Deep Learning based Diagnostics of Orbit Patterns in rotating machinery

10/05/2016

UNIST, Korea

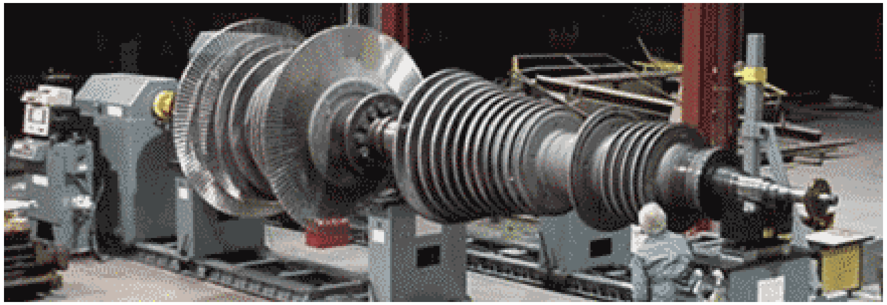
Haedong Jeong, Sunhee Woo, Suhyun Kim, Seungtae Park, Heechang Kim, and Seungchul Lee

Contents

- Orbit Analysis for Rotating Machinery
- Deep Learning
- Pre-processing Steps
- Experimental Results
- Implementation
- Conclusions

Rotating Machinery

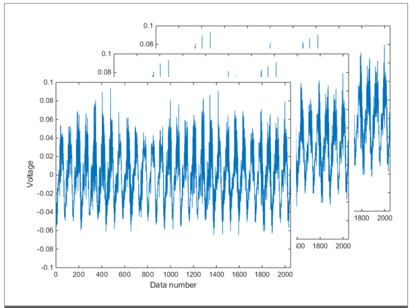
- Mechanical component
- Key components to generate electric power (in power plants)
- Performance degradation and entire system break downs
  - Plant operation/maintenance cost
  - Level of safety



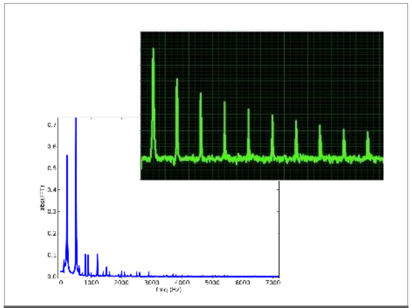
UNIST

Monitoring Systems

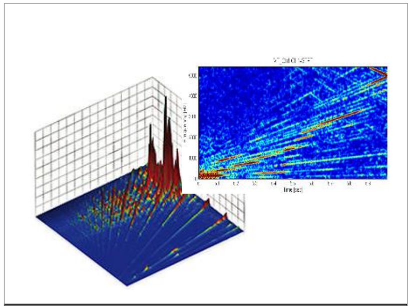
- Prognostics and Health Management (PHM) approach
- Prevent/Predict system failures



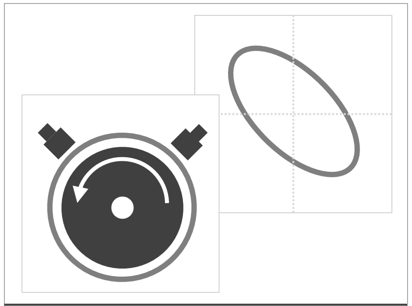
Time Domain



Frequency Domain



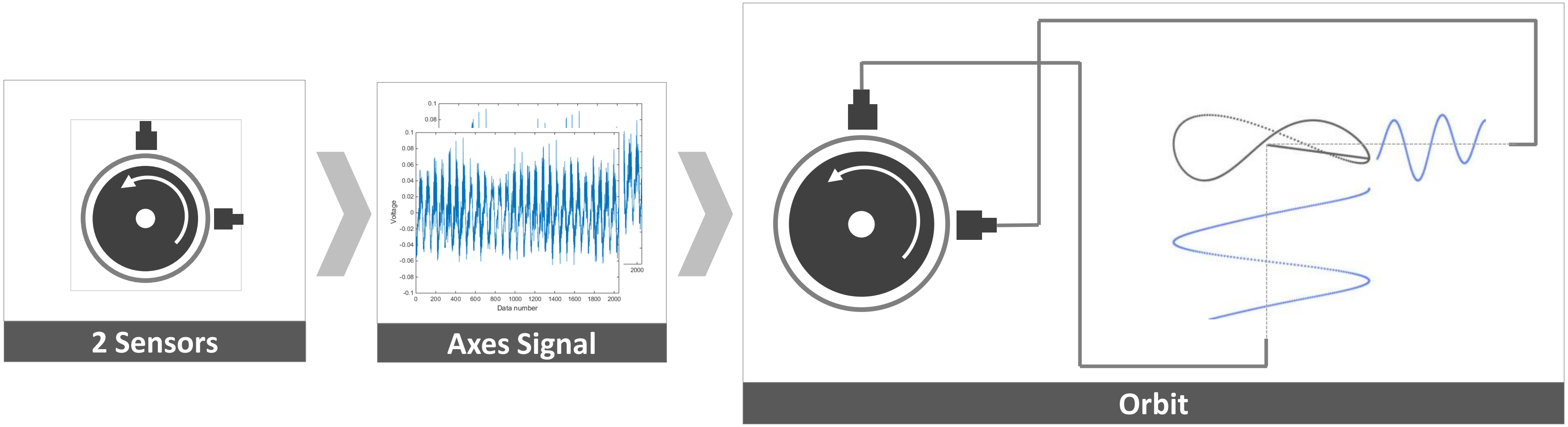
Time-frequency



Orbit Analysis

Orbit Analysis for Rotating Machinery

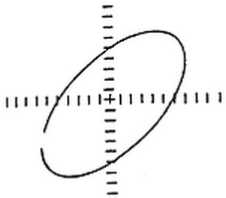
- Visualize shaft movement
  - Vibration information in 2D



- Integrated analysis possible
  - Different dynamic behaviors → change orbit shape
  - But,
  - Quantified method is not developed
  - Numerical features is not defined easily
- Still manually monitored by human operators in most power plants

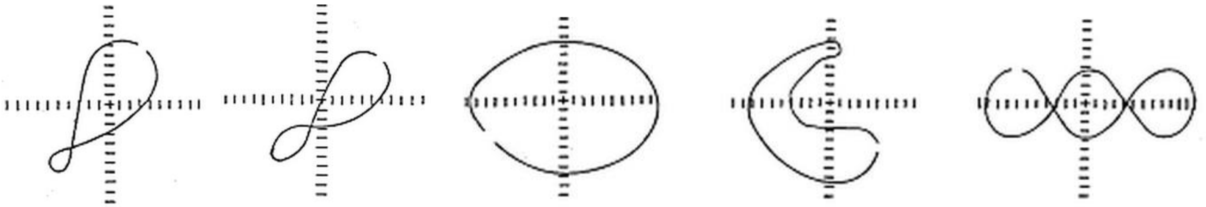
Known-Fault Modes from Orbit Shapes

- Unbalance



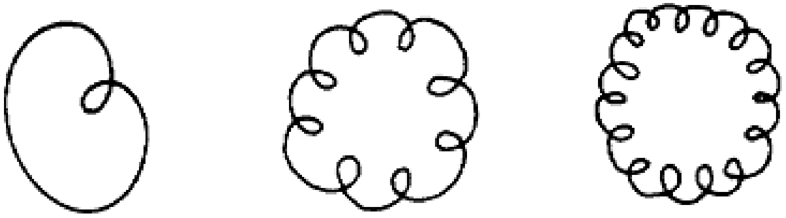
Orbit shape of unbalance

- Misalignment



Orbit shape of misalignment

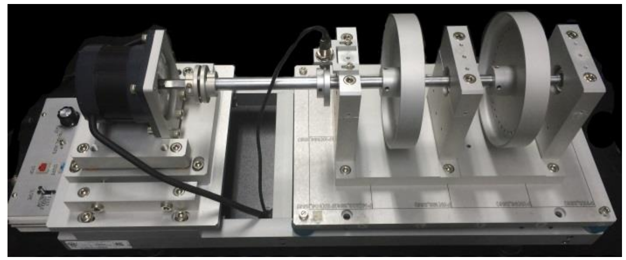
- Hit and rubbing



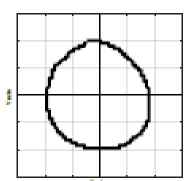
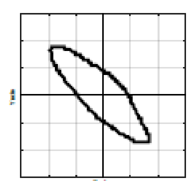
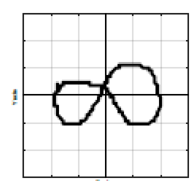
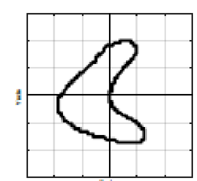
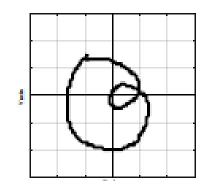
Orbit Shape of hit and bounce rub

Training Data (Data-driven Method)

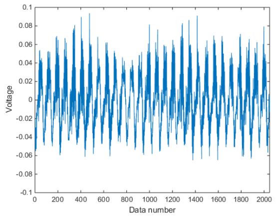
- The orbit vibration data are collected from the rotor kit



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

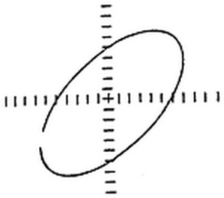
	Normal	Unbalance	Misalignment		Rubbing
Fault	Circle (C)	Ellipse (E)	Eight (8)	Heart (H)	Tornado (T)
Orbit Shape					

Proposed Idea



Orbit Shape → **Deep Learning** → **Fault Detection**

- Signal to image



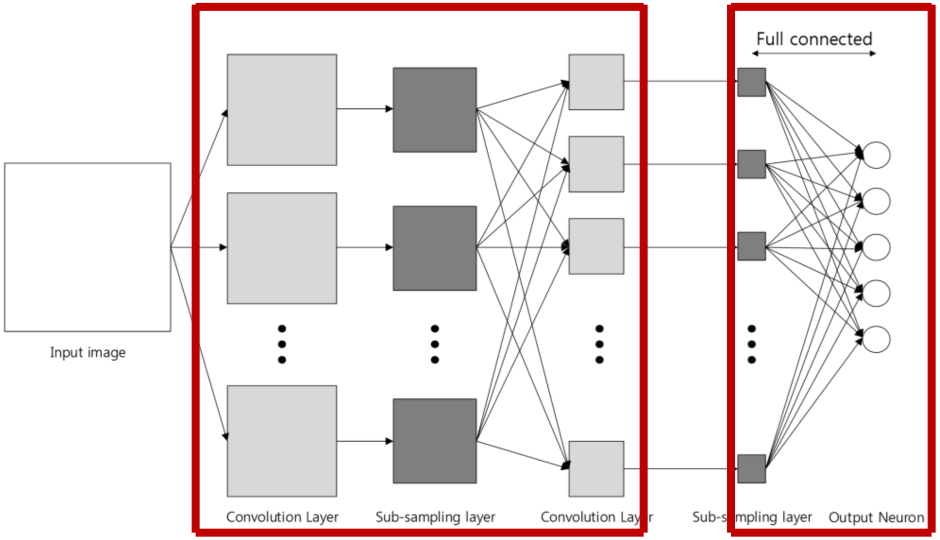
- Image pattern recognition
- Deep learning
  (Google, Facebook, …)

- 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

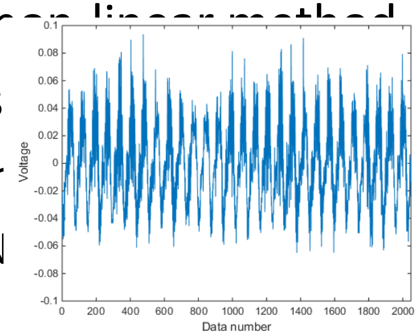
Feature Extractor Learned Classifier

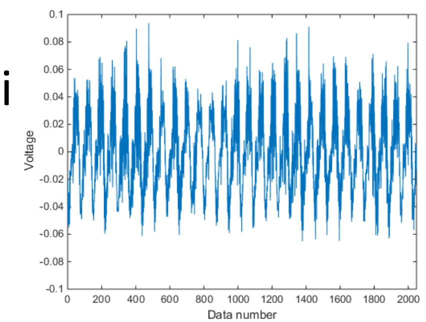


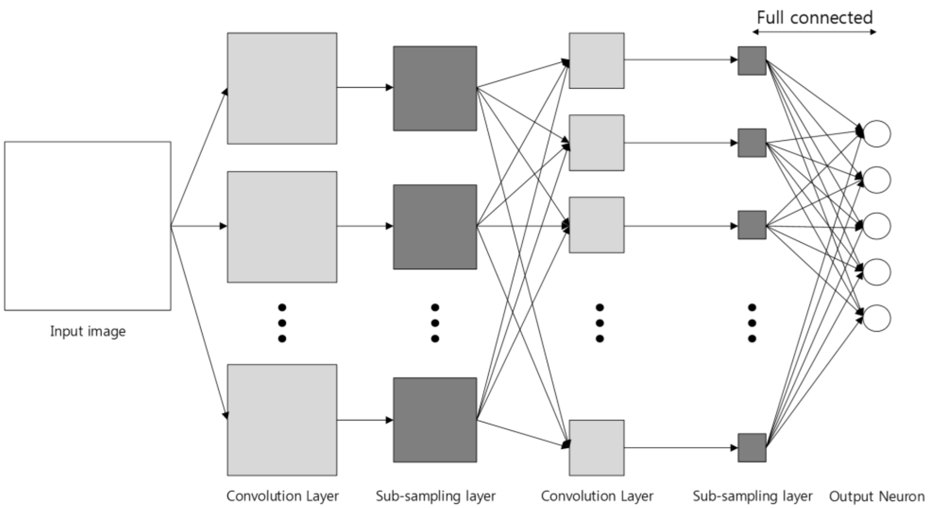
Structure of Convolutional Neural Networks

Deep Learning

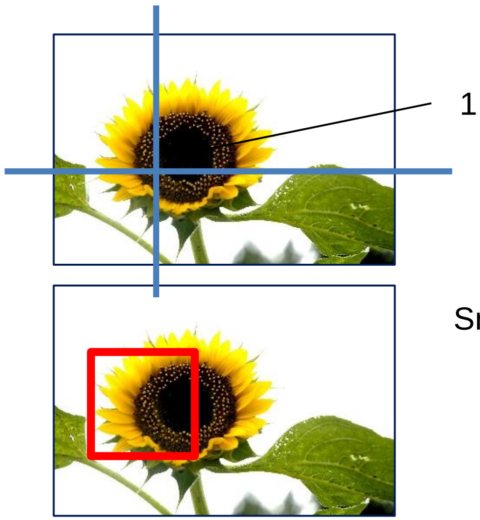
- Neural networks
  - Simple neurons, nonlinear activation functions
- Abstraction from combination of r
- Automatic discovery of the repres cati
- Image pattern recognition probler
  - <u>Convolutional</u> Neural Networks (CN
  - Perception like human







Structure of Convolutional Neural Networks



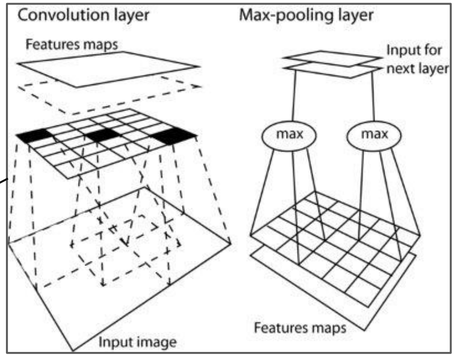
RGB = [0 0 0]
1 Pixel cannot explain any information

Small area can explain context of image

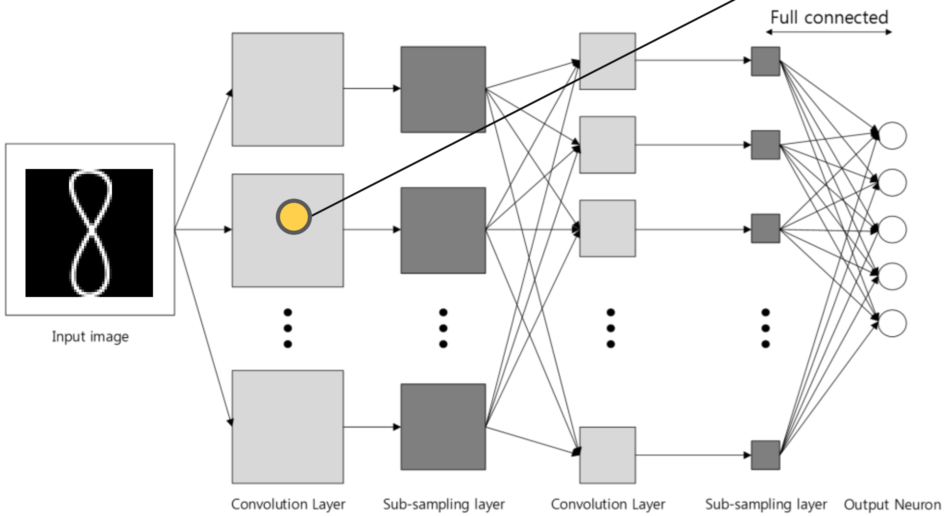
Key idea of Convolutional Neural Networks

Convolutional Neural Networks (CNN)

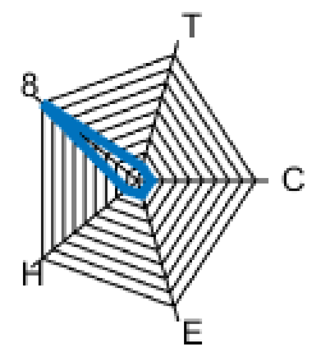
- Max pooling
  - Invariance to local translation/rotation
- 5 output neurons
  - Value of neuron means the degree of activation
    - Probability of classification
  - Each neuron represent each class
    - $[1\ 0\ 0\ 0\ 0]$ = Class 1
    - $[0.3\ 0.9\ 0\ 0\ 0]$ = Class 2



Convolution layer and Subsampling layer

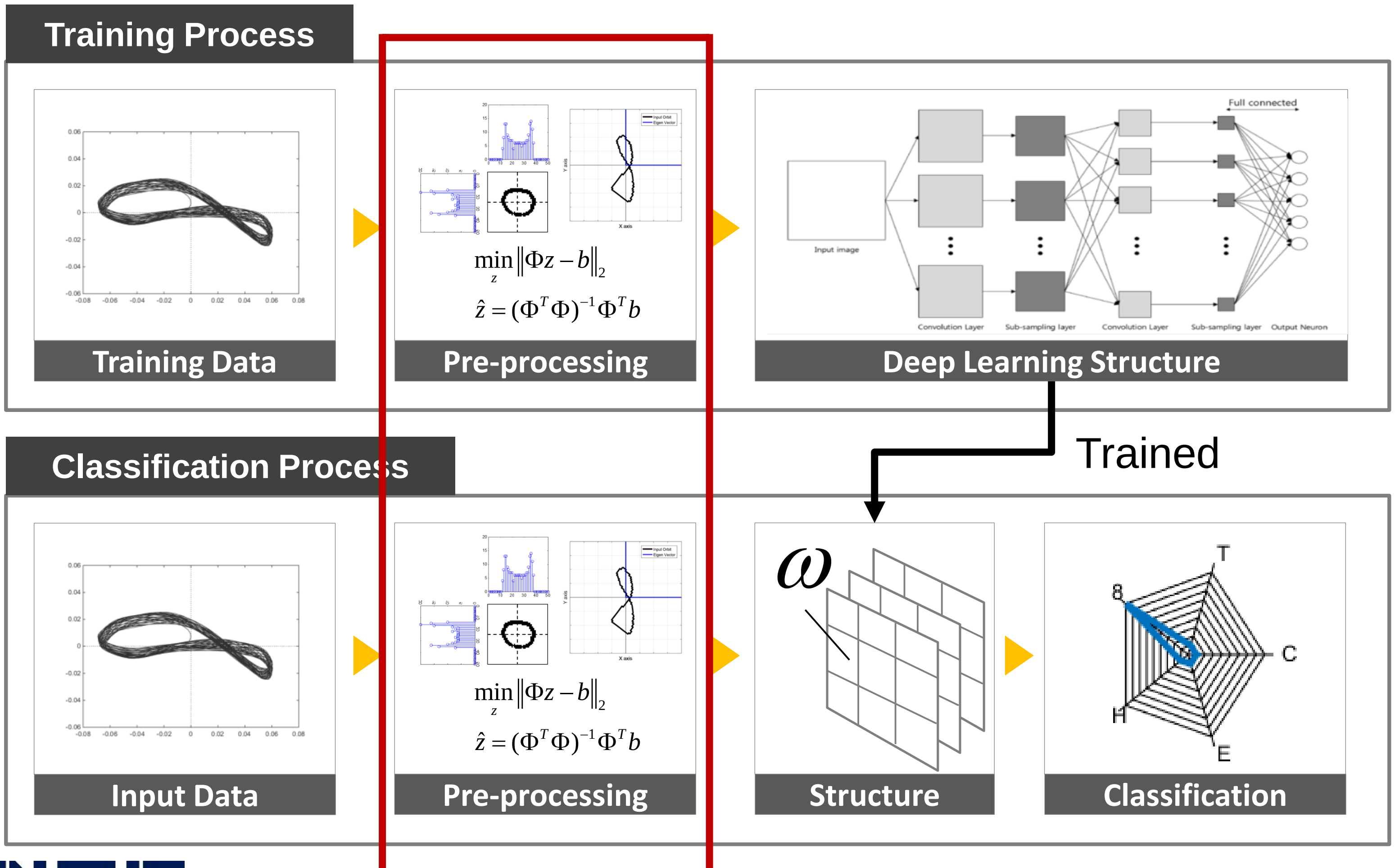


$$\begin{bmatrix} 0.1 \\ 0.1 \\ 0.9 \\ 0.2 \\ 0.1 \end{bmatrix}$$



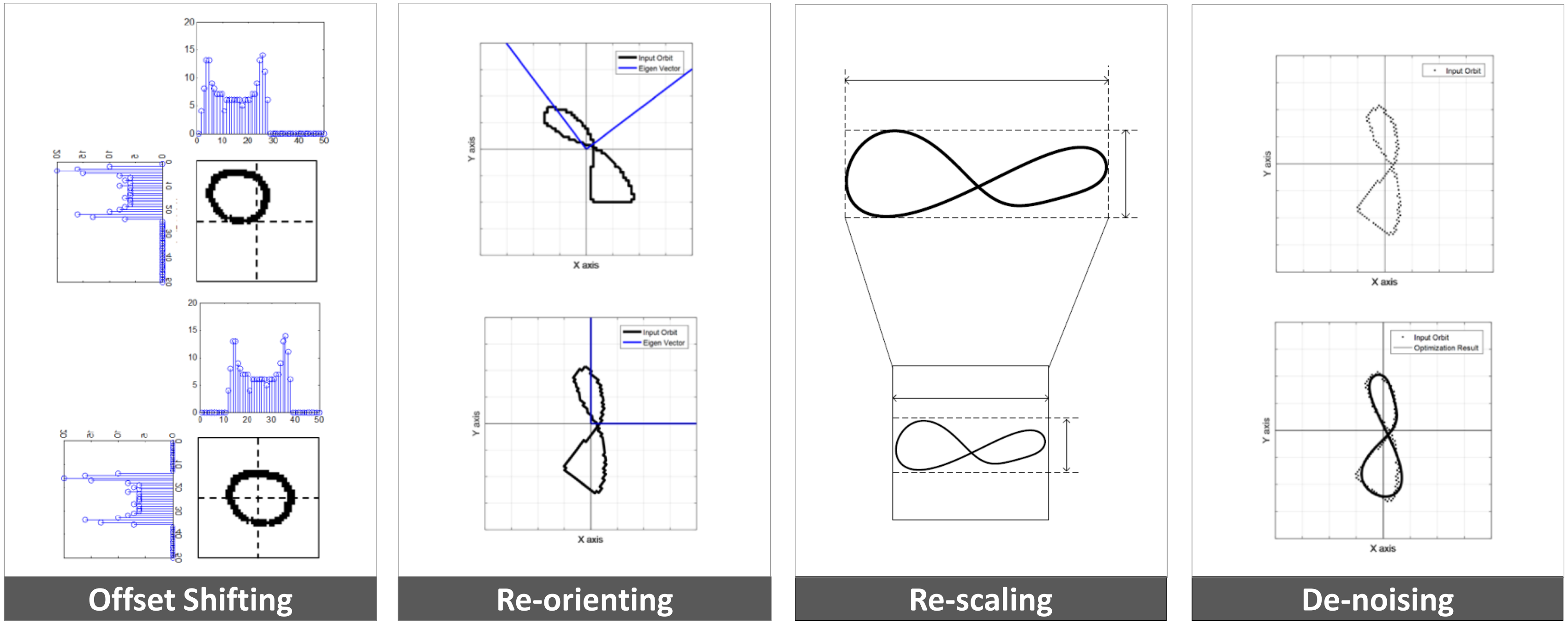
Deep Learning on Orbit Images

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



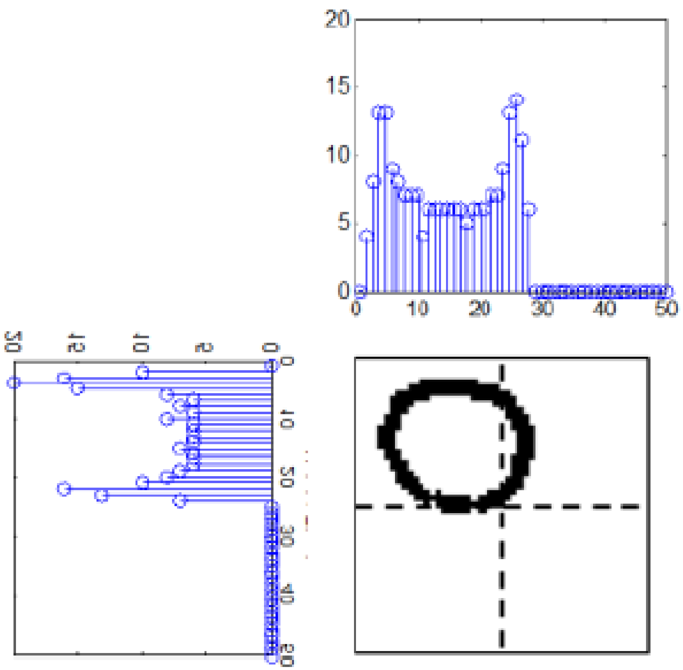
Pre-processing Steps for Better Classification

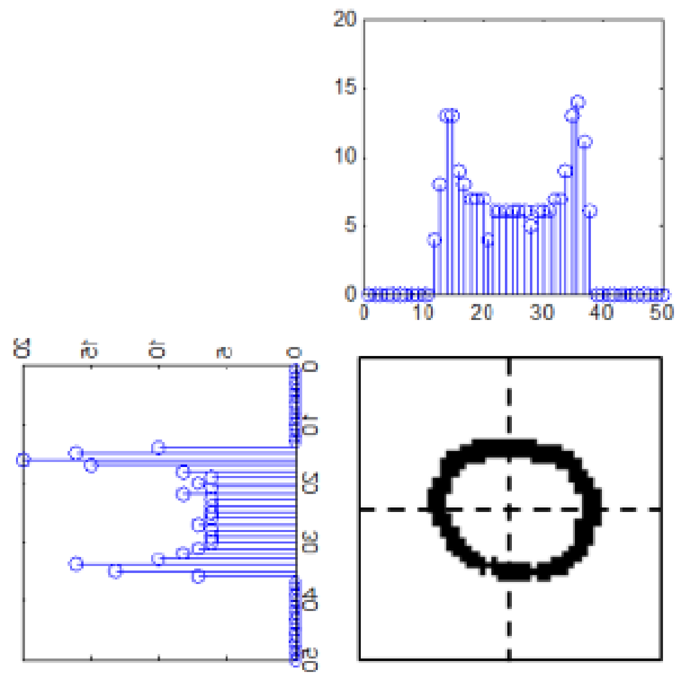
- Independent of orbit image pattern
  - Location, rotated angle and size
- Maximize performance of training data set
  - Although CNN is kind of capable to handle such local variations



1) Offset Shift (Image Centering)

- Pattern: Invariance of the center position
- Shifted position is calculated by subtracting mean values





2) Re-orienting

- Pattern: Invariance of the tilted angle
- Eigen-analysis

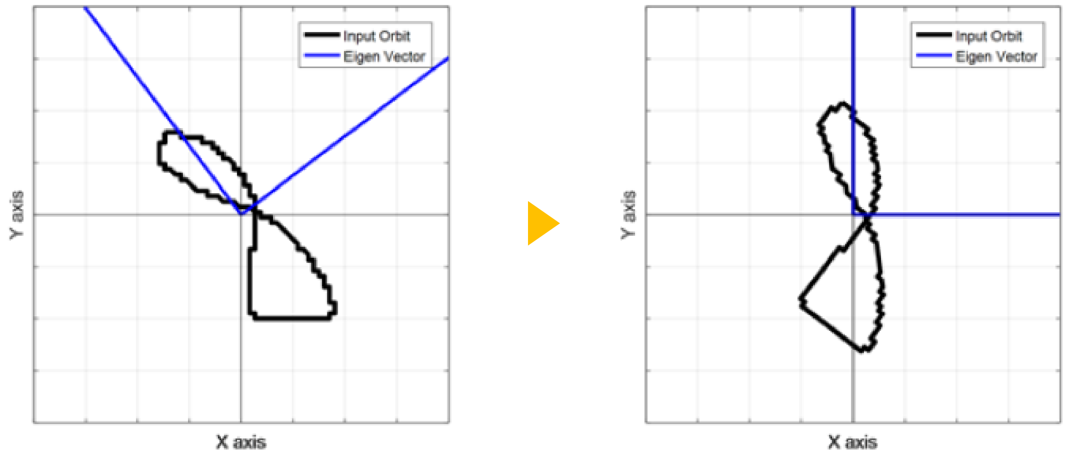
$$C = A^T A = V \Lambda V^T$$

$$A_R = AV$$

C : **covariance matrix**

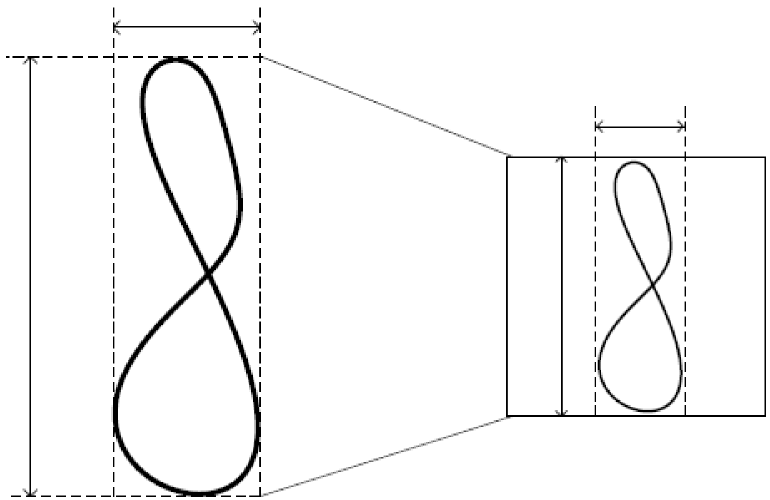
V : **eigenvector matrix**

Λ : **eigenvalue matrix**



3) Orbit image Re-scaling (Normalizing)

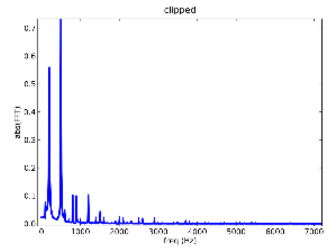
- Normalization of the scale of orbit with maintaining a ratio
- Resize the original image to the training image size



- Size of orbit shape is related to the degree of machine malfunction
  - The fault type classification is not depend on the size of image

4) Optimization for De-noising

- Orbit Shape De-noising
  - Generally the orbit signal contains a sensor noise
  - Decompose into fundamental harmonic signals
  - Optimization method based on the mathematical orbit model



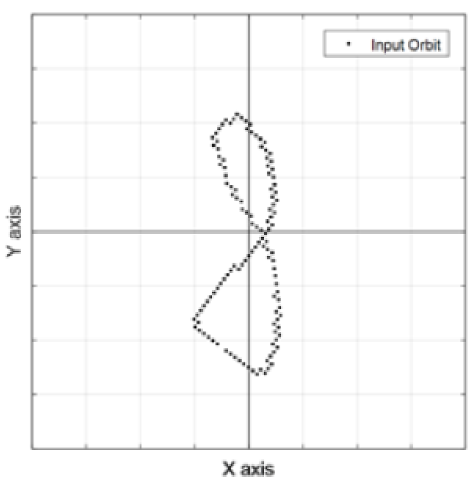
$$\min_z \|\Phi z - b\|_2$$

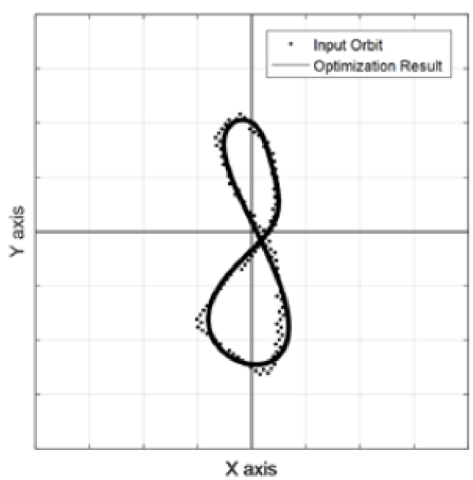
$$\hat{z} = (\Phi^T \Phi)^{-1} \Phi^T b$$

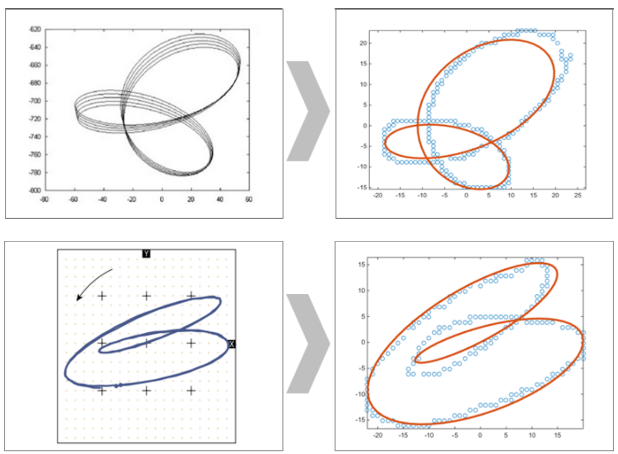
$$\Phi = \begin{bmatrix} e^{j\omega n} & e^{-j\omega n} & e^{j2\omega n} & e^{-j2\omega n} & e^{j3\omega n} & e^{-j3\omega n} \end{bmatrix}$$

$$b = x + jy$$

$$z \in \mathbb{C}$$







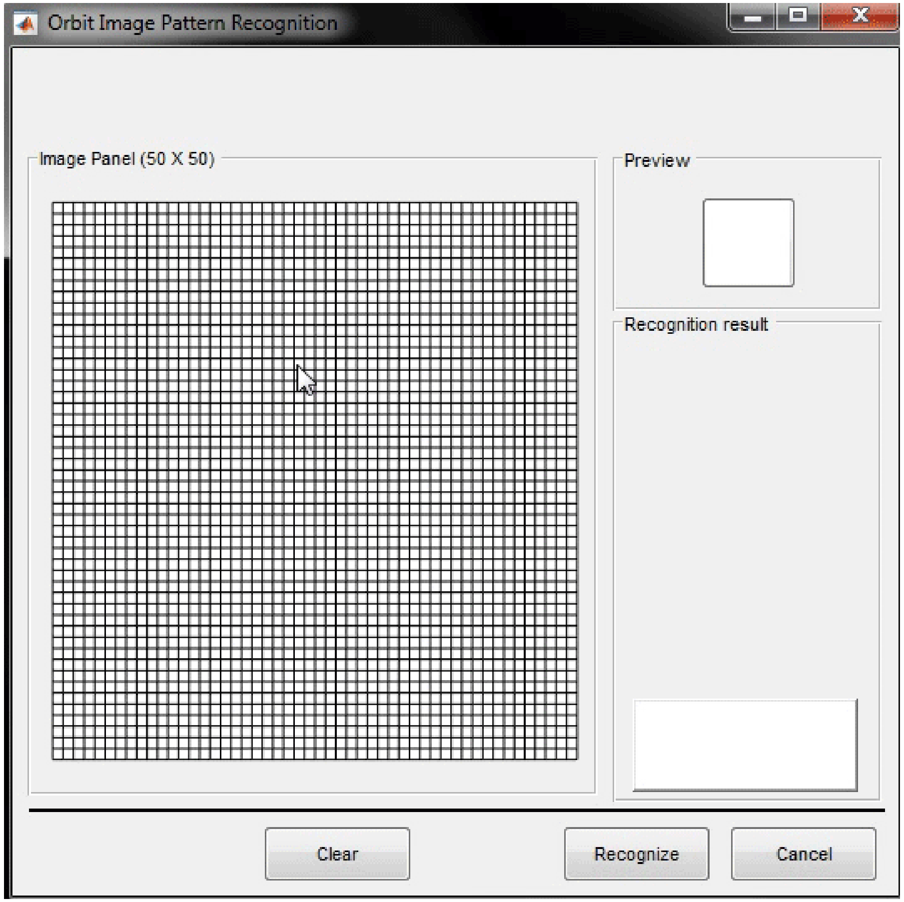
Classification Performance

- Artificially generated-orbit image set is used to measure classification performance
  - The orbit shapes and orientation are similar to those of the real rotor test kit

Various Orbit Images	Classified
	C
	E
	H
	8
	T

Classification Performance

- Artificially generated-orbit image set is used to measure classification performance
  - The orbit shapes and orientation are similar to those of the real rotor test kit

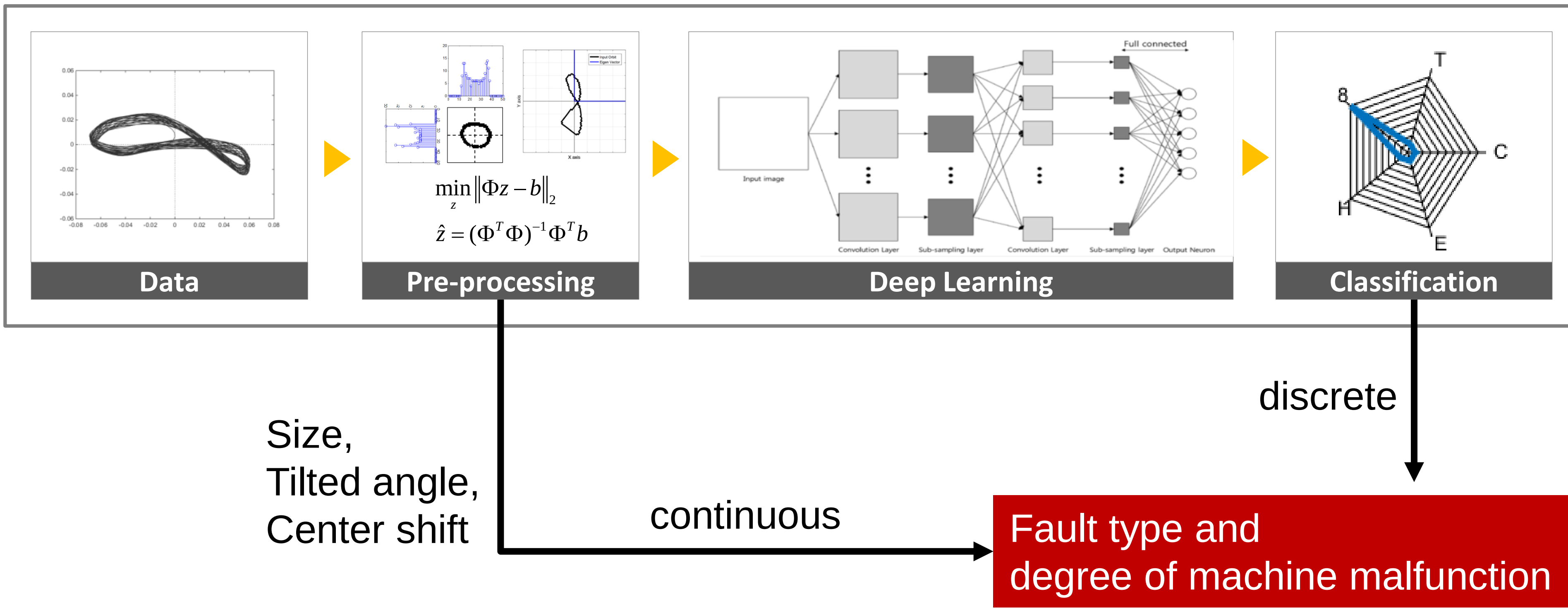


Demo

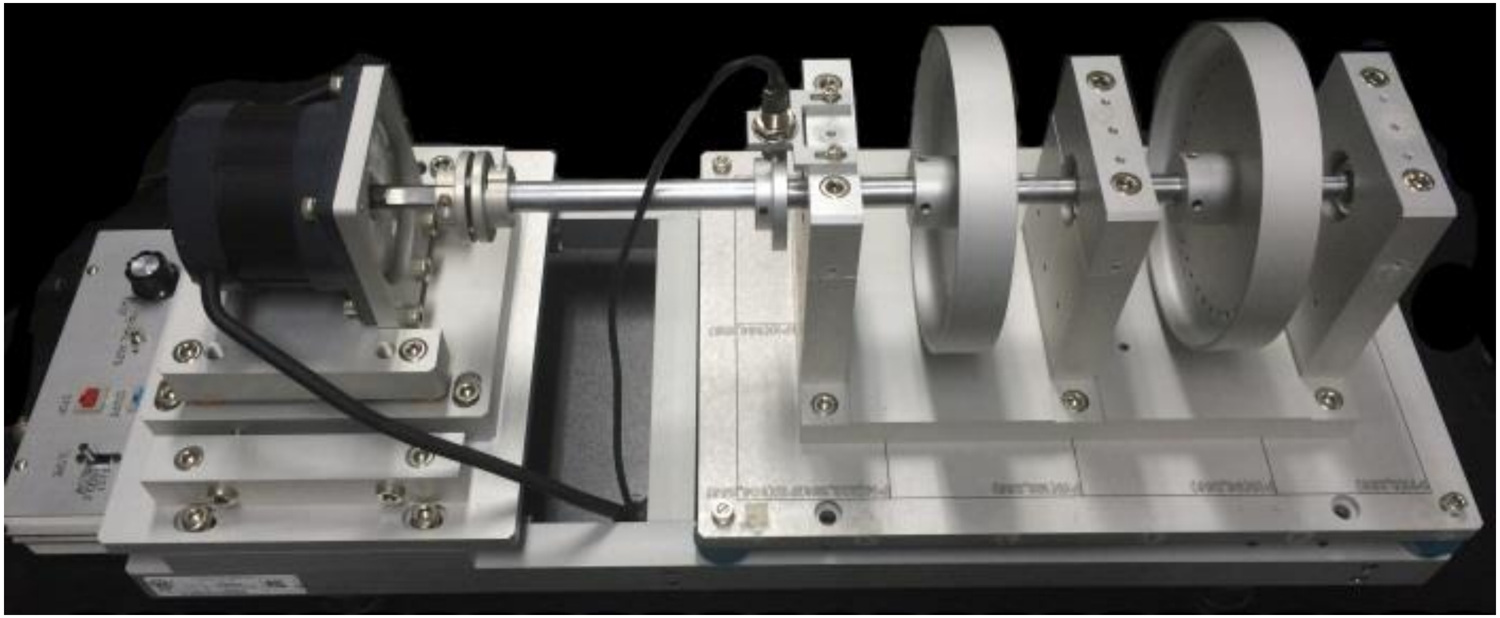

ULSAN NATIONAL INSTITUTE OF
SCIENCE AND TECHNOLOGY
2 0 0 9
iSystems Design Lab
Ulsan National Institute of Science and Technology

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



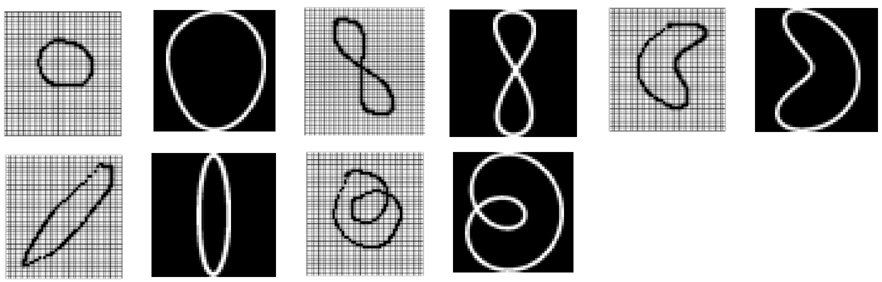
Experiment Results

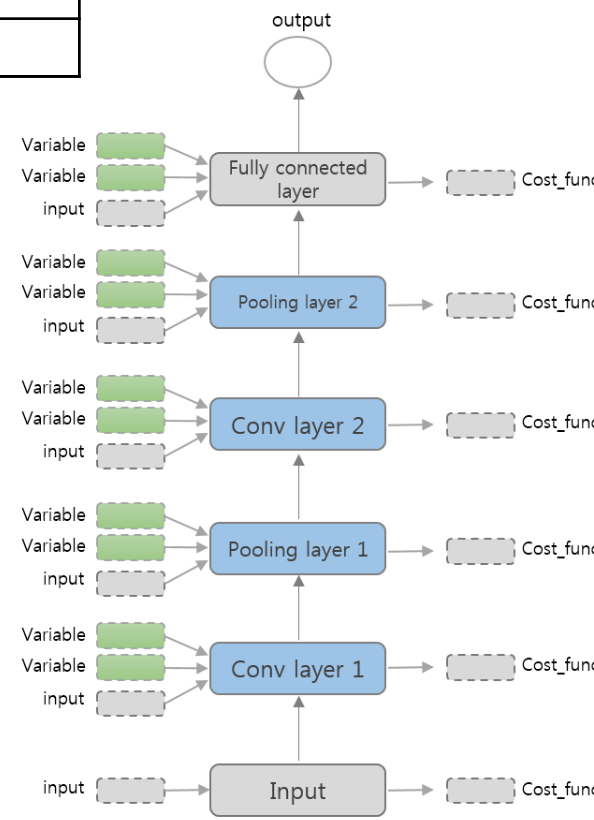


Experiment

- Total 750 orbit images are used for training
- Vibration signals to 50×50 pixel image
- 3 layers structure (convolutional and sub-sampling layer, and fully connected to 5 output neurons)

Training Set	Number of patterns	Activation Function	Epoch	Batch Size
150 × 5 = 750	5	ReLU	~ 250	50

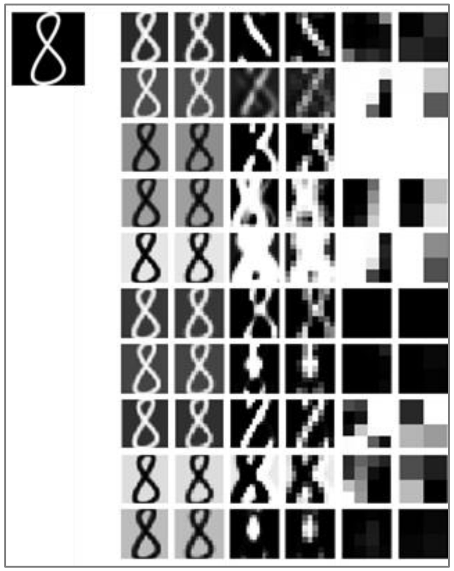




Result

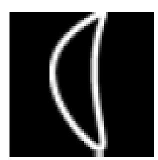
- 350 orbit images are used for validation
- Total misclassification for the given test set is overall **1.1%**

Result of CNN



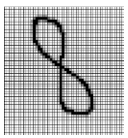
Confusion matrix

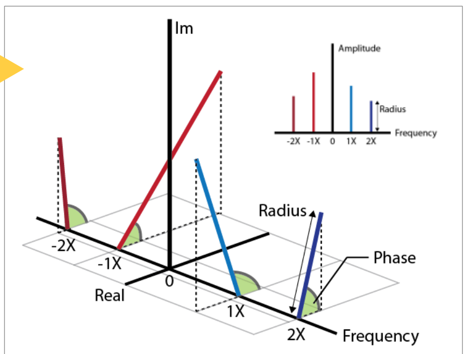
True Shape	Classified				
	C	E	H	8	T
C	70	0	0	0	1
E	0	70	1	0	0
H	0	0	67	0	0
8	0	0	2	70	0
T	0	0	0	0	69

True Class	Heart	Heart	Tornado
Orbit Image			
Result of Classification	Ellipse	Eight	Circle

Benchmark:

- Hand-crafted features: 8×1 Vector (full spectrum)
- Total misclassification for the given test set is overall **6.0%**





Full Spectrum
Orbit Decomposition
(Radius & Phase)

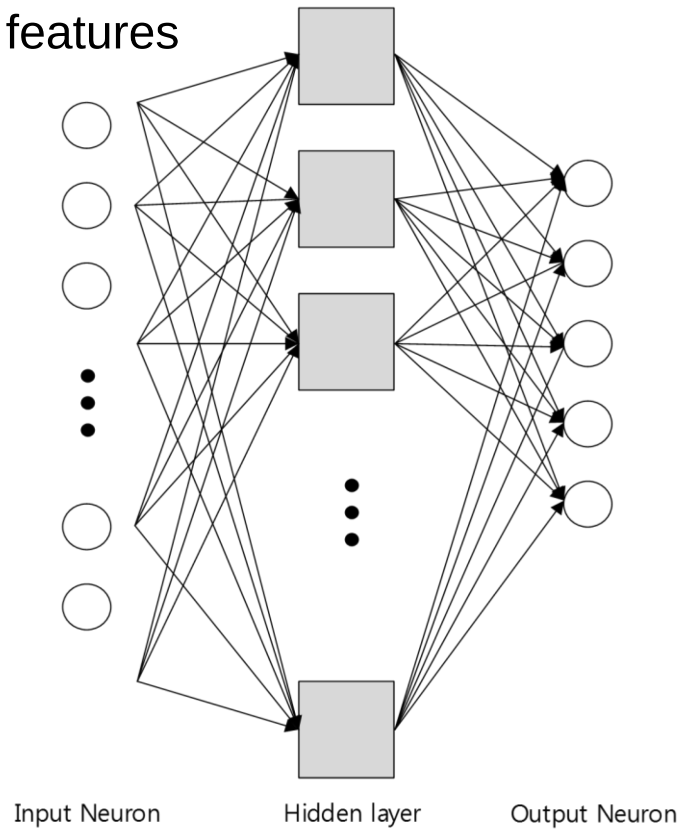
$$z = a + bj$$

$$\mathbf{real}(z), \mathbf{imag}(z)$$

Feature Extraction
(Real and imaginary value, 8-dim)

Benchmark: Neural Network

- Hand-crafted features: 8×1 Vector (full spectrum)
- Total misclassification for the given test set is overall **8.5%**



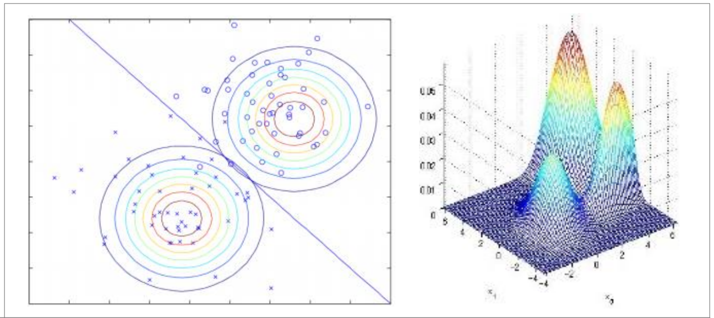
True Shape	Classified				
	C	E	H	8	T
C	68	0	0	0	0
E	0	69	6	0	0
H	0	0	54	8	0
8	2	1	10	62	3
T	0	0	0	0	67

- 1 Input Layer
  - 8 neurons
- 1 Hidden Layer
  - 100 neurons
- 1 Output Layer
  - 5 neurons

Structure

Benchmark: Gaussian Discriminant Analysis (GDA)

- Input : 8×1 Vector
- Total misclassification for the given test set is overall **6.0%**



GDA

True Shape	Classified				
	C	E	H	8	T
C	69	5	0	0	0
E	1	64	0	0	0
H	0	1	68	12	0
8	0	0	2	58	0
T	0	0	0	0	70

Benchmark: Comparison

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%

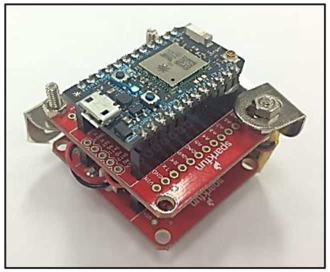
Artificial Neural Networks (ANN)	Harmonics forward, backward vector coefficients
	
	• Real Value
	• Imaginary Value
		8×1
		Vector
			• 1 Input Layer
			  ▪ 8 neurons
			• 1 Hidden Layer
			  ▪ 100 neurons
			• 1 Output Layer
			  ▪ 5 neurons
				8.5%

Gaussian Discriminant Analysis (GDA)		8×1 Vector	• Mean Vector • Covariance Matrix	6.0%

Implementation
(IoT sensors + Cloud platform)

IoT Sensor

- System
  - Wi-fi Micro-controller
  - IMU Accelerometer
  - Lithium-ion battery



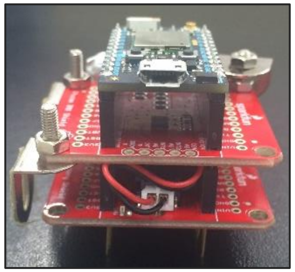
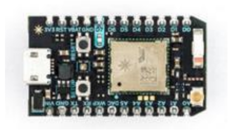
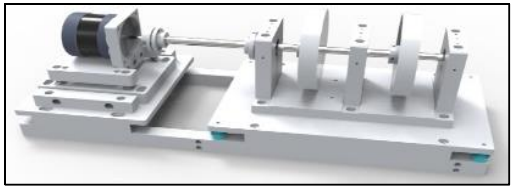
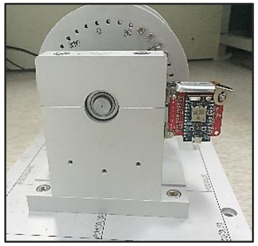


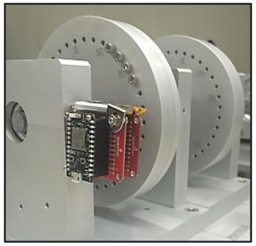
	Image	Spec
Particle Photon		Broadcom BCM43362 Wi-Fi chip STM32F205 120Mhz ARM Cortex M3 1MB flash, 128KB RAM https://store.particle.io/
IMU Sensor		3 acceleration channels 16-bit data output 1 kHz Sample Rate https://www.sparkfun.com

* Wi-fi Communication Maximum Speed : 11 MBit/s

- Training Data Acquisition
  - Rotor Testbed





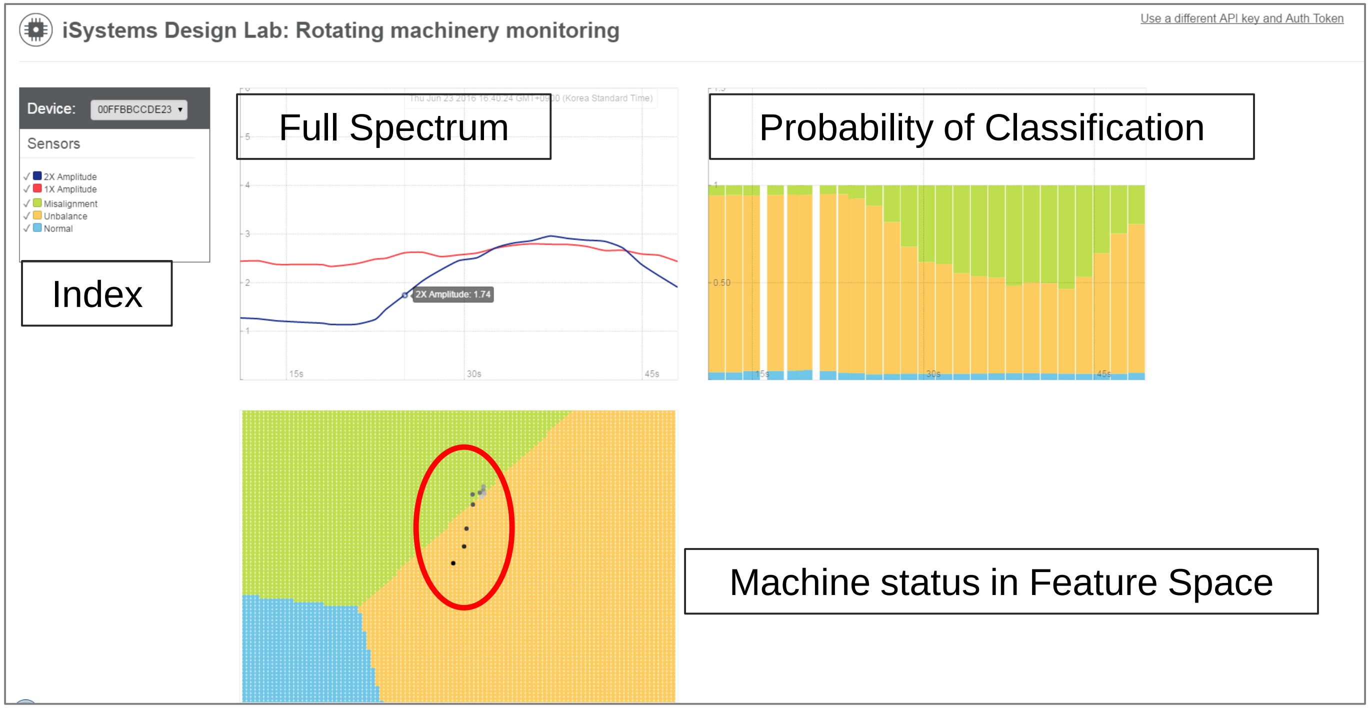


Rotor Testbed			
RPM	1500		
Fault Mode	Normal	Unbalance	Misalignment
Sensor Position	Bearing Housing		
Sensor	X axis accelerometer		
Sample Rate	1 kHz		

Web-based Dashboard

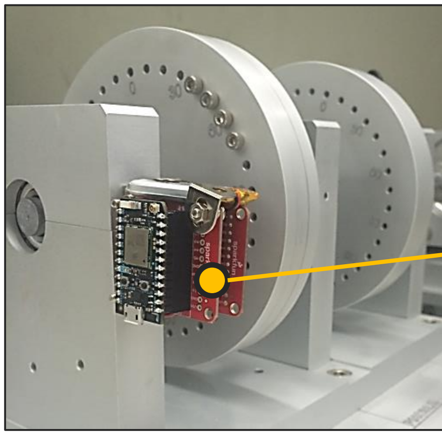
- Web-based service
  - Cloud Server
  - Various devices can access
- Full spectrum Information
- Probability of Machine state

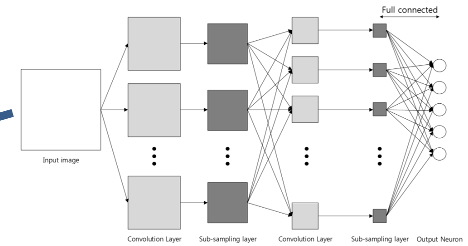
Traditional machine learning applied

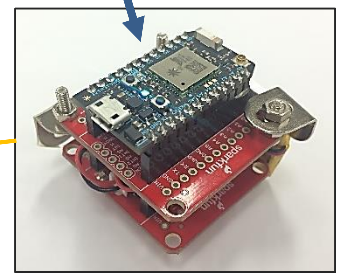


IoT Sensor with Deep Learning

- Algorithm Embedded (C++)
  - Data acquisition
  - Trained deep learning classification model

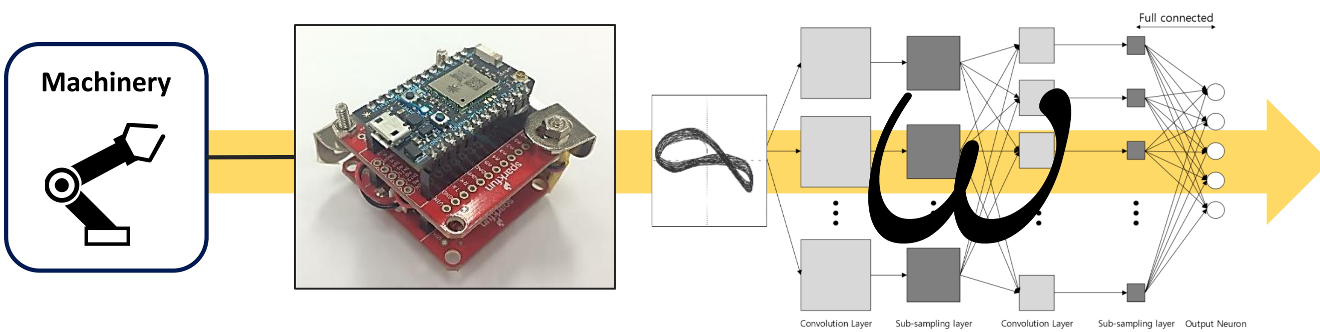






- Data Acquisition
- FFT
- Deep Learning

- Data processing process



Probability of Machine State

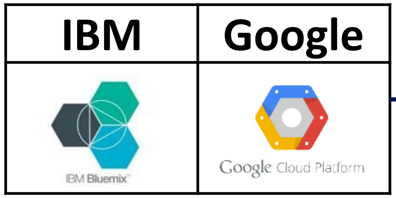
Conclusions

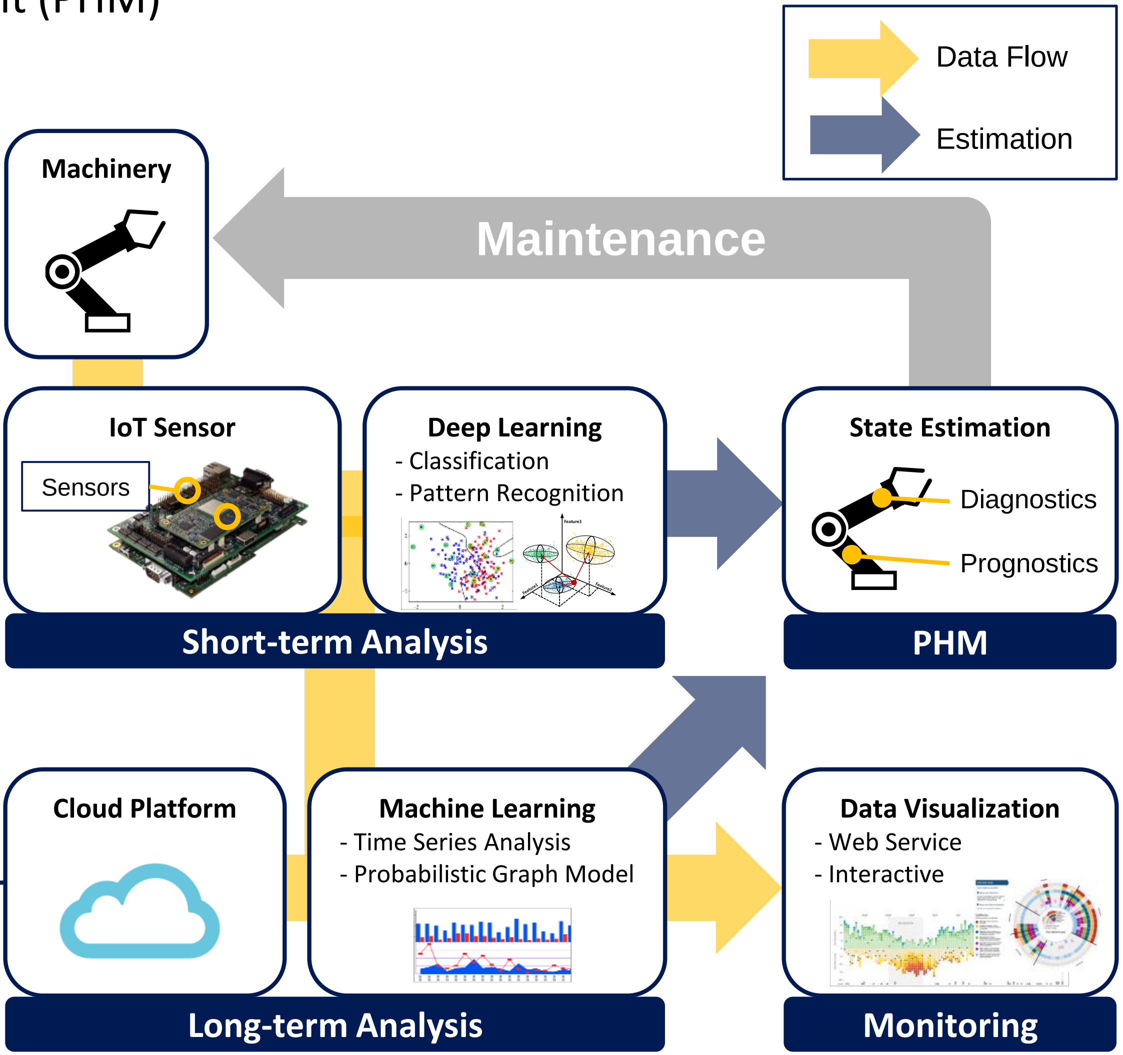
- Orbit Image as Features for Machine Diagnosis
- Deep Learning for Better Estimation Accuracy
- Validate with a Testbed
- Implementation using IoT and Cloud Platform

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

PHM with IoT and Cloud Platform

- Prognostic Health Management (PHM)
  - Short-term Analysis
    - IoT Sensors
    - Local Analysis
    - Machine state diagnosis
    - Fault mode classification
  - Long-term Analysis
    - Cloud Computing
    - Integral Analysis
    - Trend Analysis
    - Time Series Analysis and Causality
- Monitoring Systems
  - Data Visualization
    - Intuitive Information
    - Interactive Information
  - Web-based Service





UNIST

- Ulsan National Institute of Science and Technology (UNIST)
- Established in 2009
- Specialized in science and technology
- Ulsan, South Korea

UNIST

iSystems Design Lab

Department of System Design and Control Engineering
Ulsan National Institute of Science and Technology (UNIST)
Tel: +82-52-217-2726
Fax: +82-52-217-2708
E-mail: seunglee@unist.ac.kr
http://isystems.unist.ac.kr

Professional Experience

- 2013-Present: Assistant Professor, UNIST
- 2010-2013: Postdoctoral Research Fellow, The University of Michigan at Ann Arbor

Education

- 2010: Ph.D. Mechanical Engineering, The University of Michigan at Ann Arbor
- 2007: M.S. Mechanical Engineering, The University of Michigan at Ann Arbor
- 2001: B.S. Mechanical and Aerospace Engineering, Seoul National University

iSystems Design Lab

- **immune** engineering for self-sustainable system and maintenance-free machine design
- **informatics** for visualization and machine health monitoring
- **internet of things** for smart factories