Error-tolerant Image Compositing

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Adobe Systems Inc.
naïve compositing
Poisson compositing
our result
Objectives

Seamless compositing

• Robust to inaccurate selection
• Output Quality
  - Limit color bleeding
• Time-Performance
  - Efficient method
Related Work: Poisson Compositing

Pasting gradients instead of pixels
Pérez 03, Georgiev 06, ...

Pros:
• Blends seamlessly
• Linear computation

Cons:
• Bleeding visible
• Foreground to background bleeding

Poisson Compositing Result
Related Work: $L_1$ Norm

Introduced in shape from shading
Reddy 09

Pros:
- Reduced bleeding

Cons:
- Nonlinear
  - Computationally intensive

$L_1$ Norm Result
Related Work: Moving Boundaries

Move the boundaries to avoid bleeding
Jia 06

Pros:
• Avoids bleeding

Cons:
• We don’t want boundaries to change
• Changed composition
Contributions

• Conceal bleeding in textured areas
• Better gradient field at boundary
• Efficient linear scheme
Overview

→ Problem Description
  • Hiding Residuals with Visual Masking
  • Generating a low-curl boundary
  • Results and Comparisons
Algorithm Overview

Foreground

Selection

Background
Algorithm Overview

Foreground

Selection

Background

grad

grad
Algorithm Overview

1. **Selection**
   - Background
   - Foreground

2. **Grad**
   - Foreground
   - Background

3. **Grad Field**
   - Target gradient field

4. **Paste**
   - Target image
Algorithm Overview

Foreground

Selection

+ 

Grad

Background

Grad

Target gradient field

Result

Grad

Paste

Integrate
We seek image $I$ with gradients close to target $\mathbf{v}$.

**target gradient field**

$$
\mathbf{v} = \begin{cases} 
\nabla \text{Foreground} & \text{within selection} \\
\nabla \text{Background} & \text{out of selection} \\
\frac{\nabla \text{Foreground} + \nabla \text{Background}}{2} & \text{boundary of selection}
\end{cases}
$$
We seek image $I$ with gradients close to target $\mathbf{v}$.

**target gradient field**

$$
\mathbf{V} = \begin{cases} 
\nabla \text{Foreground} & \text{within selection} \\
\nabla \text{Background} & \text{out of selection} \\
\frac{\nabla \text{Foreground} + \nabla \text{Background}}{2} & \text{boundary of selection}
\end{cases}
$$

**Least-squares:**

$$
\int \| \nabla I - \mathbf{v} \|^2
$$

**output gradient field**
Our Approach

We seek image $I$ with gradients close to target $\mathbf{v}$.

target gradient field

$$\mathbf{v} = \begin{cases} \nabla \text{Foreground} & \text{within selection} \\ \nabla \text{Background} & \text{out of selection} \\ \text{value that minimizes curl} & \text{boundary of selection} \end{cases}$$

Weighted least-square:

$$\int W_P \left\| \nabla I - \mathbf{v} \right\|^2$$

weight output gradient field
Overview

• Problem Statement

  ➡ Hiding Residuals with Visual Masking
  • Generating a low-curl boundary
  • Results and Comparisons
Our Strategy

• Use the weights to locate integration residuals where they are less visible

• Exploit perceptual effect: visual masking
  – human perception affected by texture.
Visual Masking Demo

Can you spot all the dots?
Visual Masking Demo

Texture hides low-frequency content
Visual Masking Demo

Can you spot all the dots?
Design of the Weights

\[ \int W_P \| \nabla I - v \|^2 \]

- Smooth region: needs high weight to prevent bleeding
- Textured regions: low weight is ok because bleeding less visible

Weights (white is high)
Estimating the Amount of Texture

RGB gradient field

\[ T_{\sigma_1, \sigma_2}(g) = \frac{G_{\sigma_1} \otimes \|g\|}{G_{\sigma_2} \otimes \|g\|} n(\|g\|) \]

\[ \sigma_1 < \sigma_2 \]
Estimating the Amount of Texture

\[ T_{\sigma_1, \sigma_2}(g) = \frac{G_{\sigma_1} \otimes \|g\|}{G_{\sigma_2} \otimes \|g\|} n(\|g\|) \]

RGB gradient field

Small Gaussian convolution

Noise controlling function

Large Gaussian convolution
Estimating the Amount of Texture

$$T_{\sigma_1, \sigma_2}(g) = \frac{G_{\sigma_1} \otimes \|g\|}{G_{\sigma_2} \otimes \|g\|} n(\|g\|)$$

small Gaussian \hspace{1cm} large Gaussian

gradient field $g$
Estimating the Amount of Texture

Texture Map Output (white indicates more texture)
Weight Formula

\[ W_P = 1 - T(v) \]

- \( v \) depends only on foreground and background
  - does not depend on the unknown \( I \)
  - weights are constant in the optimization
- our energy is a classical least-squares optimization

\[ \int W_P \left\| \nabla I - v \right\|^2 \]
Hiding Residuals with Visual Masking

Bleeding only in textured areas

Poisson compositing

With texture weights
Hiding Residuals with Visual Masking

Residuals $\|\nabla I - v\|^2$

Poisson compositing

With texture weights
Hiding Residuals with Visual Masking

Reduced bleeding but not fully

Poisson compositing

With texture weights
Overview

• Problem Statement
• Hiding Residuals with Visual Masking

Generating a low-curl boundary

• Results and Comparisons
Boundary Problems

• Target field $v$ integrable iff $\text{curl}(v)=0$
• Only boundary has non-zero curl
  – Consequence of target field construction (see paper)

• Our strategy: reducing the curl
Naïve Approach

• Minimize $\int_\beta [\text{curl} \ (\mathbf{v})]^2$

• Unfortunately, the result is not seamless:

output of naïve approach

close-up
Our Approach: Least Squares Trade-off

- Unknowns: target field $\mathbf{v}$ along boundary
- Weights depend on texture (detail in paper)

$\int_\beta \left( [\text{curl} (\mathbf{v})]^2 + W_\beta \left[ \mathbf{v} - \frac{1}{2} (\nabla B + \nabla F) \right]^2 \right)$
Overview

• Problem Statement
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• Generating a low-curl boundary

Results and Comparisons
Results and Comparisons

Copy-and-paste
Results and Comparisons

Poisson Reconstruction: Pérez 03, Georgiev 06, ...
Results and Comparisons

Maximum Gradient : Pérez 03
Results and Comparisons

Diffusion: Agrawal 06
Results and Comparisons

Lalonde 07
Results and Comparisons

$L_1$ Norm : Reddy 09
Results and Comparisons

Our Result
Results and Comparisons

<table>
<thead>
<tr>
<th>Method</th>
<th>Running Time (Seconds)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Our Result</td>
<td></td>
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<tr>
<td>L_1 Norm</td>
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</tr>
<tr>
<td>Lalonde</td>
<td></td>
</tr>
<tr>
<td>Diffusion</td>
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</tr>
<tr>
<td>Max</td>
<td></td>
</tr>
<tr>
<td>Poisson</td>
<td></td>
</tr>
</tbody>
</table>

- The graph shows the running time (in seconds) for different methods: Our Result, L_1 Norm, Lalonde, Diffusion, Max, and Poisson.
- The L_1 Norm method has the highest running time, followed by Lalonde, Diffusion, Max, and Poisson with the lowest running time.
Results and Comparisons

Poisson
Results and Comparisons

Our Result
Results and Comparisons

Poisson
Results and Comparisons

Our Result
Discussion

• Several parameters
  - all examples use the same parameters

• Discoloration may happen
  - happens in all gradient based operators

• Our model of visual masking is simple
  - good for performance
  - more complex model could be used
Conclusion

• Robust compositing using visual masking
• Better gradient field at boundary
• Efficient linear scheme
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Conclusion

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![Poisson Reconstruction](image1)

![Our Result](image2)
Results and Comparisons

- max gradient
- Poisson
- diffusion
- Lalonde
- ours
- L1

bleeding compared to Poisson

running time (log scale)
Results and Comparisons

Poisson
Results and Comparisons

Our Result