# Morphological Operations Applied to Digital Art Restoration

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29 April 2014
UMM CSci Senior Seminar Conference
University of Minnesota, Morris

# 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

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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

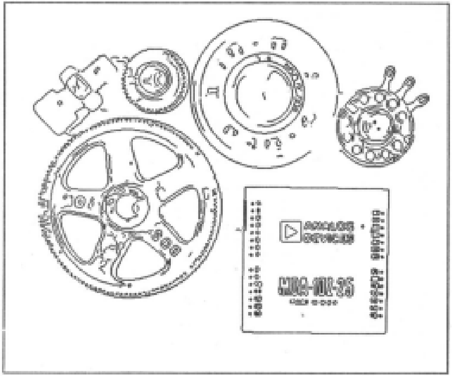
# Canny Algorithm II

4 Compare intensity of remaining pixels to thresholds.

Original Image


Canny

Edge Mask



Canny

# Outline

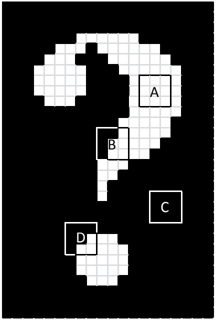
1. Edge Detection
2. Morphological Operations
   - Erosion
   - Dilation
   - Opening
   - Closing
3. Methods of Crack Detection
4. Inpainting
5. Results

# Morphological Operations

Binary and Greyscale Images

Two Inputs:

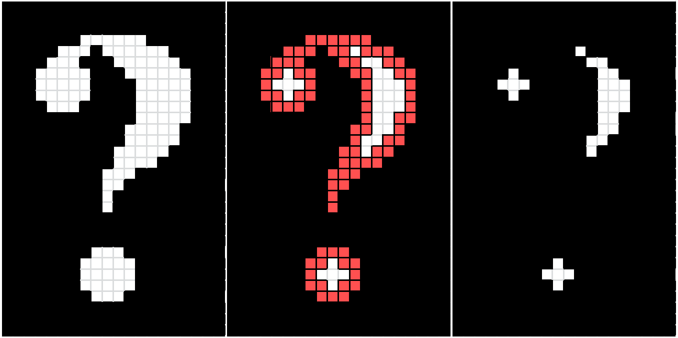
- Original Image
- Structuring Element



# Erosion

Erosion removes foreground pixels.

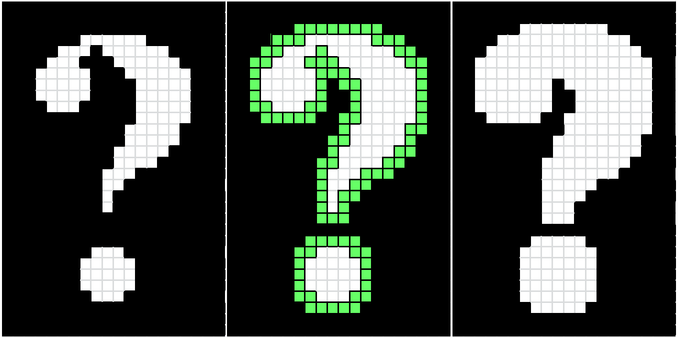
$$g = f \ominus s$$



# Dilation

Dilation adds foreground pixels.

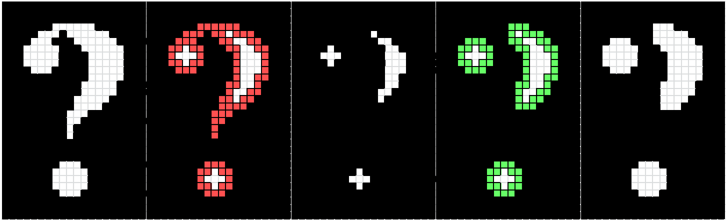
$$g = f \oplus s$$



# Opening

Opening removes foreground pixels... neatly.

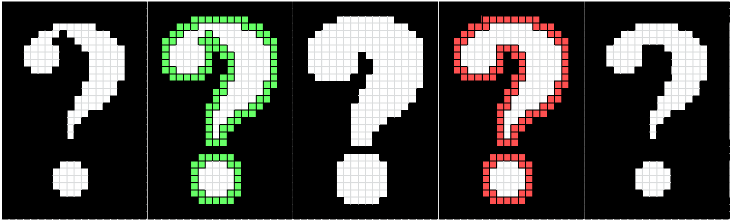
$$g = f \circ s = (f \ominus s) \oplus s$$



# Closing

Closing adds foreground pixels... neatly.

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



# Outline

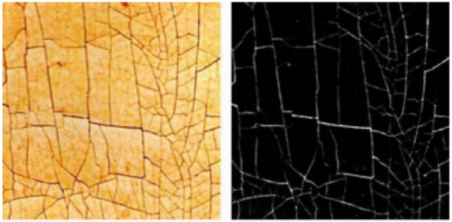
1. Edge Detection
2. Morphological Operations
3. Methods of Crack Detection
   - Top-Hat Transform
   - Alternative Method
4. Inpainting
5. Results
6. Conclusions

# Top-Hat Algorithm

## Black Top-Hat

darker details on
lighter background

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

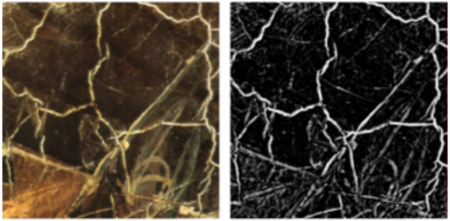


Spagnolo and Somma

## White Top-Hat

lighter details on
darker background

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



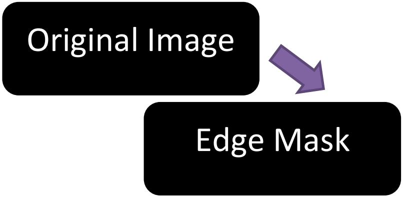
Spagnolo and Somma

# Alternative Method I

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

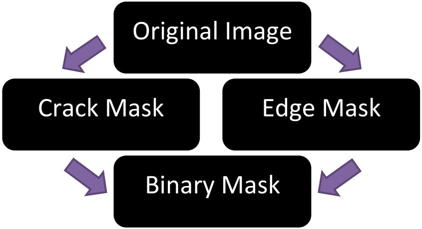
# Alternative Method II

3. Apply edge detection.
4. Apply dilation.



# Alternative Method III

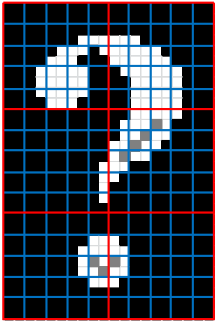
5. Join to form binary mask.
6. Apply erosion.



# Outline

# Inpainting Process I

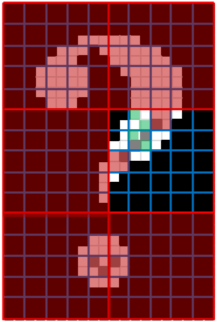
The image is broken down.



# Inpainting Process II

For each defective pixel $i$:

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

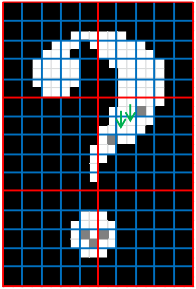


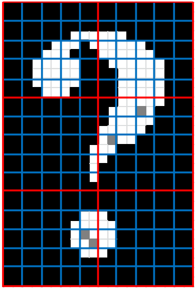
# Inpainting Process III

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 | |
|---|---|---|---|
| | | Crack | No Crack |
| Predicted Value | Crack | True Positive | False Positive |
| | No Crack | False Negative | True Negative |

## Equations:

False and True Positive Rate

$$FP = fp/(fp + tn)$$
$$TP = tp/(tp + fn)$$

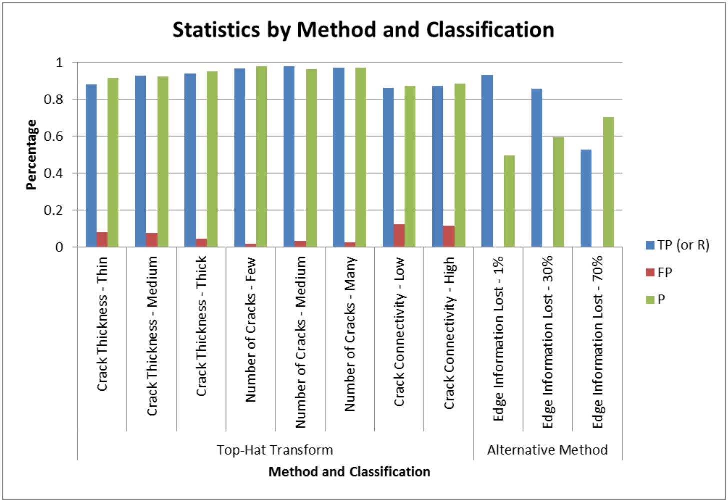
Precision and Recall

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

# Statistics I

| **Method** | **Classification** | ***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!

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Questions?

# References I


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