Seminar: Medical Image Processing

A robust approach for automatic detection and segmentation of cracks in underground pipeline images

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July 13th, 2006

Roadmap

Discussed papers

- Shivprakash Iyer and Sunil K. Sinha: A robust approach for automatic detection and segmentation of cracks in underground pipeline images. *Image and Vision Computing*, 23:921-933, 2005.

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- Frederic Zana and Jean-Claude Klein: Segmentation of vessel-like patterns using mathematical morphology and curvature evaluation. *IEEE Transactions on Image Processing*, 10(7):1010-1019, July 2001.

The situation

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Large underground sewer networks need continuous checks.

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Reliable *automated defect detection* and classification system desirable to compensate these problems

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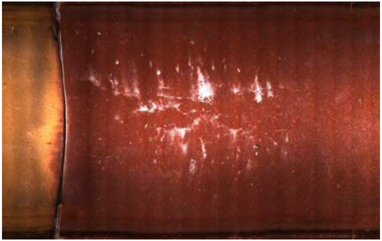
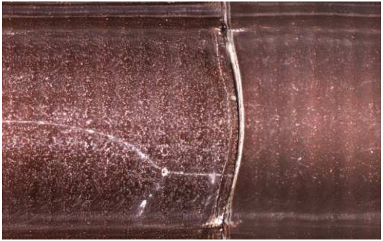
- Retinal vessels: similar features $\Rightarrow$ similar method works to segment vessels

Examples (cracks and retinal vessels)





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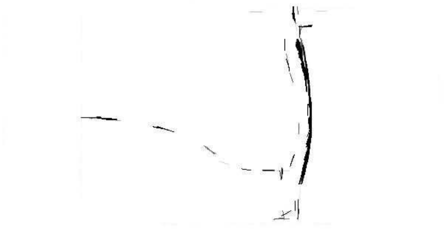

Examples (cracks and retinal vessels)

Processing pipeline structure

- Usage of mathematical morphology (MM) and linear filters (LF)

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1. Preprocessing (contrast enhancement)
2. Enhancement of cracks (MM and LF)
3. Segmentation of cracks (MM alternating filters)

Introduction

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- Extract features based on a priori knowledge about object geometry
- Set-theoretic method providing a quantitative description of geometric structures
- Based on expanding and shrinking operations with regard to a given structuring element (knowledge about object)
- Originally for B/W images, extended for gray images (interesting case here)

Definitions

Images are defined as a function mapping from points to intensity values (here: grayscale, $I_{min} = 0$ and $I_{max} = 255$):

$$F : \mathbb{Z}^2 \mapsto [I_{min}, I_{max}]$$

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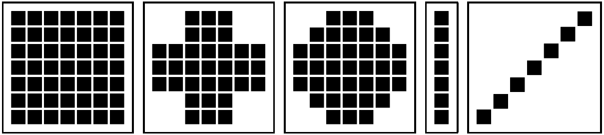

Important notation specialties for crack detection

General MM:

- Foreground: white
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General MM:	**Crack detection MM:**
Foreground: white	Foreground: black
Background: black	Background: white

Some items change meaning:

Hole	Object
Object	Hole

Some operations change meaning:

Expanding	Shrinking
Shrinking	Expanding

Dilation

$$\delta_B^e(F)(P_0) = \max_{P \in P_0 \cup e \cdot B(P_0)}(F(P))$$

B	Structuring element (SE)
e	SE dimension scaling factor (default: $e = 1$)
F	Image
P_0	Point in image (repeat for every point)

- Basic *expanding* operation.

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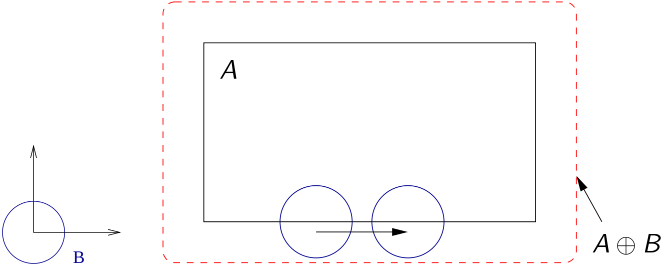

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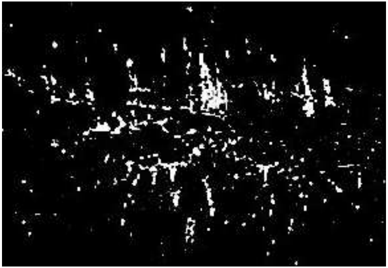

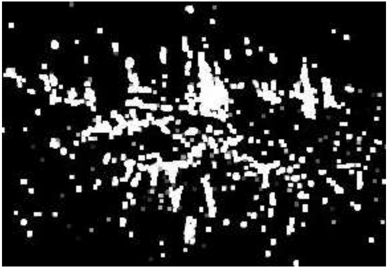

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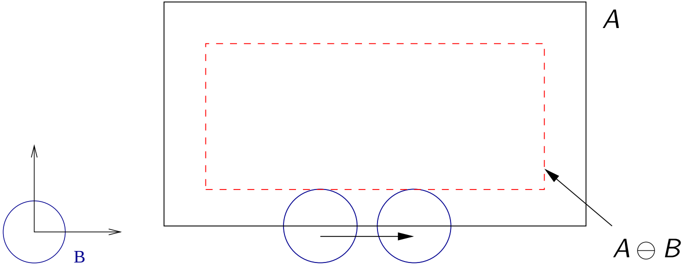

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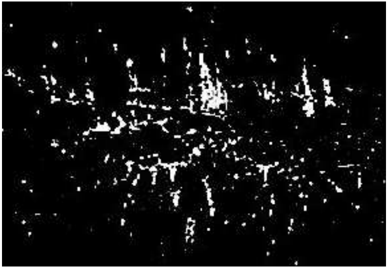

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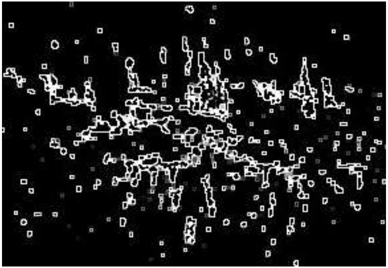

(edge detection by top-hat: top-hat with original image)

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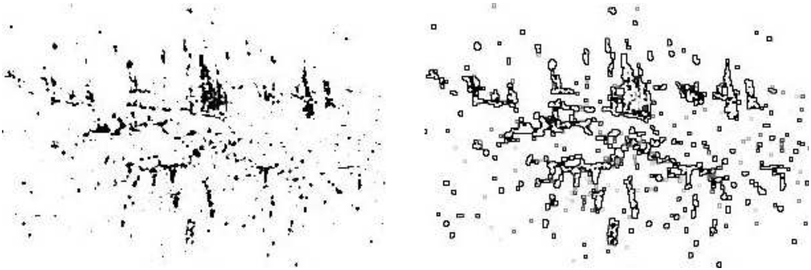

(edge detection by top-hat: inverted result)

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- Geodesic: Extracts connected components based on distance
- Can be used with different morphological operations

Geodesic reconstruction by erosion (geodesic closing)

$$\Phi(F, G) = \varepsilon_G^{(n)}(F) = \max\left(G, \varepsilon_G^{(n-1)}\left(\varepsilon_B(F)\right)\right)$$

B	Isotropic structuring element
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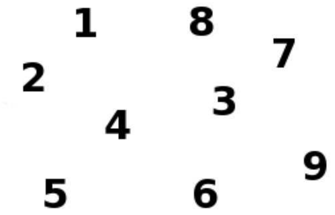

(segment 1 and 4: original image)

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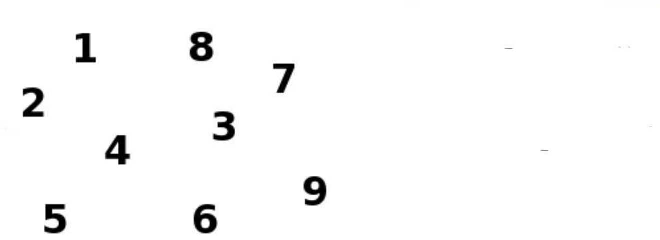

(segment 1 and 4: dilation by linear SE, length = 45 pixel, vertical)

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(segment 1 and 4: marked dilation result)

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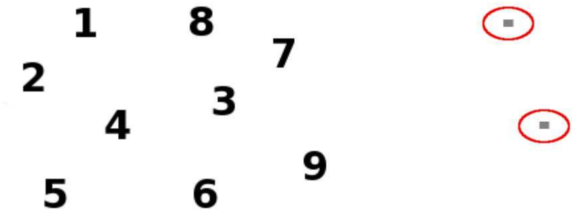

(segment 1 and 4: dilation by linear SE, length = 7, horizontal)

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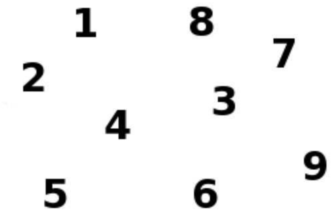

(segment 1 and 4: un-marked dilation result)

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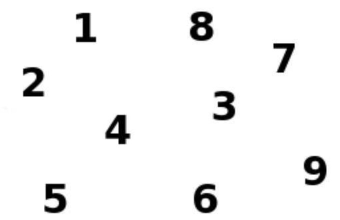

(segment 1 and 4: geodesic reconstruction with original as mask)

Geodesic reconstruction by dilation (geodesic opening)

$$\Gamma(F,G) = \delta_G^{(n)}(F) = \min\left(G, \delta_G^{(n-1)}\left(\delta_B(F)\right)\right)$$

B	Isotropic structuring element
F	Image (Marker)
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δ	Dilation $\delta_{B,G}^{(0)}(F) = F$
n	number of iterations until stability has been reached ($\delta_{B,G}^{(n)}(F) = \delta_{B,G}^{(n+1)}(F)$ holds)

1. Dilate marker image
2. Take minimum of dilated image and mask image
3. If image has been changed in this iteration goto 1

Structuring elements

- Based on observation of cracks specific SEs are chosen

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- Linear SE

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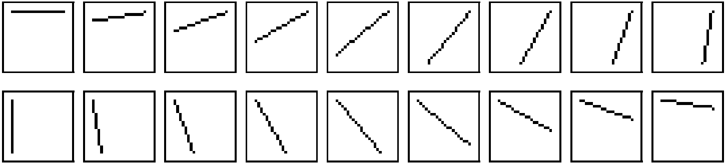
- Linear SE
- SE length: 12 pixel
- Degree of rotation: every 10° from 0° to 180°

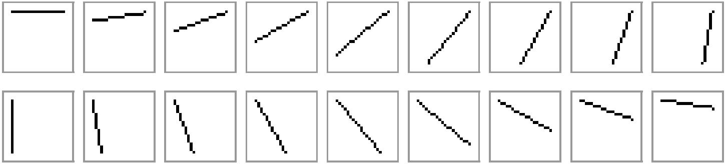
Structuring elements

- Based on observation of cracks specific SEs are chosen
- Linear SE
- SE length: 12 pixel
- Degree of rotation: every 10° from 0° to 180°



Structuring elements

- Based on observation of cracks specific SEs are chosen
- Linear SE
- SE length: 12 pixel
- Degree of rotation: every 10° from 0° to 180°



- Filters have been chosen for dark features

Linear filters

- Pictures of zebras and dalmatians both have black and white pixels

Linear filters

- Pictures of zebras and dalmatians both have black and white pixels
- They appear in about the same amount

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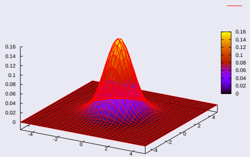
- Weights defined as matrix (kernel)
- Here: edge detection

Gaussian

- Smoothing an image

Gaussian kernel

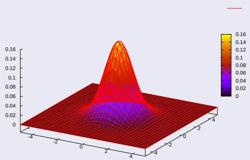


$$\mathcal{G}_\sigma(x, y) = \frac{1}{2\pi\sigma^2} exp\left(-\frac{(x^2+y^2)}{2\sigma^2}\right)$$

Gaussian

- Smoothing an image
- Discrete Gaussian kernel from Gaussian function

Gaussian kernel



$$\mathcal{G}_\sigma(x, y) = \frac{1}{2\pi\sigma^2} exp\left(-\frac{(x^2+y^2)}{2\sigma^2}\right)$$

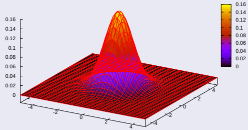
$$G_1 = \begin{bmatrix} \frac{1}{16} & \frac{2}{16} & \frac{1}{16} \\ \frac{2}{16} & \frac{4}{16} & \frac{2}{16} \\ \frac{1}{16} & \frac{2}{16} & \frac{1}{16} \end{bmatrix}$$

Gaussian

- Smoothing an image
- Discrete Gaussian kernel from Gaussian function

(a) Original (b) Gaussian

Gaussian kernel



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Laplacian of Gaussian

- Classic method for edge detection

Laplacian of Gaussian kernel

Laplacian of Gaussian

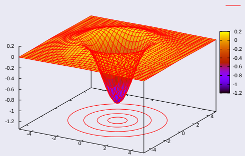
- Classic method for edge detection
- Laplacian operator:
  $(\nabla^2 f)(x,y) = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$

Laplacian of Gaussian kernel

Laplacian of Gaussian

- Classic method for edge detection
- Laplacian operator: $(\nabla^2 f)(x,y) = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$
- Natural to smooth before applying laplacian $\Rightarrow$ Gaussian as function

Laplacian of Gaussian kernel



$$\mathcal{L}_\sigma = \frac{(x^2+y^2-2\sigma^2)}{\sigma^4} exp\left(-\frac{(x^2+y^2)}{(2\sigma^2)}\right)$$

Laplacian of Gaussian

- Classic method for edge detection
- Laplacian operator: $(\nabla^2 f)(x,y) = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$
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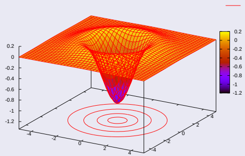
- $LoG_\sigma^w(F) = F \circ L_\sigma^w$
  (F convolved with L)

Laplacian of Gaussian kernel



$$\mathcal{L}_\sigma = \frac{(x^2+y^2-2\sigma^2)}{\sigma^4} exp\left(-\frac{(x^2+y^2)}{(2\sigma^2)}\right)$$

$$L_1^5 = \begin{bmatrix} -1 & -3 & -3 & -3 & -1 \\ -3 & 0 & 6 & 0 & -3 \\ -3 & 6 & 21 & 6 & -3 \\ -3 & 0 & 6 & 0 & -3 \\ -1 & -3 & -3 & -3 & -1 \end{bmatrix}$$

Laplacian of Gaussian

- Classic method for edge detection
- Laplacian operator:
  $(\nabla^2 f)(x, y) = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$
- Natural to smooth before applying laplacian $\Rightarrow$ Gaussian as function
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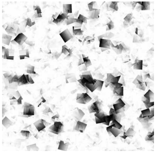
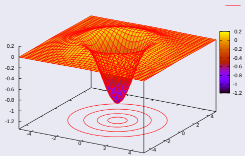


Laplacian of Gaussian kernel



$$\mathcal{L}_\sigma = \frac{(x^2+y^2-2\sigma^2)}{\sigma^4} exp\left(-\frac{(x^2+y^2)}{(2\sigma^2)}\right)$$

$$L^5_1 = \begin{bmatrix} -1 & -3 & -3 & -3 & -1 \\ -3 & 0 & 6 & 0 & -3 \\ -3 & 6 & 21 & 6 & -3 \\ -3 & 0 & 6 & 0 & -3 \\ -1 & -3 & -3 & -3 & -1 \end{bmatrix}$$

Processing pipeline structure

- Usage of mathematical morphology (MM) and linear filters (LF)
- Results in binary crack map
- Basic 3-step processing pipeline

1. Preprocessing (contrast enhancement)
2. Enhancement of cracks (MM and LF)
3. Segmentation of cracks (MM alternating filters)

Preprocessing

- Goal: Enhance contrast between cracks and background

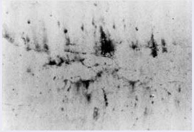
Preprocessing pipeline

Preprocessing

- Goal: Enhance contrast between cracks and background

0 Original grayscale image

Preprocessing pipeline

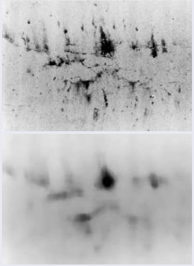


Preprocessing

- Goal: Enhance contrast between cracks and background

0. Original grayscale image
1. Median (15×15)

Preprocessing pipeline

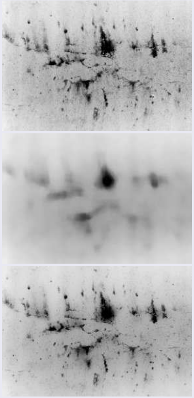


Preprocessing

- Goal: Enhance contrast between cracks and background

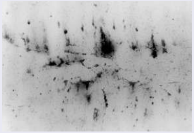
0. Original grayscale image
1. Median (15×15)
2. Compare foreground (original) and background (median) image, take minimum

Preprocessing pipeline



Crack enhancement

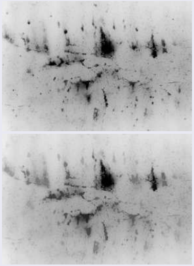
Enhancement pipeline



Crack enhancement

1. Closing by Reconstruction
   $F_{Cl} = \Phi\left(\min_{i=1,\ldots,18}\{\phi_{B_i}(F_0)\}\right)$

Enhancement pipeline



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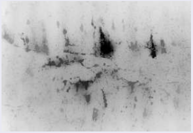
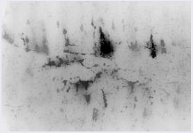


Crack enhancement

1. Closing by Reconstruction
   $F_{Cl} = \Phi\left(\min_{i=1,\ldots,18}\{\phi_{B_i}(F_0)\}\right)$
2. Sum of top-hats
   $$F_{th} = \sum_{i=0}^{17} \tau_{B_i}(F_{Cl}) = \sum_{i=0}^{17} (F_{Cl} - \gamma_{B_i}(F))$$
   Wrong formula (white objects)!

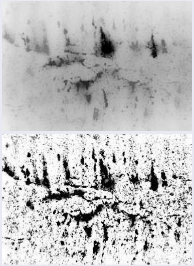
Enhancement pipeline



Crack enhancement

1. Closing by Reconstruction
   $F_{Cl} = \Phi\left(\min_{i=1,\dots,18}\{\phi_{B_i}(F_0)\}\right)$
2. Sum of top-hats
   $$F_{th} = \left(\sum_{i=0}^{17} (\phi_{B_i}(F) - F_{Cl})\right)^{-1}$$
   Very noisy results, omitted.

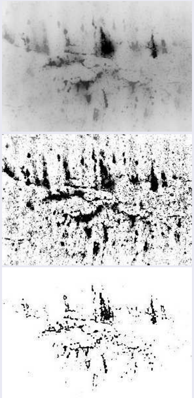
Enhancement pipeline



Crack enhancement

1. Closing by Reconstruction
   $F_{Cl} = \Phi\left(\min_{i=1,\ldots,18}\{\phi_{B_i}(F_0)\}\right)$
2. Sum of top-hats
   $$F_{th} = \left(\sum_{i=0}^{17}(\phi_{B_i}(F) - F_{Cl})\right)^{-1}$$
   Very noisy results, omitted.
3. Laplacian of Gaussian $F_{lap} = LoG_2^{12}(F_{Cl})$

Enhancement pipeline



Crack detection and segmentation

- Final segmentation of cracks

Segmentation pipeline

Crack detection and segmentation

- Final segmentation of cracks
- Alternating MM filters

Segmentation pipeline

Crack detection and segmentation

- Final segmentation of cracks
- Alternating MM filters

1. Closing by Reconstruction
   $F_1 = \Phi\left(\min_{i=1,\dots,18}\{\phi_{B_i}(F_{lap})\}\right)$

Segmentation pipeline

Crack detection and segmentation

- Final segmentation of cracks
- Alternating MM filters

1. Closing by Reconstruction
$F_1 = \Phi\left(\min_{i=1,\ldots,18}\{\phi_{B_i}(F_{lap})\}\right)$

Segmentation pipeline

Crack detection and segmentation

- Final segmentation of cracks
- Alternating MM filters

1. Closing by Reconstruction
   $F_1 = \Phi\left(\min_{i=1,\ldots,18}\{\phi_{B_i}(F_{lap})\}\right)$
2. Opening by Reconstruction
   $F_2 = \Gamma\left(\max_{i=1,\ldots,18}\{\gamma_{B_i}(F_1)\}\right)$

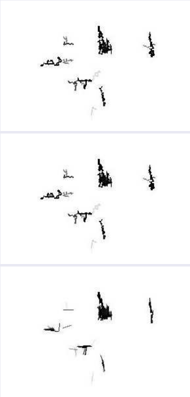
Segmentation pipeline

Crack detection and segmentation

- Final segmentation of cracks
- Alternating MM filters

1. Closing by Reconstruction
   $F_1 = \Phi\left(\min_{i=1,\ldots,18}\{\phi_{B_i}(F_{lap})\}\right)$
2. Opening by Reconstruction
   $F_2 = \Gamma\left(\max_{i=1,\ldots,18}\{\gamma_{B_i}(F_1)\}\right)$
3. Large closing with double scale
   $F_{final} = \left(\min_{i=1,\ldots,18}\{\phi^2_{B_i}(F_2)\}\right)$

Segmentation pipeline



1 Introduction

2 Morphology

3 Linear filters

4 Detection

5 Evaluation
- Evaluation results from the paper
- Experiments
- Evaluation of the paper

6 Summary

Criteria for parameter selection

- Parameters: S length of SE in pixels, D degree of rotations

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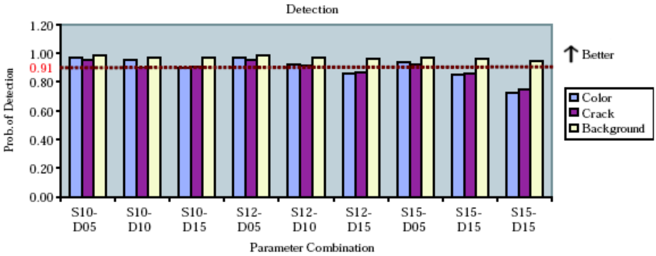
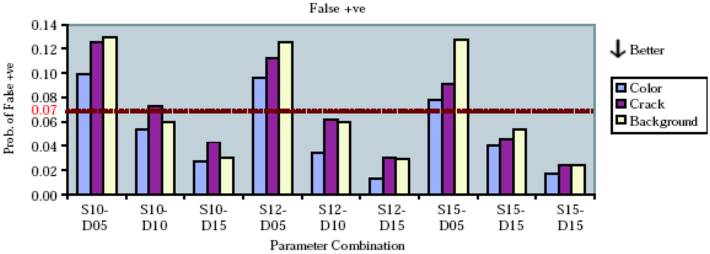
- Probability of detection



Criteria for parameter selection

- Parameters: S length of SE in pixels, D degree of rotations
- Goal: false positive rate below 7%, false negative rate below 2%

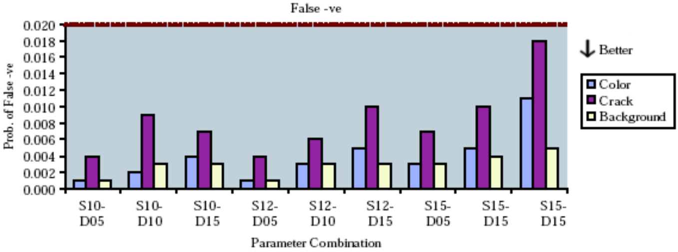
- Probability of false positive (crack detected where is none)



Criteria for parameter selection

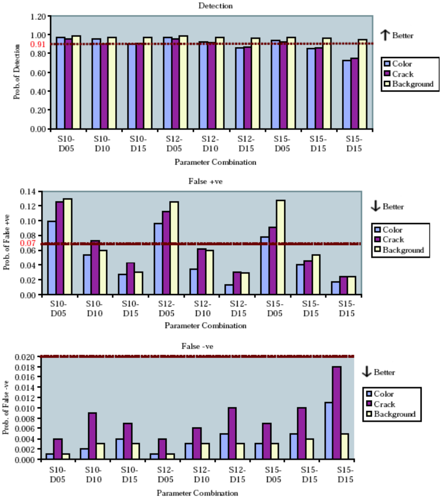
- Parameters: S length of SE in pixels, D degree of rotations
- Goal: false positive rate below 7%, false negative rate below 2%

- Probability of false negative (crack not detected)



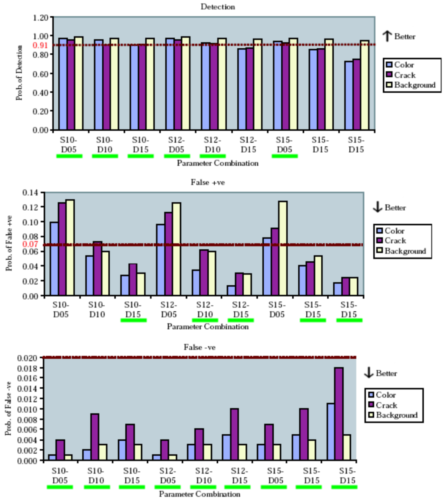
Criteria for parameter selection

- Probability of detection
- Probability of false positive
- Probability of false negative



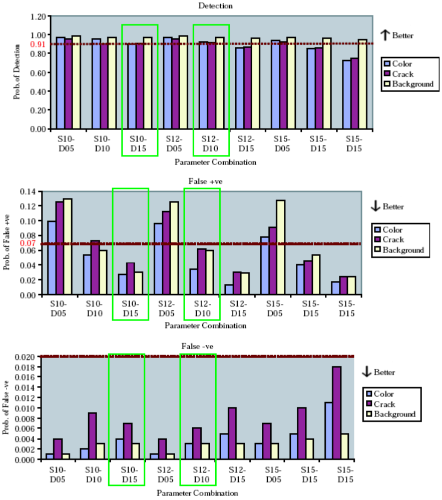
Criteria for parameter selection

- Probability of detection
- Probability of false positive
- Probability of false negative



Criteria for parameter selection

- Probability of detection
- Probability of false positive
- Probability of false negative
- Best parameters in paper: SE length $S = 12$ pixel and a degree of rotations $D =$ every 10°



Criteria for comparison to different approaches

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- Redundancy $\approx \frac{\#\text{ matched crack pixels of extr.} - \#\text{ matched pixels of ref.}}{\#\text{ crack pixels of extraction}}$ (optimal: 0)

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- Comparison based on individual evaluation of approaches
- Ground truth by manually segmenting test images (reference)
- Completeness $\approx \frac{\#\text{ matched crack pixels of ref.}}{\#\text{ crack pixels of reference}}$ (optimal: 1)
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- Redundancy $\approx \frac{\#\text{ matched crack pixels of extr.} - \#\text{ matched pixels of ref.}}{\#\text{ crack pixels of extraction}}$ (optimal: 0)
- Quality $\approx \frac{\text{compl}\cdot\text{corr}}{\text{compl} - \text{compl}\cdot\text{corr} + \text{corr}}$ (optimal: 1)

Criteria for comparison to different approaches

- Comparison based on individual evaluation of approaches
- Ground truth by manually segmenting test images (reference)
- Completeness $\approx \frac{\text{\# matched crack pixels of ref.}}{\text{\# crack pixels of reference}}$ (optimal: 1)
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- Redundancy $\approx \frac{\text{\# matched crack pixels of extr.} - \text{\# matched pixels of ref.}}{\text{\# crack pixels of extraction}}$ (optimal: 0)
- Quality $\approx \frac{\text{compl} \cdot \text{corr}}{\text{compl} - \text{compl} \cdot \text{corr} + \text{corr}}$ (optimal: 1)

- Parameters for other approaches not mentioned in paper

Different approaches

Otsu's thresholding

- Apply thresholds to detect cracks
- Separates a number of intensity classes
- Uses statistical methods to minimize variance in a class and at the same time maximize the variance between the classes

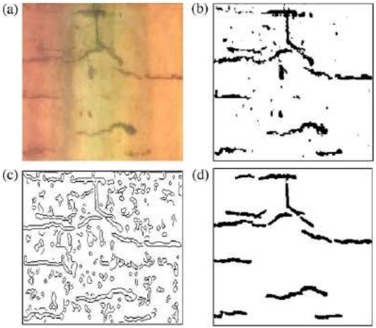


Fig. 13. Edge detection algorithms on crack pattern image: (a) original image, (b) Otsu's thresholding (c) Canny's edge detector, and (d) proposed approach.

Different approaches

Otsu's thresholding

- Apply thresholds to detect cracks
- Separates a number of intensity classes
- Uses statistical methods to minimize variance in a class and at the same time maximize the variance between the classes

Canny's edge detection

- Detect edges in the image between crack and background
- Uses linear filters (Gaussian and Sobel)
- Apply Gaussian, then apply a series of gradient filters to detect edges in different directions

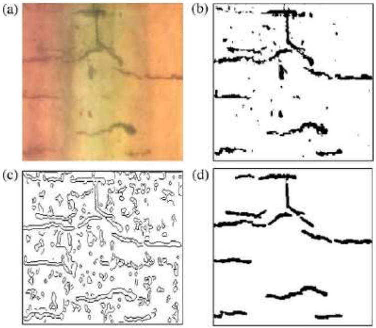


Fig. 13. Edge detection algorithms on crack pattern image: (a) original image, (b) Otsu's thresholding (c) Canny's edge detector, and (d) proposed approach.

Comparison to different approaches

- Otsu's thresholding
- Canny's edge detector
- No information about parameters in paper

Comparison to different approaches

- Otsu's thresholding
- Canny's edge detector
- No information about parameters in paper

Paper approach

Class	Cracks	Background	Color
Completeness	0.95	0.88	0.90
Correctness	0.98	0.94	0.91
Quality	0.93	0.83	0.83
Redundancy	0.00	-0.01	0.00

Comparison to different approaches

- Otsu's thresholding
- Canny's edge detector
- No information about parameters in paper

Paper approach

Class	Cracks	Background	Color
Completeness	0.95	0.88	0.90
Correctness	0.98	0.94	0.91
Quality	0.93	0.83	0.83
Redundancy	0.00	-0.01	0.00

Otsu's thresholding

Class	Cracks	Background	Color
Completeness	0.98	0.61	0.62
Correctness	0.37	0.45	0.08
Quality	0.37	0.35	0.08
Redundancy	0.22	0.23	0.24

Comparison to different approaches

- Otsu's thresholding
- Canny's edge detector
- No information about parameters in paper

Paper approach

Class	Cracks	Background	Color
Completeness	0.95	0.88	0.90
Correctness	0.98	0.94	0.91
Quality	0.93	0.83	0.83
Redundancy	0.00	-0.01	0.00

Otsu's thresholding

Class	Cracks	Background	Color
Completeness	0.98	0.61	0.62
Correctness	0.37	0.45	0.08
Quality	0.37	0.35	0.08
Redundancy	0.22	0.23	0.24

Canny's edge detector

Class	Cracks	Background	Color
Completeness	0.92	0.61	0.62
Correctness	0.20	0.44	0.07
Quality	0.20	0.34	0.07
Redundancy	0.15	0.17	0.14

Comparison to different approaches

- Otsu's thresholding
- Canny's edge detector
- No information about parameters in paper
- Very good evaluation results for proposed method in paper (not verified)

Paper approach

Class	Cracks	Background	Color
Completeness	0.95	0.88	0.90
Correctness	0.98	0.94	0.91
Quality	0.93	0.83	0.83
Redundancy	0.00	-0.01	0.00

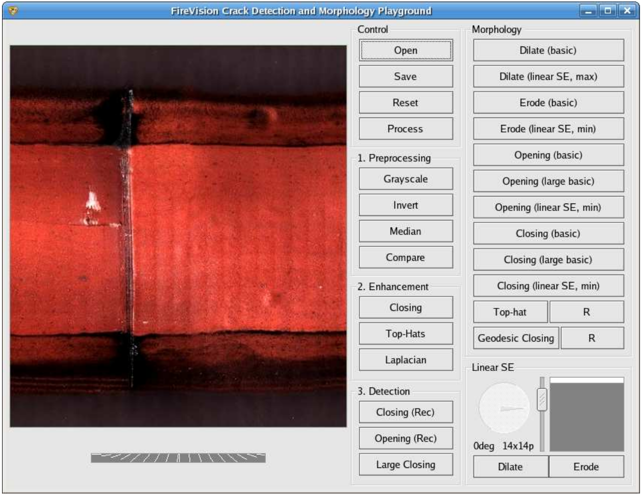
Otsu's thresholding

Class	Cracks	Background	Color
Completeness	0.98	0.61	0.62
Correctness	0.37	0.45	0.08
Quality	0.37	0.35	0.08
Redundancy	0.22	0.23	0.24

Canny's edge detector

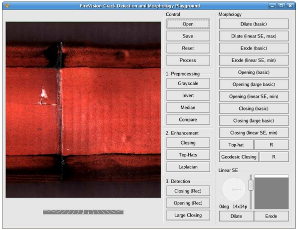
Class	Cracks	Background	Color
Completeness	0.92	0.61	0.62
Correctness	0.20	0.44	0.07
Quality	0.20	0.34	0.07
Redundancy	0.15	0.17	0.14

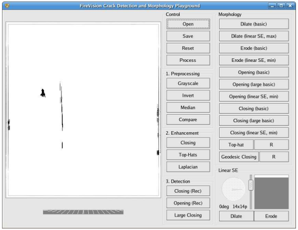
FireVision Crack Detection and Morphology Sandbox



FireVision Crack Detection and Morphology Sandbox

- Implemented in FireVision RoboCup vision framework from AllemaniACs RoboCup team





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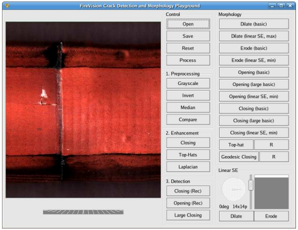

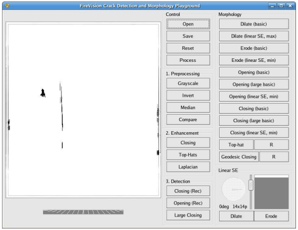

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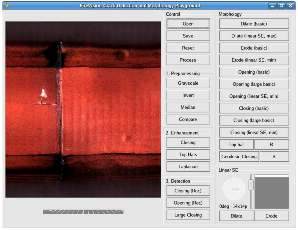
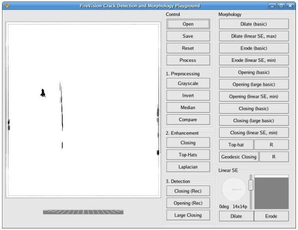
- Revealed several pieces of missing information and errors





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- Discussed paper *very* similar

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Questions?

Information compiled at
`http://www.niemueller.de/uni/crackdet/`