

# Modèles statistiques pour l'image

## Patch-based Image Processing

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# Outline

1 Patch-based processing of images

2 Visual Summary

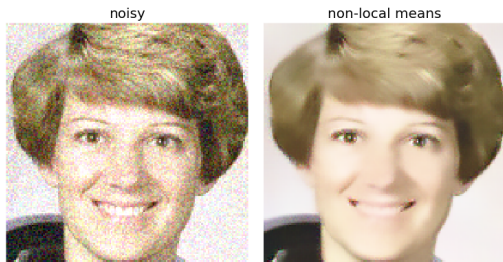
3 Efficient Similar Patch Search

# Patch-based processing

- Consider patches instead of pixels



# Similarity Analysis: Non Local Means [Buadès et al. 2005]



- Idea: denoise a point by comparing it to similar neighborhoods
- Compute local patch  $P(p)$  around each point  $p$
- Similarity measure between two points:  $w(p, q) = \exp - \frac{\text{dist}(P(p), P(q))^2}{\sigma}$
- Update of the image :

$$I_{\text{new}}(p) = \frac{\sum_{q \in I} w(p, q) I(q)}{\sum_{q \in I} w(p, q)}$$

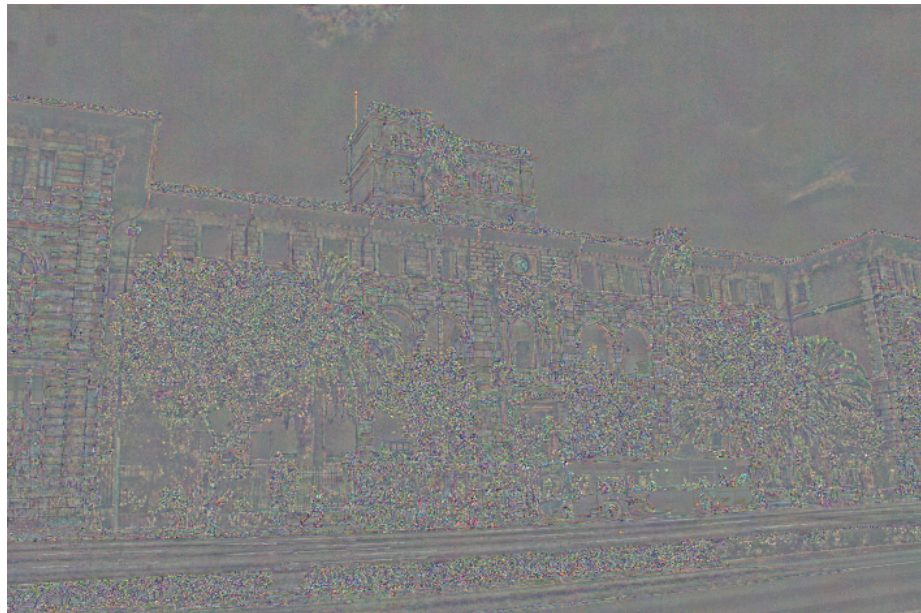
## Example



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# Initial image





## Noisy image



## Gaussian filter result



## Gaussian filter result



## Gaussian filter result



## Median result



## Median result



# NLmeans result



# Comparison



Patch-based processing of images



# Outline

1 Patch-based processing of images

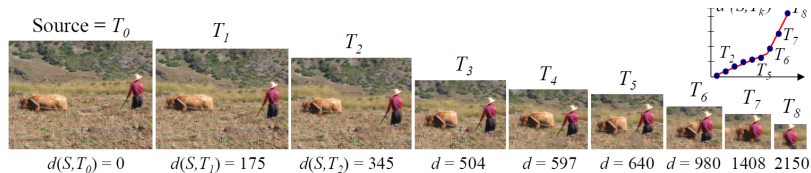
2 **Visual Summary**

3 Efficient Similar Patch Search

# Visual Summary

## Goal

Produce a smaller image that summarizes the content of the larger image



[Simakov 2008]

## Comparing two images

### Bidirectional Distance (BDS) [Simakov 2008]

Source image  $S$ , target image  $T$ :

$$d_{BDS}(S, T) = \frac{1}{N_S} \sum_{s \in S} \min_{t \in T} D(s, t) + \frac{1}{N_T} \sum_{t \in T} \min_{s \in S} D(t, s)$$

where  $s$  and  $t$  are patches of fixed size of  $S$  and  $T$ .  $D$  is the sum of squared difference between patches.

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## Reconstruction

Starting from an initial guess  $T_0$  for  $T$ , build an image iteratively as the minimizer  $T$  of  $d_{BDS}(S, T)$

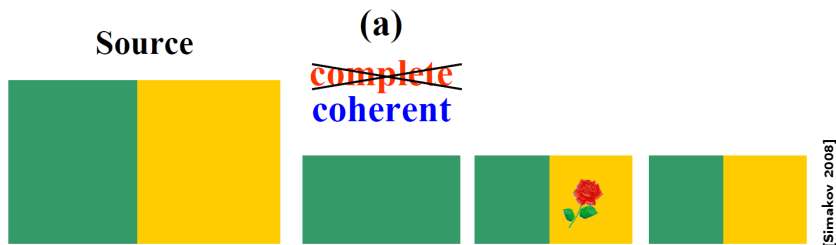
# Similarity distance

**Source**



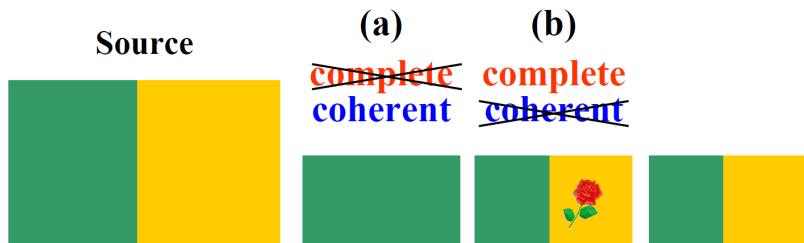
[Simakov 2008]

# Similarity distance



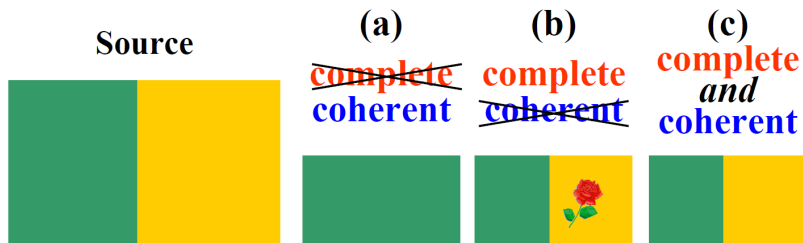


# Similarity distance



[Simakov 2008]

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$d = 667$



$d = 857$



$d = 597$

[Simakov 2008]

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## Steps 1 - 2

The two first steps consist in applying nearest patch search. It needs to be done *efficiently*.

## Aggregation Step: contribution of a pixel to the coherence measure

- Let  $q$  be a pixel of  $T$ ,  $q$  lies inside  $m$  neighboring patches  $Q_1, Q_2, \dots, Q_m$



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### Contribution

$$\frac{1}{N_T} \sum_{i=1}^m \|S(p_i) - T(q)\|_2^2$$

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$$\frac{1}{N_S} \sum_{i=1}^n \|S(\hat{p}_i) - T(q)\|_2^2$$

# Color update

## Color Update

The best  $T(q)$  should minimize:

$$\frac{1}{N_S} \sum_{i=1}^n \|S(\hat{p}_i) - T(q)\|_2^2 + \frac{1}{N_T} \sum_{i=1}^m \|S(p_i) - T(q)\|_2^2$$



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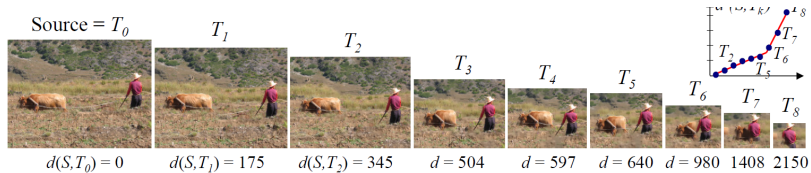
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## Color Update

$$T(q) = \frac{\frac{1}{N_S} \sum_{i=1}^n S(\hat{p}_i) + \frac{1}{N_T} \sum_{i=1}^m S(p_i)}{\frac{m}{N_T} + \frac{n}{N_S}}$$

# Visual Summary



[Simakov 2008]

# Gradual resizing

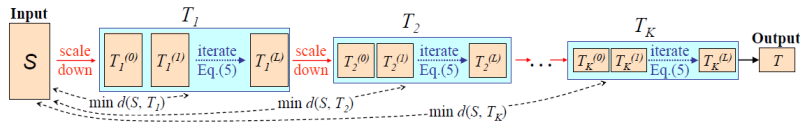
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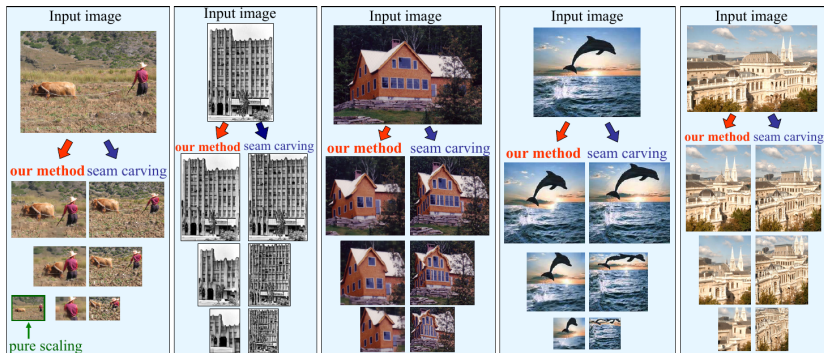
- When the target has a very different size from the source: what is a good initial guess?
- Iterative process: downsample the image and apply the reconstruction



[Simakov 2008]

video

# Visual Summary



# Montage

Input 2



Input 3



Input 1



Output montage



[Sirmakov 2008]

# Synthesis

Input



Bigger output (Synthesis)



[Simakov 2008]



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A fast method to find similar patches

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- Naive way: traverse the whole image at each query
- **Better:** put all patches in a search structure
- **Even better:** the patch match algorithm

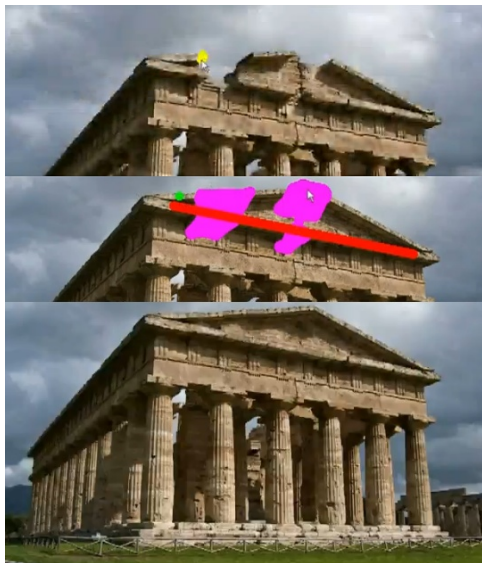
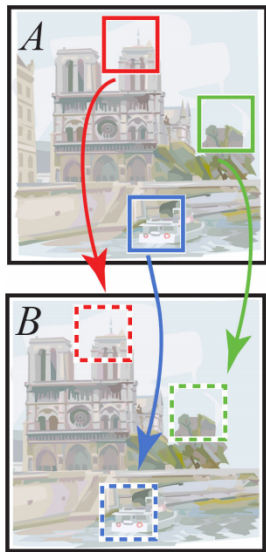
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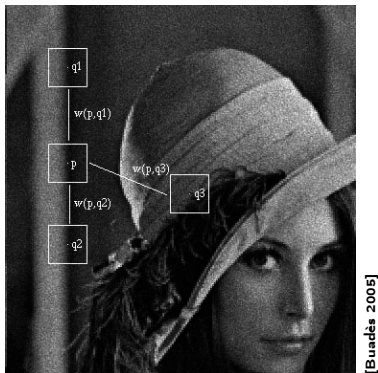
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# Patch Match [Barnes 2009]



## Similar patches



### Similarity distance

The similarity distance between two patches  $p_A$ ,  $p_B$  of size  $n \times n$  is computed as  $\sum_{1 \leq i, j \leq n} \|p_A(i, j) - p_B(i, j)\|_2^2$ .

### Similarity

Two patches are considered as similar if their similarity distance is small.

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## Goal

Given an image  $A$  and an image  $B$  find *efficiently* for all patches of image  $A$  an approximate nearest patch of image  $B$ .

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## Patch Match Principle

Assume we have found a patch  $p_B$  of  $B$  corresponding to a given patch  $p_A$  of  $A$ , assume we have a patch  $p'_A$  located close to  $p_A$  in image  $A$ , then its corresponding patch  $p'_B$  has a high probability to lie close to  $p_B$

- Look for  $p'_B$  close to  $p_B$ .



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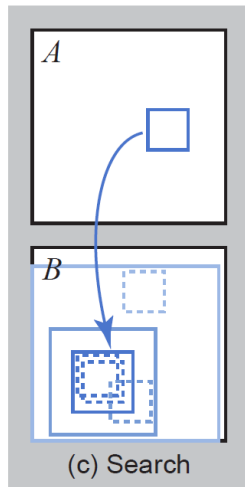
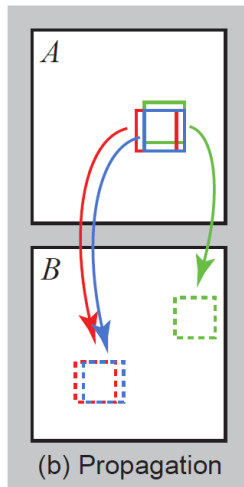
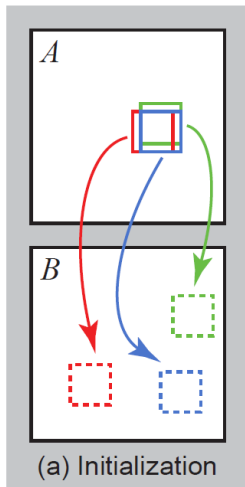
## Notation

Let  $p_A$  be a patch centered at  $a$  in image  $A$  and  $p_B$  a patch centered at  $b$  in image  $B$ . We define an **offset vector**  $f(a)$  as  $f(a) = b - a$ . The set of all offset vectors is called the **Nearest Neighbor Field (NNF)**.

# Algorithm

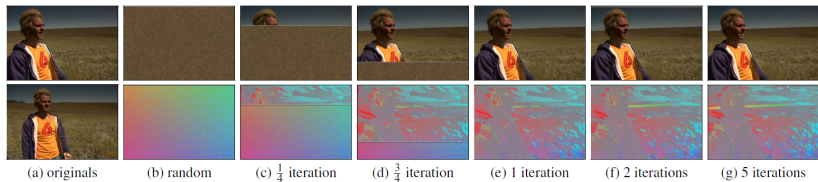
- 1 Initialize the NNF with random vectors
- 2 **Propagation:** for  $i = 1 \dots M$ , for  $j = 1 \dots M$ 
  - 1 **Evaluate** the offset  $f(i-1, j)$ ,  $f(i-1, j-1)$ ,  $f(i-1, j+1)$  and  $f(i, j-1)$
  - 2 If one of them is better than  $f(i, j)$  replace  $f(i, j)$  with it.
- 3 **Randomization:** For all  $(i, j)$ , draw a random offset  $w$ , if  $w$  is **better** than  $f(i, j)$  set  $f(i, j) = w$

# Algorithm



[Barnes 2009]

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# Probabilistic analysis

## Exercise

Assume we have two images of size  $M$  and assign randomly patches of image  $A$  to patches of image  $B$  (+ unicity of the correspondence)



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Assume that a pair is correct if a patch is assigned to a patch that is spatially close (in a neighborhood of size  $C$ ) to its true correspondence



- What is the probability that at least one patch is paired to an approximate corresponding patch?

# Reshuffling Application



(a)

(b)

(c)



(d)

(e)

(f)



(g)

(h)

(i)

(j)



(k)

(l)

(m)

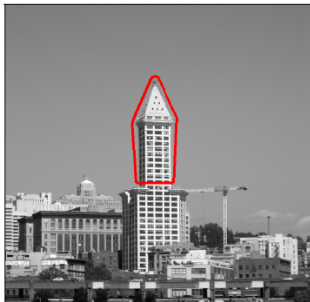


(n)

(o)

[Barnes 2009]

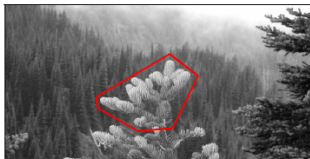
# Deformation Application



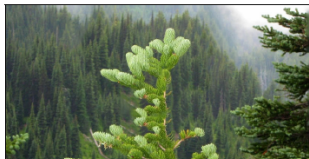
(a) building marked by user



(b) scaled up, preserving texture



(c) bush marked by user



(d) scaled up, preserving texture.

[Barnes 2009]