Deep Learning based Diagnostics for Rotating Machinery on Orbit Analysis

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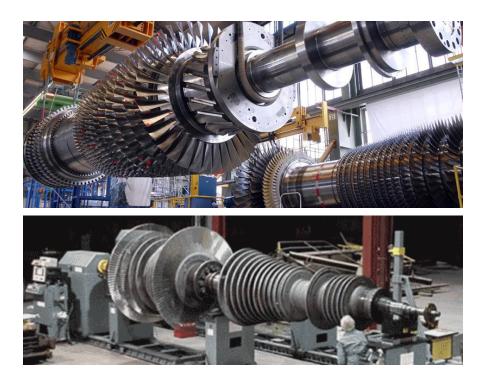
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- Orbit Analysis for Rotating Machinery
- Deep Learning
- Pre-processing Steps
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Rotating Machinery

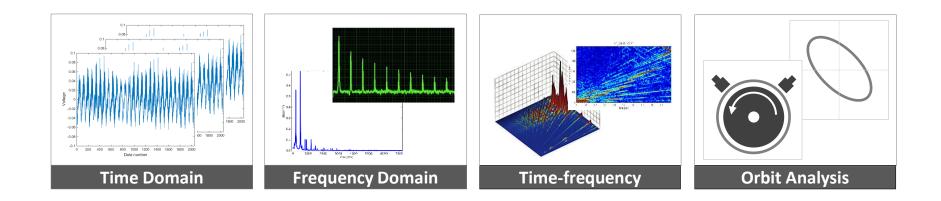
- Mechanical component
- Key components to generate electric power (in power plants)
- Performance degradation and entire system break downs
 - Plant operation/maintenance cost
 - Level of safety





Monitoring Systems

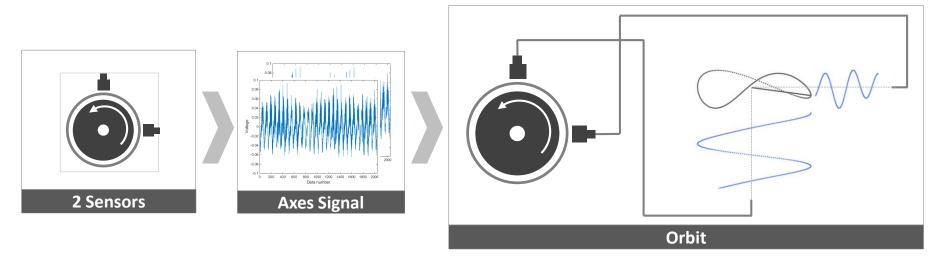
- Prognostics and Health Management (PHM) approach
- Prevent/Predict system failures





Orbit Analysis for Rotating Machinery

- Visualize shaft movement
 - Vibration information in 2D

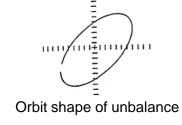


• Still manually monitored by human operators in most power plants

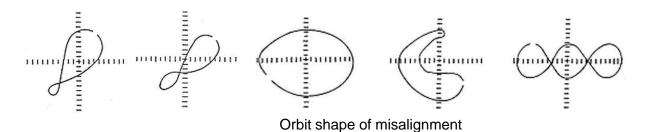


Known-Fault Modes from Orbit Shapes

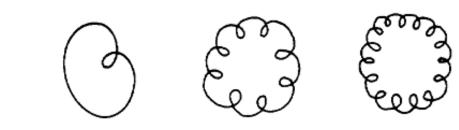
Unbalance



• Misalignment



• Hit and rubbing

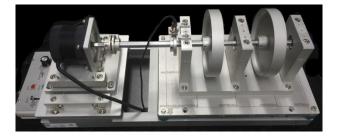


Orbit Shape of hit and bounce rub



Training Data (Data-driven Method)

• The orbit vibration data are collected from the rotor kit

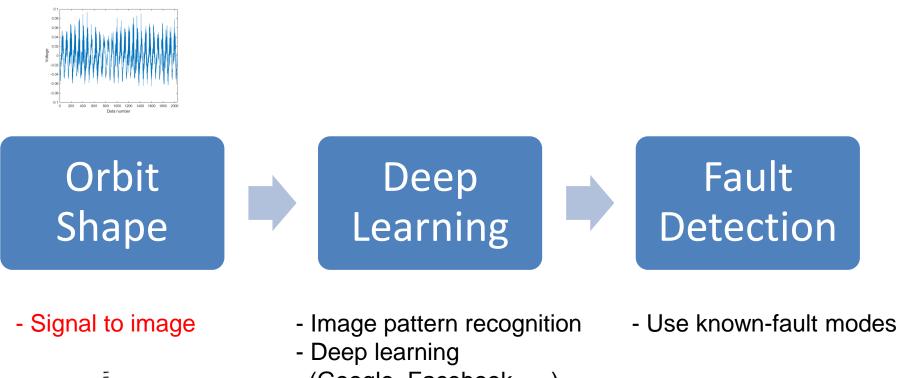


- Pre-defined 5 classes of orbit
 - Each shape is related to the specific spindle rotor status
 - 150 orbit images are acquired for each pattern

	Normal	Unbalance	Misalignment		Rubbing
Fault	Circle (C)	Ellipse (E)	Eight (8)	Heart (H)	Tornado (T)
Orbit Shape				3	



Proposed Idea

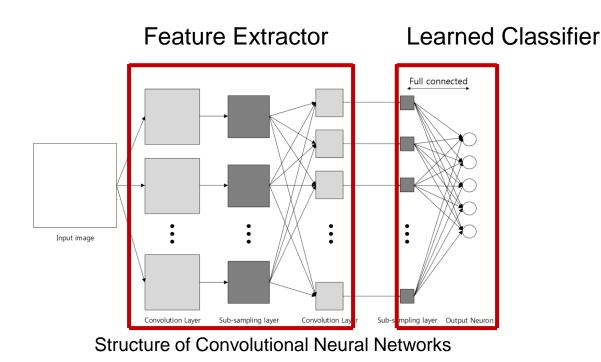




(Google, Facebook, ...)

Deep Learning

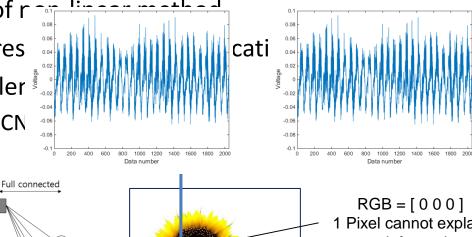
- Neural networks
 - Simple neurons, nonlinear activation functions
- Abstraction from combination of non-linear method
- Automatic discovery of the representation for classification

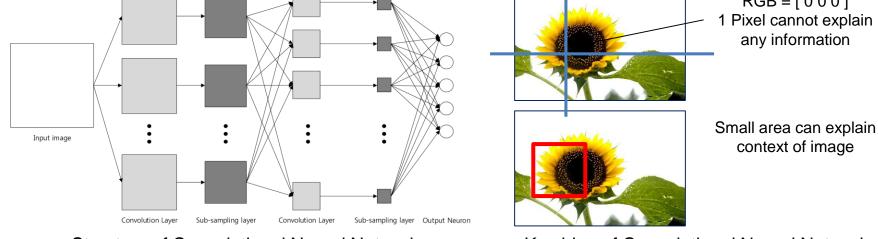


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Deep Learning

- Neural networks
 - Simple neurons, nonlinear activation functions
- Automatic discovery of the repres
- Image pattern recognition probler
 - <u>Convolutional</u> Neural Networks (CN
 - Perception like humans





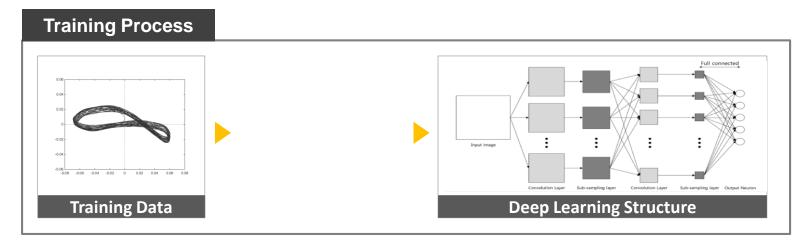
Structure of Convolutional Neural Networks

Key idea of Convolutional Neural Networks



Deep Learning on Orbit Images

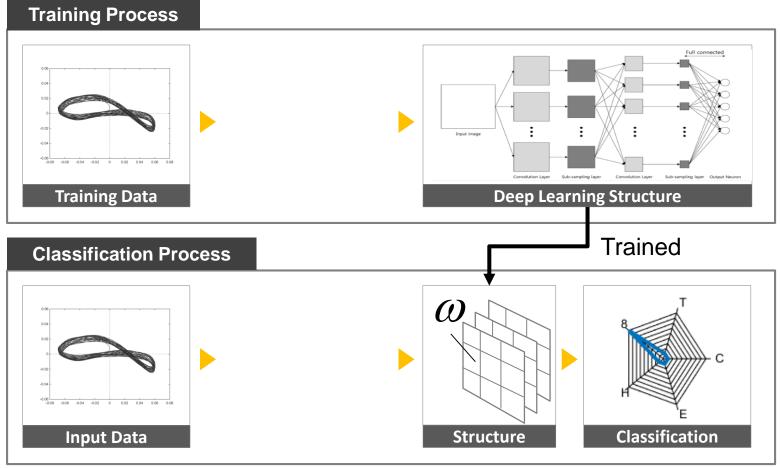
- Autonomous orbit image pattern recognition
- Two processes: Training and classification





Deep Learning on Orbit Images

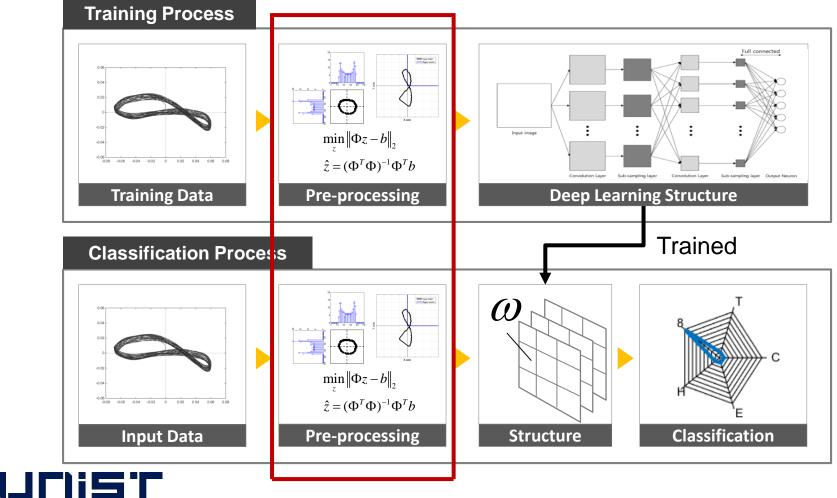
- Autonomous orbit image pattern recognition
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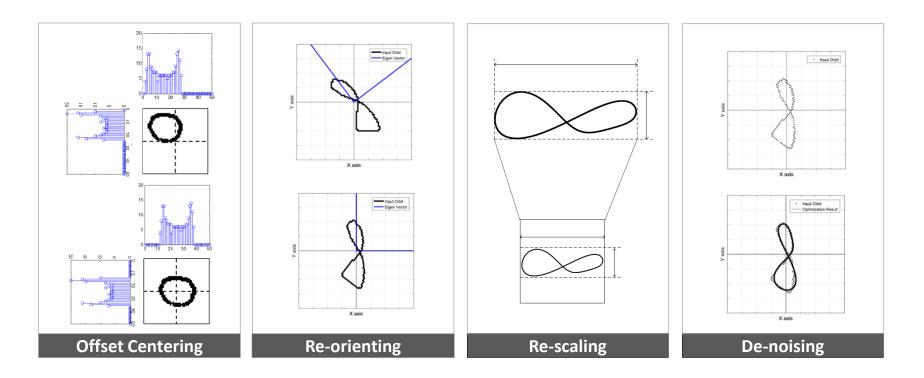
Deep Learning on Orbit Images

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



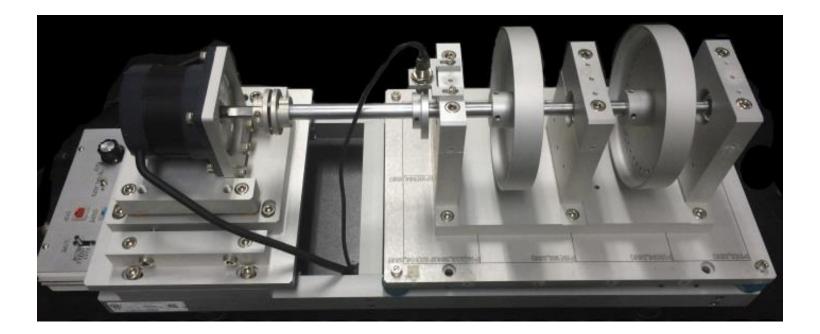
Pre-processing Steps for Better Classification

- 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



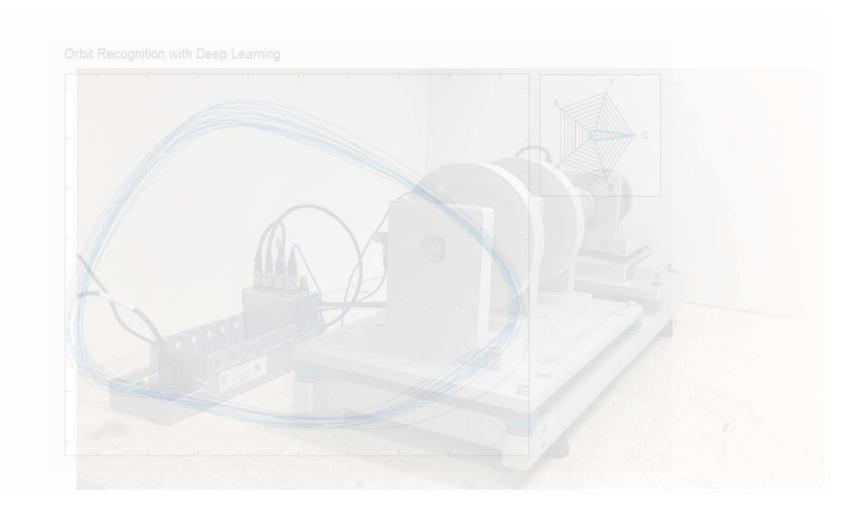


Experiment Results

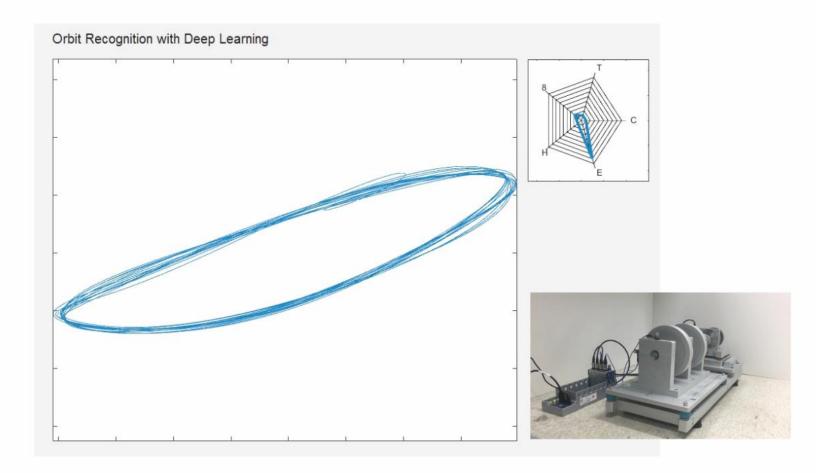




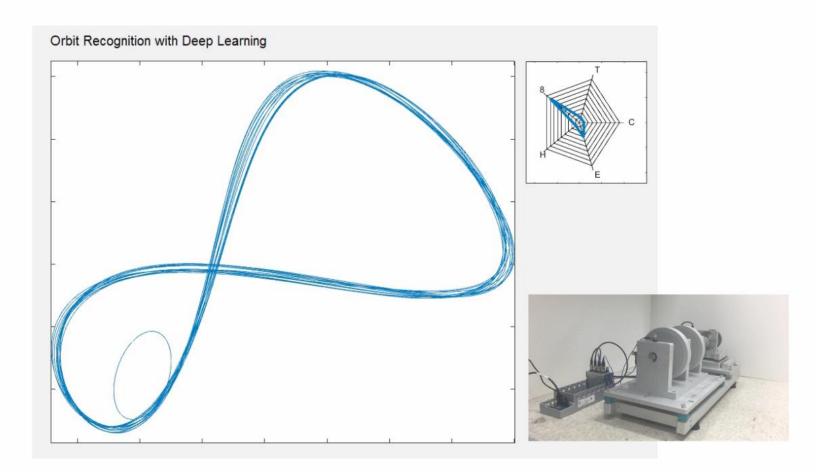
Orbit: Circle





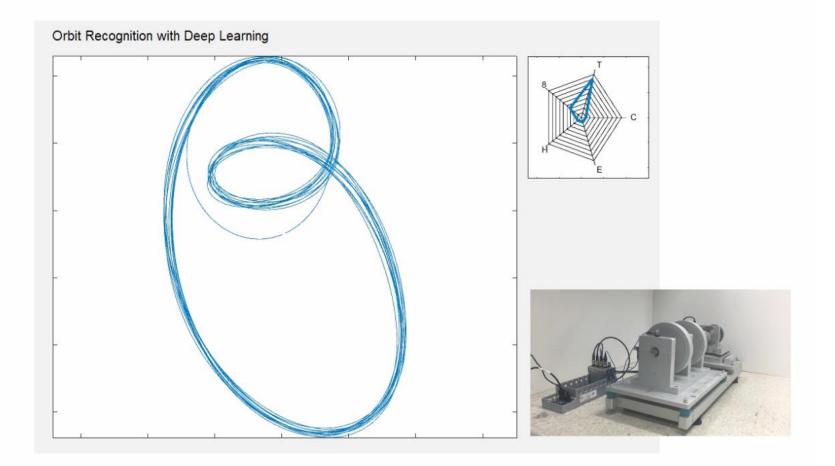






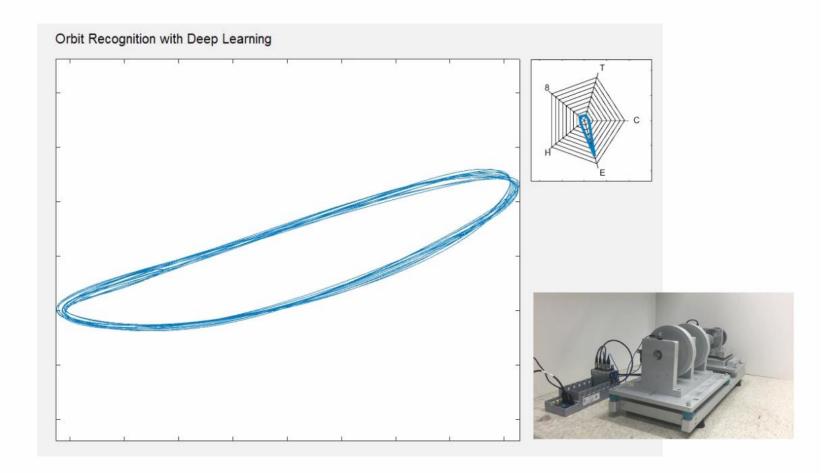


Tornado





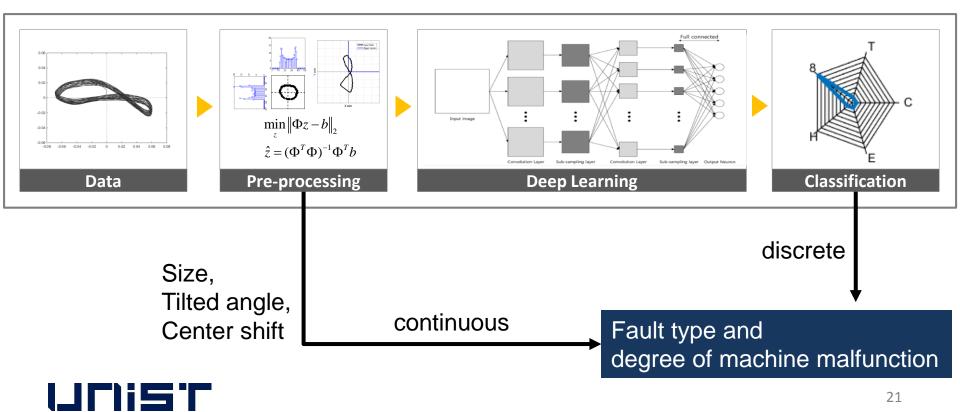
Mode Changes





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



Method	Feature	Input	Structure	Error
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 ValueImaginary Value	8×1 Vector	Mean VectorCovariance Matrix	6.0%



Conclusions

- Orbit Image as Features for Machine Diagnosis
- Deep Learning for Better Estimation Accuracy
- Validate with a Testbed

- System-based
 - Known orbit pattern \rightarrow no need a prior data collection
- Auto feature extraction via deep learning

