Fragment-Based Image Completion

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presented by

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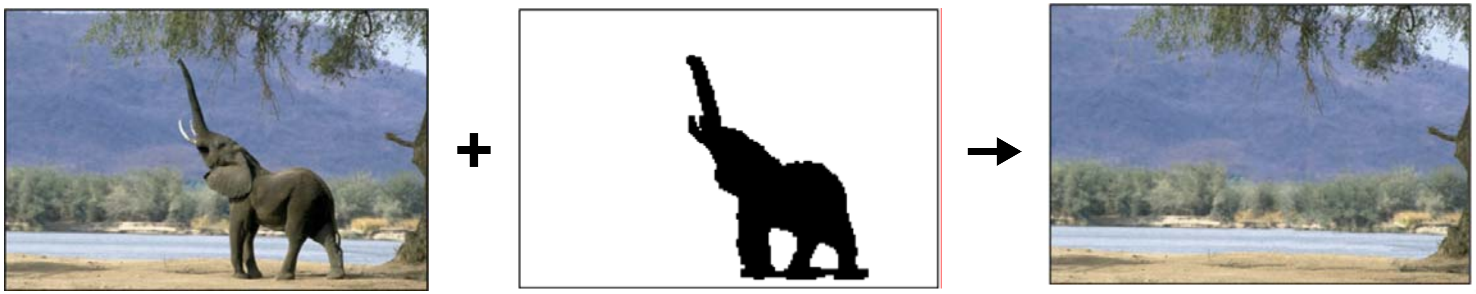
Overview

- Problem Statement
- Examples
- Algorithm
- Results
- Limitations
- Solutions
- Discussion

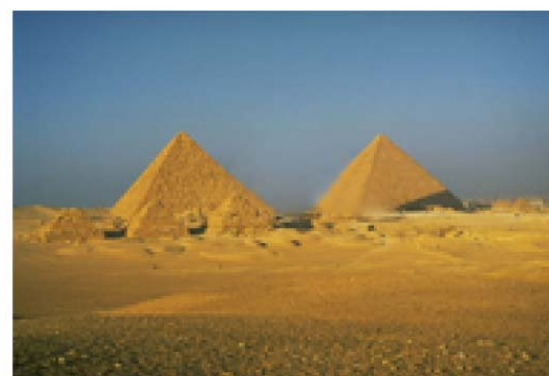
Problem Statement

- Fill holes in images caused by removal of unwanted objects
- Motivation: ability of our visual system to “fill in” missing areas

- Given an image and an inverse matte → complete unknown regions based on known regions



Examples – Photographs



Examples - Paintings

Algorithm - Overview

Input: image C, inverse matte $\bar{\alpha}$ ($\exists$ pixel with $\bar{\alpha} < 1$)

Output: completed image, $\bar{\alpha} = 1$

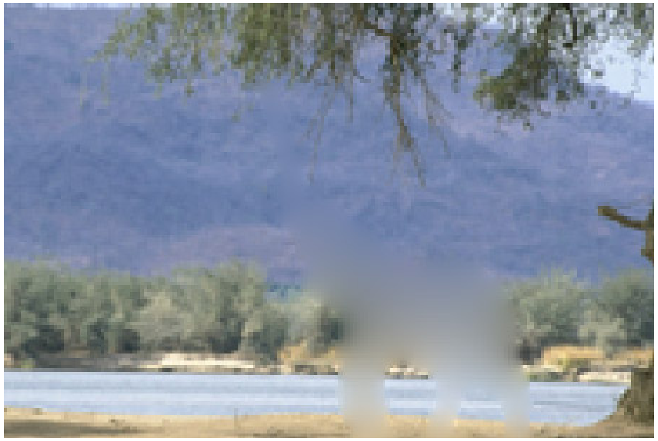
Algorithm:

For each scale from coarse to fine
    approximate image from color and coarser scale
    compute **confidence map** from $\bar{\alpha}$ and coarser scale
    compute **level set** from confidence map
    while mean confidence $< 1 - \varepsilon$
        for next target position p
            compute **adaptive neighborhood** N(p)
            search for most similar and frequent source match N(q)
            composite N(p) and N(q) at p, updating color and $\bar{\alpha}$
            compute **approximation, confidence map** and update **level set**

Algorithm –
Fast Approximation

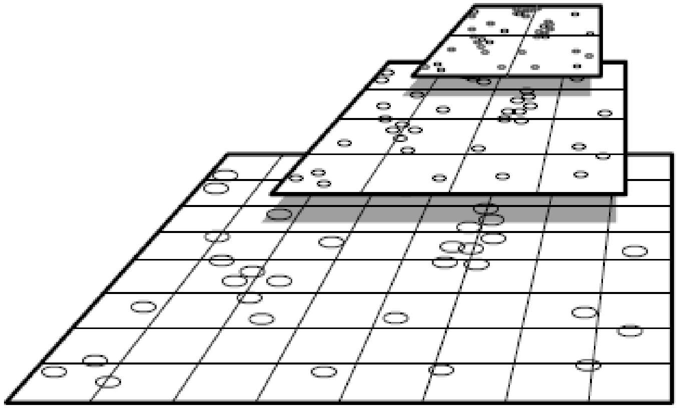
- Estimate colors of unknown region with iterative filtering of known values
- ‘Smear’ colors into unknown region

→

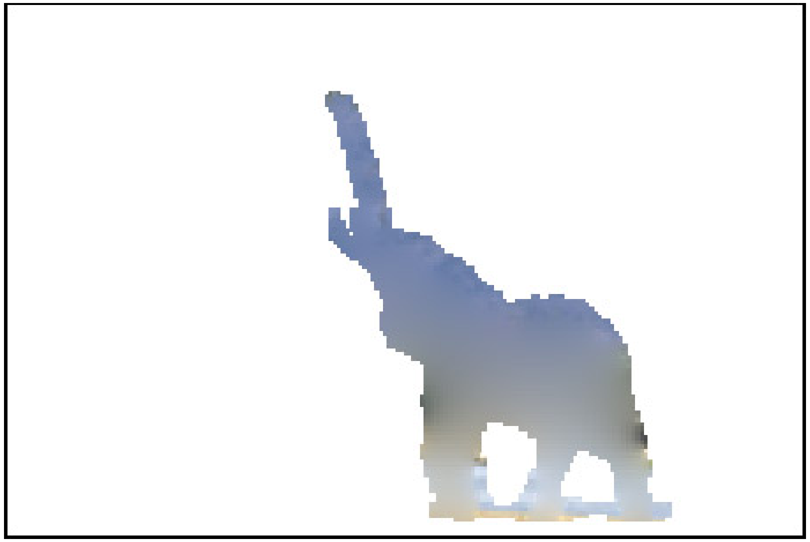


Algorithm – Fast Approximation

- Simple iterative filtering method
- Build pyramid with image at different scales
- Down-sample and up-sample image hierarchically with kernel at multiple resolutions



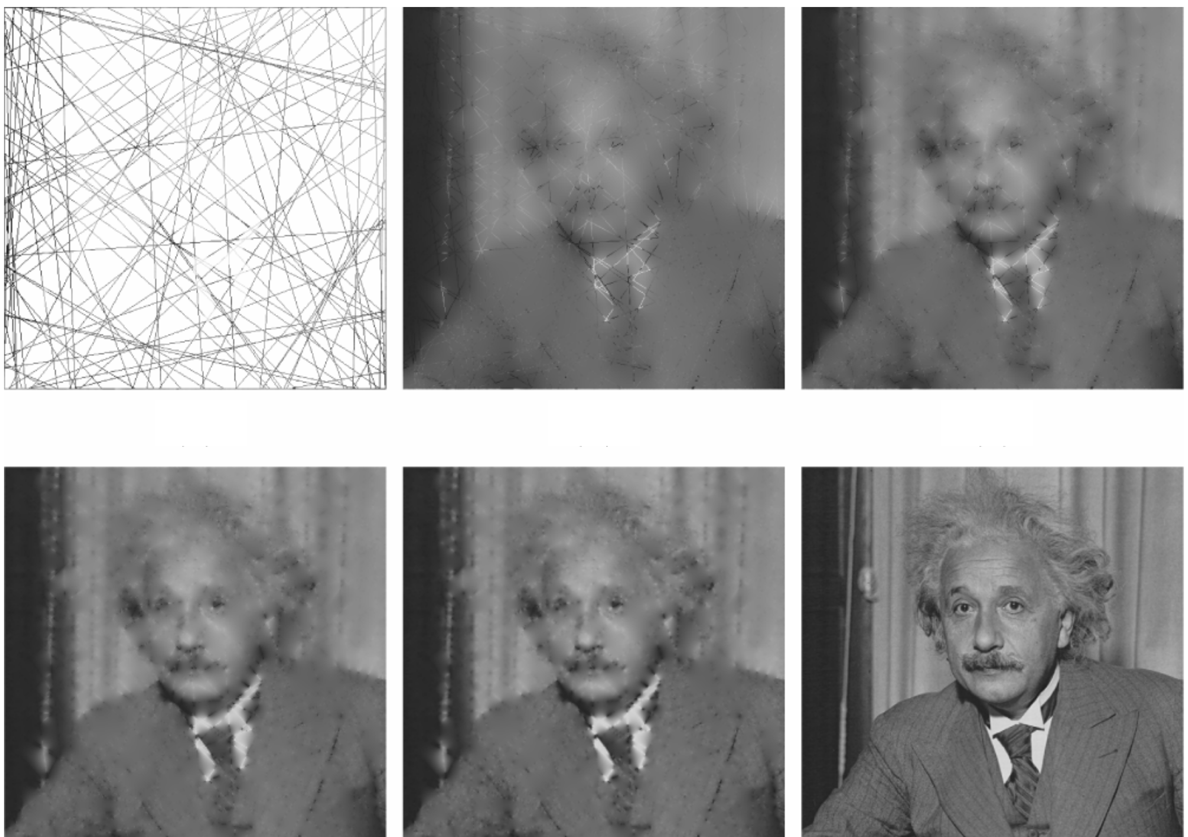
Algorithm – Fast Approximation



- Use this region for the approximation at the next level

Algorithm – Fast Approximation

- Illustration:



Algorithm - Overview

Input: image C, inverse matte $\bar{\alpha}$ ($\exists$ pixel with $\bar{\alpha} < 1$)

Output: completed image, $\bar{\alpha} = 1$

Algorithm:

For each scale from coarse to fine

  $\boxed{\textbf{approximate}}$ image from color and coarser scale

  compute $\boxed{\textbf{confidence map}}$ from $\bar{\alpha}$ and coarser scale

  compute $\boxed{\textbf{level set}}$ from confidence map

  while mean confidence $< 1-\varepsilon$

    for next target position p

      compute **adaptive neighborhood** N(p)

      search for most similar and frequent source match N(q)

      composite N(p) and N(q) at p, updating color and $\bar{\alpha}$

      compute **approximation, confidence map** and update **level set**

Algorithm – Confidence Map

- Define confidence map β by assigning a value in [0, 1] to each pixel i

$$\beta_i = \begin{cases} 1 & \text{if } \overline{\alpha}_i = 1 \\ \sum_{j \in N(i)} g_j \overline{\alpha}_j^2 & \text{otherwise} \end{cases}$$

- This tells us how confident we are in our approximation (1 = most confident)

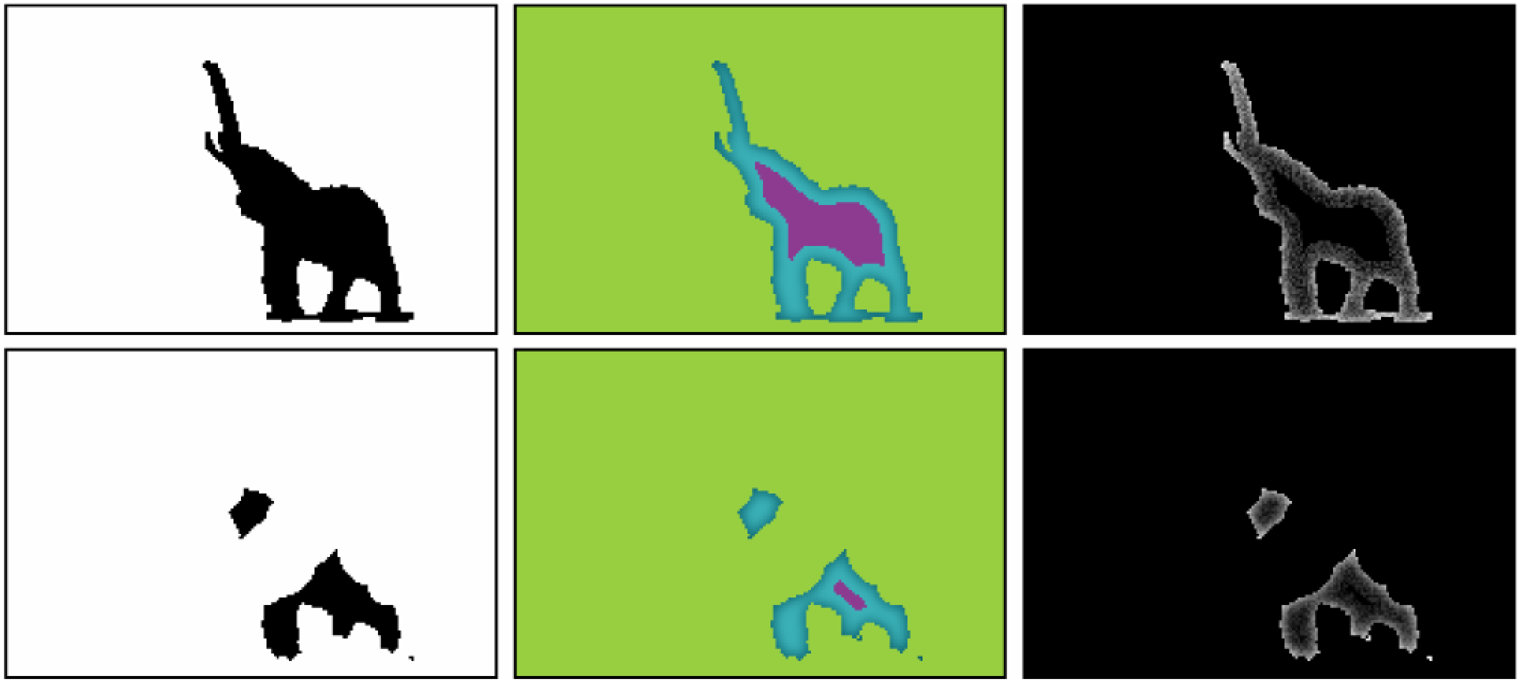
Algorithm – Level Set

- Compute Level Set with similar confidence values:

$$v_i = \begin{cases} 0 & \text{if } \beta_i > \mu(\beta) \\ \beta_i + \rho[0, \sigma(\beta)] & \text{otherwise} \end{cases}$$

- Next target position = Largest value in level set

Algorithm – Confidence Map, Level Set



Inverse matte | Confidence map | Level set

Algorithm - Overview

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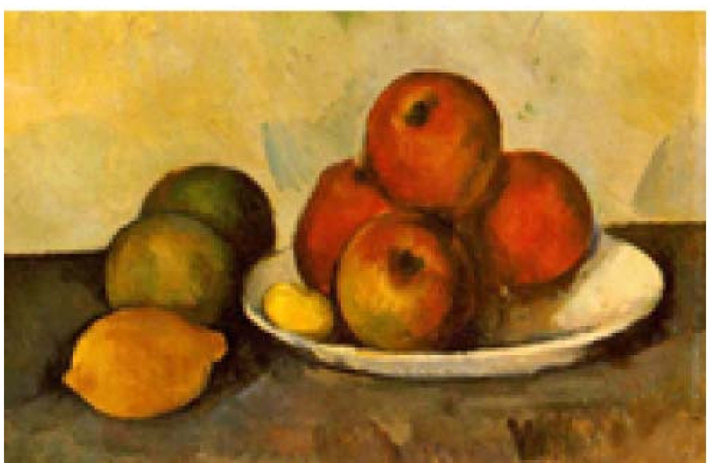
Algorithm – Adaptive neighborhood

- Determine size of neighborhood with a contrast criterion:

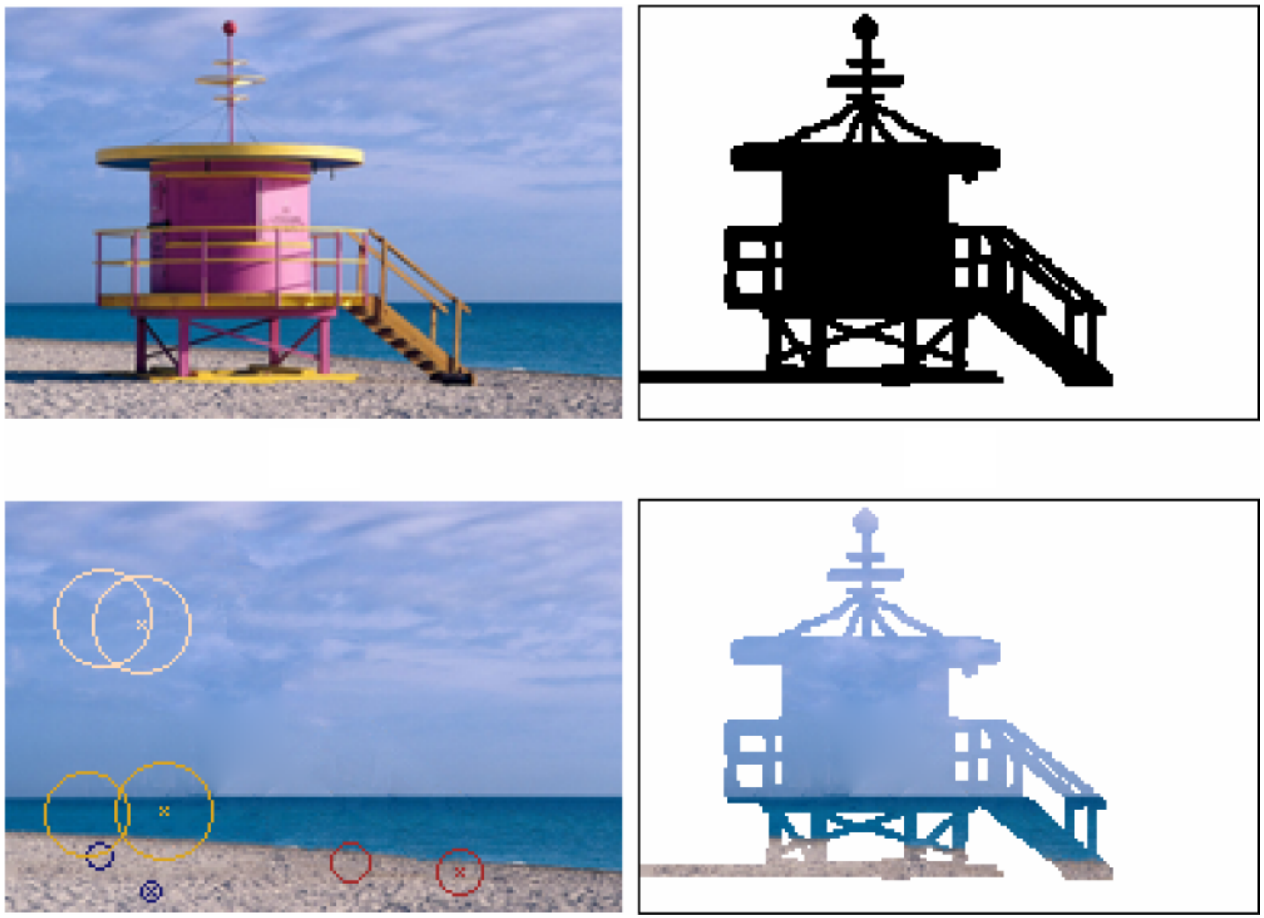
  → Absolute of difference between extreme values across color channels



Algorithm – Search for best Fragment

- For each target fragment T, search for best source fragment S over
  - all positions (x, y)
  - 5 scales l
  - 8 orientations θ
- Add detail only to kernel approximated pixels, do not modify known pixels

Algorithm – Search for best Fragment



Algorithm – Search for best Fragment

- Find position, scale and orientation of source fragment by minimizing

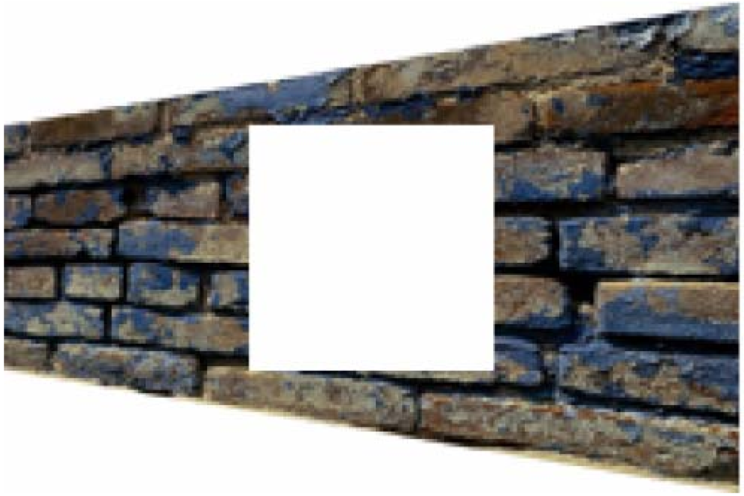
$$r^* = \arg\min_r \sum_{s=S_r(i),t=T(i),i\in N} (\underline{d(s,t)\beta_s\beta_t} + \underline{(\beta_t - \beta_s)\beta_t})$$

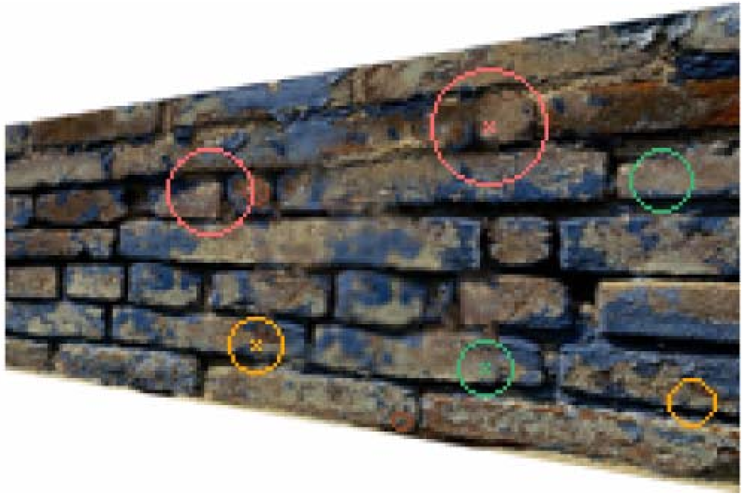
Penalizes different values in corresponding pixels with high confidence in both source and target fragment

Rewards pixels with higher confidence in source than in target, while penalizing pixels with lower confidence in source than in target

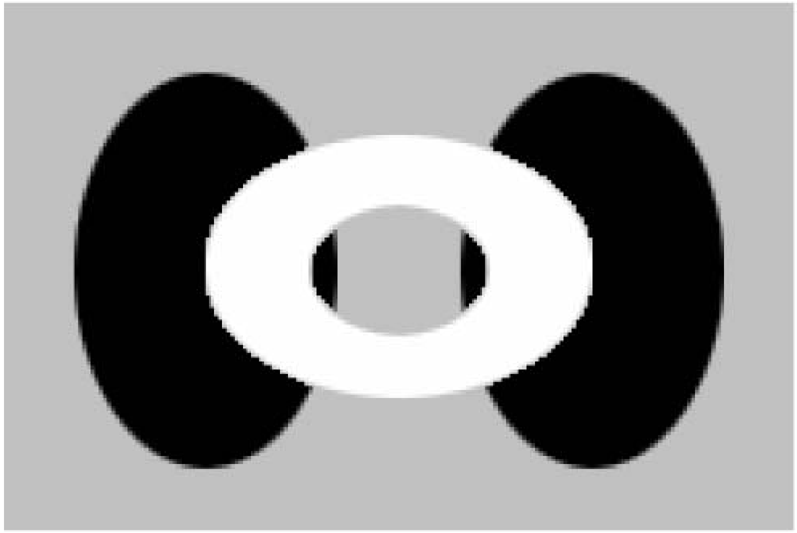
Algorithm – Search for best Fragment

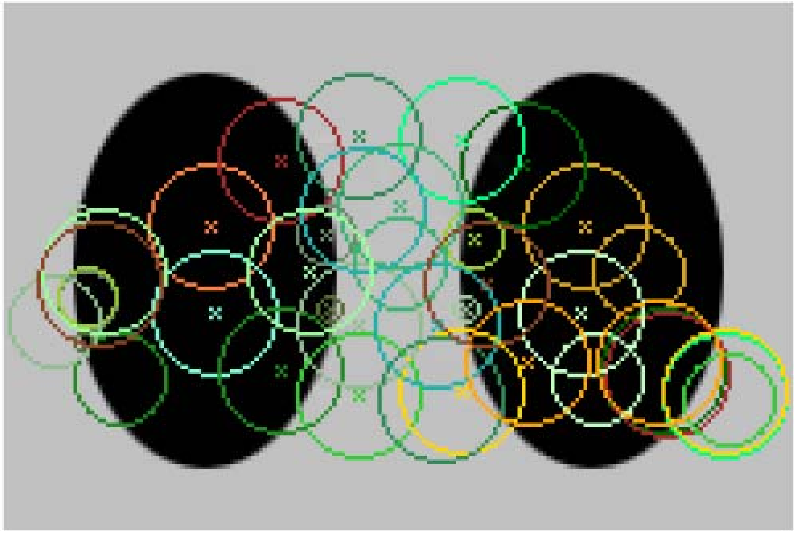
- Complete structured texture in perspective by searching in different scales





Algorithm – Search for best Fragment





- Complete symmetric shapes by searching under rotations and reflections

Algorithm - Overview

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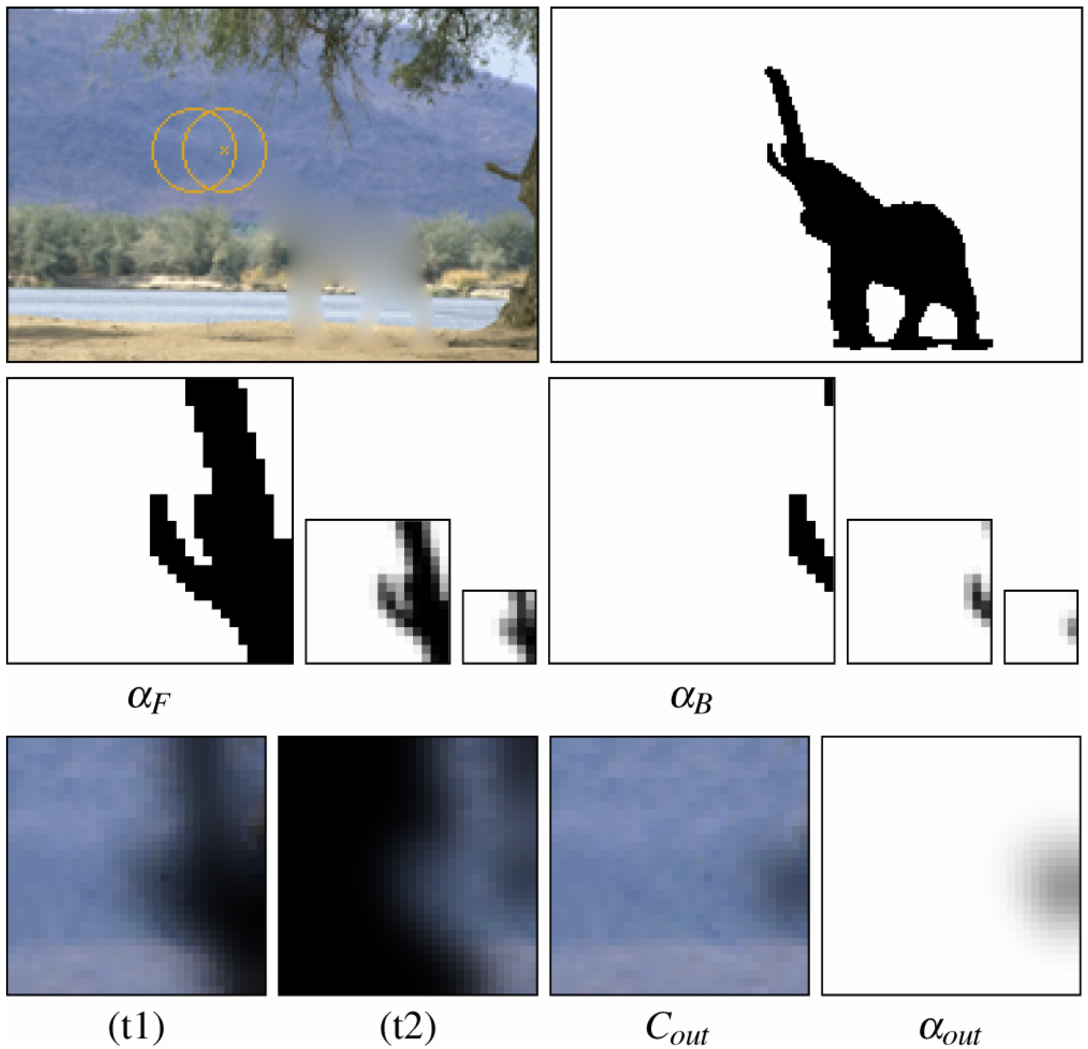
Algorithm – Composite Fragment

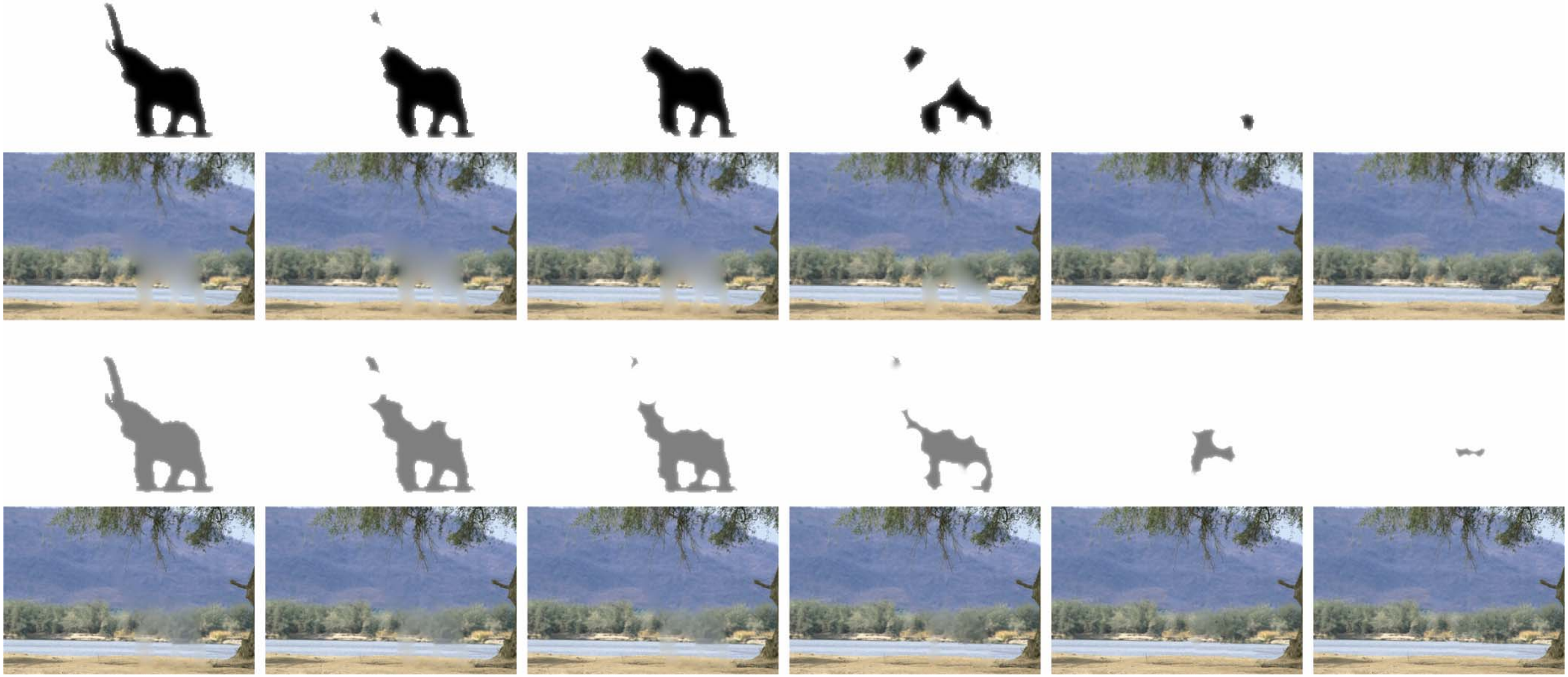
- Laplacian pyramid for smooth merging of source and target image using binary masks
  - Color components decomposed into Laplacian pyramids L
  - Binary masks decomposed into Gaussian pyramids G

$$L_k(C_{out}) = L_k(C_F)G_k(\alpha_F) + L_k(C_B)G_k(\alpha_B)G_k(1-\alpha_F)$$

Algorithm – Composite Fragment



Algorithm - Overview



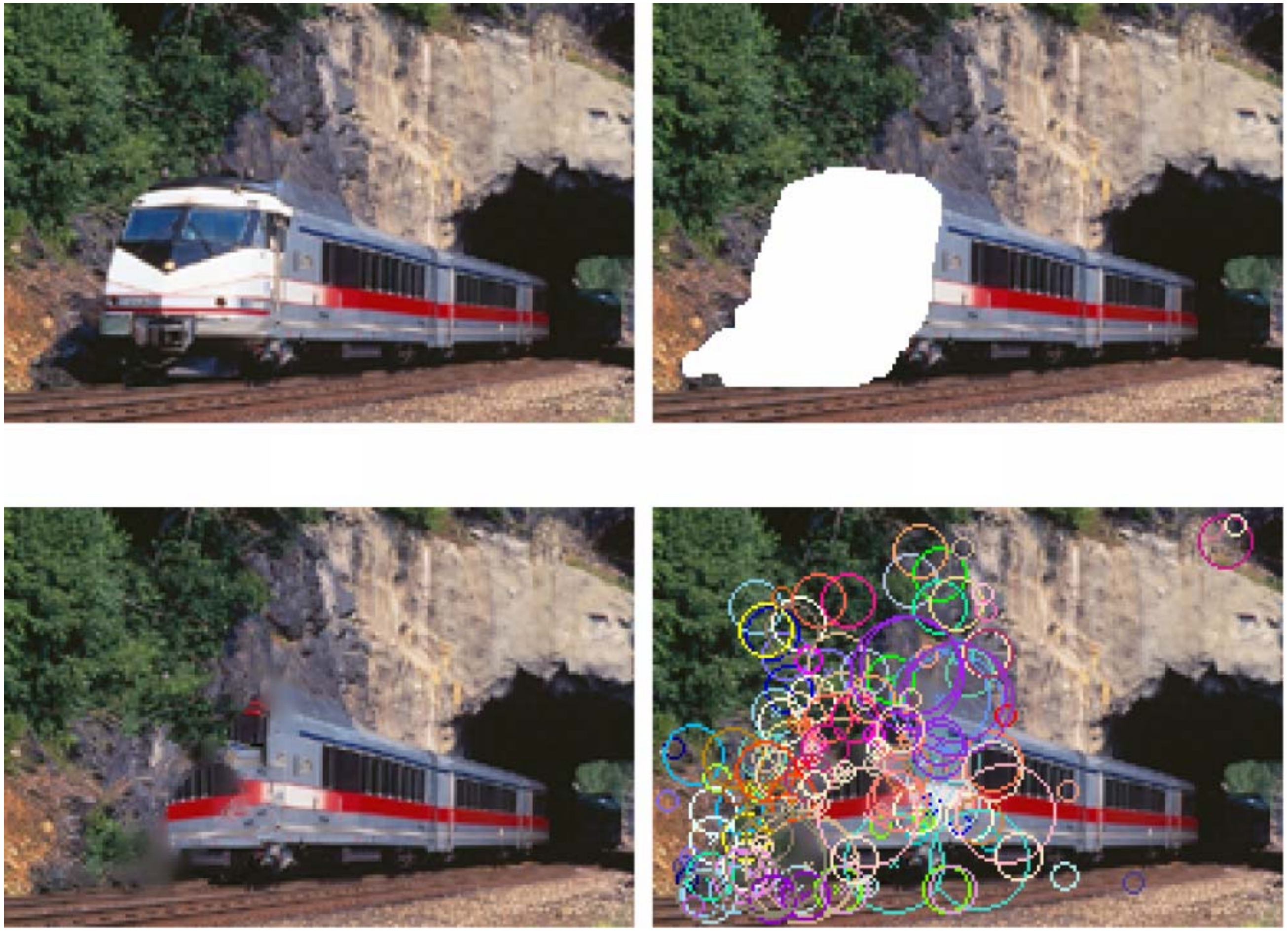
Results

- Computation time on 2.4 GHz processor initial mean confidence $\mu(\beta) > 0.7$
  - 120 to 419 seconds for 192 x 128 images
  - 83 to 158 minutes for 384 x 256 images
- 90% of the total computation time is spent on search for matching fragments
- Computation time is quadratic in the number of pixels

Limitations

- Example-based approach
  - performance is directly dependent on richness of available fragments
  - In all presented examples, training set is known region of single image → rather limited
- 2D image-based method
  - No knowledge of underlying 3D structure in image
- No distinction between figure and ground
  - Limitation for completion when inverse matte is on boundary of a figure

Limitations



Limitations

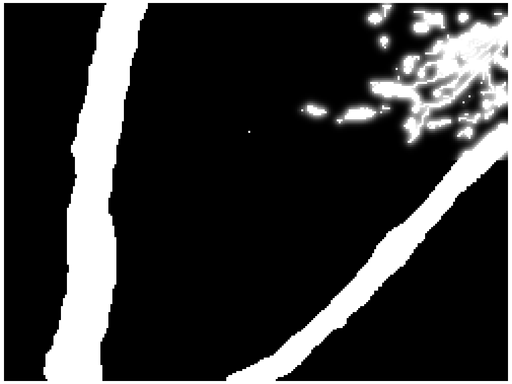
- Does not handle ambiguities in which missing area covers intersection of two perpendicular regions

Solutions

- User specifies point of interest

Solutions

- User specifies region bridges

Discussion

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