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

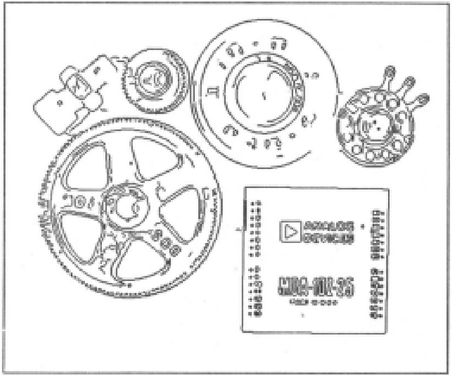
Canny Algorithm II

4. Compare intensity of remaining pixels to thresholds.

Original Image

Canny

Edge Mask



Canny

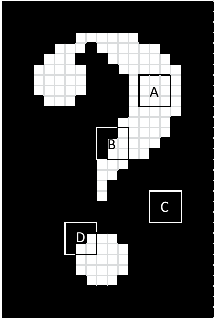
Outline

Morphological Operations

Binary and Greyscale Images

Two Inputs:

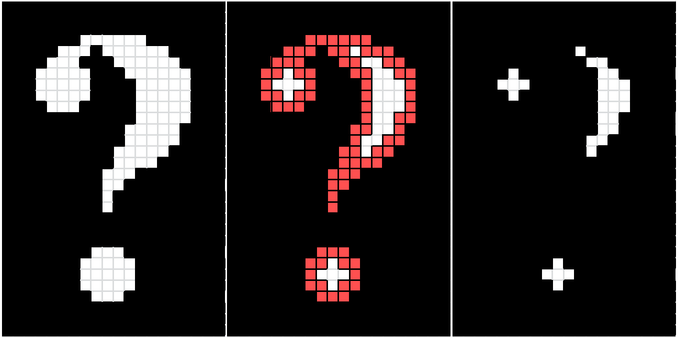
- Original Image
- Structuring Element



Erosion

Erosion removes foreground pixels.

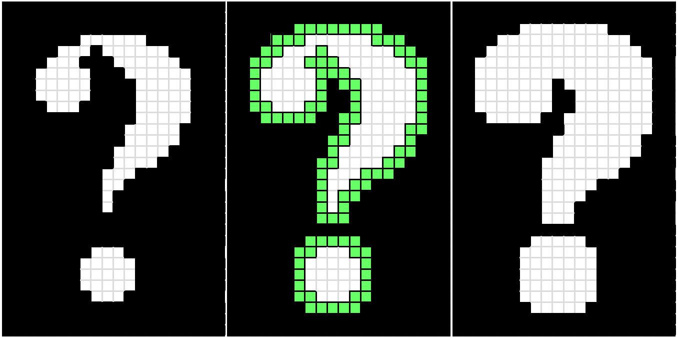
$$g = f \ominus s$$



Dilation

Dilation adds foreground pixels.

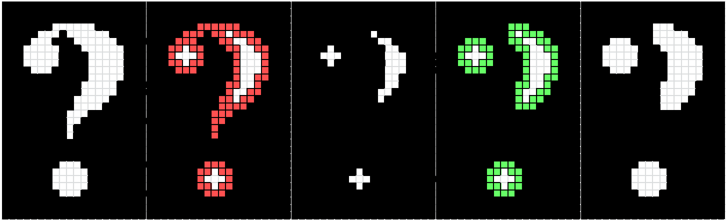
$$g = f \oplus s$$



Opening

Opening removes foreground pixels... neatly.

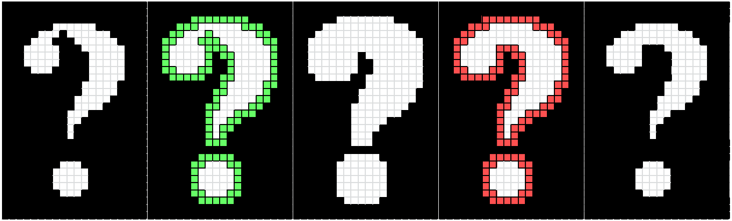
$$g = f \circ s = (f \ominus s) \oplus s$$



Closing

Closing adds foreground pixels... neatly.

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



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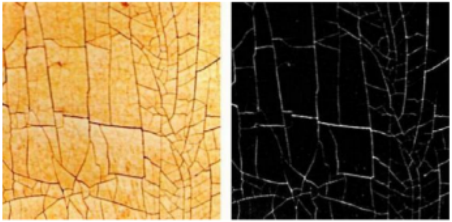
Top-Hat Algorithm

Black Top-Hat

darker details on
lighter background

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

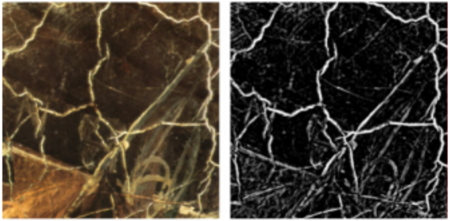


Spagnolo and Somma

White Top-Hat

lighter details on
darker background

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



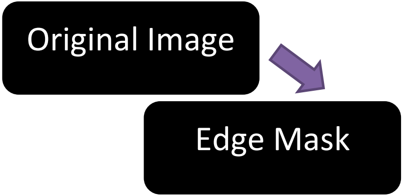
Spagnolo and Somma

Alternative Method I

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

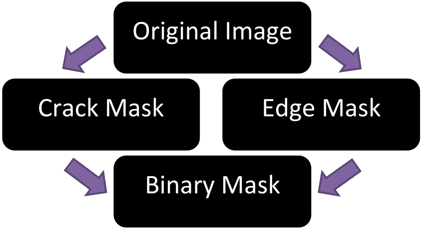
Alternative Method II

3 Apply edge detection.
4 Apply dilation.



Alternative Method III

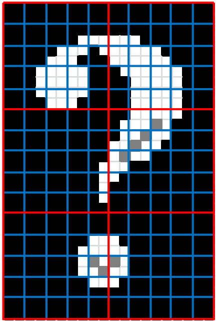
5. Join to form binary mask.
6. Apply erosion.



Outline

Inpainting Process I

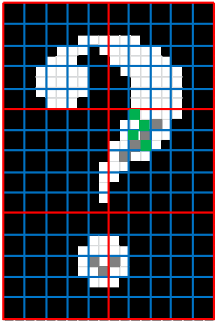
The image is broken down.



Inpainting Process II

For each defective pixel *i*:

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

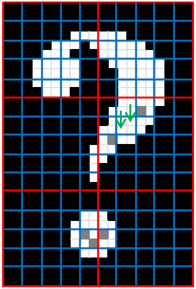


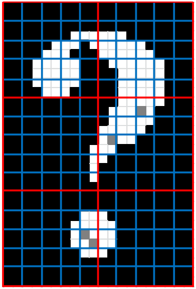
Inpainting Process III

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*)

Equations:

False and True Positive Rate

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

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

Precision and Recall

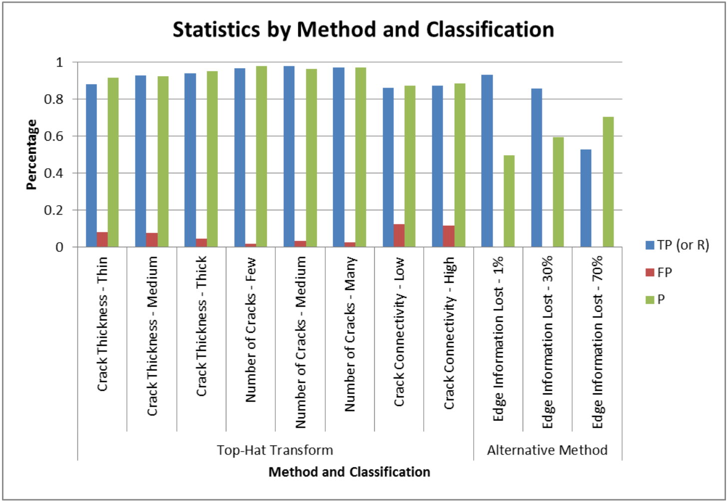
$$P = tp/(tp + fp)$$

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

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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