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

Outline

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

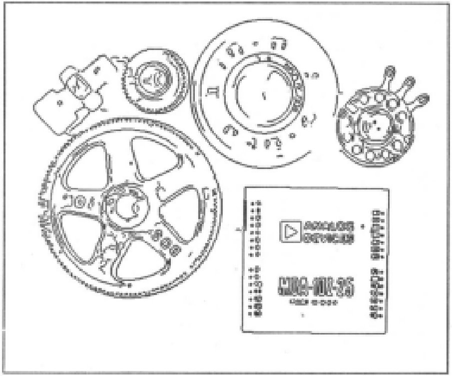
Canny Algorithm II

4 Compare intensity of remaining pixels to thresholds.

Original Image

Canny

Edge Mask



Canny

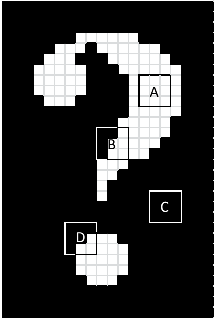
Outline

Morphological Operations

Binary and Greyscale Images

Two Inputs:

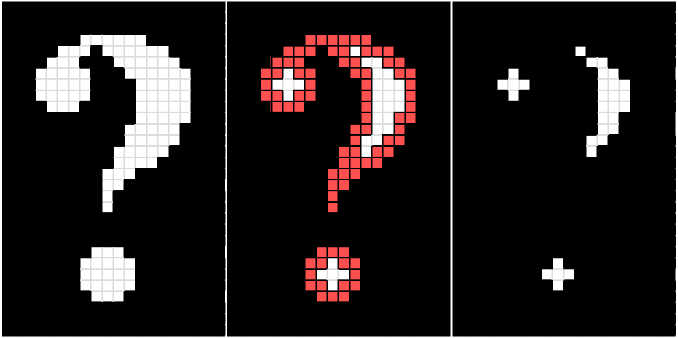
- Original Image
- Structuring Element



Erosion

Erosion removes foreground pixels.

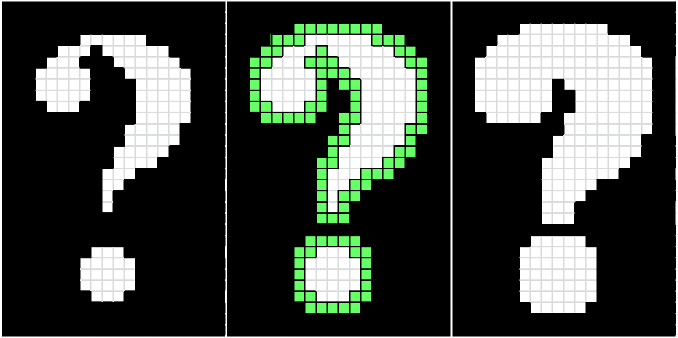
$$g = f \ominus s$$



Dilation

Dilation adds foreground pixels.

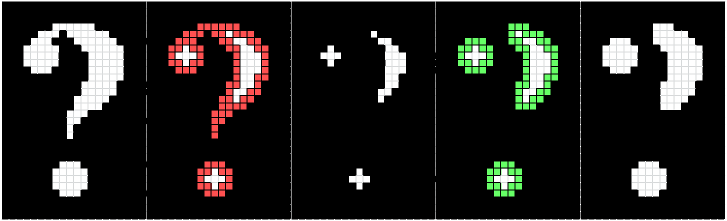
$$g = f \oplus s$$



Opening

Opening removes foreground pixels... neatly.

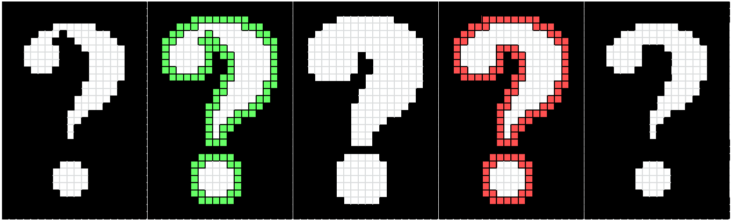
$$g = f \circ s = (f \ominus s) \oplus s$$



Closing

Closing adds foreground pixels... neatly.

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



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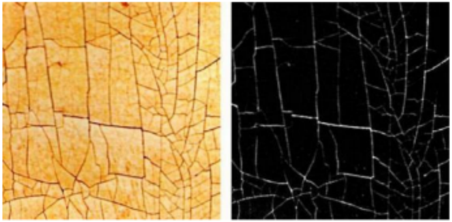
Top-Hat Algorithm

Black Top-Hat

darker details on
lighter background

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

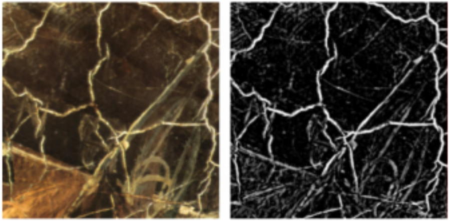


Spagnolo and Somma

White Top-Hat

lighter details on
darker background

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



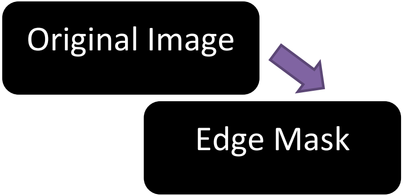
Spagnolo and Somma

Alternative Method I

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

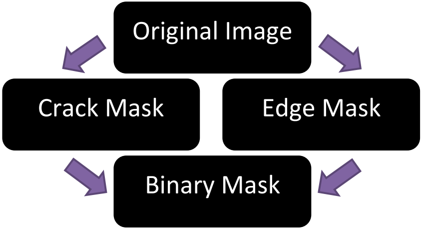
Alternative Method II

3 Apply edge detection.
4 Apply dilation.



Alternative Method III

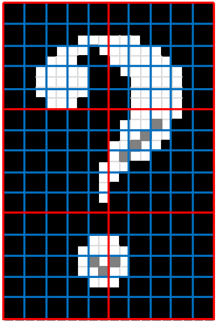
5. Join to form binary mask.
6. Apply erosion.



Outline

Inpainting Process I

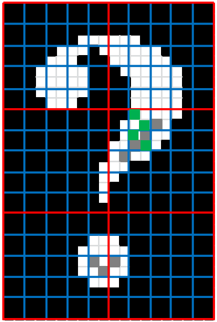
The image is broken down.



Inpainting Process II

For each defective pixel i:

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

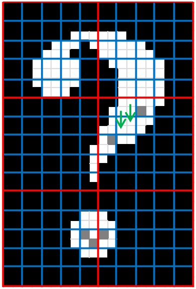


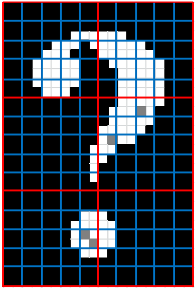
Inpainting Process III

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.





Outline

Definitions

Categories:

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

		Actual Value	
		True	False
Predicted Value	True	True Positive	False Positive
	False	False Negative	True Negative

Equations:

False and True Positive Rate

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

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

Precision and Recall

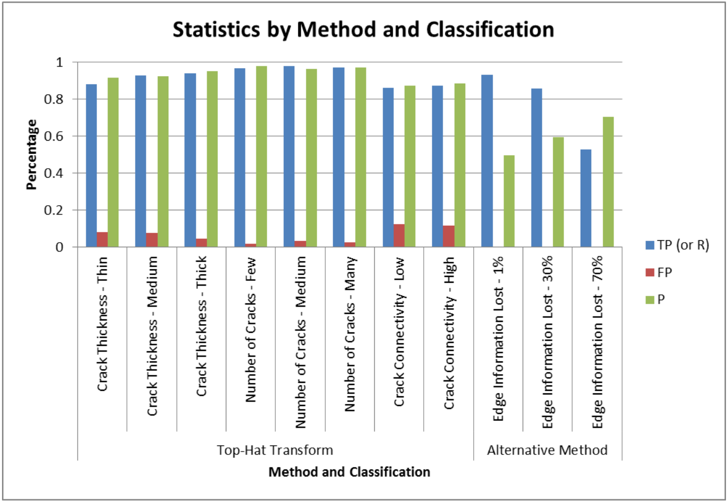
$$P = tp/(tp + fp)$$

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

Statistics I

Method	Classification	*tp*	*fn*	*tn*	*fp*	*TP* (or *R*)	*FP*	*P*
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

Cornelis et al

Restored Image

Cornelis et al

Outline

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?

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