Iowa State University
College of Engineering

Reducing Uncertainty in Wind Turbine Blade Health Inspection with Image Processing Techniques

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Introduction

2011 Summer
Intern @ ABB

2011 Fall
Start M.S. in I.E.
Iowa State University

2012 Summer
Intern @ Exelon

2012 Fall
Start Ph.D. in WESEP
Iowa State University

2013 Summer
Receive M.S. degree
Iowa State University

2013 Summer
IGERT International Experience
Bremerhaven, Germany

2013 Fall
Qualify Exam
Iowa State University

2014 Summer
NSF International Experience
Shanghai, China

2015 Spring
Preliminary Exam
Iowa State University

Career Plan

??????
Receive doctoral degree
Iowa State University

2013 – 2014
Academic Intern @ Exelon

Why Ph.D.?

- 2005 B.E. in Automation, B.S. in Mathematics
- 3 years @ Shanghai Institute of Process Automation Instrumentation
- 2 years @ ABB

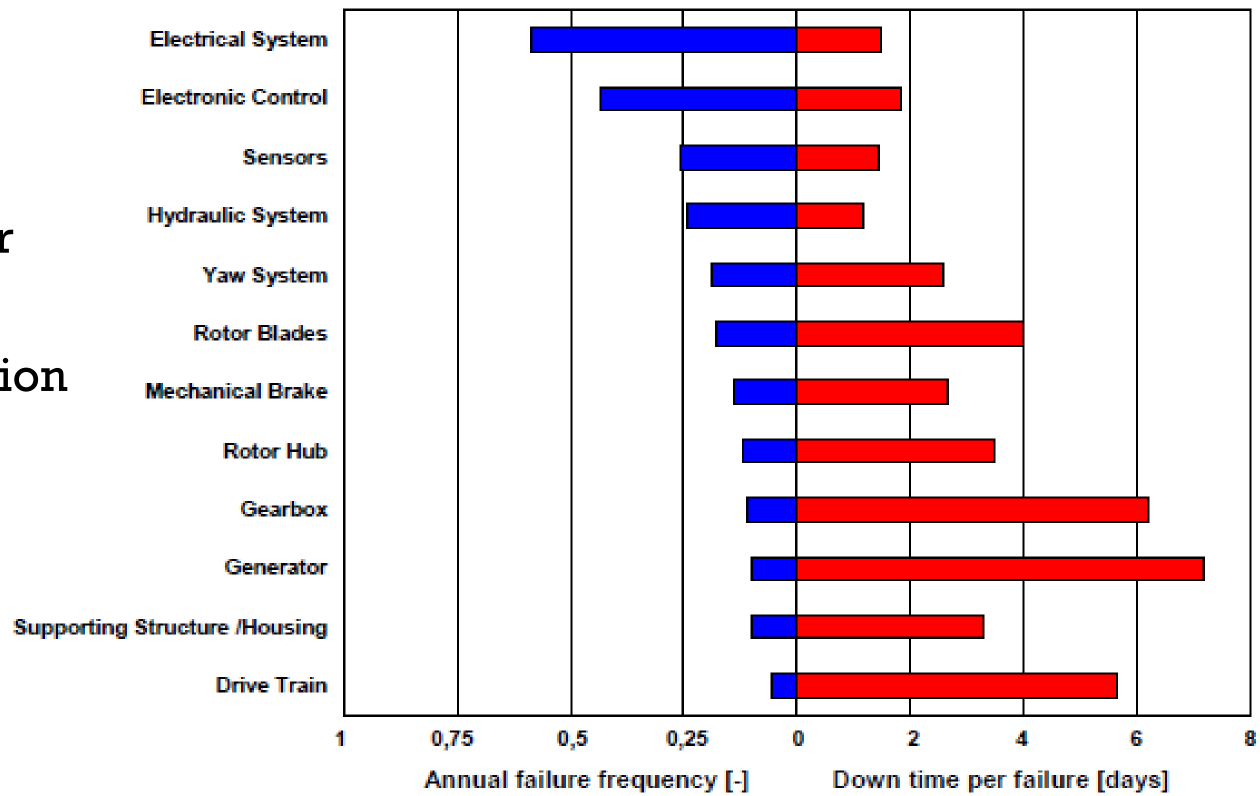
Solve complex problems | Better jobs | Promotion | Meet cool people

Academia
Vs
Industry

Wind Turbine Blade Health Inspection

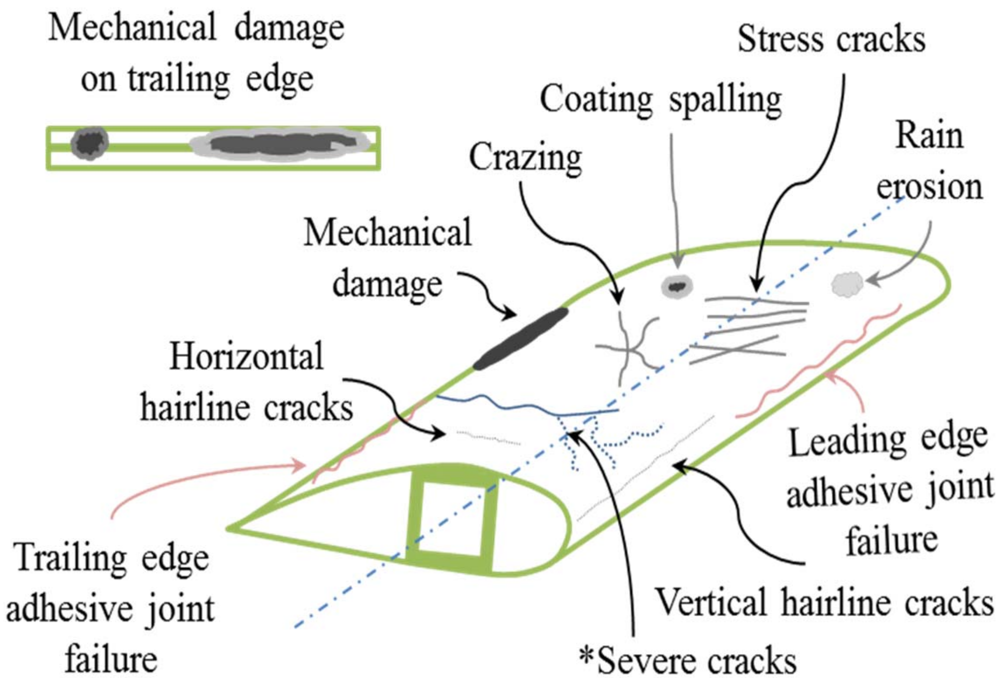
- More turbines
  - 61 GW by 2013
- Expensive component
  - 16-20%
- Easy to fail
  - 6th highest
- Costly to repair
  - Avg. 4 days
- Lost of production

Source: Hahn, 2006

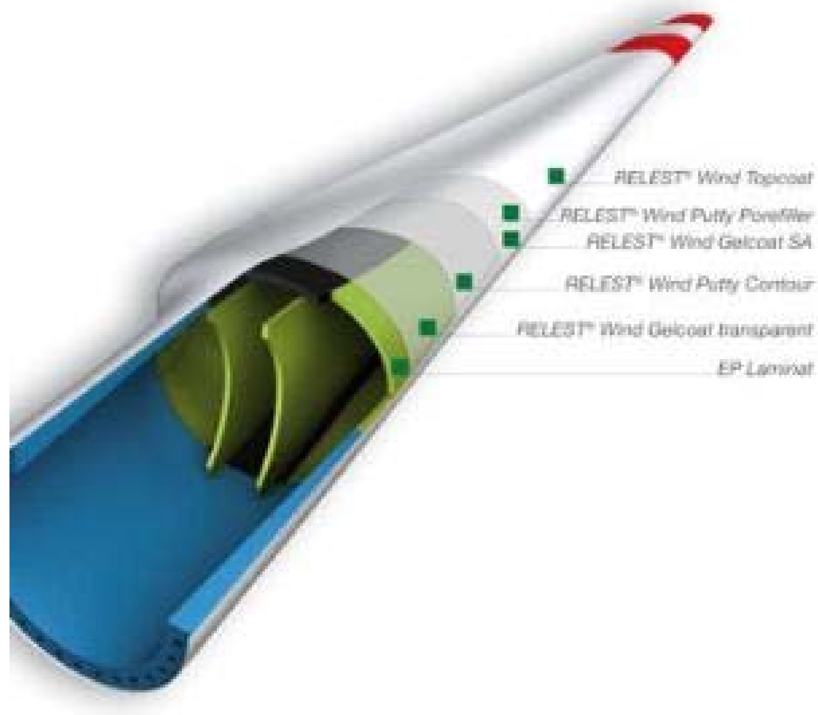


Background

- Types of blade damage



Source: Sørensen, 2004

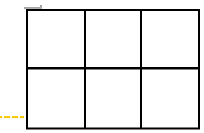


BASF coating for wind turbine blades, 2014
Coating layer health is important to the blades

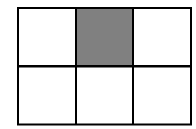
Motivation

- Current practice
  - Routine inspection
  - Complete inspection
- Proposed methods
  - Condition monitoring
  - Robotic vehicle
    - Climbing robot (GE);
    - Unmanned aerial vehicle (UAV) (CYBERHAWK UK)
  - Embedded sensors – Fiber optic sensing
- Challenges:
  - Quick routine inspection
  - Reduce downtime
  - Uncontrolled inspection environment
  - Accuracy: human eye vs. digital images with image processing

Image processing basics

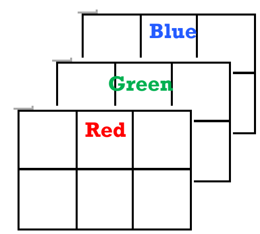


- Matrix (m-by-n) e.g. a 2-by-3 matrix

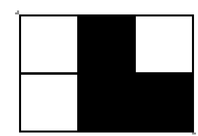


- Pixel: (1) location; (2) intensity level
  - e.g. (1) (1,2); (2) 200 or 0.78 (divided by 255)

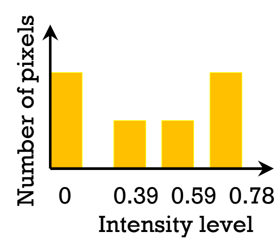
- Grayscale image (m-by-n-by-1)
  - e.g. (0, 0.78, 0, 0.39, 0.59, 0.78)



- RGB image (m-by-n-by-3)
  - RGB -> Grayscale: eliminating hue and saturation
- Threshold (0 ~ 1)



- Histogram (Distribution of intensity level)



- Variance of intensity level
  - $Var(X) = \sum_{i=1}^{n} p_i(x_i - \mu)^2$
- Image segmentation: dividing an image into multiple parts to identify objects or other relevant information (MATLAB)

Problem 1: Feasibility

- Methodology
  - Line detection

    $R = \sum_{i=1}^{8} w_i z_i$

-1	-1	-1
2	2	2
-1	-1	-1

(a) Horizontal.

2	-1	-1
-1	2	-1
-1	-1	2

(b) 45°.

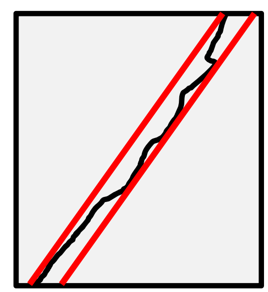
-1	2	-1
-1	2	-1
-1	2	-1

(c) Vertical.

-1	-1	2
-1	2	-1
2	-1	-1

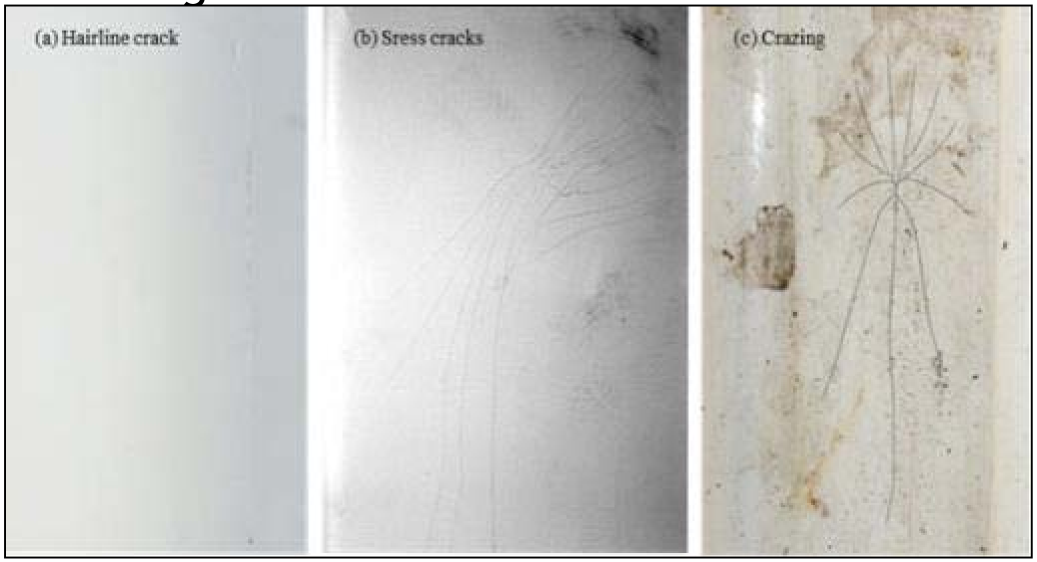
(d) -45°

    z_i is the intensity of the pixel associated with the mask coefficient w_i
  - Edge detection
    - $\nabla f = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$ with the magnitude of the vector being $g = mag(\nabla f) = \left[G_x^2 + G_y^2\right]^{1/2}$ and the angle is $\alpha(x, y) = \tan^{-1}(\frac{G_x}{G_y})$
    - Sobel $G_x = (z_7 + 2z_8 + z_9) - (z_1 + 2z_2 + z_3)$ and $G_y = (z_3 + 2z_6 + z_9) - (z_1 + 2z_4 + z_7)$.
  - Crack quantification
    - Minimum enclosing rectangle
    - Approximation line
      - fminimax function
    - Palled lines



Problem 1: Feasibility

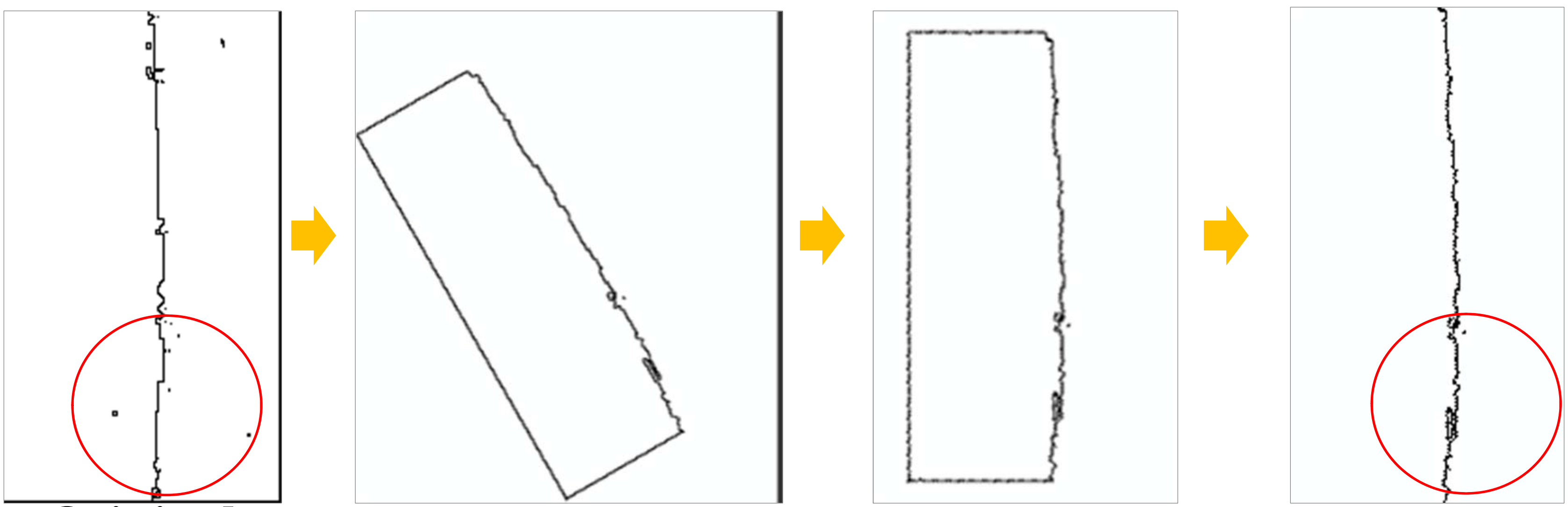
- Field images
  - Hairline crack (RGB image: 157-by-272)
    - Invisible to the human eye
  - Stress cracks (Grayscale: 247-by-350)
    - Uneven lighting
  - Crazing (RGB image: 270-by-435)
    - Background noise



Problem 1: Feasibility

- Line detection method
  - Able to capture hairline crack easily
  - The orientation of image is not a significant factor

Details are different



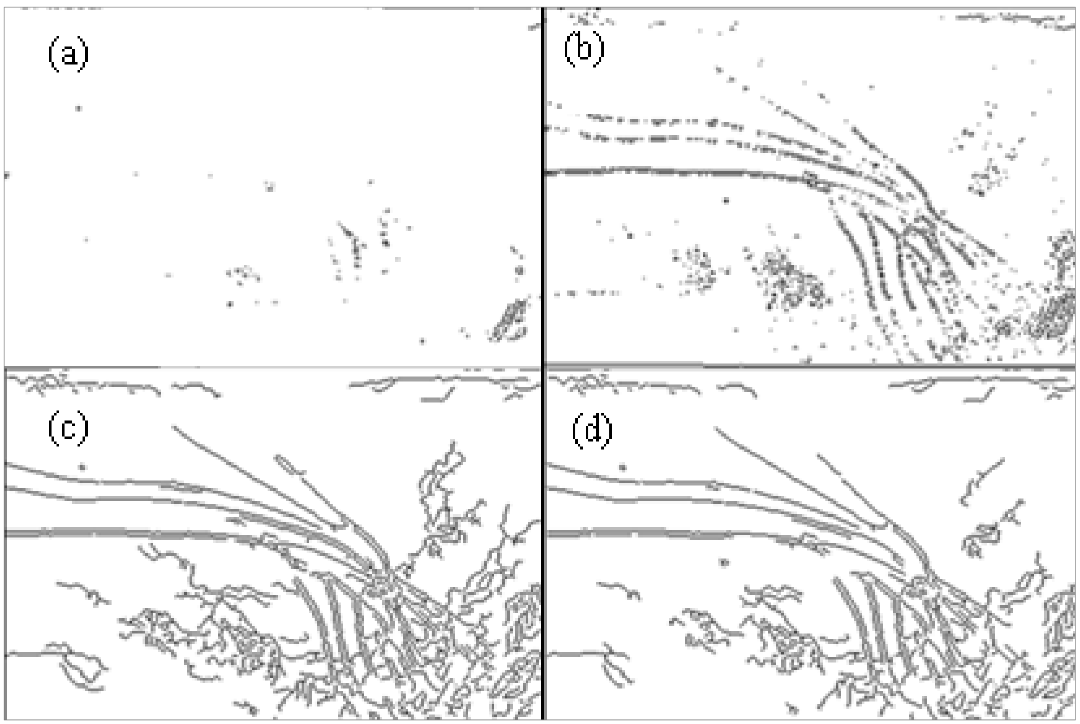
Original **Rotate 30 degree CCW** **Rotate 30 CW** **Trimmed off to the same size**

Applied the same threshold and detector masks

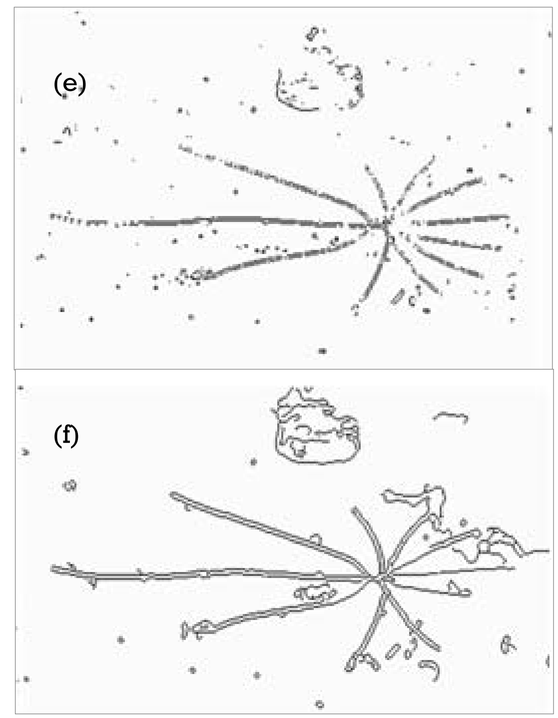
***Same Threshold number – 0.8353**

Problem 1: Feasibility

- Uneven lighting
- Background noise



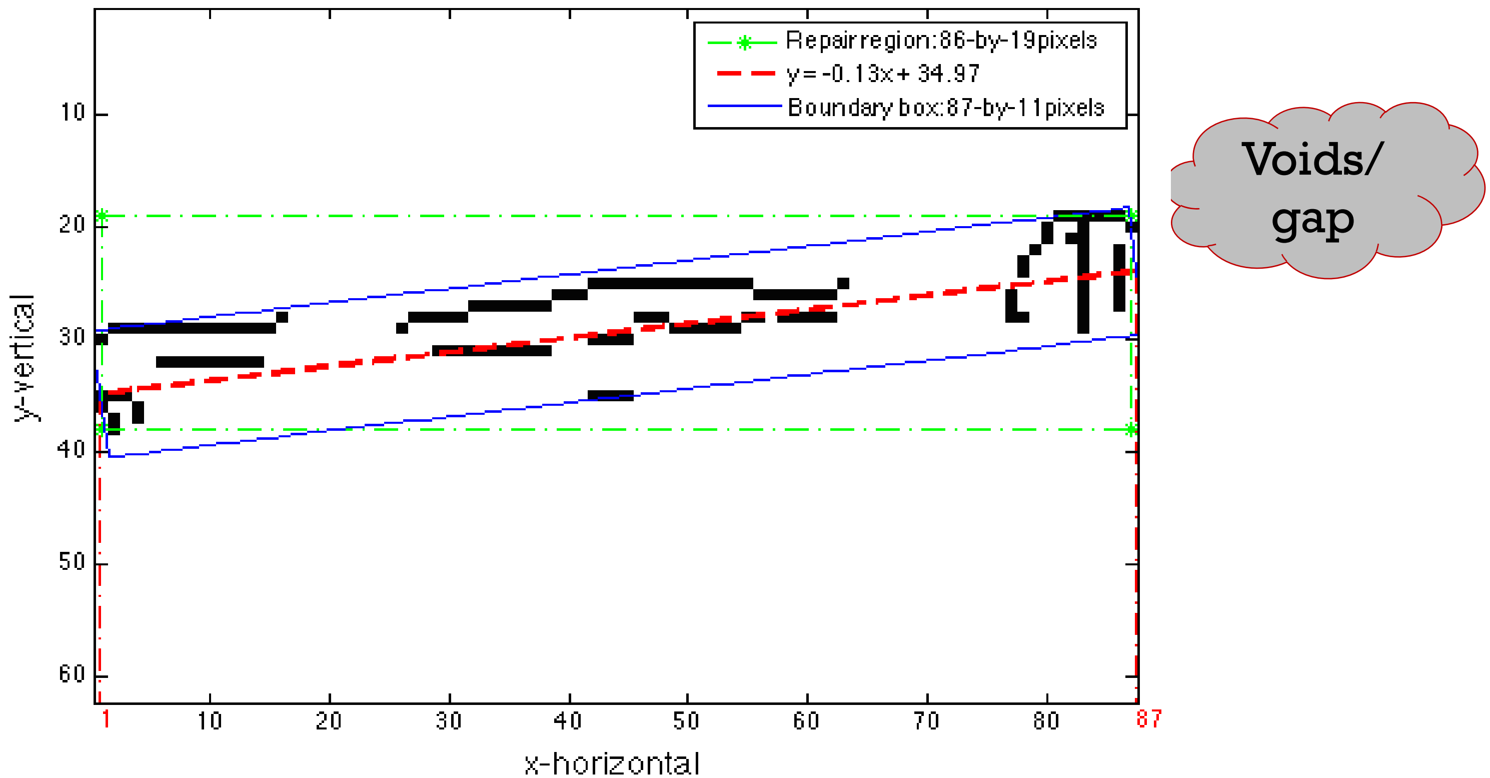
Sobel operator: (a) default threshold (b) optimal threshold
Canny operator: (c) default threshold (d) optimal threshold



(e) *Sobel* operator
(f) *Canny operator*

Problem 1: Feasibility

- Quantifying a crack (27 field images)



- Conclusion
  - It is feasible to identify surface cracks with image processing techniques
  - Need to minimize the impact of uneven lighting and background noise

International experience in Germany



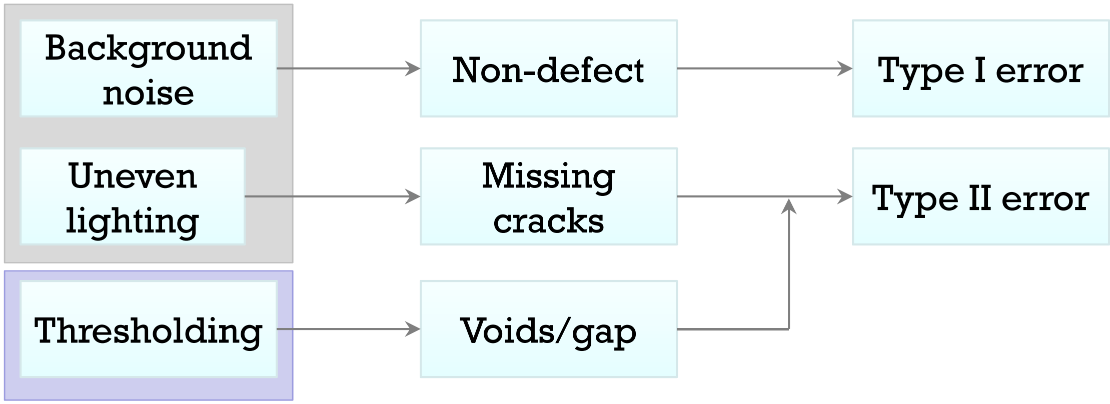

International experience in Germany

International experience in Germany

International experience in Germany

Problem 2: Reduce uncertainty

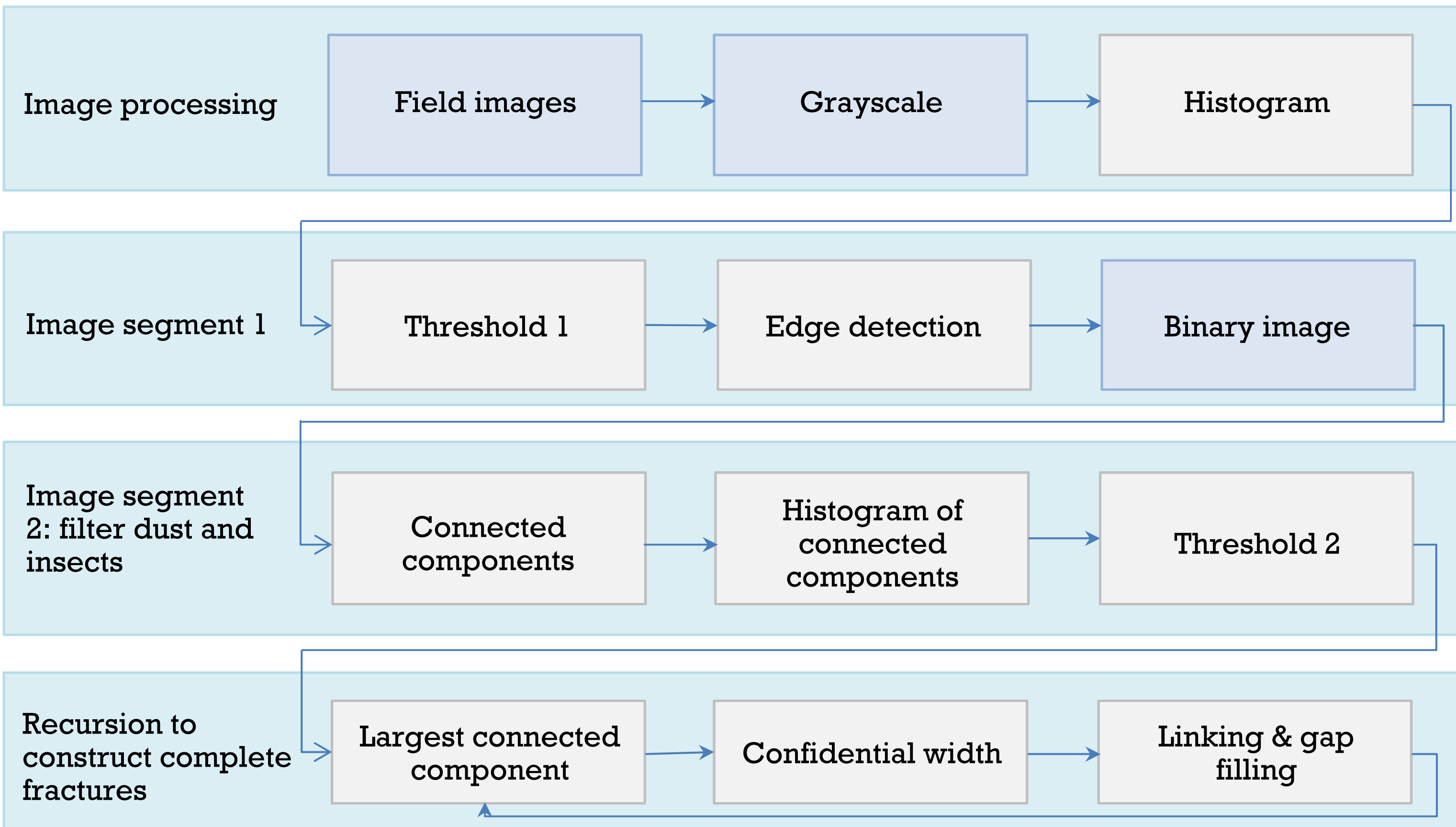
- Research problem 2: What are the uncertainty parameters that need to be addressed in blade health inspection and can an image-processing model be formulated that reduces the uncertainty of image processing results in identifying flaws on a blade surface?



Noise significantly reduces inspection accuracy
Standard image processing techniques do not remove noise (e.g., dirt and insects)

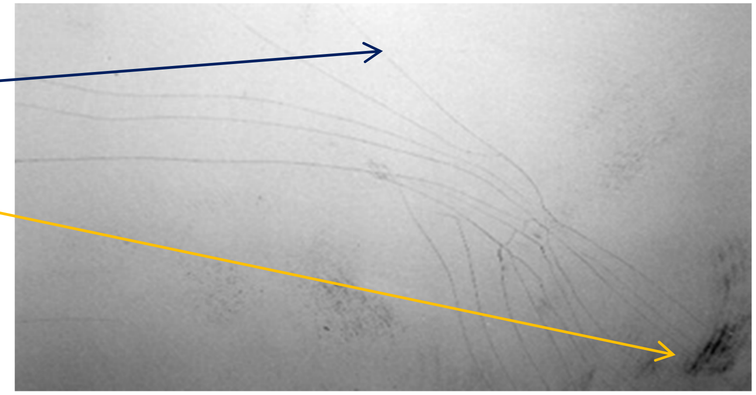
Problem 2: Reduce uncertainty

- Methodology

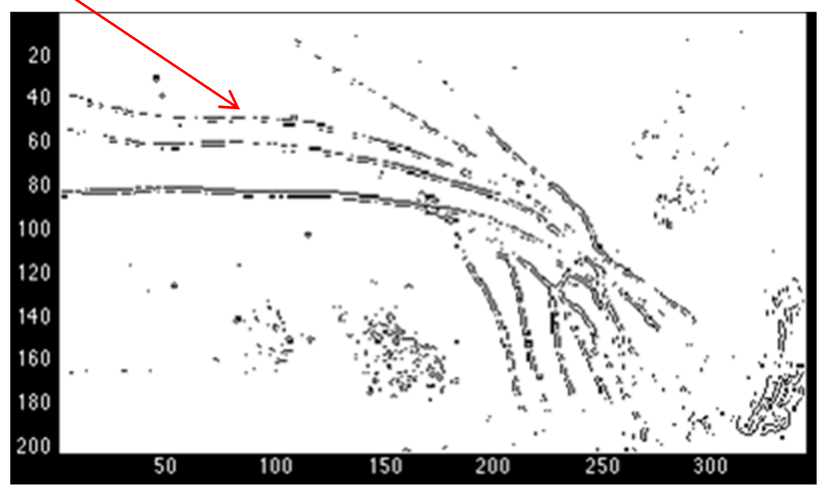


Problem 2: Reduce uncertainty

- Intermediate result
  - \+ Solved uneven illumination
  - \- Background noise remained
  - \- Gaps in crack features



Sobel operator



- The second threshold
  - Connected components

TABLE II
PIXEL CONNECTIVITY

0	0	0
0	1	0
0	0	0

[a]

0	0	0
0	1	1
0	0	1

[b]

0	1	1
1	1	1
1	1	1

[c]

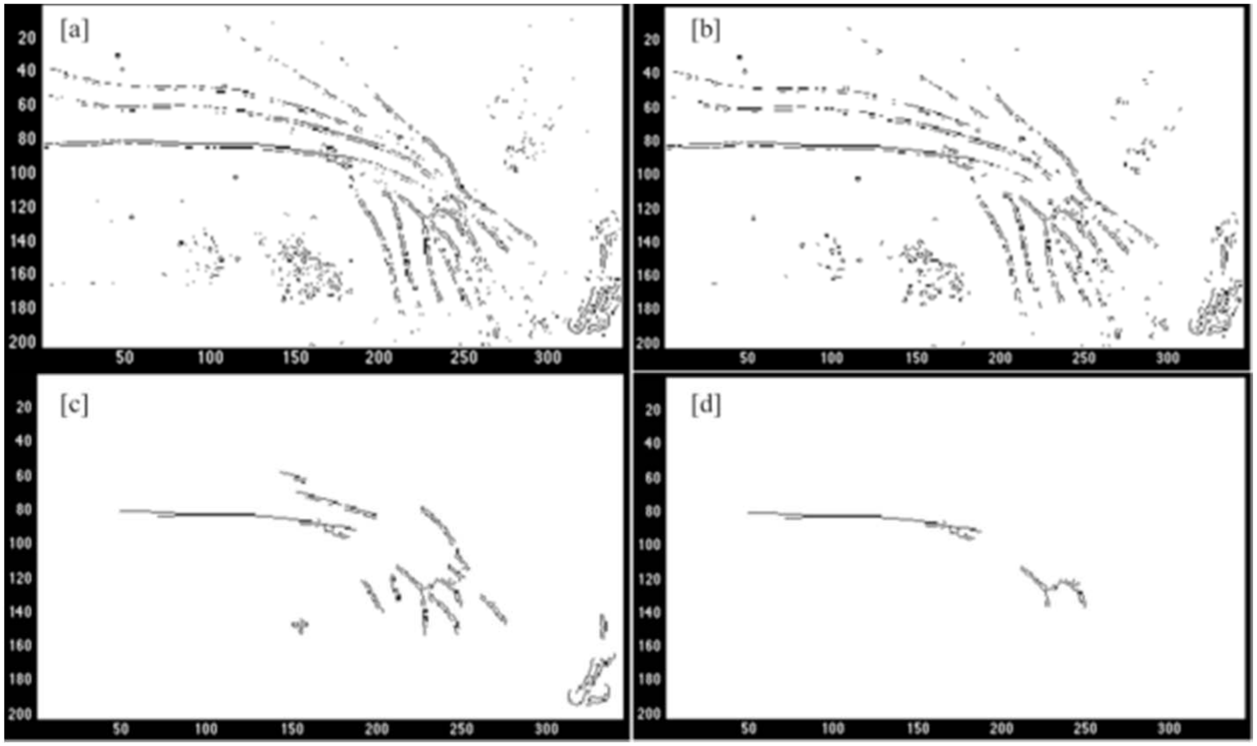
0	1	1
0	1	1
0	1	1

[d]

[a] isolated pixel [b] 8-connected [c] interior pixels [d] exterior pixels

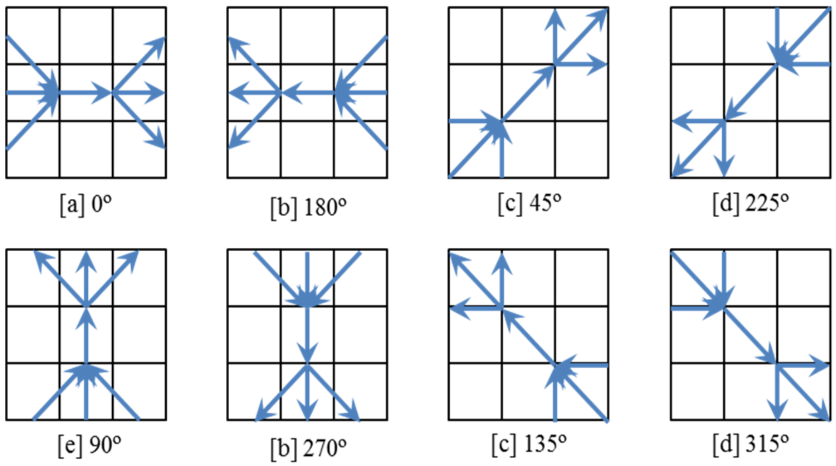
Problem 2: Reduce uncertainty

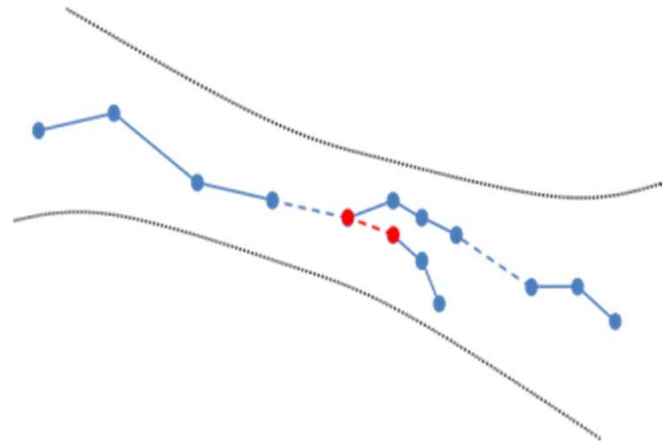
- Remove background noise based on size of connected components
  - [a] Intermediate results with *Sobel* [b] Eliminated isolated pixels
  - [c] Eliminated components $\leq$ 20 pixels [d] Eliminated components $\leq$ 80 pixels

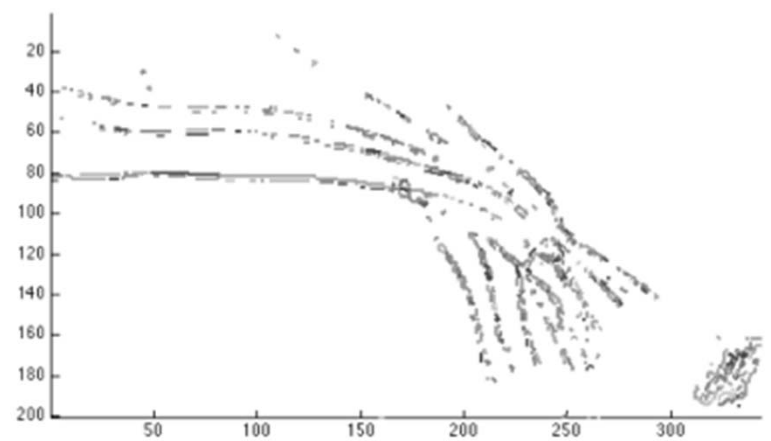


Problem 2: Reduce uncertainty

- Linkage







Results

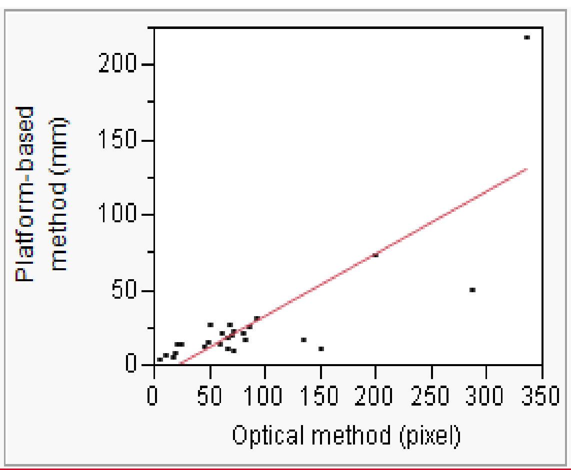
+ Uneven lighting – eliminated.
+ Background noise – removed.
+ Gaps – filled.
? Automatically compute the second threshold for connected components
? Cover all filed conditions

Problem 3: Uncertainty model for real-time on-site inspection

- Research problem 3: what are the important elements of an uncertainty model that can improve the detection results in real-time on-site inspection?
- Detectability

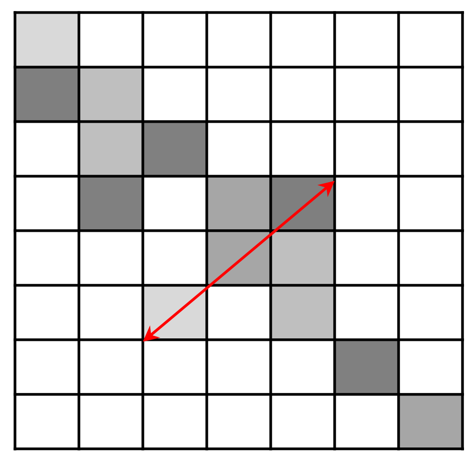
One-to-one relationship between the number of pixels and the size of the crack in millimeters

  - $|(x_n, y_i) - (x_1, y_i)| \geq 3$, for some $1 \leq i \leq m$ and $m \gg n$.
  - i.e., $width(hairline\ crack) \geq 3pixels$
  - $\overline{f_b(x,y)} - \overline{f_o(x,y)} \geq 5$, where $\overline{f_b(x,y)}$ is the average intensity level of the background and $\overline{f_o(x,y)}$ is the average intensity level of the object (hairline crack).



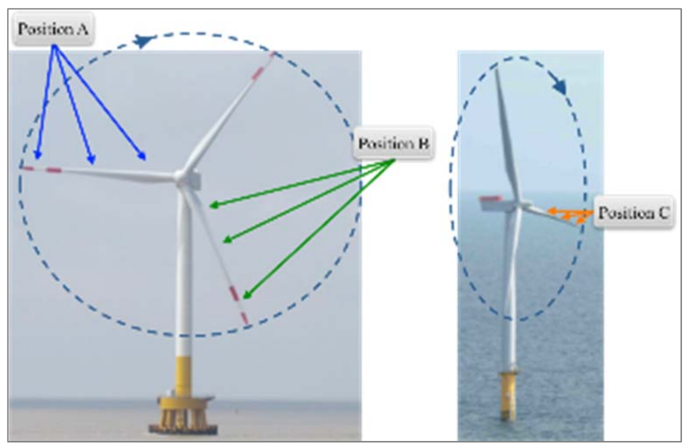
Summary of Fit

RSquare	0.643067
RSquare Adj	0.62879
Root Mean Square Error	24.82372
Mean of Response	26.52963
Observations (or Sum Wgts)	27



International experience in Shanghai, China

International experience in Shanghai, China



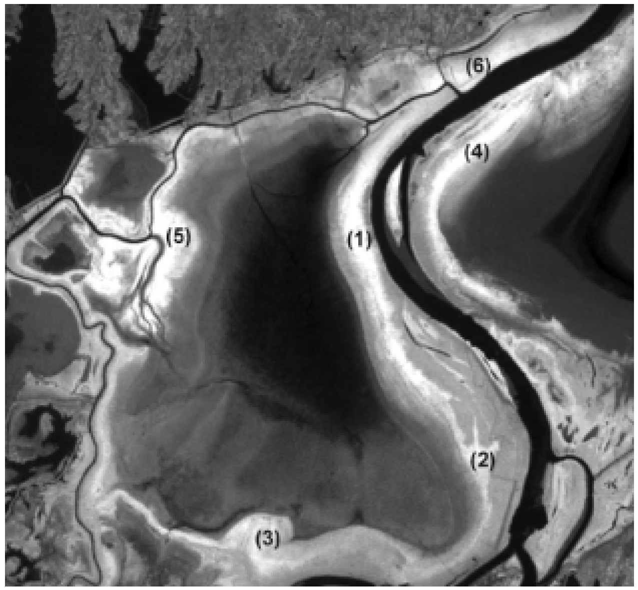
Problem 3: Uncertainty model for real-time on-site inspection

- Related work

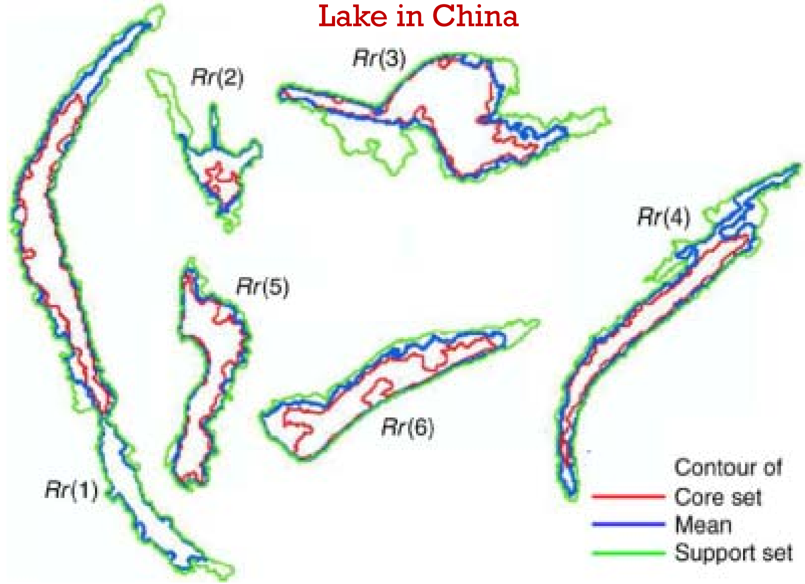
(1) Medical image

(2) Geoinformation Science

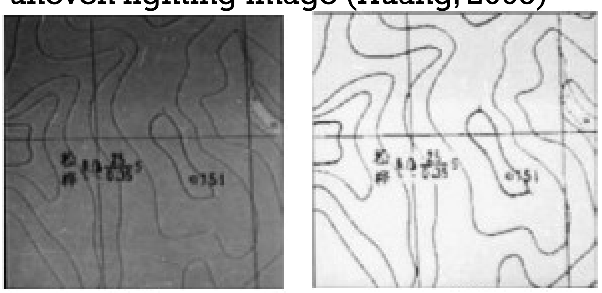
Quantification of extensional uncertainty of segmented image objects by random sets (Zhao, 2011)



Six vegetated areas of a Landsat TM image of Po Yang Lake in China

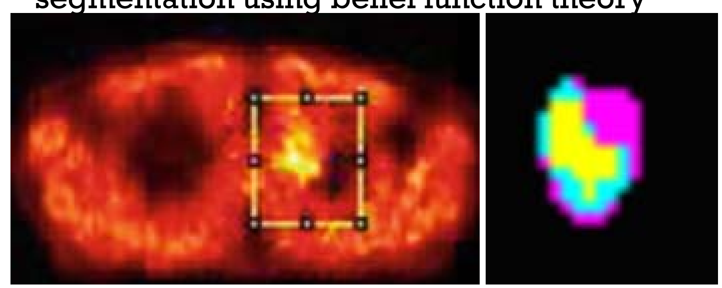


Threshoding technique with adaptive window selection for uneven lighting image (Huang, 2005)



Landscape

Dealing with uncertainty and imprecision in image segmentation using belief function theory



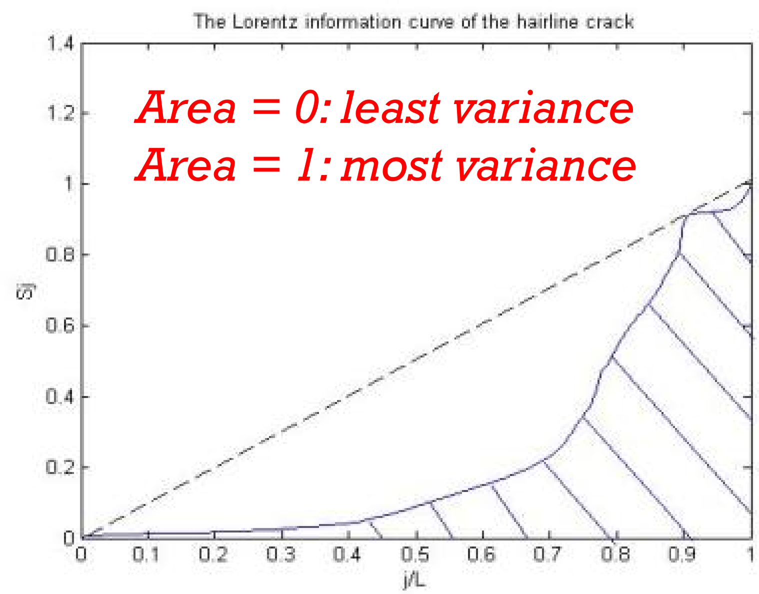
Lung cancer

Problem 3: Uncertainty model for real-time on-site inspection

- Finding the threshold – **Otsu's method**
- $\{T^* = t \colon \eta(t) = \max\left(\frac{\sigma_B^2(t_i)}{\left(\sigma_I^2(t_i)\right)}\right), 0 < i \leq L - 1\}$
  - where $\sigma_B^2(t)$ is the variance between the objects and the background and the total variance of the image $f(x, y)$ is denoted as $\sigma_I^2(t)$.
  - L is the number of gray levels of image $f(x, y)$.

Problem 3: Uncertainty model for real-time on-site inspection

- Methodology – **Lorentz information measure (LIM)**
  - Picture information measure (PIM): $h(i)$ represents the number of pixels with intensity i (i.e. the histogram of image $f(x,y)$)
    - $PIM(f) = \sum_{i=0}^{L-1} h(i) - max_i h(i)$
  - The probability of pixels having a gray level of i: $p_i = \frac{h(i)}{N(f)}$, where the total number of pixels in an image $f(x,y)$ is $N(f)$.
  - The normalized PIM (NPIM) is
    - $NPIM(f) = \frac{PIM(f)}{N(f)} = 1 - \max(p_i)$
  - Denote the normalized PIM at each gray Level as $S_j = NPIM_{L-j}(f)$.
    - $S_0 = 0$
    - $S_L = 0$
    - $S_j = \sum_{i=0}^{j-1} p_i$

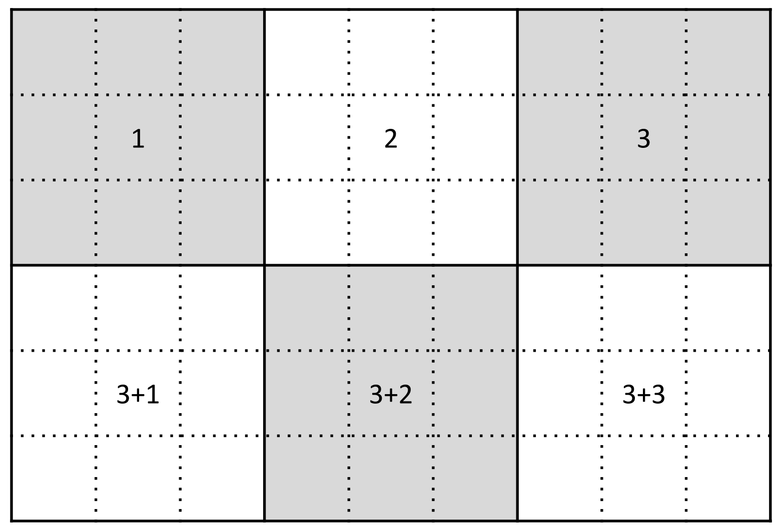


Problem 3: uncertainty model for real-time on-site inspection

- **Adaptive window size method**
  - Step 1: Divide $f(x, y)$ with size M-by-N (MN pixels) into a set of mn sub windows, $f'(x, y) = \{W_1, W_2, \ldots W_{mn}\}$, each size a-by-b pixels. Therefore, M = am, N=an.
  - Step 2: LIM of each window → 'pixel'
    - Compute T' for $f'(x, y) = \{W_1, W_2, \ldots W_{mn}\}$ with Otsu's method
  - Step 3: Apply T' to each window with LIM > T'.
  - Step 4: For those windows with LIM < T', enlarge window k to K, where K includes window k, k+1, k+m, and k+m+1
    - $f''(x, y) = \{window\ 1, window\ 2, \cdots, window\ mn, window\ K\}$.
    - Compute T'' with Otsu's method
    - Repeat steps 3 and 4 until window K becomes the entire image.

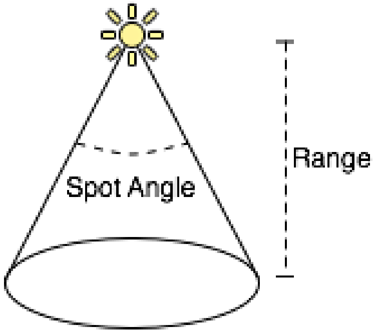
Problem 3: uncertainty model for real-time on-site inspection

- An example of the adaptive window size algorithm with LIM number
  - M = 9, N = 6 $f(x, y)$ is a 9-by-6 image
  - a = 3, b = 3: each window is 3-by-3
  - m = 3, n = 2: there are mn = 6 windows $1 \leq k \leq m$
  - $f'(x, y) = \{W_1, W_2, \ldots W_{mn}\} = \{LIM_1, LIM_2, \ldots LIM_6\}$ compute T' by Otsu's method
  - Suppose $LIM_2 < T'$, enlarge window k = 2 to window K, including windows 2, 3, 5, 6 (k, k+1, k+m, k+m+1)
  - Get new image $f''(x, y) = \{W_K\}$
  - Compute T''

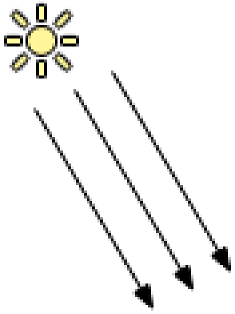


Problem 3: Uncertainty model for real-time on-site inspection

- Field image with extreme artificial uneven lighting



Spotlight



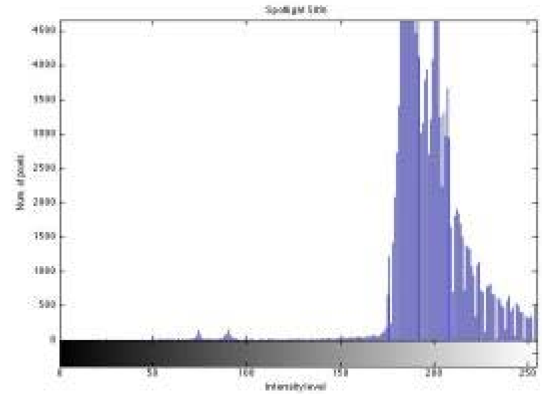
Infinite light

Problem 3: uncertainty model for real-time on-site inspection

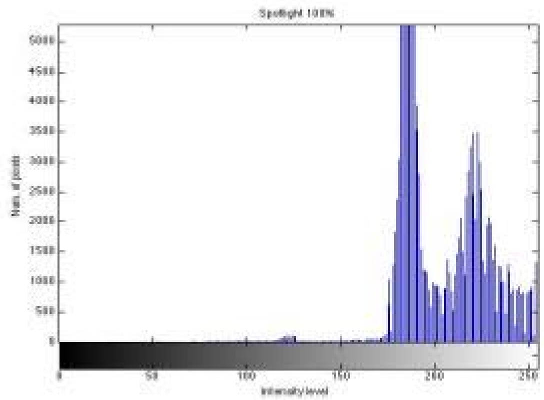
- Field images with extreme artificial uneven lighting – spot light

Spotlight with 50% intensity

Spotlight with 100% intensity



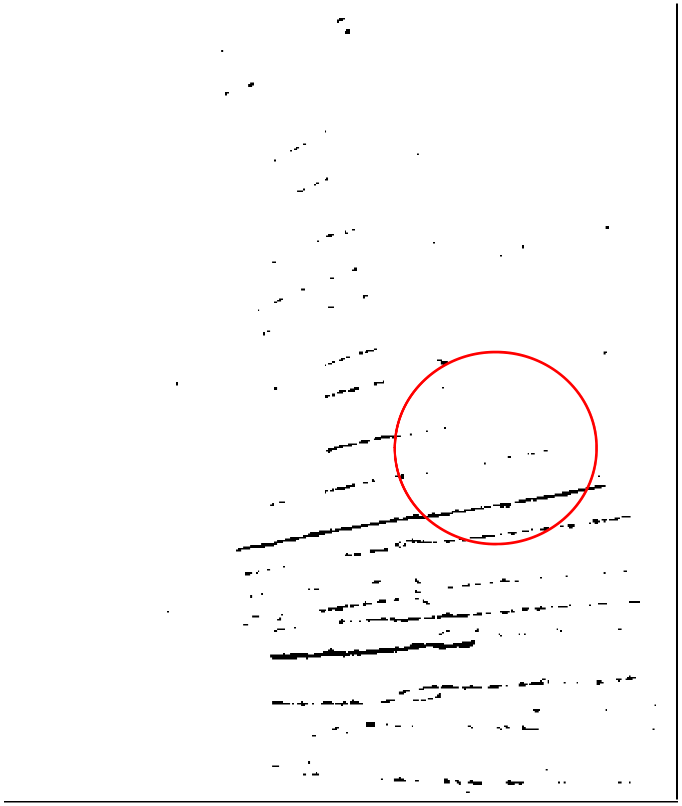
Spotlight with 50% intensity



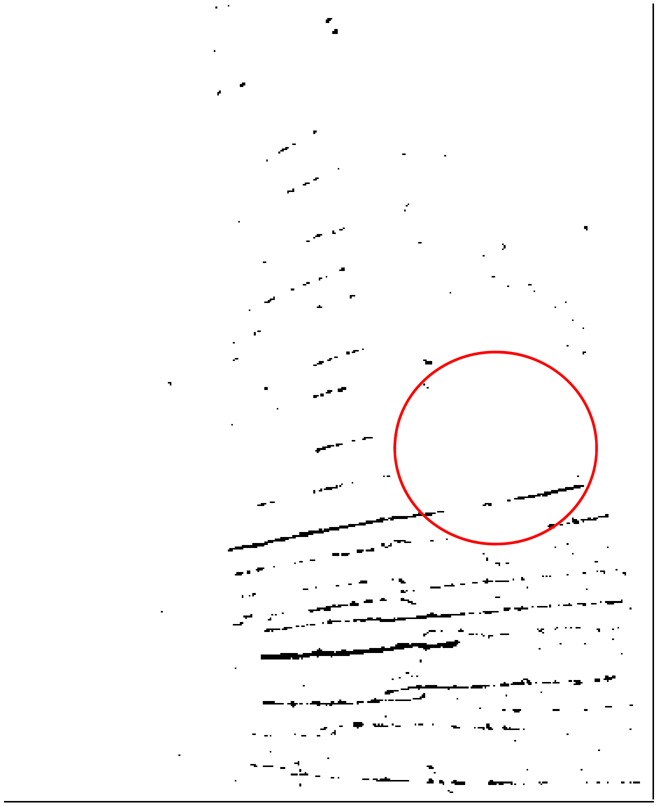
Spotlight with 100% intensity

Problem 3: uncertainty model for real-time on-site inspection

- Preliminary results



Spotlight with 50% intensity



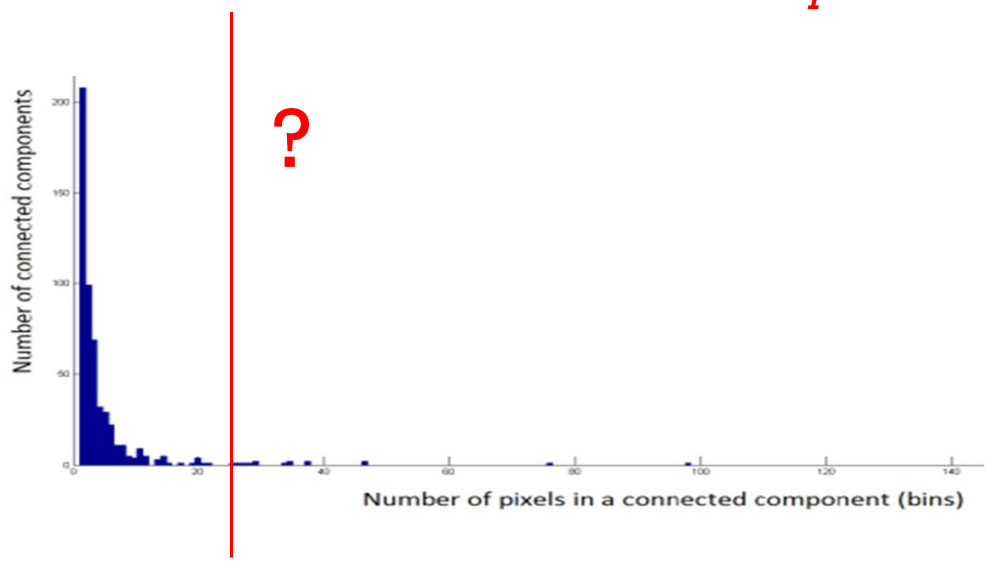
Spotlight with 100% intensity

Problem 3: Uncertainty model for real-time on-site inspection

- Following works
  - Infinite lighting
  - Severe background noises
    - Automatically compute the second threshold for connected components
  - The uncertainty evaluation algorithm

Apply Otsu's method to connected components?

Size & distribution of the connected components?



Contributions

- Automated routine inspection of WTB with image processing technique is possible. This is a new concept compared with current O&M practice and can significantly improve the inspection results.

- Developed an algorithm to quantify the cracks with a minimum envelope.

- Another contribution is that we developed a second thresholding method for connected components that will eliminate the background noise significantly.

- An uncertainty evaluation algorithm will be formulated that can evaluate the impacts of uncertainty parameters from field conditions as well as the image-processing method itself.

- This new method should be able to inspect images under complex field conditions that include severe uneven lighting and background noise.