Fast automatic anomaly characterization and risk management in gas pipelines

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Outline

- Background and overview
- Fast and automatic imaging-based anomaly detection
- Bayesian network for damage classification and risk assessment
- Reliability-based maintenance optimization (RBMO) for risk mitigation
- Conclusions and future work

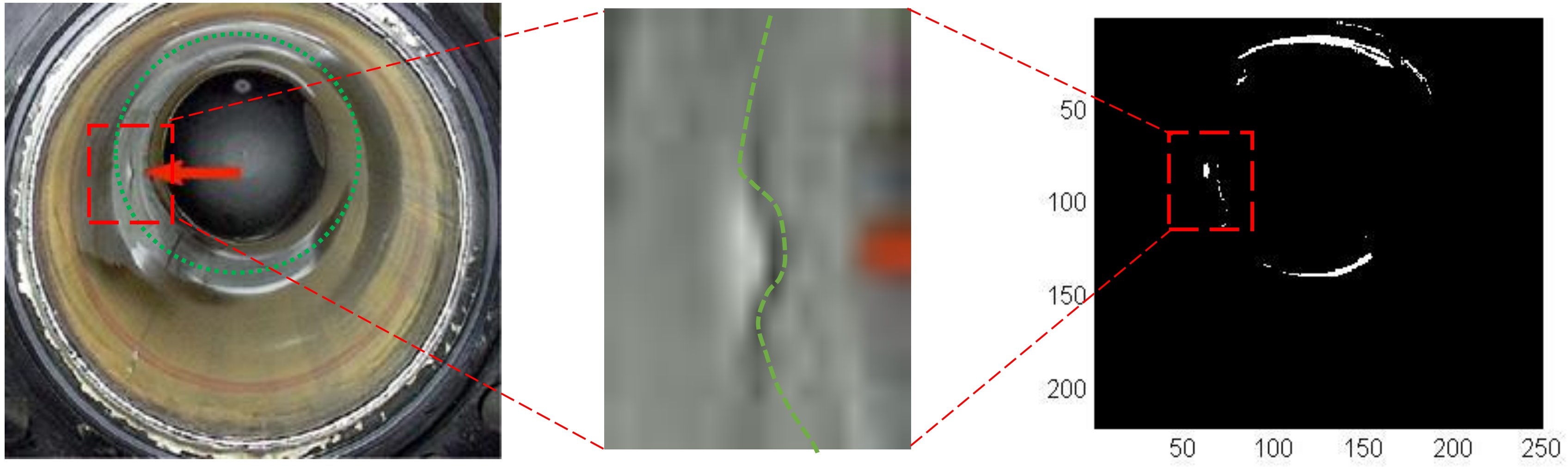
Background

- Challenge in pipeline damage diagnosis/prognosis and risk management
- Fast and automated identification, classification, and quantification of various types of damage
- Uncertainty quantification and reduction for accurate analysis and decision-making

Project objectives:

- Develop an automatic damage precursor identification methodology using Bayesian/maximum entropy network
- Develop a reliability-based maintenance scheduling optimization framework for plastic pipeline systems

Structured light-based imaging analysis

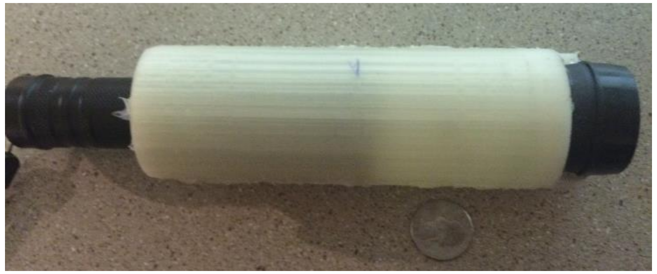


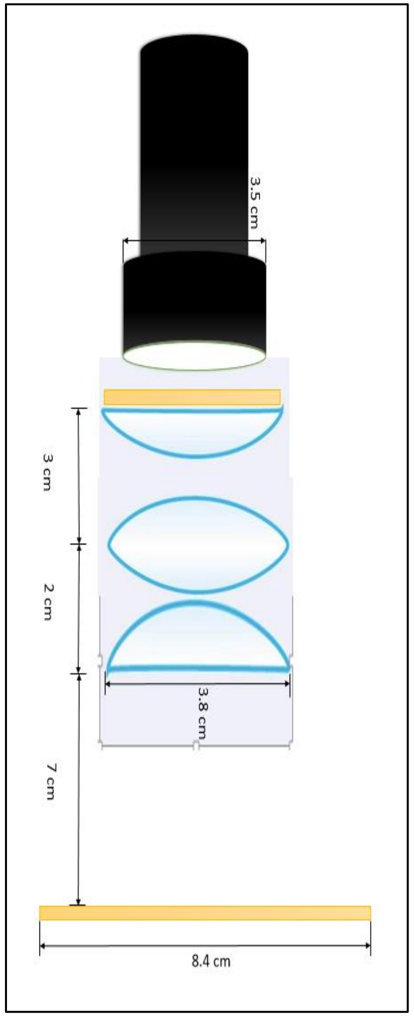
Schematic illustration of imaging analysis with structure light scanning a) raw image with inner wall damage; b) lighting ring profile at the damage site; c) structure light image assisted feature identification; (raw image obtained from http://www.swri.org/3pubs/ttoday/fall02/smartpig.htm)

- Inner pipe imaging using structured light and 3D reconstruction (MSU)
- Automatic damage identification, risk assessment, and risk mitigation (ASU)

Prototype III: Multi-color multi-ring ESLiST

- Uniquely coded colored rings are produced by projecting a strong white light into a transparency paper slides that is colored with ring patterns.
- A group of convex and concave lenses are used to collimate the light beam and focus it on pipe inner wall.

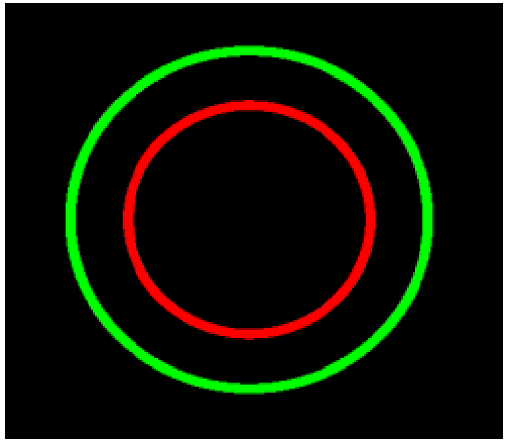




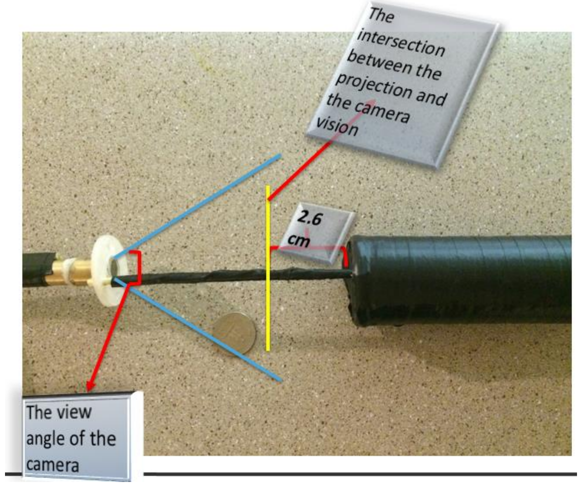
Results: Two-color two-ring ESLiST

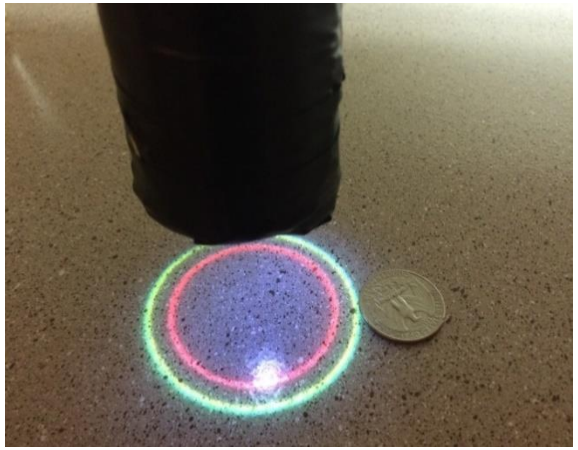
Two separated rings with different colors and diameters are used to demonstrate the ability of the ESLiST

- Sample 162012-004 - 2″ IPS DUPONT ALDYL-A PE2306, ~38″ long, contains a squeeze-off point and a tee fitting

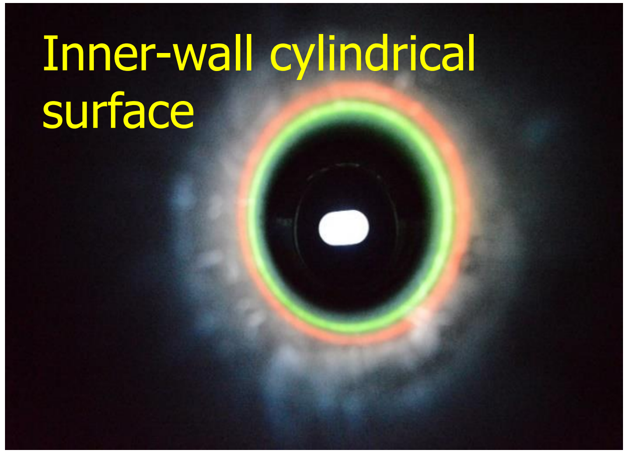


Projected pattern



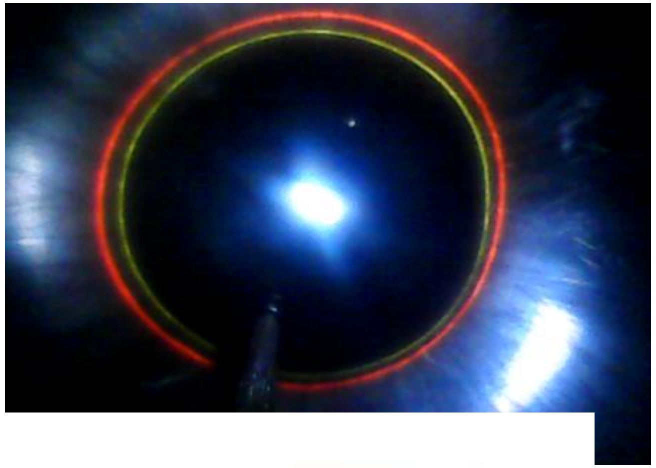


Projection on flat surface



Projection inside pipe

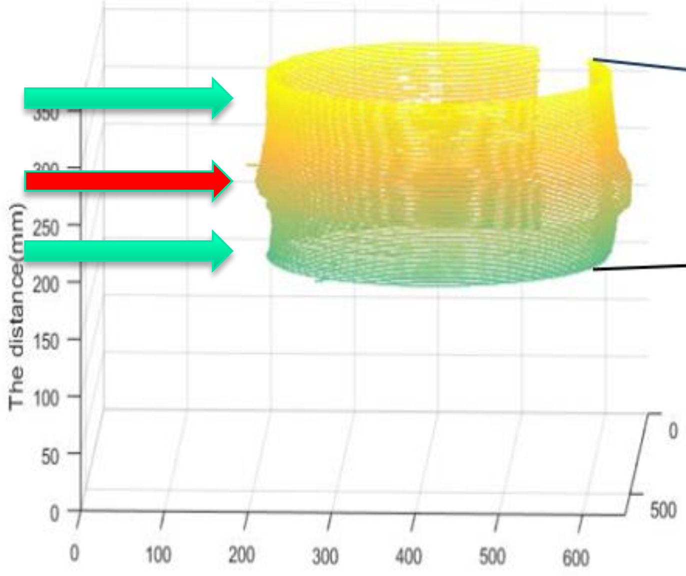
Results: Two-color two-ring ESLiST

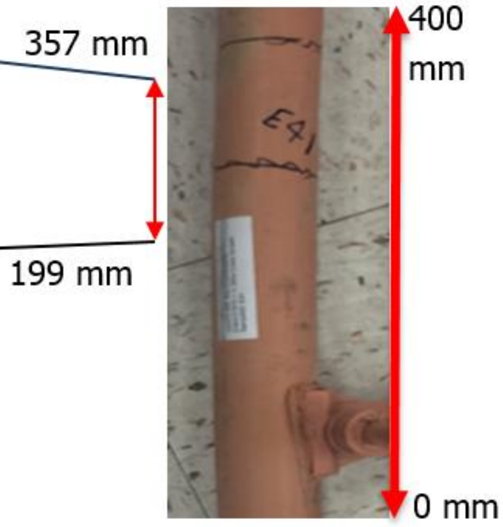


No Damage

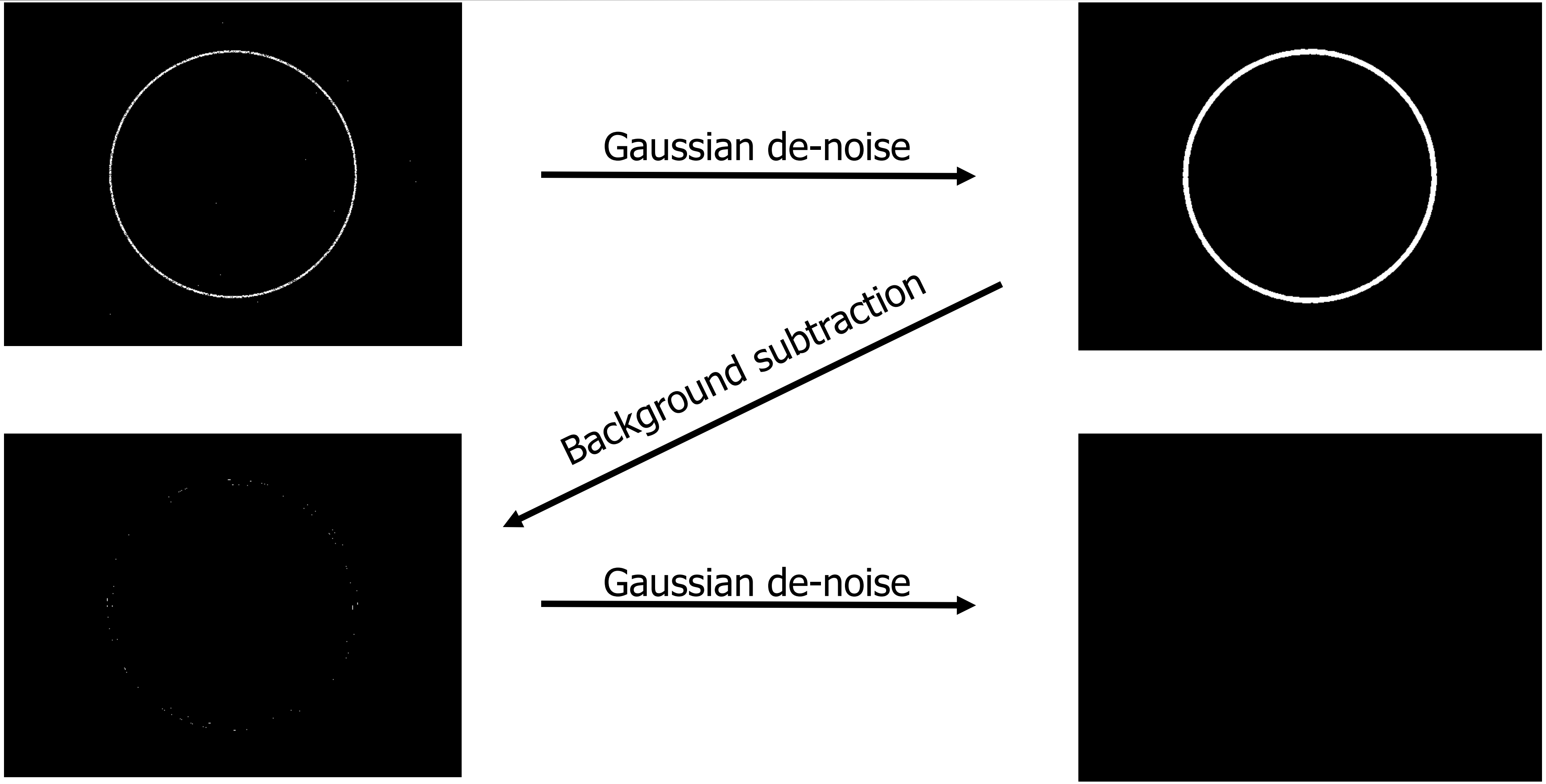
Damage

No Damage



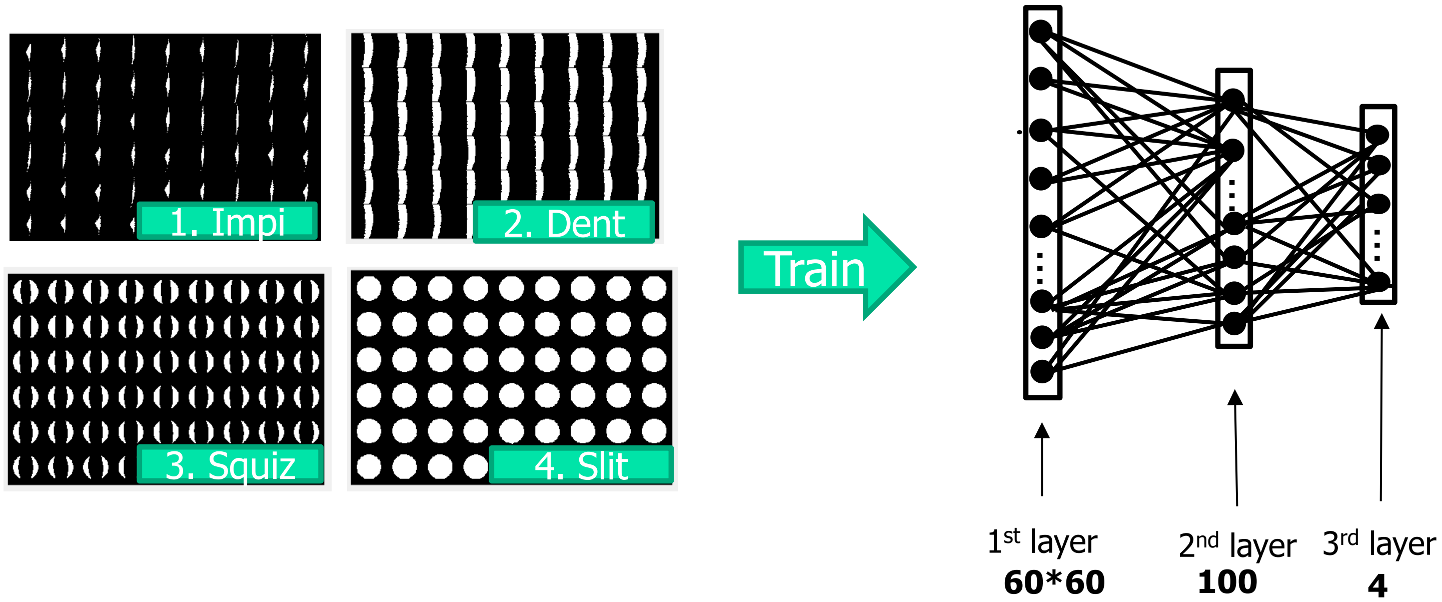


Imaging processing for denoising



Machine learning and classification

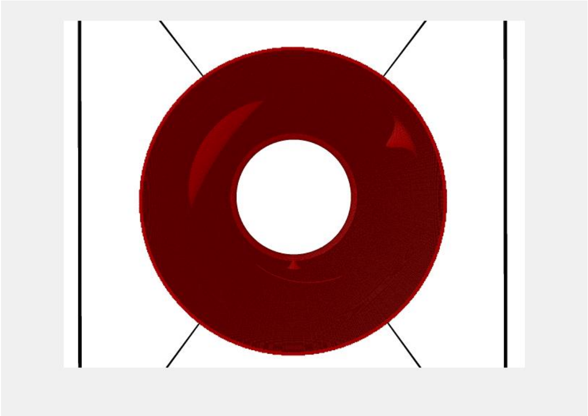
- Different damage images to train the classifier

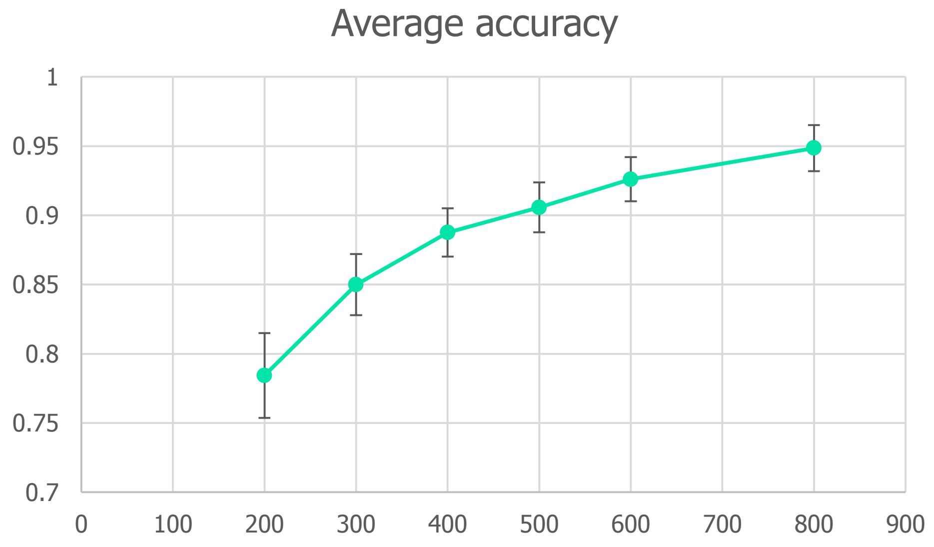


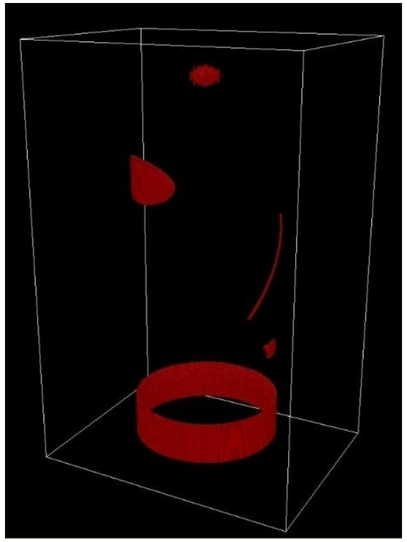
- Pros: No information loss and the accuracy increases
- Cons: Large number of nodes and training needs longer time

Full imaging training and classification - 3

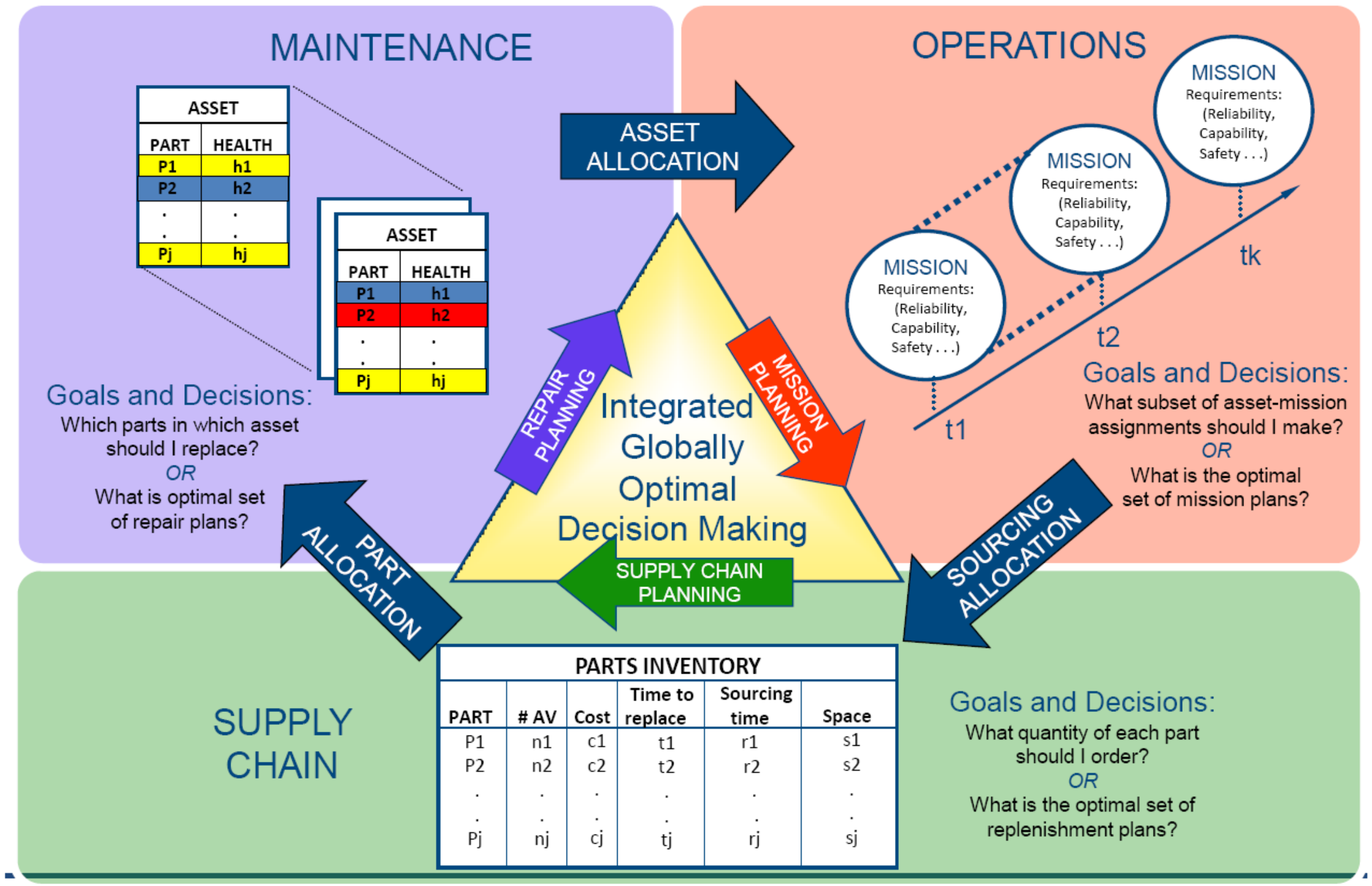
- Naïve Bayes network with image input
- High accuracy of damage detection
- Near real-time computation







Diagnostics, prognostics, and risk management



Reference: *"Framework for Post-Prognostic Decision Support", N. Iyer, K. Goebel, P. Bonissone. 2006 Aerospace Conference, Big Sky, MT*

- Why we need this?
- How to use this for decision making?
- What is the return of investment?
- What are the benefits for operators and regulators?

Reliability-Based Maintenance Optimization (RBMO) for risk mitigation

RBMO formulation - 1

- Terminology
  - *Q* groups of pipes
  - *S* deterioration stage (depending on a classification of damage level, e.g., crack length)

condition states	Excellent	Very good	Good	fair	poor	very poor
crack size	≤ 1mm	1mm ~ 3mm	3mm ~ 5mm	5mm ~ 8mm	8mm ~ 15mm	≥ 15mm

  - $\boldsymbol{D}(S,1)$ condition vector (percentage in each stage)

RBMO formulation - 2

- Terminology:
  - $\boldsymbol{M}_m(\boldsymbol{S},\boldsymbol{S})$ maintenance transition matrix for method m (do nothing, repair, replace)
  - $\boldsymbol{P}(S,S)$ degradation matrix (related to specific physical mechanisms, e.g., fatigue or slow crack growth)
  - $\boldsymbol{X}(M,S)$ maintenance decision matrix
  - $\boldsymbol{C}(M,S)$ cost matrix

RBMO formulation - 3

- Pipe condition estimation

$$D_{new} = \sum_m D \times X(m,:) \times M_m \times P$$

D(1×S)·×Xm(1×S) gives a (1×S) matrix, meaning the percentage of samples in each condition that will have maintenance m

The product of D×Xm, (1×S), times Mm(S×S) gives another (1×S) matrix, meaning the condition vector for those that have maintenance m done.

The condition after maintenance, (1×S), times the degradation matrix gives the new predicted condition vector (1×S) for the group that has maintenance m done after Δt.

The sum over m gives the overall condition vector (1×S).

RBMO formulation - 4

- The calculation for maintenance cost

$$\text{Budget} = \sum_{m} Q \times D \times X(m,:) \times C(m,:)$$

Q times the product of D×Xm, (1×S), gives a quantity vector (1×S). Each value means the quantity of samples that will do maintenance m.

D(1×S)·×Xm(1×S) gives a (1×S) matrix, meaning the percentage of samples in each condition that will have maintenance m

The quantity vector (1×S) times the cost vector (1×S) gives a scaler meaning the total cost for doing maintenance m according to the decision X.

RBMO formulation - 5

- Maximum condition status with constrained budget

  Maximize total condition : $D_{new} = \sum_m D \times X(m,:) \times M_m \times P$

  Constraint: $\sum_m Q \times D \times X(m,:) \times C(m,:) \leq Budget$

- Minimize budget with constrained condition threshold

  Minimize: $\mathrm{Cost} = \sum_m Q \times D \times X(m,:) \times C(m,:)$

  Constraint: $D_{new} = \sum_m D \times X(m,:) \times M_m \times P \leq RBCN$

Demonstration example - 1

- Fatigue crack growth rate-based life prediction

- Stress intensity factor (SIF)

$$\Delta K = \Delta\sigma \sqrt{\pi a} Y \qquad (1)$$

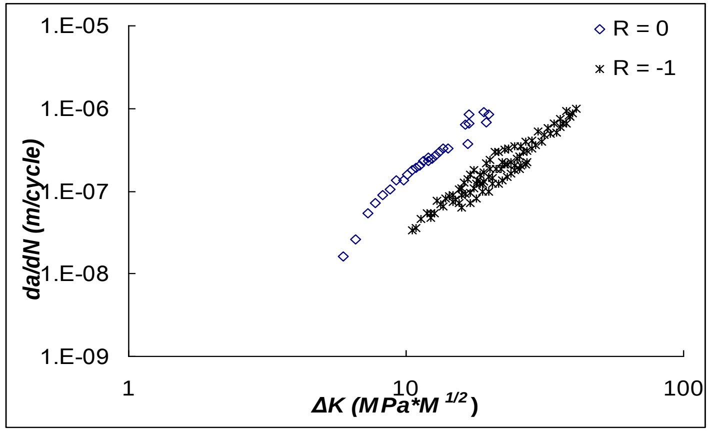
- The material fatigue crack growth curve can be expressed as

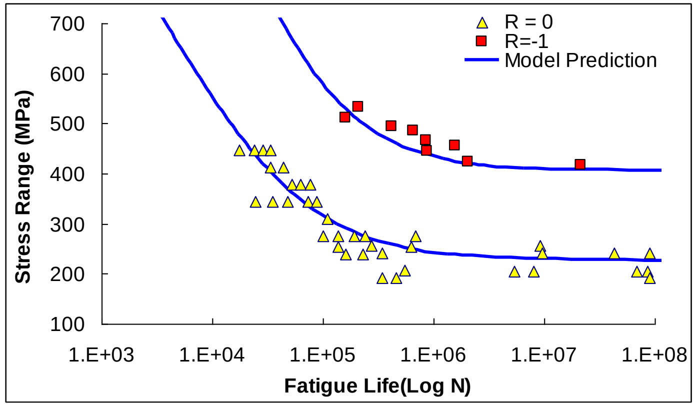
$$da/dN = C[\Delta K - \Delta K_{th}]^m \qquad (2)$$

- Fatigue life N can be obtained as:

$$N = \int_0^N dN = \int_{a_i}^{a_c} \frac{1}{C[\Delta K - \Delta K_{th}]^m} da \qquad (3)$$

a: crack length; ***Y***: geometry correction factor: ***N***: fatigue life;
a_i: initial crack length: ***a_c***: critical crack length





Xiang Y, Lu Z, Liu Y. Crack growth-based fatigue life prediction using an equivalent initial flaw model. Part I: Uniaxial loading. International Journal of Fatigue,2010;32(2):341-349.

Demonstration example - 2

- S=6 (number of condition states, 6 is excellent, 5 is very good,4 good,…)
- Q=[6] (total quantity of pipes A and B)
- M=3 (do nothing; repair; replacement)
- C= $\begin{vmatrix} conditions\,tate & 1 & 2 & 3 & 4 & 5 & 6 \\ do\_nothing & 0 & 0 & 0 & 0 & 0 & 0 \\ repair & 0 & 400 & 600 & 800 & 1600 & 1800 \\ replacement & 0 & 0 & 1600 & 1600 & 3000 & 3000 \end{vmatrix}$

Demonstration example - 3

P(P^1 do nothing; P^2 repair I; P^3 repair II)

$$P^1 = \begin{vmatrix} 0.9956 & 0.0043 & 0.0001 & 0 & 0 & 0 \\ 0 & 0.8818 & 0.1065 & 0.0112 & 0.0004 & 0.0001 \\ 0 & 0 & 0.9246 & 0.0344 & 0.0307 & 0.0103 \\ 0 & 0 & 0 & 0.9161 & 0.0532 & 0.0307 \\ 0 & 0 & 0 & 0 & 0.9238 & 0.0762 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{vmatrix}$$

$$P^2 = \begin{vmatrix} 0.8325 & 0.0875 & 0.0373 & 0.0344 & 0.0073 & 0.0010 \\ 0.8325 & 0.0875 & 0.0373 & 0.0344 & 0.0073 & 0.0010 \\ 0.8325 & 0.0875 & 0.0373 & 0.0344 & 0.0073 & 0.0010 \\ 0.8325 & 0.0875 & 0.0373 & 0.0344 & 0.0073 & 0.0010 \\ 0.8325 & 0.0875 & 0.0373 & 0.0344 & 0.0073 & 0.0010 \\ 0.8325 & 0.0875 & 0.0373 & 0.0344 & 0.0073 & 0.0010 \end{vmatrix}$$

$$P^3 = \begin{vmatrix} 0.9406 & 0.0370 & 0.0114 & 0.0099 & 0.0010 & 0.0001 \\ 0.9406 & 0.0370 & 0.0114 & 0.0099 & 0.0010 & 0.0001 \\ 0.9406 & 0.0370 & 0.0114 & 0.0099 & 0.0010 & 0.0001 \\ 0.9406 & 0.0370 & 0.0114 & 0.0099 & 0.0010 & 0.0001 \\ 0.9406 & 0.0370 & 0.0114 & 0.0099 & 0.0010 & 0.0001 \\ 0.9406 & 0.0370 & 0.0114 & 0.0099 & 0.0010 & 0.0001 \end{vmatrix}$$

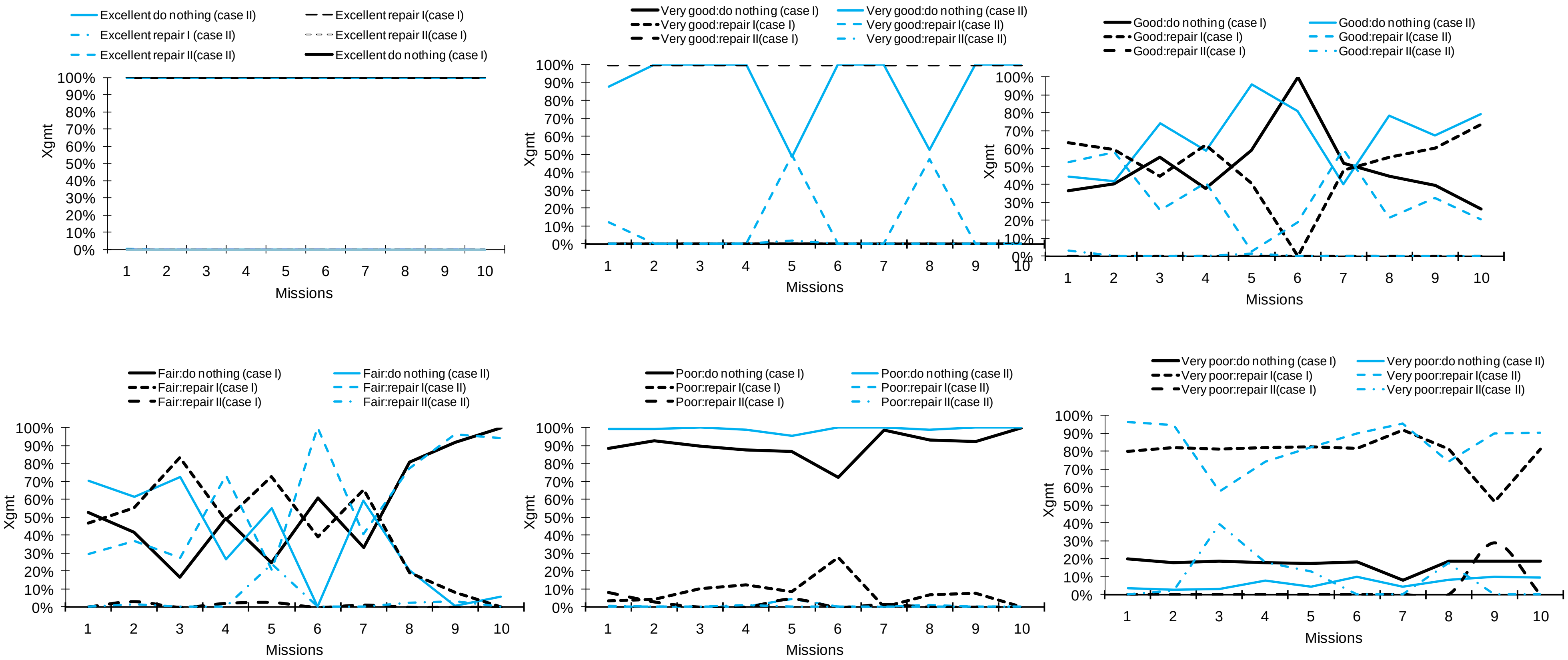
- The budget in each mission=

[10000 8000 9000 12000 10000 8000 9000 8000 8000 9000];

- The total budget = $65000
- The pipes in very poor condition is less than 5% after each mission

Demonstration example - 4

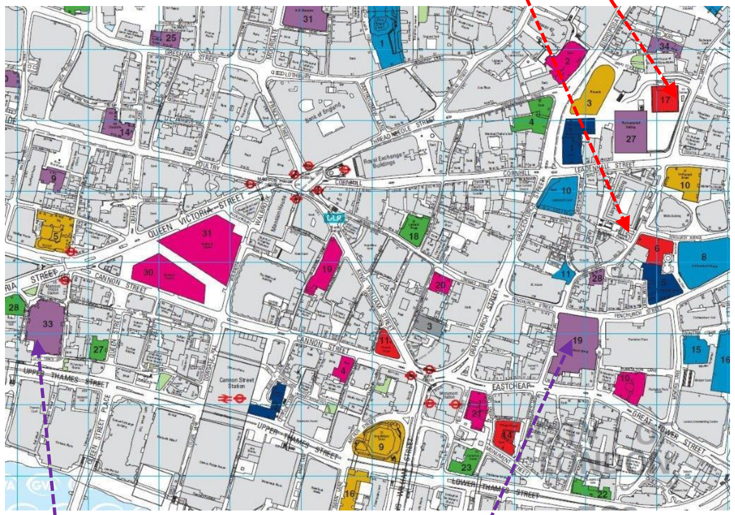
- Maintenance plan with different damage rates *(case I higher rate and case II lower rate)*



Demonstration example - 5

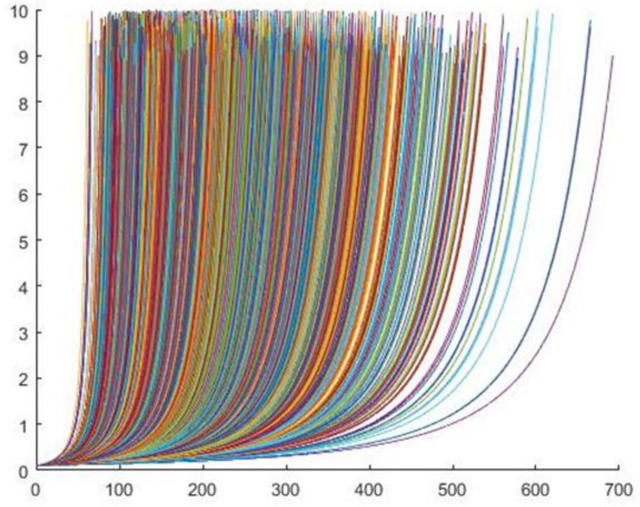
- Above discussion only considers the maintenance cost
- Consequence cost for distribution pipelines, what happens if failure happens?
- Mapping with the geometric importance areas (hospital, public building, residential building, etc.)
- Weighted optimization problem

High consequence - larger weight

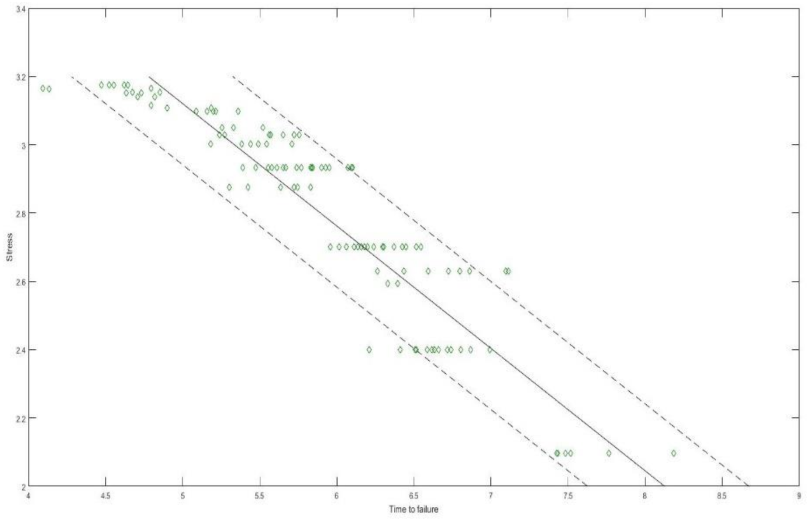


Moderate consequence - medium weight

Demonstration example - 6



Monte Carlo Simulation for slow crack growth



Verification and validation for remaining life prediction

$$P = \begin{bmatrix} 0.7127 & 0.2856 & 0.0018 & 2.808e\text{-}05 & 2.8871e\text{-}06 \\ 0 & 0.3296 & 0.4950 & 0.1473 & 0.0280 \\ 0 & 0 & 0.0457 & 0.3525 & 0.6018 \\ 0 & 0 & 0 & 0.0024 & 0.9976 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Risk assessment and classification

- Integrated anomaly detection, rate process modeling, probabilistic methods, and optimization algorithms

Demonstration example - 7

- Example with consequence weight:
  - G=3; ~~~ 3 groups of pipe
  - Q=[100 100 100]; ~~ Number of samples in each group
  - Dgt=[0.1 0.2 0.5 0.15 0.05;
    0.1 0.2 0.5 0.15 0.05;
    0.1 0.2 0.5 0.15 0.05]; ~~~ initial condition
  - weight=[10 5 1];
  - TTC=$500000 ~~~ total cost
- Optimization is done using the generic algorithm

Consider weighted group

- Results:
  - New condition: $$D_{new} = \begin{bmatrix} 0.6994 & 0.28506 & 0.0090 & 0.0032 & 0.0035 \\ 0.6883 & 0.2826 & 0.0123 & 0.0054 & 0.0113 \\ 0.6614 & 0.2742 & 0.0172 & 0.0178 & 0.0293 \end{bmatrix}$$
  - Cost for each group: $$Budget = \begin{bmatrix} 163060 \\ 160851 \\ 155115 \end{bmatrix}$$
- *These examples are demonstration purpose only and do not represent the practical scenarios !!!*
- *Need experts' opinions and operational information to improve the pure academic research !!!*

Conclusions

- Fast in-line imaging tools for high-resolution anomaly detection
- Automatic and near real-time damage classification and risk assessment
- Integrated diagnostics and prognostics for decision making and risk mitigation
- Need help from industry to revise, improve and apply this methodology to practice

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Thanks! Questions?