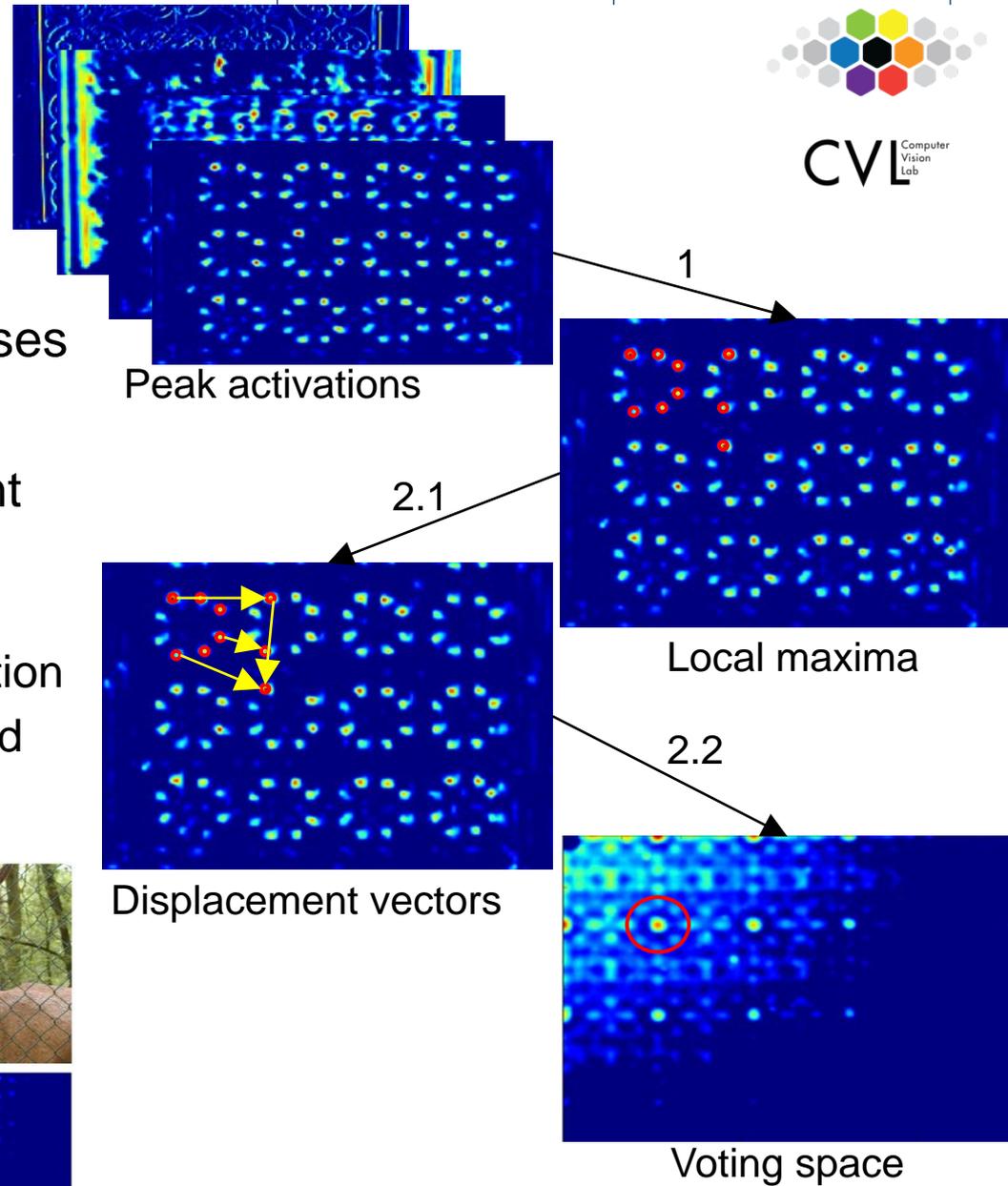
1. Vote for strong consistent **displacement vectors** between **peak activations** in Hough space
2. Deduce repetition centroids in image-space using an **Implicit Pattern Model**
3. Find the best **near-regular grid** to align on it





Our Method – 1. Displacement Vector Voting

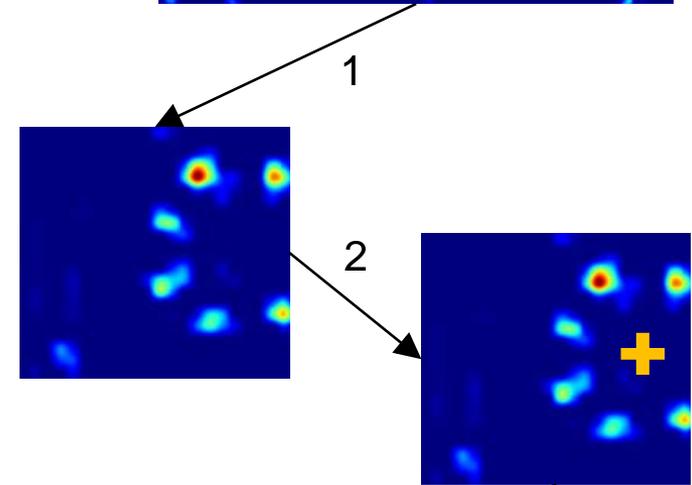
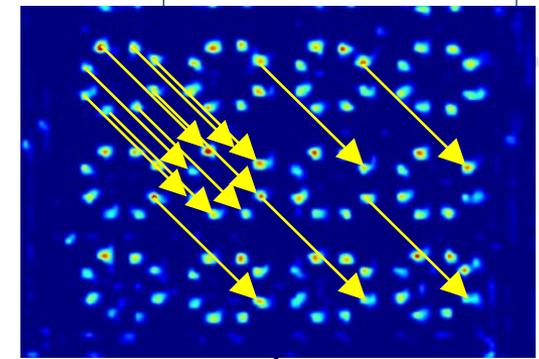
1. Extract peak activation responses
 - Non-maxima suppression
2. Vote for strongest displacement vectors
 1. Calculate displacement vectors between maxima of filter activation
 2. Count occurrence of vectors and vote in Hough space





Our method – 2. Implicit Pattern Model

2. Deduce an IPM in image space (inspired by Implicit Shape Model)
 1. Select activations that voted for the winning vector and project in modulo space
 2. Find their centroids
 3. Project back in image space

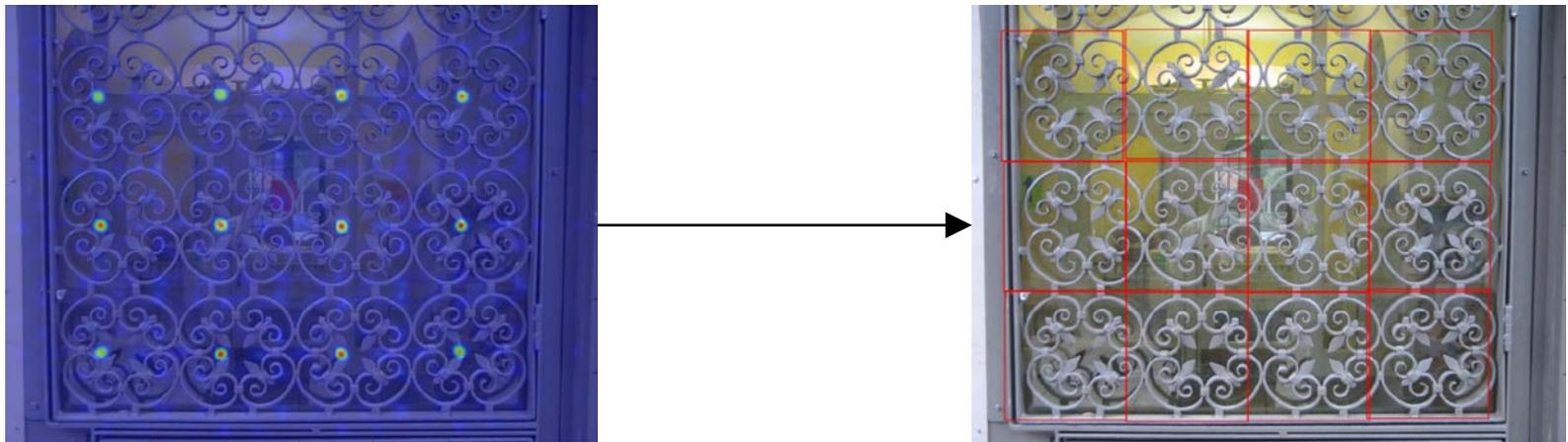




Our Method – 3. Regular Grid

3. Fit elastic model of 2D grid

- Choose a grid that is consistent with a majority of activations

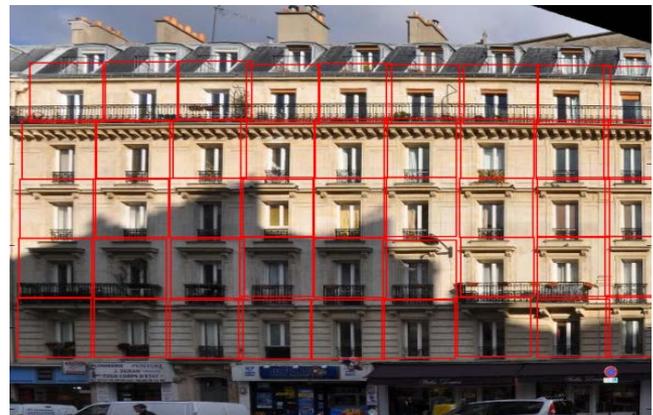
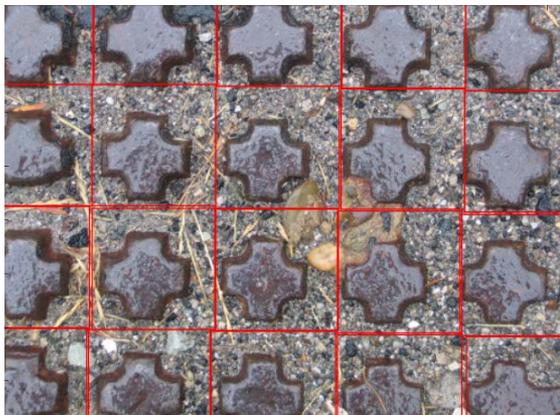
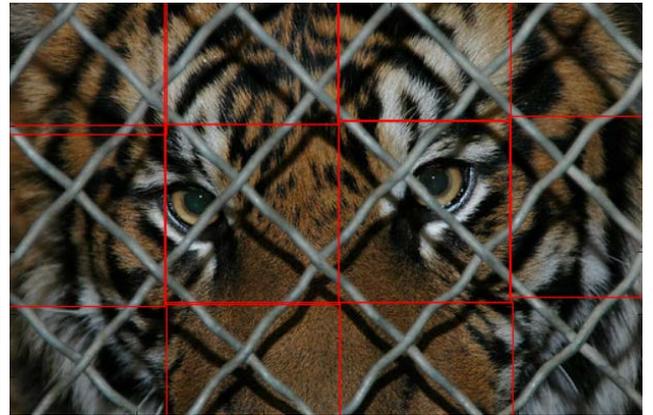
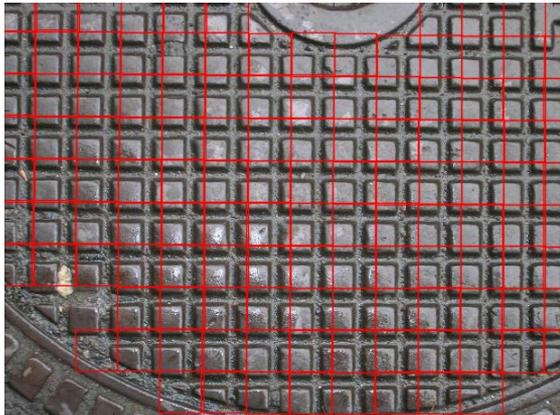


- For more details: please see the paper.



Results – Overview

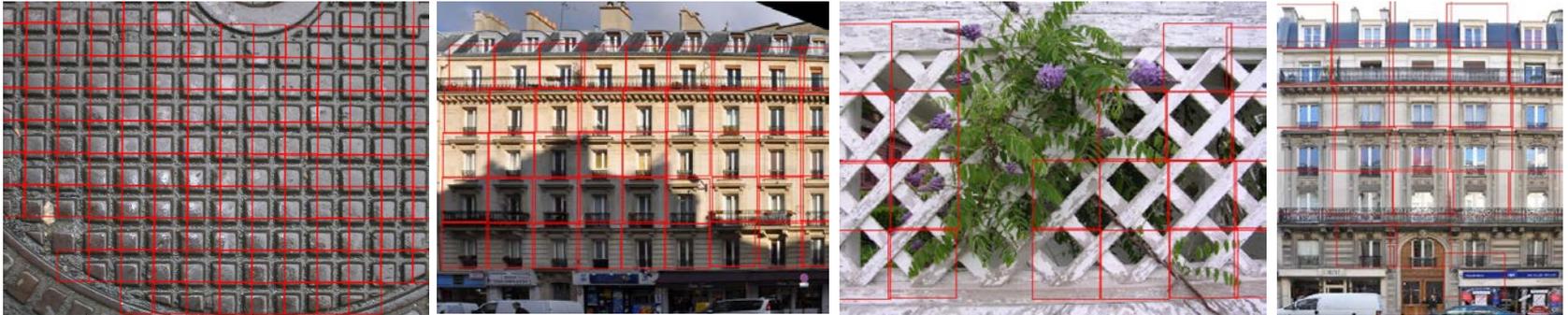
- Tested on database (around 150 images) without any tuning:
<http://people.ee.ethz.ch/~lettryl/repetitions/>





Results – comparison

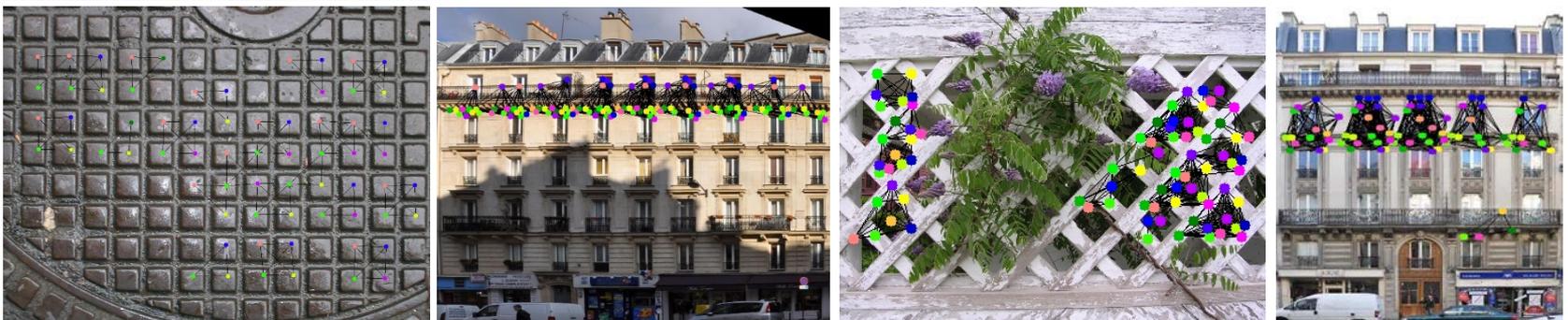
Our
(determin.)



[Park et al. 14]
(Best of 5)



[GRASP]
(Best of 5)

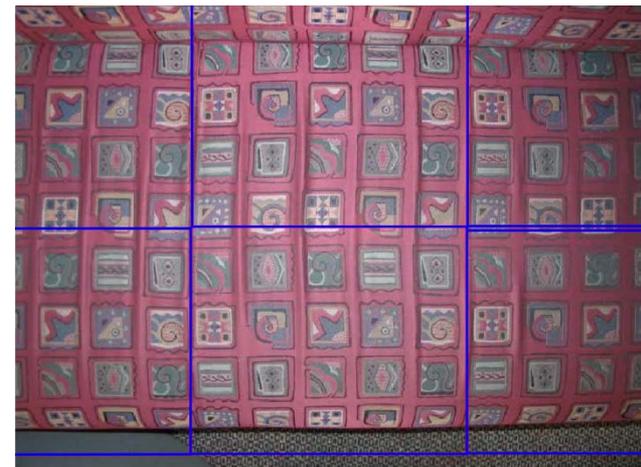




Results – Discussion

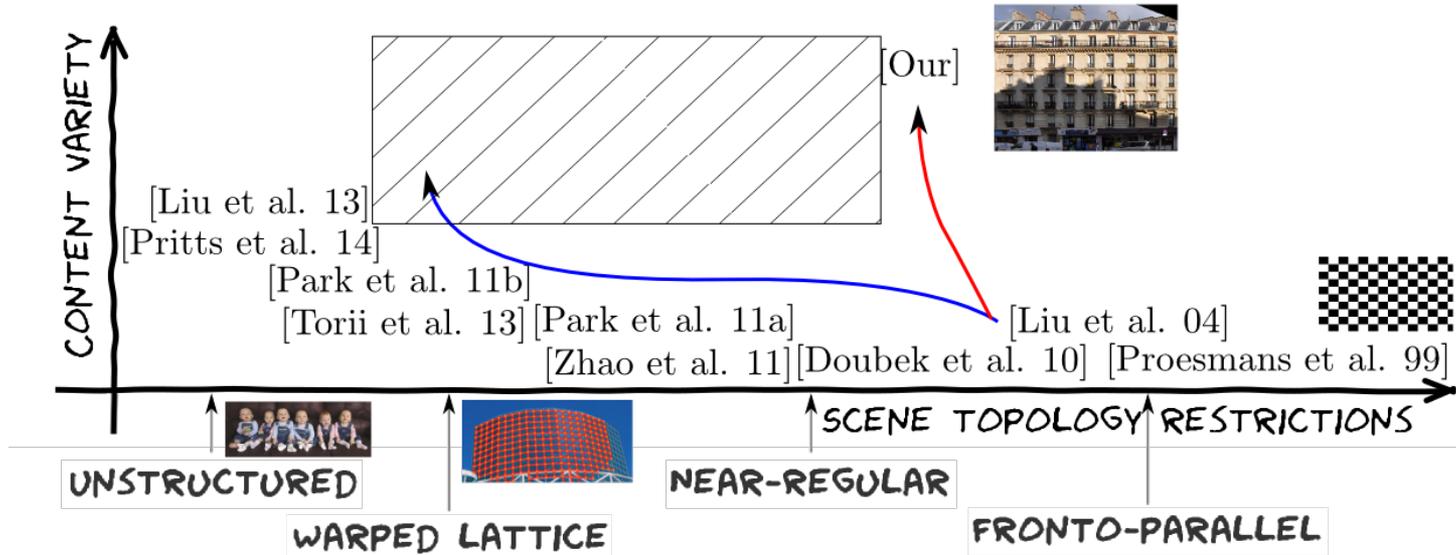
- Quantitative evaluation against a baseline algorithm
 - We annotated “ground truth” repetitions and quantified precision/recall
 - Deep features dramatically improve detection robustness
- Speed
 - One pass through CNN is faster than keypoint description and clustering
 - Around 1-3min for our algorithm, same time for state of the art
 - Less hassle in fine-tuning parameters

- Limitations



Conclusion & Future Work

STATE OF THE ART IN REPETITION DETECTION



- Move away from regularity assumption
- Further analyze activation layers

Thank you for your attention!

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 -  project *Wildtrack*
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