Deep Learning based Diagnostics for Rotating Machinery on Orbit Analysis

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- Deep Learning
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Rotating Machinery

- Mechanical component
- Key components to generate electric power (in power plants)
- Performance degradation and entire system break downs
  - Plant operation/maintenance cost
  - Level of safety
Monitoring Systems

- Prognostics and Health Management (PHM) approach
- Prevent/Predict system failures
Orbit Analysis for Rotating Machinery

• Visualize shaft movement
  – Vibration information in 2D

• Still manually monitored by human operators in most power plants
Known-Fault Modes from Orbit Shapes

- **Unbalance**

  ![Orbit shape of unbalance](image)

- **Misalignment**

  ![Orbit shape of misalignment](image)

- **Hit and rubbing**

  ![Orbit Shape of hit and bounce rub](image)
Training Data (Data-driven Method)

• The orbit vibration data are collected from the rotor kit

• Pre-defined 5 classes of orbit
  – Each shape is related to the specific spindle rotor status
  – 150 orbit images are acquired for each pattern

<table>
<thead>
<tr>
<th>Fault</th>
<th>Normal</th>
<th>Unbalance</th>
<th>Misalignment</th>
<th>Rubbing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Orbit Shape</td>
<td><img src="image1.png" alt="Circle" /></td>
<td><img src="image2.png" alt="Ellipse" /></td>
<td><img src="image3.png" alt="Eight" /></td>
<td><img src="image4.png" alt="Heart" /></td>
</tr>
</tbody>
</table>
Proposed Idea

- Signal to image
- Image pattern recognition
- Deep learning (Google, Facebook, …)
- Use known-fault modes
Deep Learning

• Neural networks
  – Simple neurons, nonlinear activation functions
• Abstraction from combination of non-linear method
• Automatic discovery of the representation for classification

Structure of Convolutional Neural Networks
Deep Learning

- Neural networks
  - Simple neurons, nonlinear activation functions
- Abstraction from combination of non-linear method
- Automatic discovery of the representation for classification
- Image pattern recognition problems
  - Convolutional Neural Networks (CNN)
  - Perception like humans

Structure of Convolutional Neural Networks

Key idea of Convolutional Neural Networks

RGB = [ 0 0 0 ]
1 Pixel cannot explain any information
Small area can explain context of image
Deep Learning on Orbit Images

- Autonomous orbit image pattern recognition
- Two processes: Training and classification
Deep Learning on Orbit Images

- Autonomous orbit image pattern recognition
- Two processes: Training and classification

Training Process

1. Training Data
2. Deep Learning Structure
3. Trained

Classification Process

1. Input Data
2. Structure
3. Classification
Deep Learning on Orbit Images

- Autonomous orbit image pattern recognition
- Two processes: Training and classification

Training Process
- Training Data
- Pre-processing
- Deep Learning Structure
- Trained

Classification Process
- Input Data
- Pre-processing
- Structure
- Classification

\[
\min_z \| \Phi z - b \|_2 \\
\hat{z} = (\Phi^T \Phi)^{-1} \Phi^T b
\]
Pre-processing Steps for Better Classification

- Independent of orbit image pattern
  - Location, rotated angle and size
- Maximize performance of training data set
  - Although CNN is kind of capable to handle such local variations
Experiment Results
Orbit: Circle
Ellipse

Orbit Recognition with Deep Learning

[Image of an ellipse and related diagrams]
Eight, 8
Tornado

Orbit Recognition with Deep Learning
Mode Changes

Orbit Recognition with Deep Learning
Advantages

- No need data from fault modes
  - One of challenges of data-driven PHM approach
  - Orbit pattern from rotor dynamics (system-based or model-based)

- Continuous health condition status

\[
\hat{z} = (\Phi^T \Phi)^{-1} \Phi^T b
\]

Fault type and degree of machine malfunction
## Benchmark: Comparison

<table>
<thead>
<tr>
<th>Method</th>
<th>Feature</th>
<th>Input</th>
<th>Structure</th>
<th>Error</th>
</tr>
</thead>
</table>
| Deep Learning                        | Auto Extraction                              | 50×50 Image      | • Convolutional Neural Networks  
  • 1 Input Layer  
  • 3 Layers  
  ▪ Convolution Layer  
  ▪ Sub-sampling Layer  
  • 1 Output Layer          | 1.1%   |
| Artificial Neural Networks (ANN)     | Harmonics forward, backward vector coefficients | 8×1 Vector       | • 1 Input Layer  
  ▪ 8 neurons  
  • 1 Hidden Layer  
  ▪ 100 neurons  
  • 1 Output Layer  
  ▪ 5 neurons       | 8.5%   |
| Gaussian Discriminant Analysis (GDA) | • Real Value  
  • Imaginary Value                           | 8×1 Vector       | • Mean Vector  
  • Covariance Matrix                                                      | 6.0%   |

Feature selection/Extraction
Conclusions

• Orbit Image as Features for Machine Diagnosis

• Deep Learning for Better Estimation Accuracy

• Validate with a Testbed

• System-based
  – Known orbit pattern → no need a prior data collection

• Auto feature extraction via deep learning