Image inpainting with a single-scale approach: From still images to stereoscopic videos.
Why is it a tough problem?
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Doing it manually: Clone tool
Why is it a tough problem?

Doing it manually with the *Clone* tool
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Why is it a tough problem?

[Automatic reconstruction by Criminisi, Pérez et Toyama ’03]
Why is it a tough problem?

[Wexler et al. ’07 (multi-scale approach)]
A non-exhaustive overview of inpainting approaches
A non-exhaustive overview of inpainting approaches

- Purely geometry-driven methods

[Masnou et Morel ’98] - “Level line based disocclusion”

**Idea**: Link together the isophotes external to the inpainting mask

Minimization of an energy functional using dynamic programming
A non-exhaustive overview of inpainting approaches

► Purely geometry-driven methods

[Bertalmio et al. '00] - “Image inpainting”

Idea: Transport equation to propagate isophotes
A non-exhaustive overview of inpainting approaches

- Purely geometry-driven methods

[Chan et al. '01] - “Non-Texture Inpainting by Curvature-Driven Diffusions”

Idea: Diffusion equation guided by the isophotes directions/curvatures
A non-exhaustive overview of inpainting approaches

- Purely geometry-driven methods
A non-exhaustive overview of inpainting approaches

▶ Patch/texture-based methods

[Efros and Leung '99] - "Texture synthesis by non-parametric sampling"

Idea: Texture synthesis pixel by pixel, exploiting texture auto-similarities
A non-exhaustive overview of inpainting approaches

▶ Patch/texture-based methods

[Criminisi et al. ’03] - "Region Filling and Object Removal by Exemplar-Based Image Inpainting"

**Idea**: Mixing texture synthesis and local analysis of the image geometry.
A non-exhaustive overview of inpainting approaches

- Patch/texture-based methods

[Criminisi et al. 2003], "Region Filling and Object Removal by Exemplar-Based Image Inpainting"
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D. Tschumperlé
Technicolor Workshop on Multimedia Inpainting
19 Avril 2016
A non-exhaustive overview of inpainting approaches

Patch/texture-based methods

[lemeur et al. '11] - "Examplar-based inpainting based on local geometry"

Idea: Improve [criminisi et al '03] with a better geometry analysis (tensor-based) and a better patch synthesis (means of K best patches).
A non-exhaustive overview of inpainting approaches

▶ Patch/texture-based methods

PatchMatch \textit{[Barnes et al. '09]}

- A very fast algorithm for matching similar patches between two images
- Works for \textit{full} images (non-masked patches)

Used in several efficient image and video inpainting techniques (\textit{multi-scale approaches}) :

- \textit{[Wexler et al. '07]} + PatchMatch ➤ Photoshop
- \textit{[Newson et al. '14]} ➤ PatchMatch 3D

▶ Solving the problem for \textit{different image scales}, using the solution at one scale as an initialization for the upper scale (\textit{may increase error propagation} !)
A non-exhaustive overview of inpainting approaches

- Patch/texture-based methods

2 key steps with space for improvements

1. The analysis of the image geometry
2. The synthesis of the best patchs to copy/paste

- Problems with curved structures to reconstruct
- Visible bloc effects
A non-exhaustive overview of inpainting approaches

Patch/texture-based methods

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Contributions

A few improvements to

[Criminisi, Pérez et Toyama ’03]
Single-scale inpainting: data term

\[ D_p = \frac{|\nabla I_p^\perp \cdot n_p|}{\alpha} \]  \hspace{1cm} (1)

"The gradient \( \nabla I_p \) is computed as the maximum value of the image gradient in \( \Psi_p \cap I \)."

\[ \nabla I_p^\perp = \{ \nabla I_q^\perp \mid \arg \max_{q \in ((I-\Omega) \cap \psi_p)} \| \nabla I_q \| \} \]  \hspace{1cm} (2)
Single-scale inpainting: data term

\[ D_p = \frac{|\nabla I_p^\perp \cdot n_p|}{\alpha} \]  

(1)

"The gradient \( \nabla I_p \) is computed as the maximum value of the image gradient in \( \Psi_p \cap I \)."

\[ \nabla I_p^\perp = \{ \nabla I_q^\perp \mid \text{arg max}_{q \in ((I - \Omega) \cap \psi_p)} \| \nabla I_q \| \} \]  

(2)
A better data term

Data term based on the smoothed structure tensor field

$$\tilde{D}_p = \|G_p \cdot \vec{n}_p\|$$ \hspace{1cm} (3)

with

$$G_p = \sum_{q \in N_p \cap (I-\Omega)} w_p(q) \nabla \hat{I}_q \nabla \hat{I}_q^T$$ \hspace{1cm} (4)

$$w_p : 2d \text{ gaussian function, centered on } p.$$
A better data term

Data term based on the smoothed structure tensor field

\[
\tilde{D}_p = \|G_p \cdot \vec{n}_p\| \quad (3)
\]

with

\[
G_p = \sum_{q \in \mathcal{N}_p \cap (\mathcal{I} - \Omega)} w_p(q) \vec{\nabla} I_q \vec{\nabla} I_q^T \quad (4)
\]

\(w_p\) : 2d gaussian function, centered on \(p\).
Original data term from [Criminisi et al. '03]
Our data term
Inpainting result with original data term from [Criminisi et al. ’03]
Inpainting result with our data term
A better patch lookup strategy

- Inspired from [Ashikhmin ’01, PatchMatch ’09]
- Local/Global scheme
- Using location of already-reconstructed patches

Idea: Enhance the geometric cohesion of patches pasted side by side.
A better patch lookup strategy

\[
\psi_{\hat{p}} = \{ \psi_q \mid q = \arg \min_{r \in S(p)} d(\psi_p, \psi_r) \} \quad \text{avec} \quad S(p) = \bigcup_{i \in \Phi(p)} \mathcal{W}_{\hat{i} + p - i} \tag{5}
\]
A better patch lookup strategy

$$\psi_{\hat{p}} = \{ \psi_q \mid q = \arg \min_{r \in S(p)} d(\psi_p, \psi_r) \} \quad \text{avec} \quad S(p) = \bigcup_{i \in \Phi(p)} W_{i+p-i} \quad (5)$$
A better patch lookup strategy

$$
\psi_\hat{p} = \{\psi_q \mid q = \arg \min_{r \in S(p)} d(\psi_p, \psi_r)\} \quad \text{avec} \quad S(p) = \bigcup_{i \in \Phi(p)} \mathcal{W}_{i+p-i}
$$
Results

512 × 384

Original image
Results

512 × 384

Masked image
Results

512 × 384

Inpainting result with [Criminisi et al. '03] (4.5s)
Results

512 × 384

Inpainting result with our improvements (3.2s)
Results

800 × 450

Original image
Results

800 × 450

Masked image
Results

800 × 450

Inpainting result with [Criminisi et al. ’03] (1.7s)
Results

800 × 450

Inpainting result with our improvements (0.8s)
Contributions

A patch blending technique for inpainting
Patch blending: Idea
Patch blending: Idea
Patch blending: Idea
Patch blending: Idea
Patch blending : Method

► Idea : Visually minimize block artifacts due to side-by-side pasted patches.

1. Detect the locations of the artifacts
   ► Remember the location of the pasted patches

2. Spatial blending of the patches
   ► Reduce the block artifacts
Detect artifact locations

We build an estimated “map of artifacts”

- 2 hypotheses on their location
  - Local discontinuity in Color/Luminosity
  - Discontinuity in the source patch localization

Model by

\[ P_A = \| \nabla I \| \cdot div(\phi) \]

with \( \phi \) the shiftmap of the inpainting step done previously

Example of \( \phi \)
Detect artifact locations

We build an estimated “map of artifacts”
Detect artifact locations

We build an estimated “map of artifacts”
Detect artifact locations

We build an estimated “map of artifacts”
Detect artifact locations

Keep only the more visible

- Apply a simple threshold by a value $\tau \in [0, 1]$

$$L_A = \{ p \mid P_A(p) > \tau \}$$
Detect artifact locations

Keep only the more visible

- Apply a simple threshold by a value $\tau \in [0, 1]$

$$L_A = \{ p \mid P_A(p) > \tau \}$$
Detect artifact locations

Build a “blending amplitude map”.

\[
\sigma(p) = \rho \cdot \frac{\sum_{q \in L_A} w(p, q)}{\max_{r \in I} \sum_{q \in L_A} w(p, q)}
\]  

(6)

with

\[
w(p, q) = \exp \left( - \frac{\|p - q\|^2}{2 \cdot PA(q)^2} \right)
\]  

(7)

where \( \rho \) is the maximum blending bandwidth
Detect artifact locations

Build a “blending amplitude map”.
Detect artifact locations

Build a “blending amplitude map”.
Spatial blending of patches

Compute a weighted average of pixels from patches that overlap:

\[ J(p) = \frac{\sum_{\psi_q \in \Psi_p} w(p, q) \cdot \psi_q(p - q)}{\sum_{\psi_q \in \Psi_p} w(q, p)} \]  

(6)

- \( w(p, q) = \exp \left( -\frac{d(p, q)^2}{2 \cdot \sigma(p)^2} \right) \)
- \( d(p, q) = \min_{r \in \mathcal{N}_q} \| p - q \| \)
- \( \Psi_p = \{ \psi_q \mid \psi_q \cap \psi_p \neq \emptyset \} \)

- Computational complexity equivalent to a 2d convolution (with a spatially varying kernel)
  - But, fast algorithm when \( \sigma \) is quantized.
Spatial blending of patches

Masked image
Spatial blending of patches

Inpainting result with improved version of [Criminisi et al. ’03]
Spatial blending of patches

Result after patch blending
Spatial blending of patches

Original image
Spatial blending of patches

Masked image
Spatial blending of patches

Inpainting result with improved version of [Criminisi et al. ’03]
Spatial blending of patches

Result after patch blending (1.2 s)
Inpainting result with improved version of [Criminisi et al. ’03]
Result after patch blending (isotropic blending)
Is it possible to take the local geometry of the image contours into account?
Analog with image regularization

Anisotropic image regularization

image bruitée  
tenseurs de structure  
tenseurs de structure lissés de manière isotope  
tenseurs de diffusion  
image lissée avec contours préservés

lissage d’image anisotope
Analogy with image regularization

Anisotropic blending of patches
A tensor model for patch blending

From structure tensors:

- Eigenvalues of the blending tensors

\[ \lambda_{Bi} = \frac{1}{(1 + \hat{\lambda}_{S1} + \hat{\lambda}_{S2})\gamma_i} \]

where \( \gamma_i \) is a parameter related to the overall anisotropy of the tensors.

- Blending tensors are computed as:

\[ B = \lambda_{\sigma B1} e_{S1}^\perp . T e_{S1}^\perp + \lambda_{\sigma B2} e_{S2}^\perp . T e_{S2}^\perp \]  

(7)

- \( e_{Si} \): eigenvectors of the (inpainted) structure tensor
- \( \lambda_{\sigma Bi} = \sigma_B \lambda_{Bi} \)
- \( \sigma_B \): maximal bandwidth of the blending
A tensor model for patch blending

Example of blending tensor field
A tensor model for patch blending

\[ J(p) = \sum_{\psi_q \in \Psi_p} \frac{w(p, q) \cdot \psi_q(p - q)}{\sum_{\psi_q \in \Psi_p} w(p, q)} \]

\[ w(p, q) = \begin{cases} 
\exp \left( -\frac{||p-q||^2}{2\sigma(p)^2} \right) & \text{isotropic} \\
\exp \left( X^T B(p)^{-1} X \right) & \text{anisotropic (edge-oriented)}
\end{cases} \]

where \( X = q - p \)
Inpainting result with improved version of [Criminisi et al. ’03] without patch blending
After *isotropic* patch blending
After *anisotropic* patch blending
Masked image
Inpainted without blending
After isotropic blending
After anisotropic blending
Original image
Inpainted with [Criminisi et al. 2003]
Inpainting with anisotropic patch blending
Contributions

Extension to video sequences
Video inpainting

- Inpainting priorities are still computed frame by frame
- But patches and lookup regions are now in 3d
  - e.g. with size $5 \times 5 \times 3$
Video inpainting

Patch lookup strategy is easily extended in 3D
Video inpainting

Adding a temporal term to the blending tensors (that are now 3x3)

\[
B = \lambda_{\sigma B_1} e_{S_1} \cdot T e_{S_1} + \lambda_{\sigma B_2} e_{S_2} \cdot T e_{S_2} + \lambda_{\sigma B_3} e_{S_3} \cdot T e_{S_3}
\]

(8)
Video inpainting

Beach Umbrella

Video + mask

Without blending

With blending
Video inpainting

Fontaine Chatelet

Video + mask

Without blending

With blending
Reconstruction of Resynthetized Stereoscopic Views
Initial image (from stereo pair)
Resynthesized viewpoint (from stereo + depth-map)
Inpainted with standard inpainting algorithm.
Inpainting depth-map

We have designed a specified inpainting algorithm to reconstruct missing regions in depth-map:

1. Segment the original depth-map (the one without holes) $J_o$
2. Estimate the motion of those super-pixels between $J_o$ and $J_s$ \textit{(registration)}
3. Reconstruct missing pixels in $J_s$ from interpolating several correspondent in $J_o$. 
Algorithm [Criminisi, Pérez et Toyama ’03] with our improvements + taking the depth into account:

- Modification of the confidence term $C_p$
- Modification of the lookup strategy
- Modification of the patch synthesis step
- A single additional parameter
  - $\lambda$: Threshold to gather/differenciate pixels considered to have same/different depths
Inpainting with depth-map

- Modification of the confidence term $C_p$

\[ C_p = \frac{1}{N_p} \sum_{q \in N_p \cap (\mathcal{I}_s - \Omega)} |J_s(p) - J_s(q)| < \lambda \]

(9)
**Inpainting with depth-map**

- **Modification of the confidence term** $C_p$

\[
C_p = \frac{1}{N_p} \sum_{q \in N_p \cap (I_s - \Omega)} C_q
\]

\[
|J_s(p) - J_s(q)| < \lambda
\]

(9)
Inpainting with depth-map

Patch lookup strategy

\[ \psi_{\hat{p}} = \left\{ \psi_q \in I_o \mid \arg\min_{q} d(\psi_p, \psi_q) \right\} \]

\[ \text{arg min} |J_o(q) - J_s(p)| < \lambda \]

(10)
Inpainting with depth-map

- Patch synthesis, only for pixels with same depth

\[
\psi_p(q) = \psi_{\hat{p}}(r) \quad \text{if} \quad q \in N_p \cap \Omega \quad \text{and} \quad |J_o(r) - J_s(q)| < \lambda
\]  

(11)
Inpainting with depth-map
Inpainting with depth-map

Resynthesized viewpoint
Inpainting with depth-map

Inpainted viewpoint, with depth constraints
Inpainting with depth-map

Resynthesized viewpoint (without depth constraints)
Inpainting algorithm with spatial patch blending in:

[http://gmic.eu]