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

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Introduction

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

2011 Summer
Intern @ ABB

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

2012 Summer
Intern @ Exelon

2012 Fall
Qualify Exam
Iowa State University

2013 Summer
IGERT International Experience
Bremerhaven, Germany

2013 Fall
Preliminary Exam
Iowa State University

2013 Summer
NSF International Experience
Shanghai, China

2014 Spring
Preliminary Exam
Iowa State University

2015 Spring
Receive doctoral degree
Iowa State University

Career Plan

2013 – 2014
Academic Intern @ Exelon

IOWA STATE UNIVERSITY

College of Engineering
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

IOWA STATE UNIVERSITY
College of Engineering
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

Mechanical damage on trailing edge
Stress cracks
Coating spalling
Crazing
Rain erosion
Mechanical damage
Horizontal hairline cracks
Leading edge adhesive joint failure
Vertical hairline cracks
*Severe cracks
Trailing edge adhesive joint failure

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)
  - 0: background, T: threshold value, 1: object
- 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
    \[ R = \sum_{i=1}^{g} w_i z_i \]
    \[ z_i \] is the intensity of the pixel associated with the mask coefficient \( w_i \)
  - Edge detection
    - \[ \nabla f = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} \]
    with the magnitude of the vector being \( g = \text{mag}(\nabla f) = \left[ G_x^2 + G_y^2 \right]^{1/2} \)
    and the angle is \( \alpha(x, y) = \tan^{-1}\left( \frac{G_x}{G_y} \right) \)
    - 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
      - \( \text{fminimax function} \)
    - 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

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

1. **Image processing**
   - Field images
   - Grayscale
   - Histogram

2. **Image segment 1**
   - Threshold 1
   - Edge detection
   - Binary image

3. **Image segment 2: filter dust and insects**
   - Connected components
   - Histogram of connected components
   - Threshold 2

4. **Recursion to construct complete fractures**
   - Largest connected component
   - Confidential width
   - Linking & gap filling
Problem 2: Reduce uncertainty

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

- The second threshold
  - Connected components

\[\text{Sobel operator}\]

**TABLE II**

<p>| | | |</p>
<table>
<thead>
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</tbody>
</table>

- [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 ≤ 20 pixels
  - [d] Eliminated components ≤ 80 pixels
Problem 2: Reduce uncertainty

- **Linkage**

  ![Linkage Diagrams]

+ 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**

  \[ |(x_n, y_i) - (x_1, y_i)| \geq 3, \text{ for some } 1 \leq i \leq m \text{ and } m \gg n. \]

  - i.e., \( \text{width(hairline crack)} \geq 3 \text{pixels} \)
  - \( f_b(x, y) - f_o(x, y) \geq 5, \) where \( f_b(x, y) \) is the average intensity level of the background and \( f_o(x, y) \) is the average intensity level of the object (hairline crack).

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

Table: Summary of Fit

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Value</th>
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<tbody>
<tr>
<td>RSquare</td>
<td>0.643067</td>
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<tr>
<td>RSquare Adj</td>
<td>0.62879</td>
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<tr>
<td>Root Mean Square Error</td>
<td>24.82372</td>
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<tr>
<td>Mean of Response</td>
<td>26.52983</td>
</tr>
<tr>
<td>Observations (or Sum Wgts)</td>
<td>27</td>
</tr>
</tbody>
</table>
International experience in Shanghai, China
International experience in Shanghai, China
Problem 3: Uncertainty model for real-time on-site inspection

- **Related work**
  - Quantification of extensional uncertainty of segmented image objects by random sets (Zhao, 2011)
  - Threshoding technique with adaptive window selection for uneven lighting image (Huang, 2005)

(1) Medical image
(2) Geoinformation Science

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

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**

• \( T^* = t: \eta(t) = \max \left( \frac{\sigma^2_B(t_i)}{\sigma^2_I(t_i)} \right), 0 < i \leq L - 1 \)

  • where \( \sigma^2_B(t) \) is the variance between the objects and the background and the total variance of the image \( f(x, y) \) is denoted as \( \sigma^2_I(t) \).
  
  • \( L \) 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 \( S_j = NPIM_{L-j}(f) \).
    - \( S_0 = 0 \)
    - \( S_L = 0 \)
    - \( S_j = \sum_{i=0}^{j-1} p_i \)

\[ \text{Area} = 0: \text{least variance} \]
\[ \text{Area} = 1: \text{most variance} \]
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 \( \rightarrow \) ‘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 \( k+m+1 \)
    - \( f''(x, y) = \{\text{window 1, window 2, \ldots, window mn, window } K\} \)
    - 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
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
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.