Texture Synthesis using Sparse Representation

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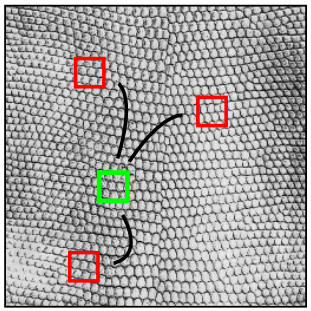
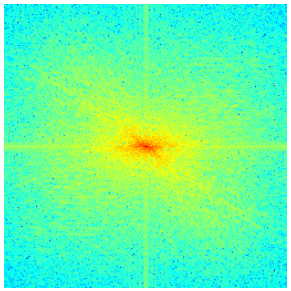
Introduction

Texture Synthesis Approaches

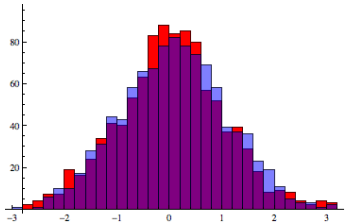
- Find similar patches
- Preserve power spectrum
- Preserve wavelet coefficients distribution
- ...





Our approach

- Work with patches
- Find a good representation of patches
- Control some statistics



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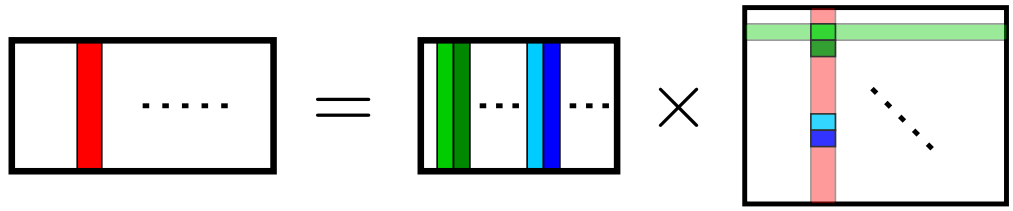
Outline

Outline

Patches Approximation

Image

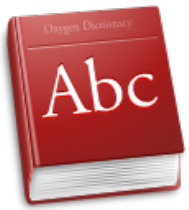
Patches



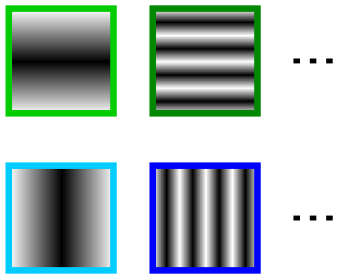
$$P = D \times W$$

$$\mathbf{p}_k = \sum_n w_k^n \mathbf{d}^n$$

Dictionary



Atoms



Sparse Decomposition

Simple Example: Orthogonal Dictionary

- Dictionary D: patches orthogonal DCT basis
- Best decomposition: $\tilde{w} = D^\top p$
- Sparse solutions w^*: obtained by thresholding $\tilde{w}$

General Case: Arbitrary Dictionary

$$\min_w ||p - Dw||_2^2 \quad \text{s.t.} \quad ||w||_0 \leq L$$

$\rightarrow$ NP-Complete!

1st approach

Replace $||\cdot||_0$ by $||\cdot||_1$

- Convex optimization
- Sparsity is induced by $||\cdot||_1$

2nd approach

Use a heuristic

- Find an approximation
- Usually greedy algorithms

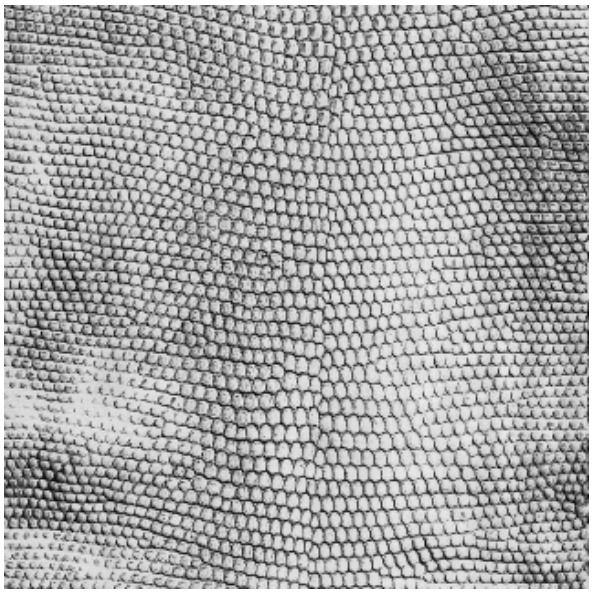
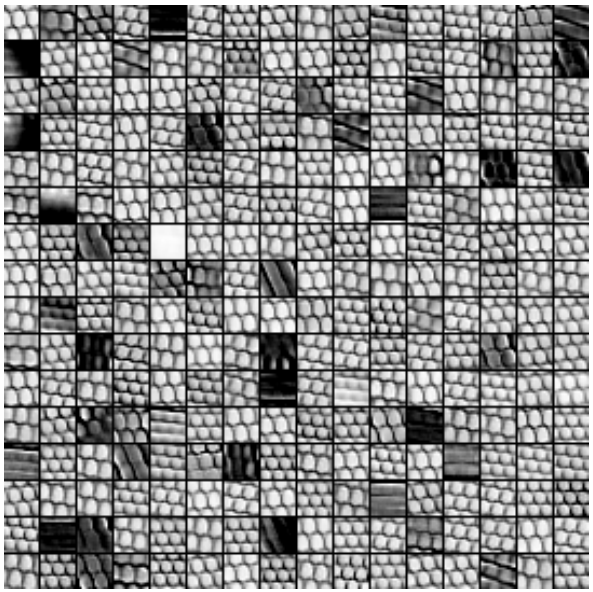
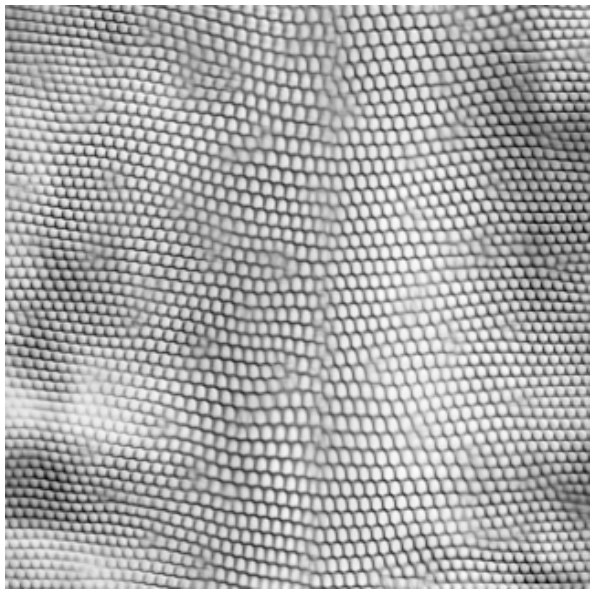
Dictionary Learning

Problem

$$\min_{D,W} \sum_k ||p_k - Dw_k||_2^2 \quad \text{s.t.} \quad ||w_k||_0 \leq L$$

$\rightarrow$ alternate coordinates minimizations [Mairal et al., 2009]

Example of Decomposition, $L = 4$

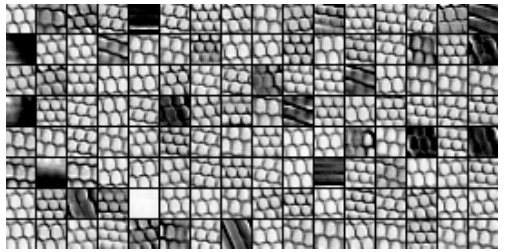




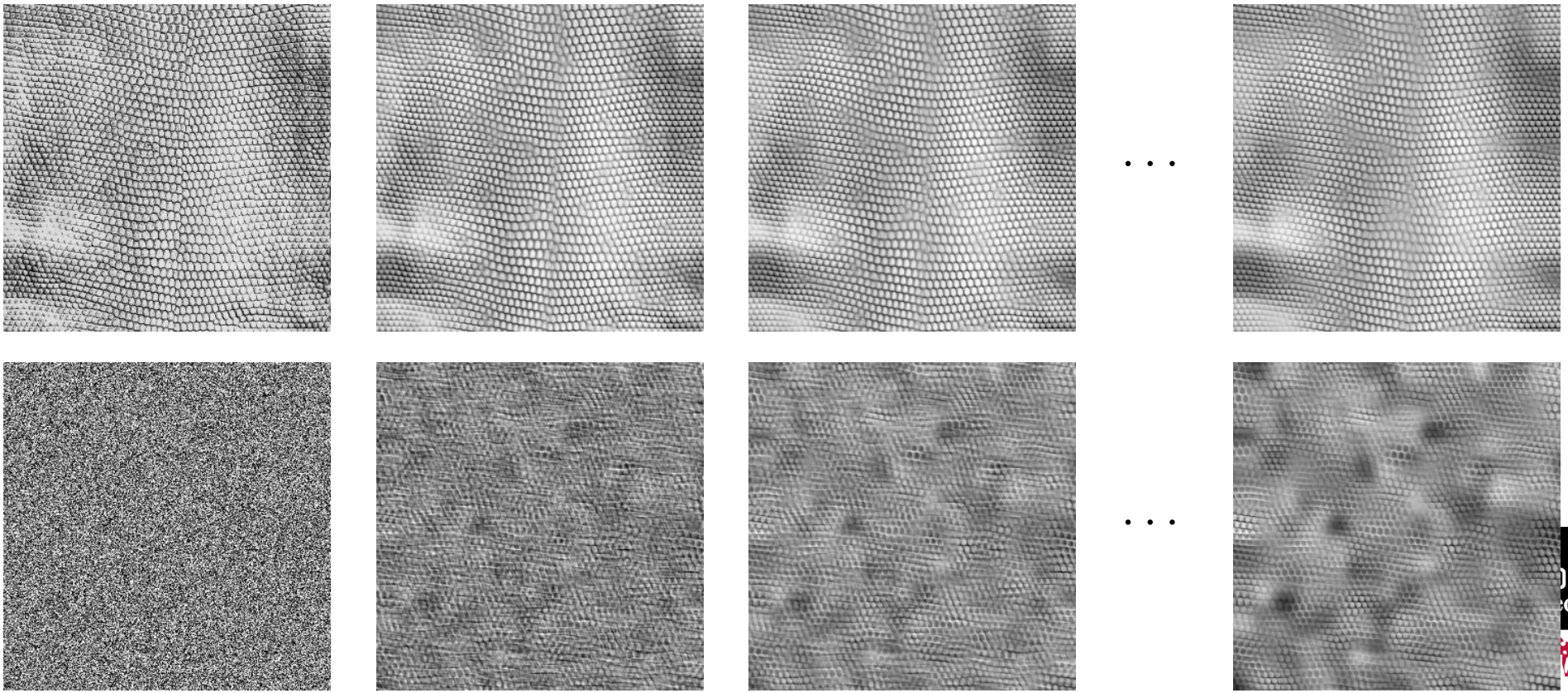
Outline

Sparse-Coding Experiment

Fixed Dictionary D from I_0

- Choose an initial image
- Approximate it in D... again... and again...





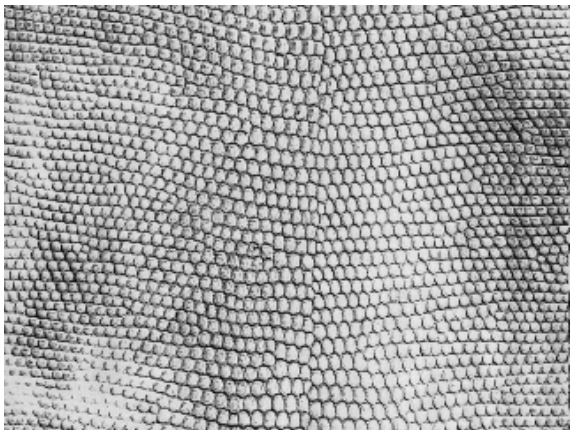
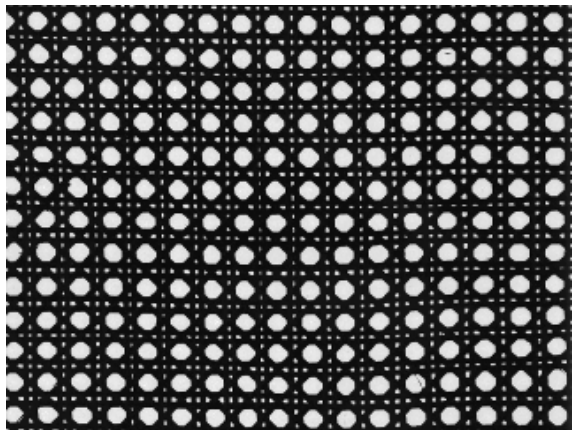
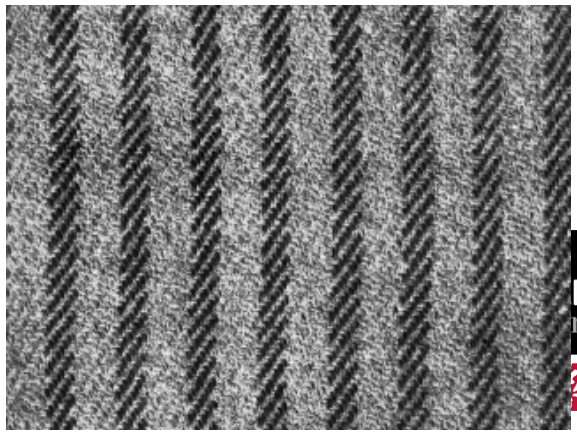
Initial Algorithm

Algorithm

0. Start from a random image I
1. Approximate its patches P_I in D:

$$\min_W ||P_I - DW||_F^2 \quad \text{s.t.} \quad ||w_k||_0 \leq L$$

2. Reconstruct image I' from patches $P' = DW$: average overlaps
3. Transfer I_0 gray-level histogram to I'
4. Loop from 1 with $I \leftarrow I'$

Atom Frequency Constraint

Observation

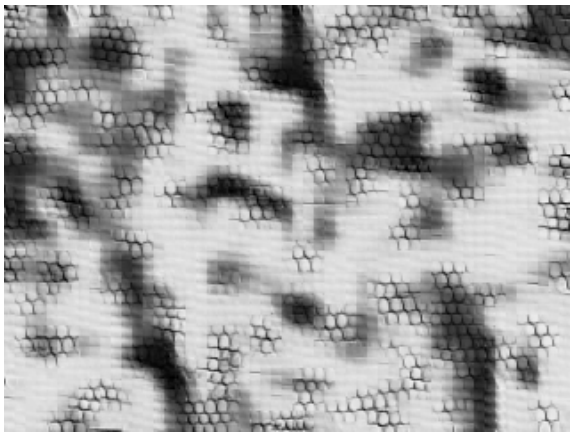
Some atoms are not used

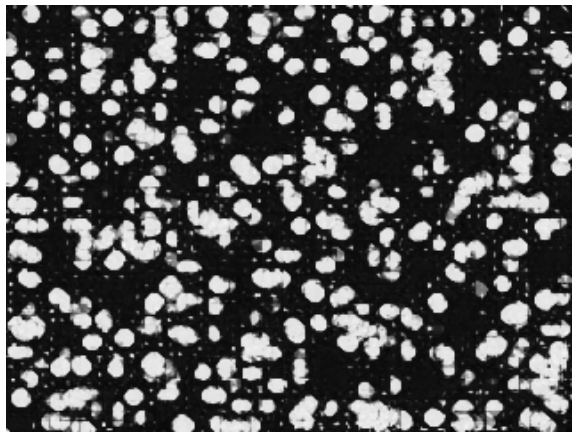
$\rightarrow$ flat regions

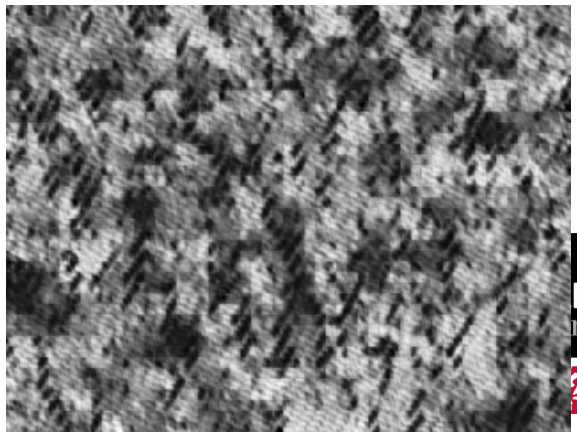
Constraint

Use atoms with the same frequencies of appearance:

$$\min_W ||P - DW||_F^2 \quad \text{s.t.} \quad \begin{cases} ||w_k||_0 \leq & L \\ ||w^n||_0 \leq & F^n \end{cases}$$







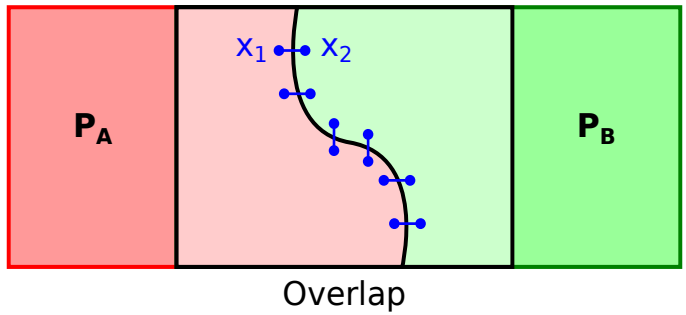
Graph-Cut Reconstruction

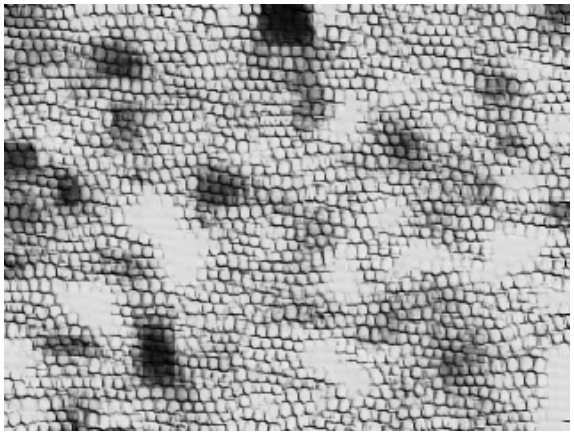
Observation

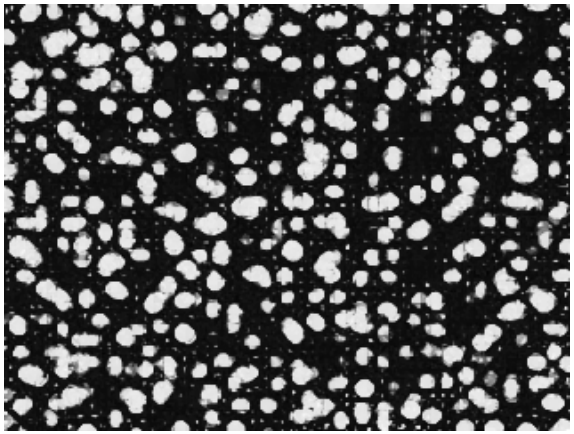
Overlapping patches are averaged
$\rightarrow$ some structures are lost

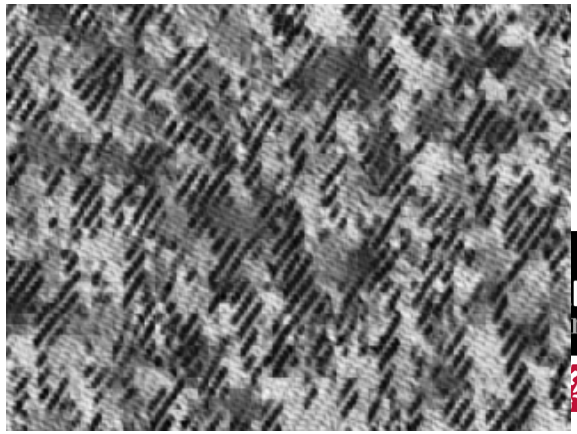
Improvement

Patches are blended together along a cut: [Kwatra et al., 2003]









Multi-scale Synthesis

Observation

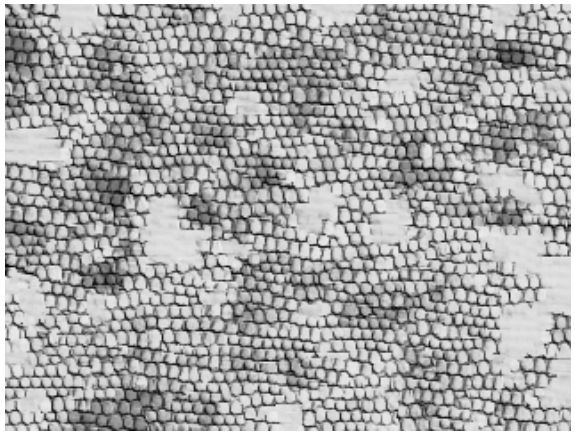
Patches are too small

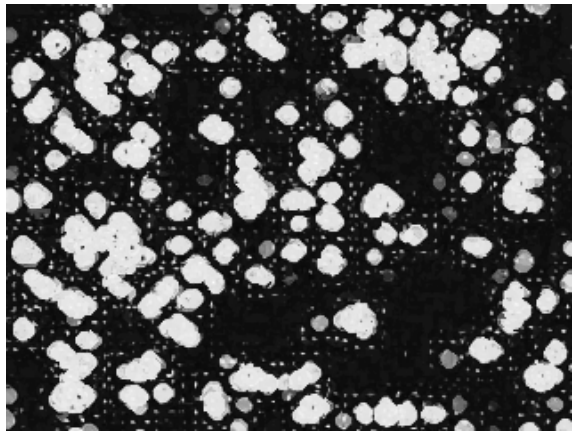
$\rightarrow$ big structures cannot be synthesized

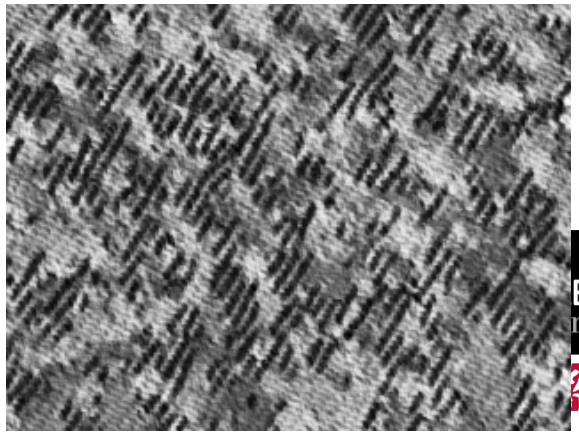
Improvement

Perform a multi-scale synthesis

$\rightarrow$ current scale is initialized by up-sampling previous scale synthesis







Low-Frequency Removal

Observation

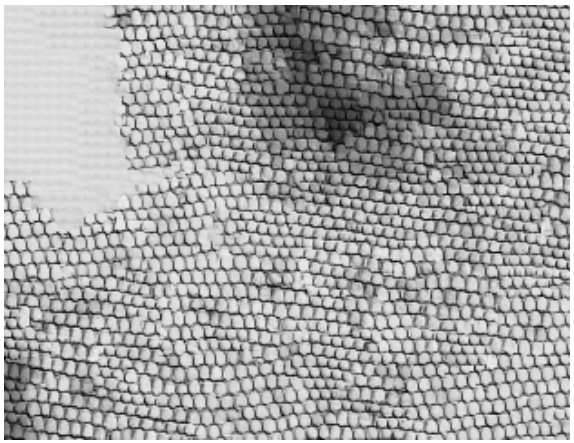
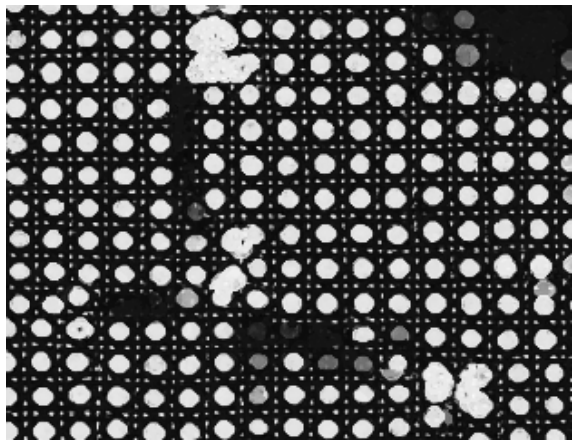
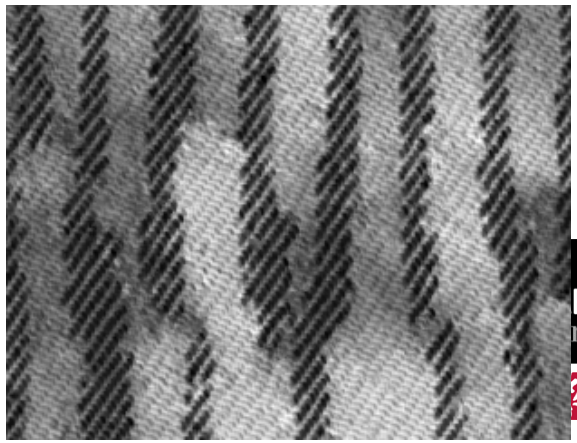
Patches cannot control low frequencies
$\rightarrow$ low-frequency artifacts appear

Improvement

Transfer low-frequencies. For first scale:

$$I'' \leftarrow I' - h \star (I' - I_0)$$

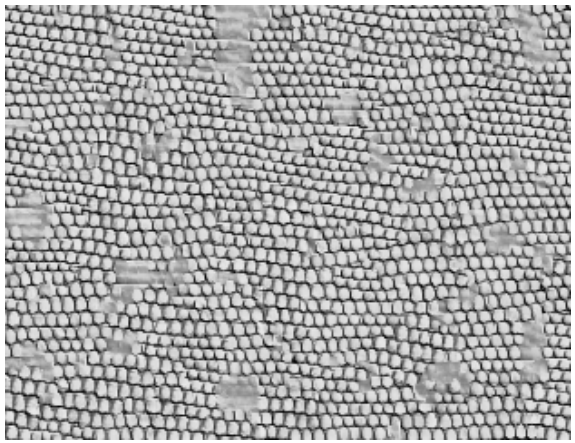
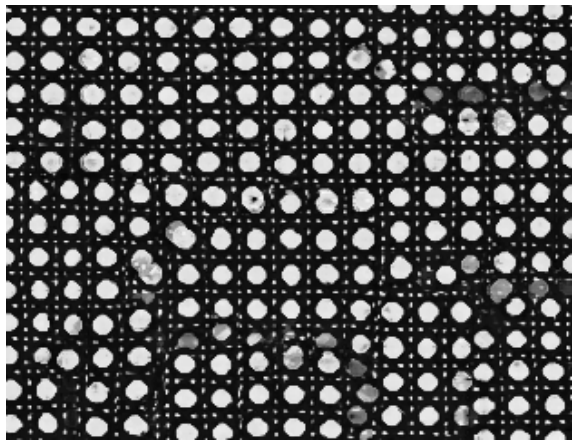
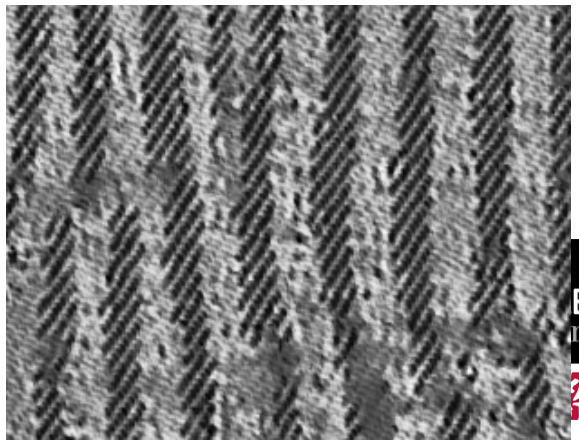
with h a low-pass kernel

Summary

Iterative Multi-scale Algorithm

0. Start from a random image
1. Decompose it sparsely in the dictionary
   Constraint A: respect atoms distribution
2. Reconstruct the image using cuts between patches
   Constraint B: no low frequency (patches artifacts)
   Constraint C: use the original gray values distribution
3. Repeat from 1

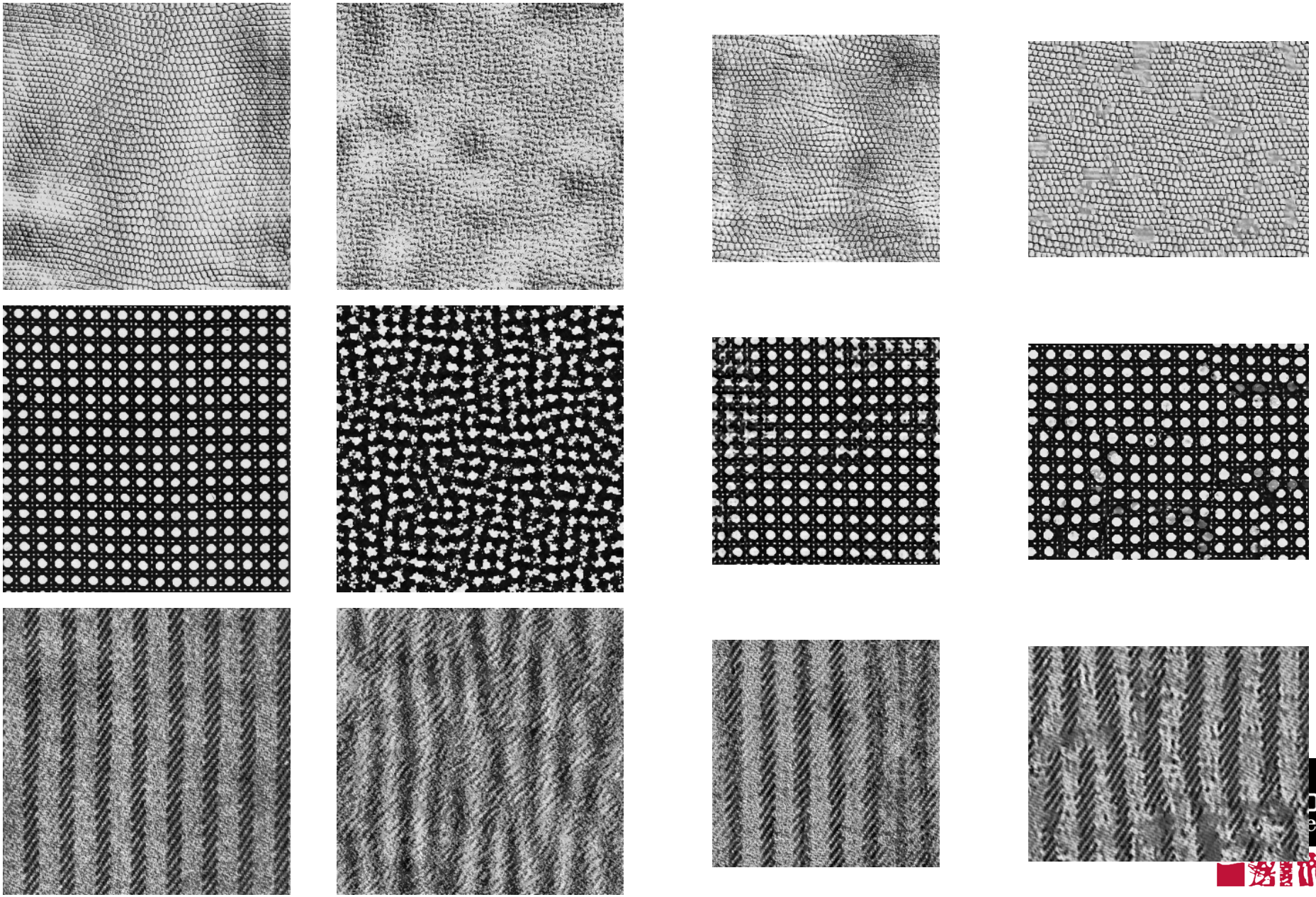




Examplar

[Heeger and Bergen, 1995]

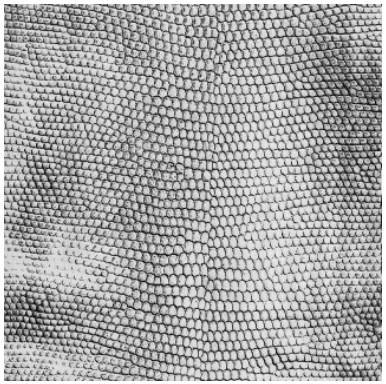
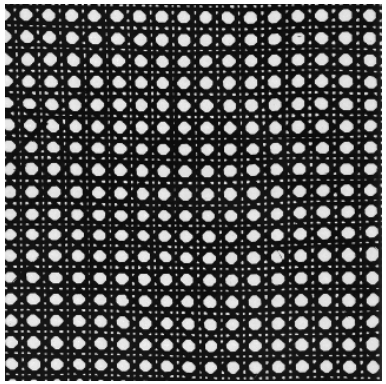
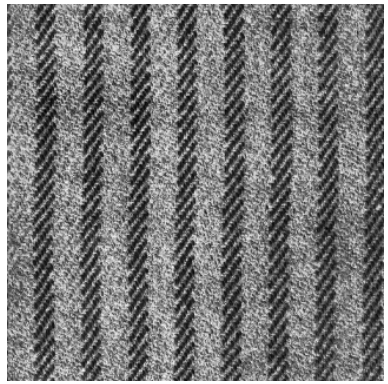
[Portilla and Simoncelli, 2000]

Our method

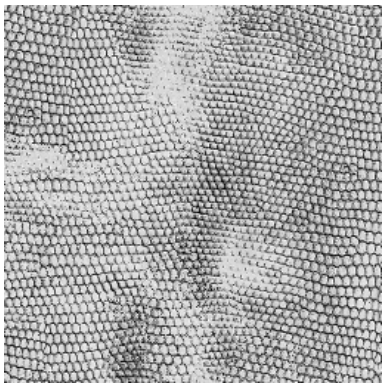
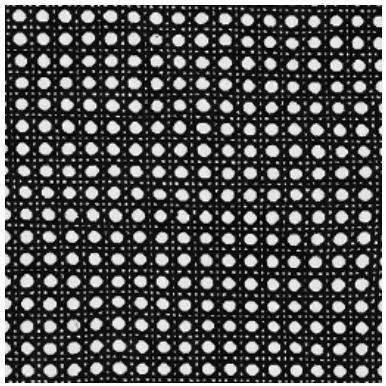
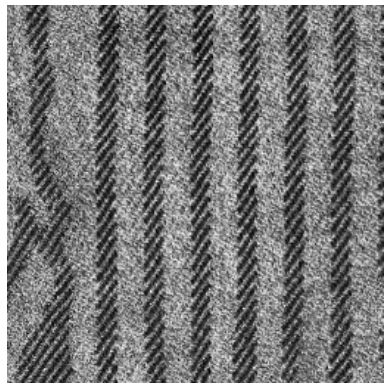


Pixel "Copy-and-Paste" Approach

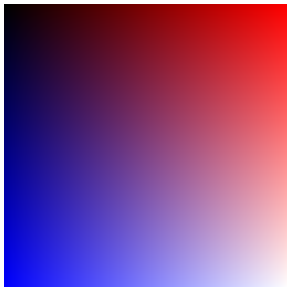
Original

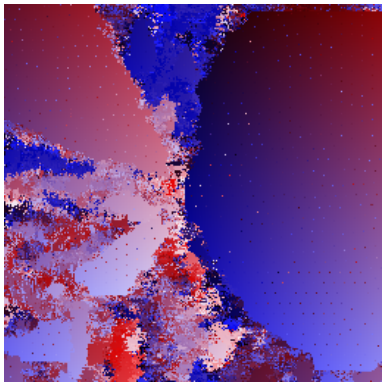
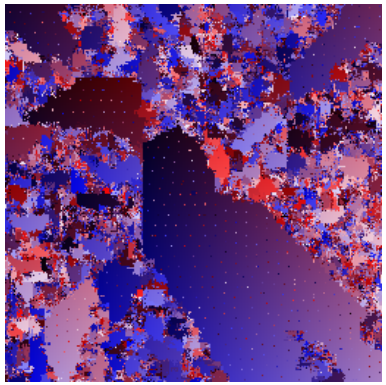
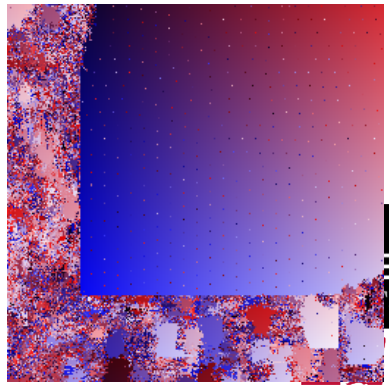




[Efros and Leung, 1999]

Coordinates



Outline

Synthesis → Minimization Problem

Sparsity Term

$$||P - DW||_F^2 + \iota_A(W) + \iota_B(W)$$

with constraints:

$$(A) \quad ||w_k||_0 \leq L$$
$$(B) \quad ||w^n||_0 \leq F^n$$

Histogram Matching Term

With I_0 the exemplar texture:

$$d_\Sigma^2(\mu_I, \mu_{I_0}) = \min_{\sigma \in \Sigma} ||I - I_0 \circ \sigma||_2^2$$

Low-Frequency Removal Term

For a given low-pass kernel h:

$$||h \star (I - I_0)||_2^2$$

Convolutive Dictionary

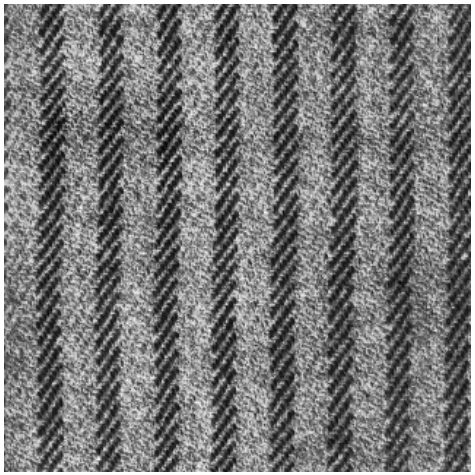
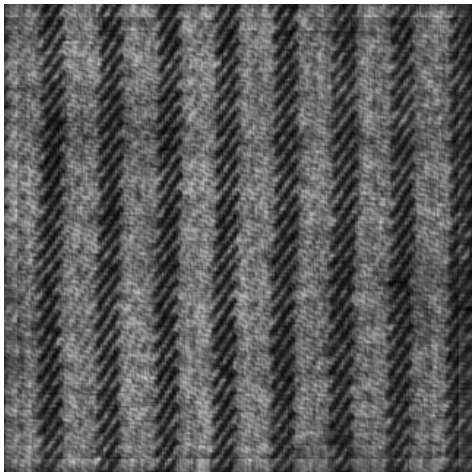
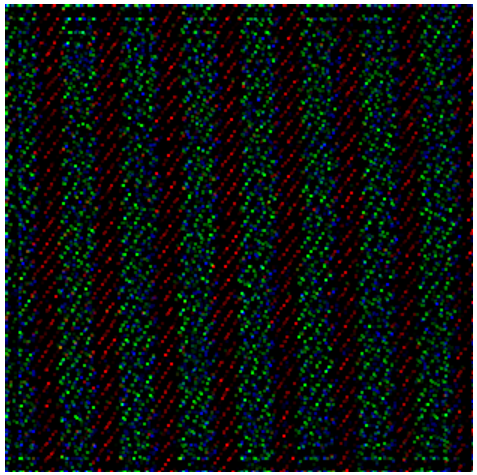
Decomposition Problem

- Relaxed L_1 penalty:

$$\min_{\varphi, W} ||I - \sum_n \varphi_n \star W_n||^2 + \lambda ||W||_1$$

- Few non-zeros coefficients
- Very few atoms, no redundancy

Image, Approximation, Coefficients

Dictionary


4%


7%


7%

Conclusion

Contribution

- Sparsity for texture synthesis
- Statistics on sparse decomposition of patches
- Greedy algorithm for sparse decomposition under frequency constraint
- Reconstruction method from patches using cuts

Conclusion and Limitations

- Sparse decomposition capture most of the texture's information
- Adapted to structured textures, not to micro-textures
- Patch-based framework has some drawback
- Dictionary has some redundancy

The End

Thank you

Any questions?

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