Servo Motor Diagnostics using Anomaly Detection

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- Monitoring Systems for Robot Diagnosis
- Prognostics and Health Management (PHM) for robot
- Simulation Study
 - Model-based Fault Detection and Isolation (FDI)
- Servo Motor Demonstration and Comparison
 - Model-based FDI
 - Unsupervised Learning
- Conclusion



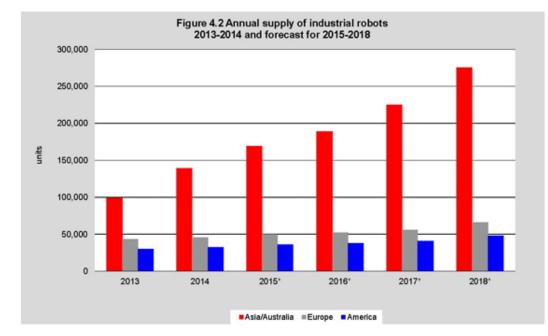
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Industrial Robots

Increased robot usage on factory





- Breakdown of robot
 - 2015 GM Russia Operation Breakdown for 2 Months
 - Losses over \$100 million
 - Approximately \$1.6 million a day



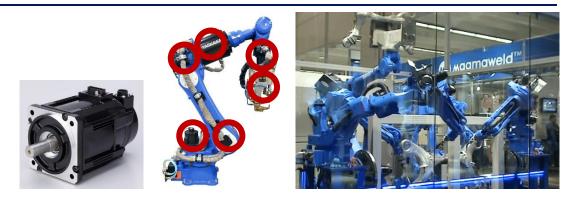


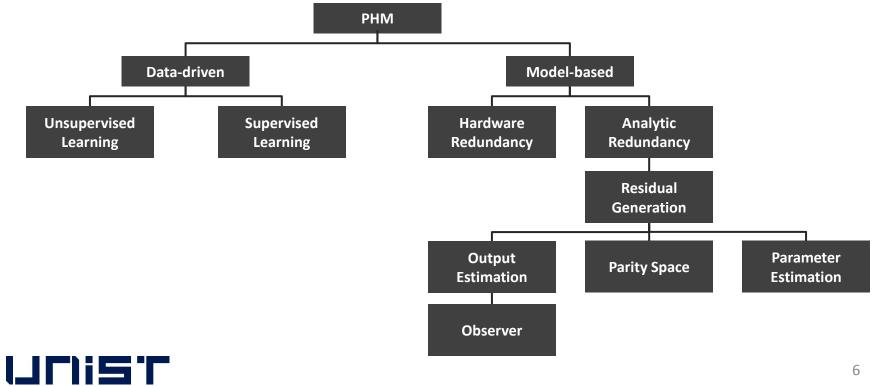
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Prognostics and Health Management (PHM)

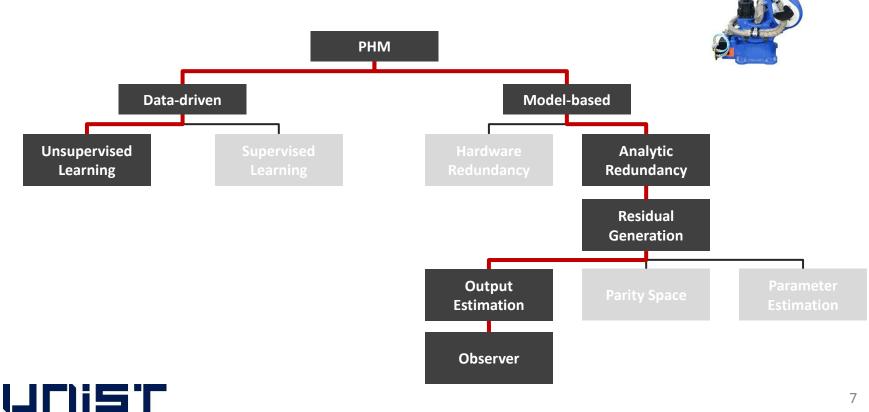
- Key component •
 - Servo motor
- Dynamic movement (6-axis) •





Prognostics and Health Management (PHM)

- Difficult to attach sensors due to dynamic movement of the arm •
 - Mostly existing instrumentation are used (Encoder, Torque)
- In may cases, failure data is not available ۲

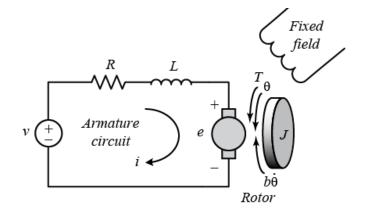


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DC Motor Position: System Modeling

• System representation in state space



$$\frac{d}{dt} \begin{bmatrix} \theta \\ \dot{\theta} \\ i \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & -b/J & K/J \\ 0 & -K/L & -R/L \end{bmatrix} \begin{bmatrix} \theta \\ \dot{\theta} \\ i \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1/L \end{bmatrix} V + Ff$$
$$y = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} \theta \\ \dot{\theta} \\ i \end{bmatrix}$$

- θ : angle
- *i* : armature current
- V:volatage
- J: moment of intertia of the rotor
- *b* : motor viscous friction constant

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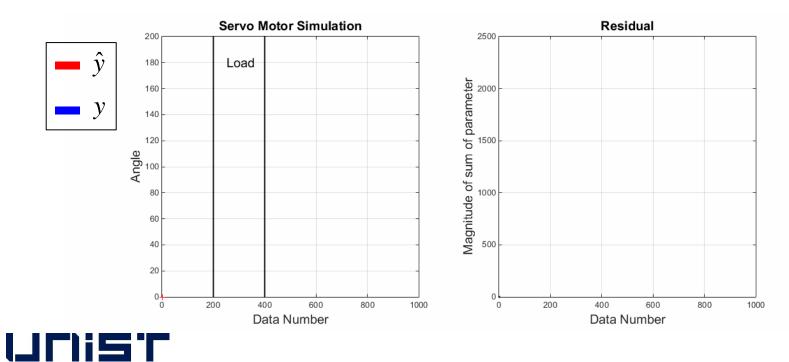
- *K* : motor torque constant
- *R* : electric resistance
- L: electric inductance
- *F* : fault matrix
- f : fault



Fault Modeling and Residual Design

- Fault modeling
 - Physically a load torque that acts on the inertia of the motor
- Residual Design
 - Parameter estimation from output error (Luenberger observer)

Fault	Observer	Residual
$F = \begin{bmatrix} 0 & 1 & 0 \end{bmatrix}^T$	$\dot{\hat{x}} = A\hat{x} + Bu + L(y - C\hat{x})$	$y - \hat{y} = C\Phi\theta$
f(t): General Fault	$\hat{y} = C\hat{x}$	Φ : fault transition matrix

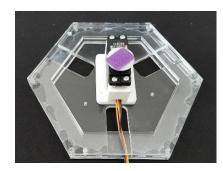


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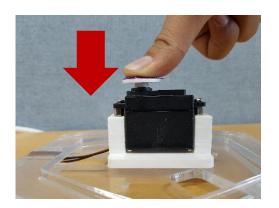


Demo Specifications

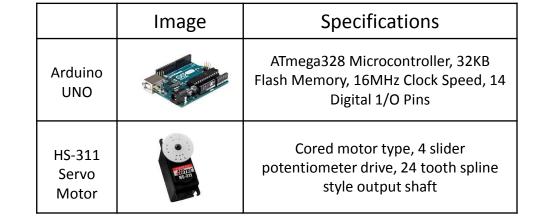
- System configuration
 - Arduino UNO
 - Servo motor



- Load generation
 - Anomaly is induced through manual press

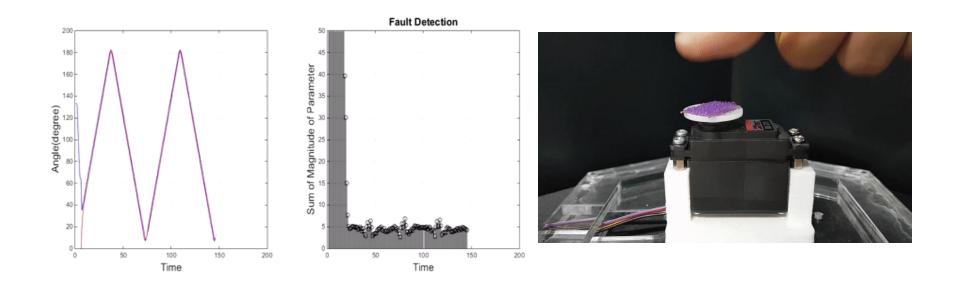


Servo Motor Testbed		
Operations	Repetitive movement (0 - 180 degree)	
Sensor	Internal encoder	
Sample Rate	50 Hz	



Demo for Model-based FDI

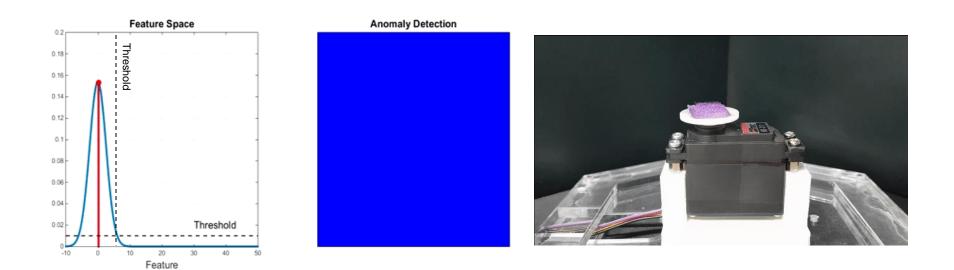
• Residual = sum of magnitude of parameter



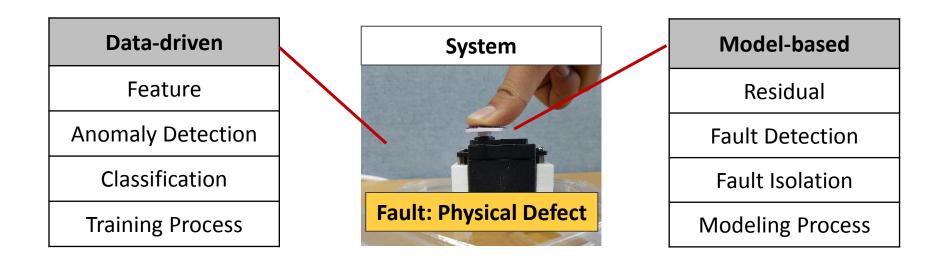


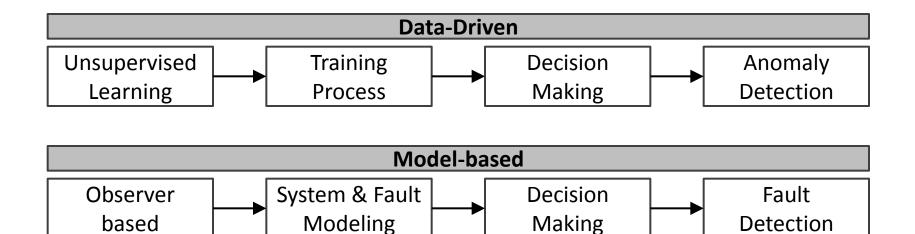
Demo for Unsupervised Data-driven Method

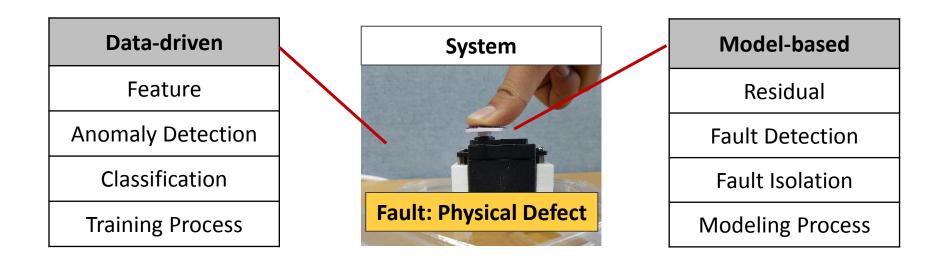
- Unsupervised Learning
 - Selected Feature: u[k] y[k]
 - Normal state training: Gaussian distribution
 - Decision Making: Mahalanobis distance

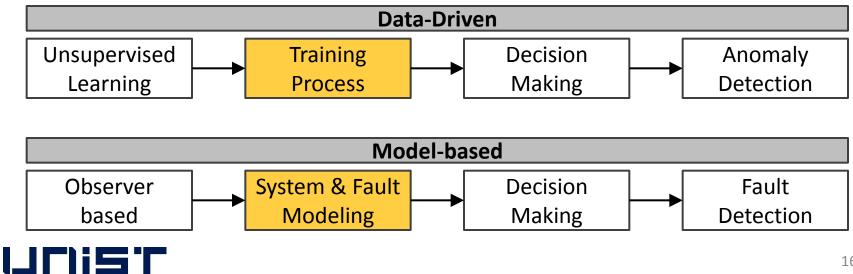










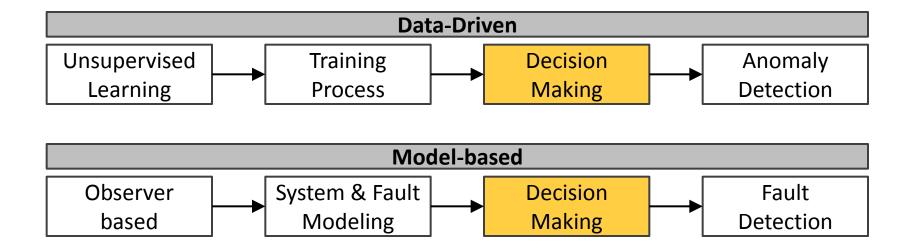


- Data-driven methods
 - Normal states based on feature
- Model-based methods
 - Normal states based on residual

 Acquire normal data Feature extraction Represents normal state Normal state cluster in feature space feature3 feature3 Fault Modeling $f[k] = \sum_n R_{n+} e^{j\alpha_{n+}} e^{j(n\omega)k} + R_{n-} e^{j\alpha_{n-}} e^{-j(n\omega)k}$ Residual Design 	Training Process	System & Fault Modeling
Data Feature f_{resture} f_{resture} f_{resture} f_{resture} $residual = \begin{cases} = 0 & \text{if no fault} \\ \neq 0 & \text{if fault exists} \end{cases}$	 Acquire normal data Feature extraction Represents normal state Normal state cluster in feature space India Feature Feature 	• System representation x[k+1] = Ax[k] + Bu[k] $y[k] = Cx[k]$ • Fault Modeling $f[k] = \sum_{n} R_{n+} e^{j\alpha_{n+}} e^{j(n\omega)k} + R_{n-} e^{j\alpha_{n-}} e^{-j(n\omega)k}$ • Residual Design

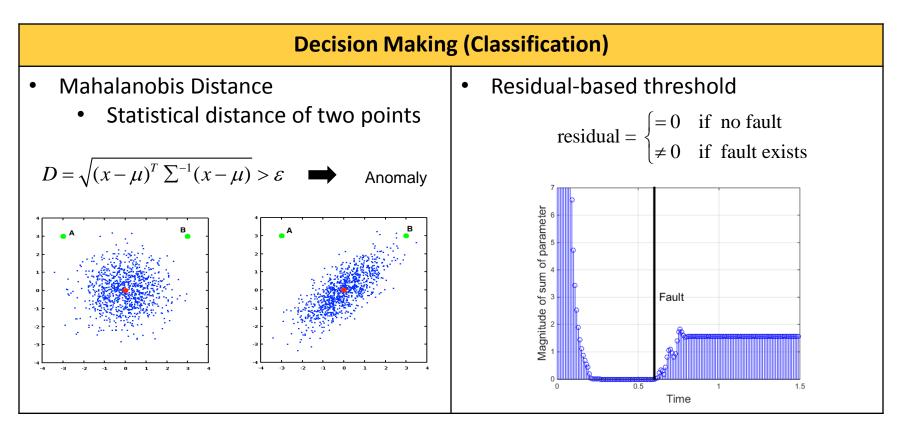


- Classify the state
 - based on the similarity of the predefined normal state
- Similarity can be represented differently





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Conclusion

- Importance of robot diagnosis has increased
 - More robots are being adopted
 - Servo motors are the key component of robots
- Anomaly detection and fault detection
 - Unsupervised learning (Mahalanobis distance)
 - Model-based fault detection (Observer-based residual)

	Data-driven	Model-based
Training/ Modeling	• Define normal state	x[k+1] = Ax[k] + Bu[k] + Ff[k] $y[k] = Cx[k]$
Feature/ Residual	u[k] - y[k]	$y[k+1] - \hat{y}[k+1]$
Decision Making	$D = \sqrt{(x-\mu)^T \sum^{-1} (x-\mu)} > \varepsilon$	residual = $\begin{cases} = 0 & \text{if no fault} \\ \neq 0 & \text{if fault exists} \end{cases}$

