

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, and
- an approximation of the initial appearance.



Cornelis et al

Outline

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

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Criteria

Terms

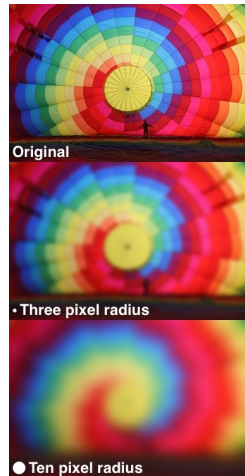
Edge boundaries between areas of varying intensity

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 I

- 1 Smooth image.
- 2 Find jumps in intensity.
- 3 Search regions for local maximum.

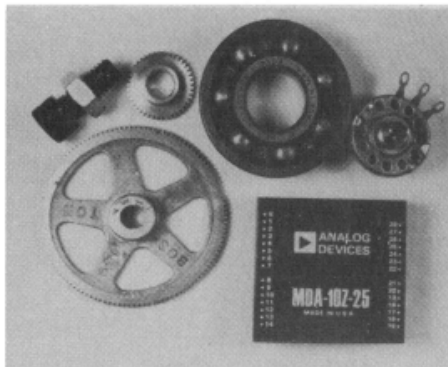


Wikipedia

Canny Algorithm II

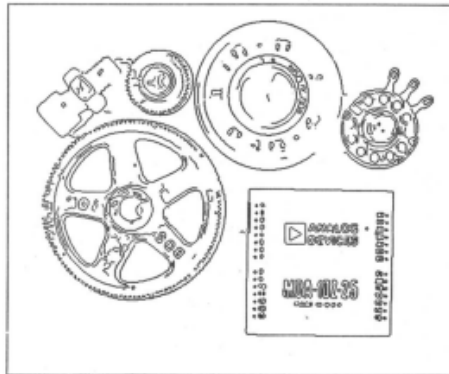
4 Compare intensity of remaining pixels to thresholds.

Original Image



Canny

Edge Mask



Canny

Outline

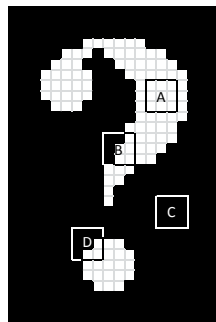
- 1 Edge Detection
- 2 Morphological Operations
 - Erosion
 - Dilation
 - Opening
 - Closing
- 3 Methods of Crack Detection
- 4 Inpainting
- 5 Results

Morphological Operations

Binary and Greyscale Images

Two Inputs:

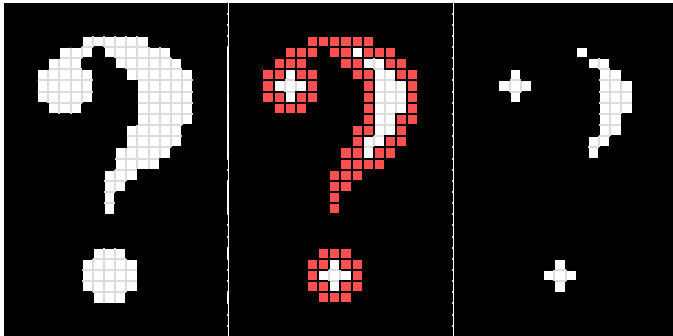
- Original Image
- Structuring Element



Erosion

Erosion removes foreground pixels.

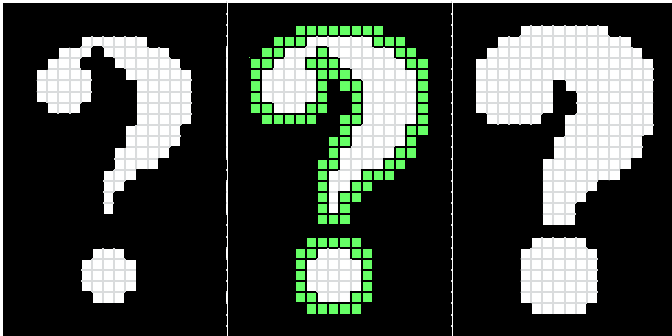
$$g = f \ominus s$$



Dilation

Dilation adds foreground pixels.

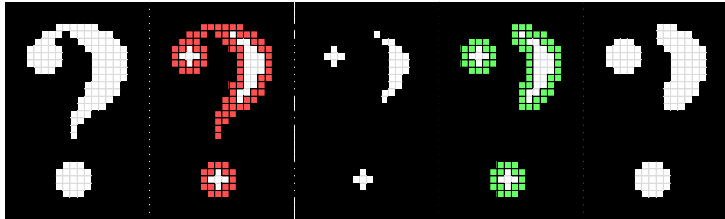
$$g = f \oplus s$$



Opening

Opening removes foreground pixels... neatly.

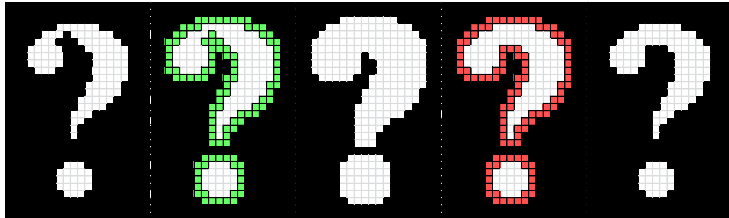
$$g = f \circ s = (f \ominus s) \oplus s$$



Closing

Closing adds foreground pixels... neatly.

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



Outline

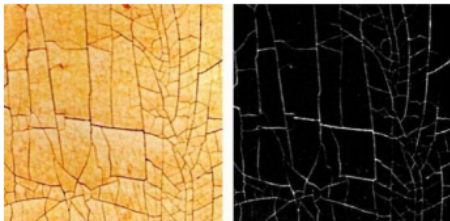
- 1 Edge Detection
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 - Top-Hat Transform
 - Alternative Method
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Top-Hat Algorithm

Black Top-Hat

darker details on
lighter background

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

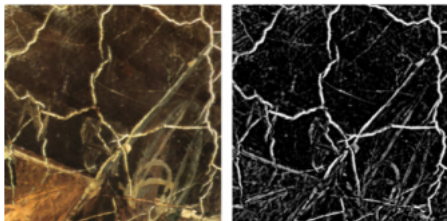


Spagnolo and Somma

White Top-Hat

lighter details on
darker background

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



Spagnolo and Somma

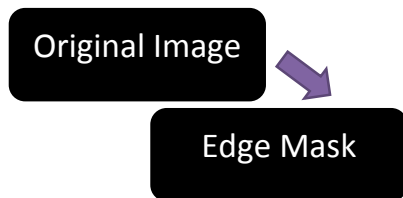
Alternative Method I

- 1 Compare pixels to threshold.
- 2 Apply closing.



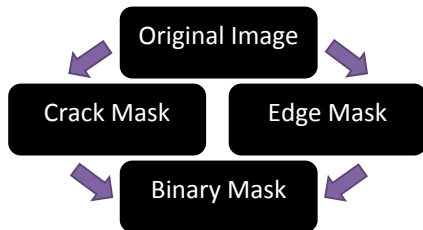
Alternative Method II

- 3 Apply edge detection.
- 4 Apply dilation.



Alternative Method III

- 5 Join to form binary mask.
- 6 Apply erosion.

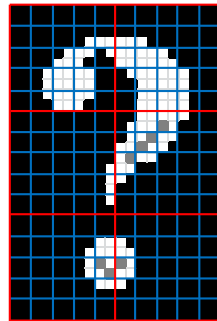


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Inpainting Process I

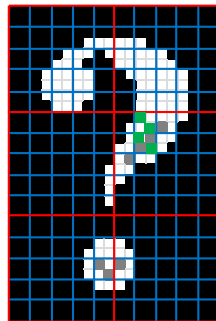
The image is broken down.



Inpainting Process II

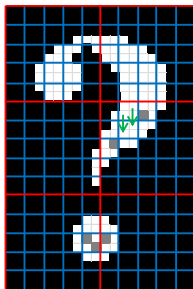
For each defective pixel i :

- 1 Find the context of i .
- 2 Find most similar neighborhood in region.

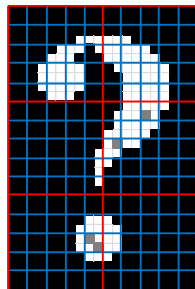


Inpainting Process III

- 3 Replace all defective pixels in the neighborhood of i with corresponding pixels from most similar neighborhood. OR



- 3 Replace pixel i with the median value of all non-defective pixels within its neighborhood.



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Definitions

Categories:

- true positives (*tp*)
- false positives (*fp*)
- true negatives (*tn*)
- false negatives (*fn*)

		Actual Value	
		Crack	No Crack
Predicted Value	Crack	True Positive	False Positive
	No Crack	False Negative	True Negative

Equations:

False and True Positive Rate

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

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

Precision and Recall

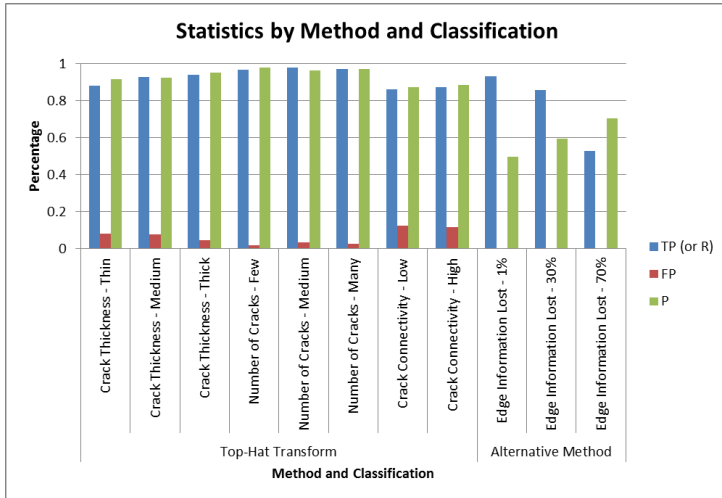
$$P = tp / (tp + fp)$$

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

Statistics I

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

Statistics II



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!

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Questions?

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