An Integrated System for Digital Restoration of Prehistoric Theran Wall Paintings

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1 Automatic detection of missing areas

- Morphological Processing & Edge Detection
- Interactive graph cuts

2 Inpainting

- Total variation inpainting

3 Image stitching and non-local inpainting

- The big picture
- Seamless image stitching

The problem

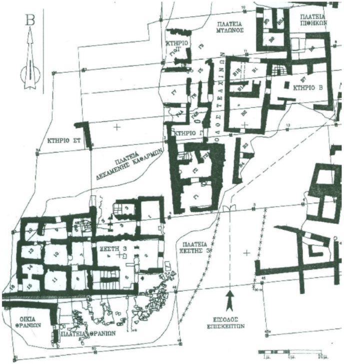
Goal

The semi-automatic digital restoration of wall paintings that have been found at the prehistoric settlement Akrotiri, Santorini, Greece by leveraging methods from the areas of Computer Vision, Image Processing and Pattern Recognition.

Motivation

We want to replace or support the highly demanding and time-consuming work of the specialist.

Topological diagram of archaeological site



The digitization of wall paintings was done by George Papandreou during his PhD at NTUA CVSP lab (cvsp.cs.ntua.gr).

The wall painting *"Saffron gatherer & Potnia"*

Κροκοσυλλέκτρια & Πότνια.

The wall painting *"Men in procession"*

Ακολουθία Ανδρών.

The wall painting *"Women in procession"*

Ακολουθία Γυναικών.

Outline

Crack detection using Morphological Processing and Edge Detection (region & boundary based approach)

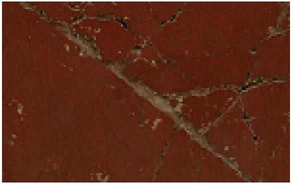
Exploiting gradient information (*region* based processing)

- We find the areas where our image presents high relative intensity variation along some of the main axes.
- After grouping with morphological closing, we get the region based mask.

Exploiting edge information (*boundary* based processing)

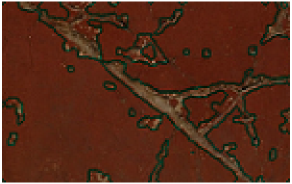
- The Canny method is used for edge detection.
- The binary image of edges is dilated with a disk.
- We calculate the logical disjunction of the binary images of dilated edges and region based mask.
- We iteratively apply erosion with the unit disk. We stop before a predefined percentage of edge information is lost.

1^{st} crack detection example



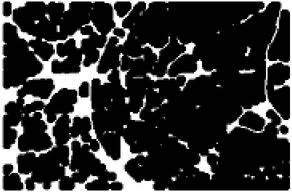
(a) Area with cracks

(b) Binary mask

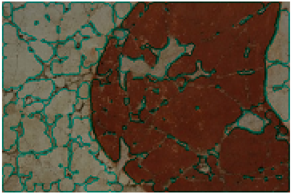


(c) Crack detection

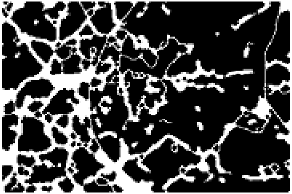
2^{nd} crack detection example



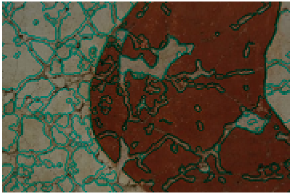
(a) Using only morphological processing



(b) Mask outline



(c) Incorporating edge information



(d) Enhanced mask outline

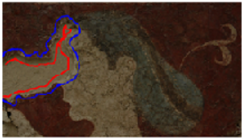
Outline

Interactive graph cuts segmentation

- The image is an array $\mathbf{z} = (z_1, \ldots, z_N)$ of grey values.
- The segmentation is the process of assigning labels $\alpha_n \in \{0, 1\}$ at each pixel.
- The user initializes the trimap $T = (T_B, T_F, T_U)$ by roughly defining the background and the foreground.
- Grey values distributions via histograms $\underline{\theta} = \{h(z; \alpha), \alpha = 0, 1\}$.
- Segmentation as minimization of functional:

$$\hat{\underline{\alpha}} = argmin_{\underline{\alpha}} \mathbf{E}(\underline{\alpha}, \underline{\theta}, \mathbf{z})$$

where $\mathbf{E}(\underline{\alpha}, \underline{\theta}, \mathbf{z}) = \underbrace{U(\underline{\alpha}, \underline{\theta}, \mathbf{z})}_{data\ \ fit} + \underbrace{V(\underline{\alpha}, \mathbf{z})}_{smoothness}$.



Y. Boykov & M. P. Jolly (ICCV, 2001).
Interactive graph cuts for optimal boundary and region segmentation of objects in N-D images.

"GrabCut" algorithm

Initialization

- The user supplies explicitly only the background:

$$T = (T_B, T_F, T_U) = (T_B, \emptyset, \overline{T_B}).$$

- "Hard" segmentation:

$$a_n = \begin{cases} 0 & n \in T_B \\ 1 & n \in T_U \end{cases}$$

- Color modelling via GMM-5, one for the background and one for the foreground.

C. Rother, V. Kolmogorov & A. Blake (ACM Trans. Graph., 2004). "GrabCut": Interactive foreground extraction using iterated graph cuts.

Iterative energy minimization

1. Assign GMM components for each pixel $n \in T_U$:

$$k_n := argmin_{k_n} \underbrace{D_n(\alpha_n, k_n, \theta, z_n)}_{data\ term\ for\ n\ pixel}$$

2. Learn GMM parameters from data $\mathbf{z}$:

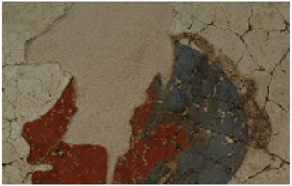
$$\underline{\theta} := argmin_{\underline{\theta}} U(\underline{\alpha}, \mathbf{k}, \underline{\theta}, \mathbf{z})$$

3. Estimating segmentation by using min cut to solve:

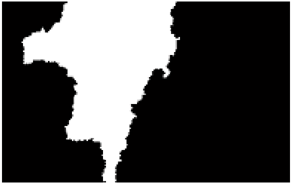
$$\min_{\{\alpha_n:\, n \in T_U\}} \min_{\mathbf{k}} \mathbf{E}(\underline{\alpha}, \mathbf{k}, \underline{\theta}, \mathbf{z})$$

4. Repeat from step 1, until convergence.

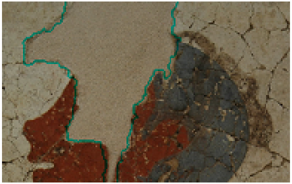
Detecting the crack boundaries with “GrabCut”



(a) Missing area



(b) The extracted mask



(d) Mask’s outline over the image

(c) The smoothed mask

Mask enhancement for major missing areas

- A tentative mask M is extracted by leveraging morphological filters and edge detection.
- Let B a circular disk. The trimap T is initialized:

$$T = (T_B,\ T_F,\ T_U) = ((M \oplus B)^c,\ M \ominus B,\ (T_B \cup T_F)^c).$$

- The "GrabCut" with inputs the initial image and the trimap T provides the enhanced mask M'.

Outline

Total variation denoising model

- Noisy image

$$u^0(x) = u(x) + n(x)$$

- Random noise

$$E[n(x)] = 0,\ E[n^2(x)] = \sigma^2$$

- Denoising as minimization:

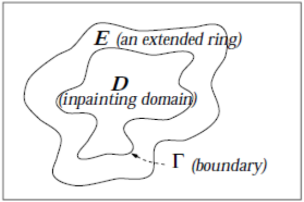
$$min J[u] = \int_\Omega |\nabla u| dx + \frac{\lambda}{2} \int_\Omega (u - u^0)^2 dx$$

under the constraints:

$$\int_\Omega u dx = \int_\Omega u^0 dx, \qquad \frac{1}{|\Omega|} \int_\Omega (u - u^0)^2 dx = \sigma^2$$

L. I. Rudin, S. Osher & E. Fatemi (Physica, 1992).
Nonlinear total variation based noise removal algorithms.

Total variation inpainting



- Locality
- Noise robustness
- Edge restoration
- Optimality

⇒ Minimization of Lagrange functional:

$$J_\lambda[u] = \int_{E \cup D} |\nabla u| dx + \frac{\lambda}{2} \int_E (u - u^0)^2 dx$$

J. Shen & T. F. Chan (SIAM Journal of Applied Mathematics, 2002). Mathematical models for local nontexture inpaintings.

1^{st} inpainting example

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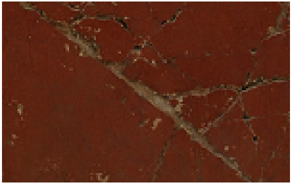
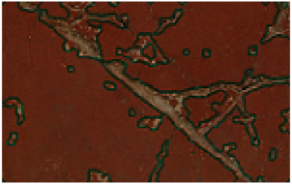
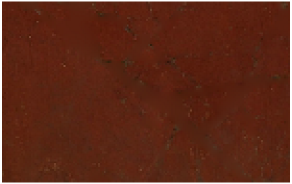


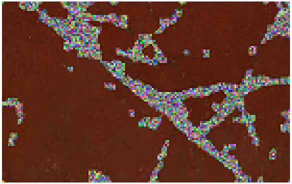
(a) Area with cracks



(b) Crack detection



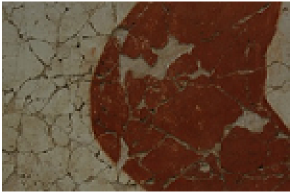
(d) Inpainted area



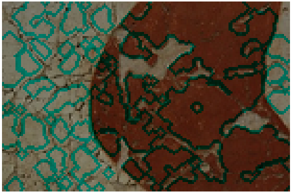
(c) Initialization

2^{nd} inpainting example

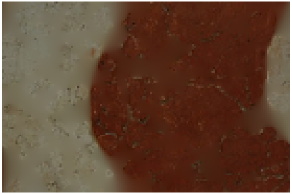
2^{nd} inpainting example



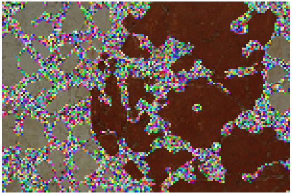
(a) Area with cracks



(b) Crack detection



(d) Inpainted area



(c) Initialization

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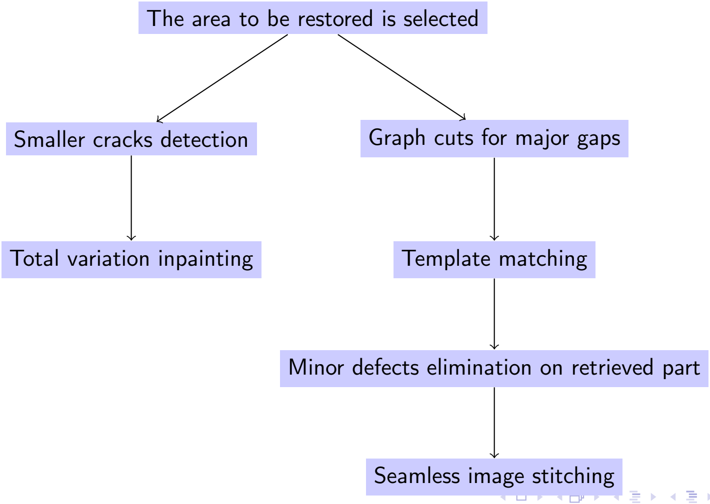
An integrated system for digital restoration



Outline

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Seamless image stitching

- The general formula for the reconstruction problem:

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

- It is minimized by solving the Poisson equation:

$$\Delta I - div(\mathbf{v}) = 0$$

- Goal-field:

$$\mathbf{v}(x,y) = \begin{cases} \nabla F & \text{if } (x,y) \in S,\ (x,y) \notin \partial F \\ \nabla B & \text{if } (x,y) \notin S \\ \frac{1}{2}(\nabla F + \nabla B) & \text{if } (x,y) \in \partial F \end{cases}$$

where S is the retrieved region from the template matching.

• *A. Levin, A. Zomet, S. Peleg & Y. Weiss (ECCV, 2004).*
Seamless image stitching in the gradient domain.

• *M. W. Tao, M. K. Johnson & S. Paris (ECCV, 2010).*
Error-tolerant image compositing.

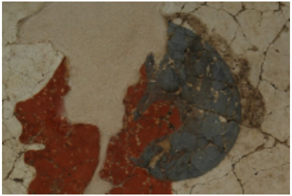
Demonstration in *"Men in procession"*

a) Template matching: the frame encloses the retrieved part, which is the geometrically and semantically more relevant patch in the wall paintings.

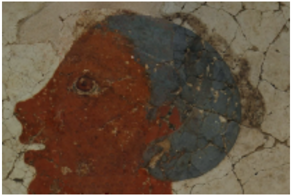
Demonstration in *"Men in procession"*

(b) Foreground

(c) Mask

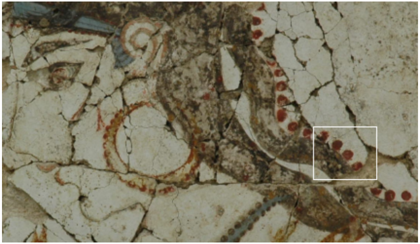


(d) Background



(e) Stitching result

Demonstration in *"Saffron gatherer & Potnia"*



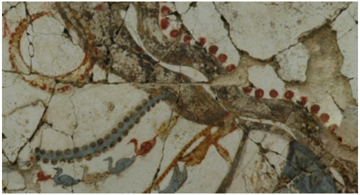
(a) Template matching

(b) The selected area to be restored

(c) The retrieved part

Demonstration in *"Saffron gatherer & Potnia"*

(d) Damaged wall painting



(e) After the partial crown restoration

Thank you!