

Morphological Operations Applied to Digital Art Restoration

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Why?

Art restoration preserves objects of artistic, cultural, or historical value. However, this process demands many resources.

Digital art restoration provides:

- a comparatively inexpensive alternative.
- a nondestructive tool.
- an approximation of the initial appearance.



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Outline

- 1 Edge Detection
- 2 Morphological Operations
- 3 Methods of Crack Detection
- 4 Inpainting
- 5 Results
- 6 Conclusions

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Criteria

Terms

Edge boundaries between areas of varying intensity

Intensity brightness or dullness of a color

- 1 Accuracy - low error rate
- 2 Localization - minimal distance between detected and actual edge
- 3 Uniqueness - only one response to a single edge

Canny Algorithm

- 1 Smooth image by applying Gaussian filter.
- 2 Take gradient of image.
- 3 Identify regions containing significant jumps in intensity.
- 4 Search regions for local maximum.
- 5 Compare remaining pixels to two thresholds.

Outline

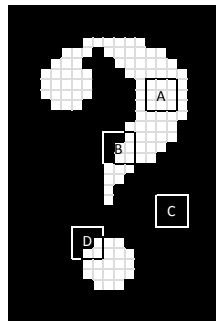
- 1 Edge Detection
- 2 Morphological Operations
 - Erosion
 - Dilation
 - Opening
 - Closing
- 3 Methods of Crack Detection
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Morphological Operations

Binary and Greyscale Images

Two Inputs:

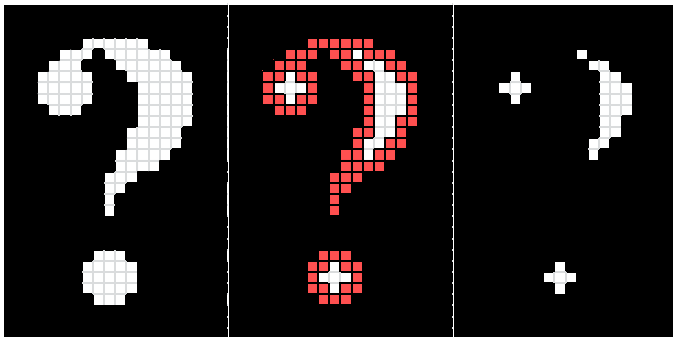
- Original Image
- Structuring Element



Erosion

Erosion strips away pixels from the boundaries of foreground regions.

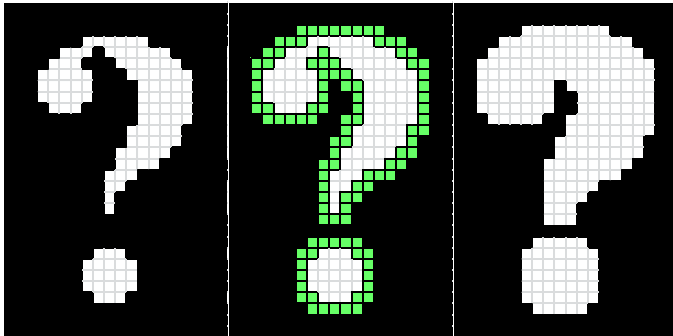
$$g = f \ominus s$$



Dilation

Dilation adds pixels to the boundaries of foreground regions.

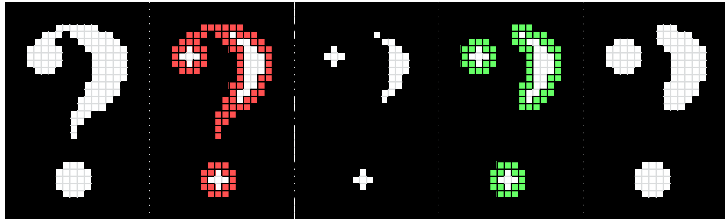
$$g = f \oplus s$$



Opening

Opening strips away pixels from the boundaries of foreground regions while preserving foreground regions that fit the shape and size of the structuring element.

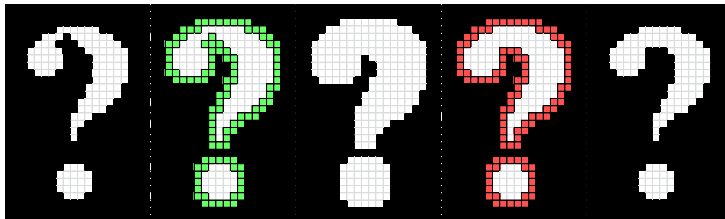
$$g = f \circ s = (f \ominus s) \oplus s$$



Closing

Closing adds pixels to the boundaries of foreground regions while preserving background regions that fit the shape and size of the structuring element.

$$g = f \bullet s = (f \oplus s) \ominus s$$



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 - Top-Hat Transform
 - Alternative Method
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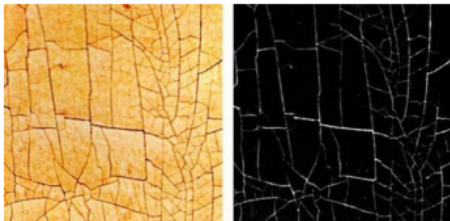
Top-Hat Algorithm

Three Variations: Black Top-Hat, White Top-Hat, Multiscale Top-Hat

Black Top-Hat

darker details on
lighter background

$$BTH = (f \bullet s) - f$$

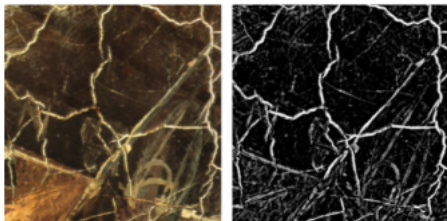


Spagnolo and Somma

White Top-Hat

lighter details on
darker background

$$WTH = f - (f \circ s)$$



Spagnolo and Somma

Alternative Method

- 1 Set threshold; pixels exceeding threshold are determined to be cracks.
- 2 Closing is applied to image, grouping isolated pixels.
- 3 Previous two steps form binary crack mask.
- 4 Canny edge detection algorithm implemented on original image to obtain edge mask.
- 5 Dilation applied to edge mask.
- 6 Crack and edge mask joined to form binary mask.
- 7 Binary mask iteratively eroded until certain percentage of edge information is lost.

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Inpainting Process

The image is broken down into regions, which are further broken down into neighborhoods. For each defective pixel i :

- 1 Find the context of i .
- 2 Examine all other neighborhoods within the region of i .
- 3 Find neighborhood most similar to context of i by sum of squared differences.
- 4 If the sum of squared errors is below a set threshold, replace all defective pixels in the neighborhood of i with corresponding pixels from most similar neighborhood.
- 5 Otherwise, replace pixel i with the median value of all non-defective pixels within its neighborhood.

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Definitions

Categories:

- True Positives
- False Positives
- True Negatives
- False Negatives

Equations:

- False and True Positive Rate

$$FP = fp / (fp + tn)$$

$$TP = tp / (tp + fn)$$

- Precision and Recall

$$P = tp / (tp + fp)$$

$$R = tp / (tp + fn)$$

Statistics

Method	Classification	<i>tp</i>	<i>fn</i>	<i>tn</i>	<i>fp</i>	<i>TP (or R)</i>	<i>FP</i>	<i>P</i>
Top-Hat Transform	Crack Thickness - Thin	220	30	230	20	0.880	0.080	0.917
	Crack Thickness - Medium	232	18	231	19	0.928	0.076	0.924
	Crack Thickness - Thick	235	15	238	12	0.940	0.048	0.951
	Number of Cracks - Few	242	8	245	5	0.968	0.020	0.980
	Number of Cracks - Medium	245	5	241	9	0.980	0.036	0.965
	Number of Cracks - Many	243	7	243	7	0.972	0.028	0.972
	Crack Connectivity - Low	215	35	219	31	0.860	0.124	0.874
	Crack Connectivity - High	218	32	221	29	0.872	0.116	0.883
Alternative Method	Edge Information Lost - 1%	-	-	-	-	0.932	-	0.497
	Edge Information Lost - 30%	-	-	-	-	0.857	-	0.594
	Edge Information Lost - 70%	-	-	-	-	0.530	-	0.704

Results

Original Image



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Restored Image



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Conclusions

The top-hat transform has been demonstrated to outperform the alternative examined here.

Further Work:

- implement other methods of crack detection
- examine effects of various forms of edge detection and inpainting
- study the detection and removal of other defects

Thanks!

Questions?

References