Diagnostic de l'état mécanique de structures par analyse de vibrations

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Outline

- Classical Methods for Machine Condition Monitoring
- Recent Methods for Structural Health Monitoring
  - Principal Component Analysis (PCA)
  - Null Subspace Analysis (NSA)
  - Kernel Principal Component Analysis (KPCA)
- Examples of Application
- Conclusion

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Predictive maintenance techniques

Two categories of inspection techniques may be used:

1. Destructive techniques
2. Non destructive techniques

- Acoustic emission (cracks in structures)
- Oil analysis (bearings and gears)
- Thermography, holography, interferometry, …
- Vibration monitoring (rotating machinery, structures)

Classical Methods

For

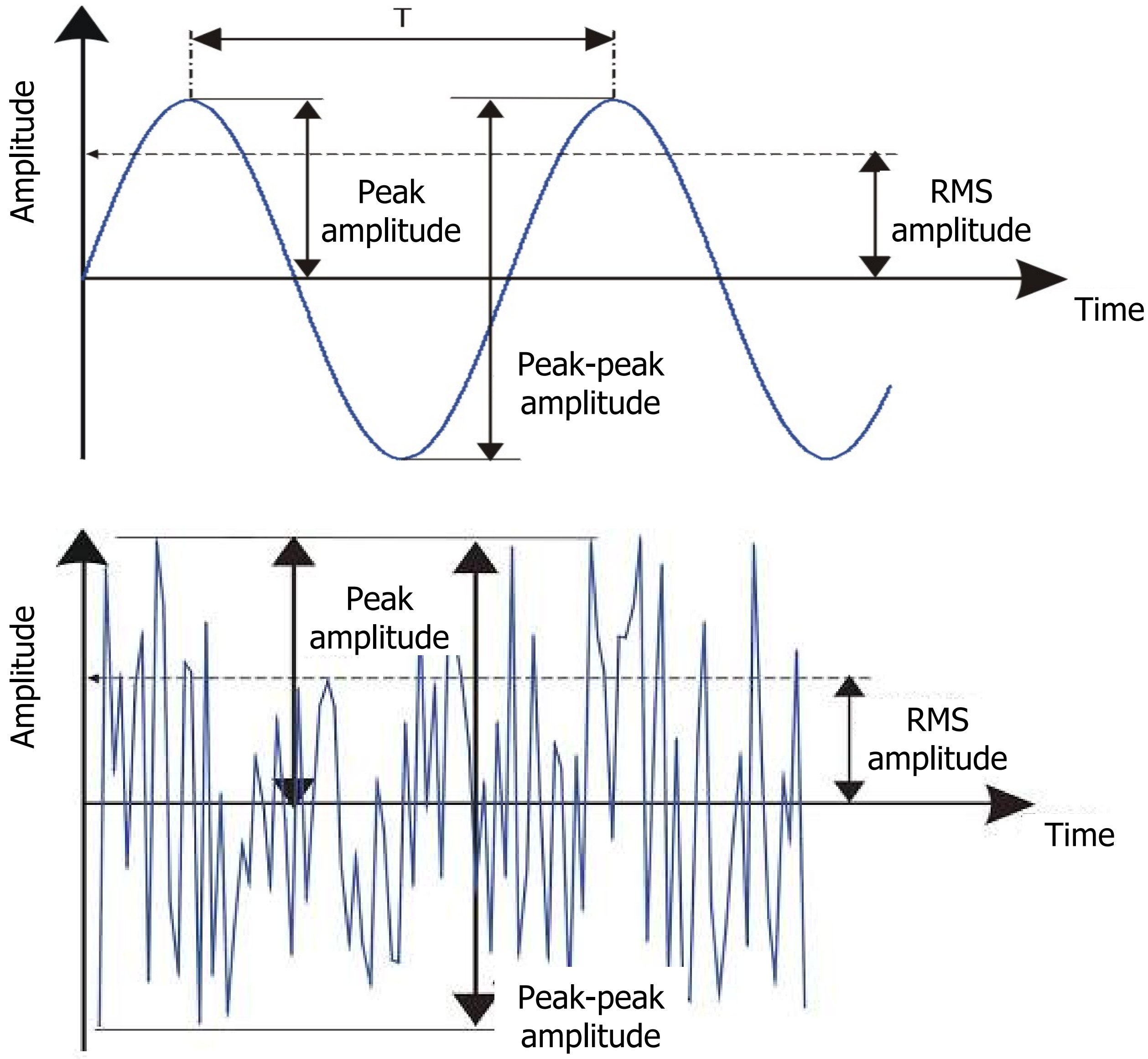
Machine Condition Monitoring

Vibration analysis – a key predictive maintenance technique

The nature

of

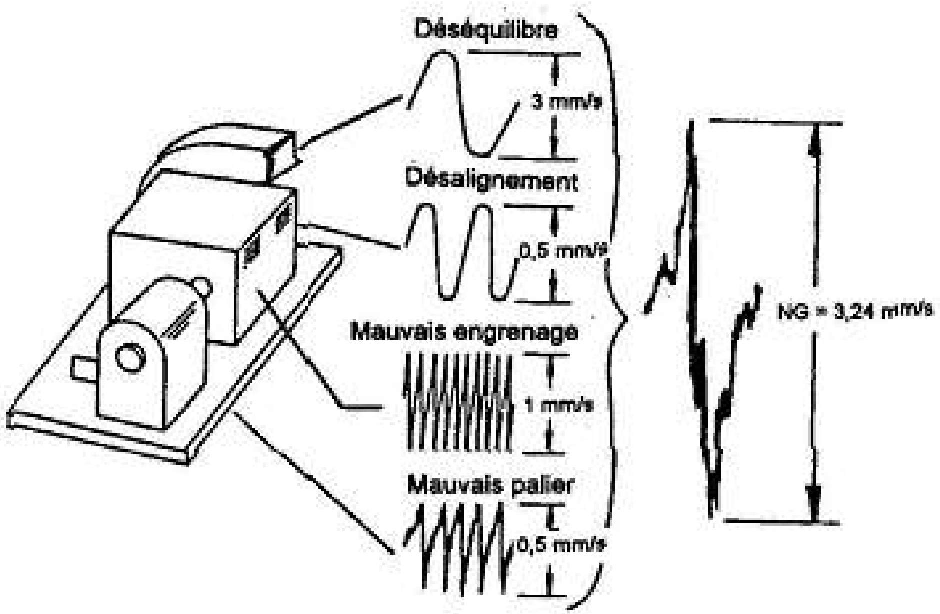
vibration



Machine Condition Monitoring (Example)

Monitoring of the global vibration amplitude level

Example of a fan driven by an electric motor through a gear box

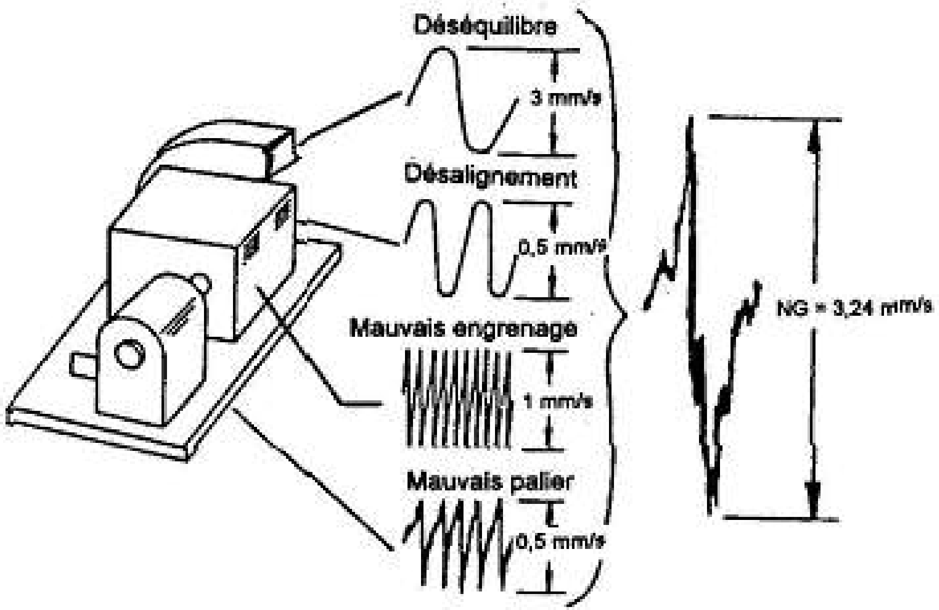


The global vibration level may be calculated as

$$NG = \sqrt{a^2 + b^2 + c^2 + d^2 + \ldots}$$

where a, b, c, d, … are the RMS amplitudes of the different signal components.

Machine Condition Monitoring (Example)



Initial RMS amplitude level

$$NG = \sqrt{3^2 + 0.5^2 + 1^2 + 0.5^2} = 3.24 \text{ mm/s}$$

A variation of 30 % on the unbalance (low severity) gives:

$$NG = \sqrt{3.9^2 + 0.5^2 + 1^2 + 0.5^2} = 4.08 \text{ mm/s} \qquad (+\ 26\ \%)$$

A variation of 300 % on the bearing defect (extreme severity) gives:

$$NG = \sqrt{3^2 + 0.5^2 + 1^2 + 1.5^2} = 3.53 \text{ mm/s} \qquad (+\ 9\ \%)$$

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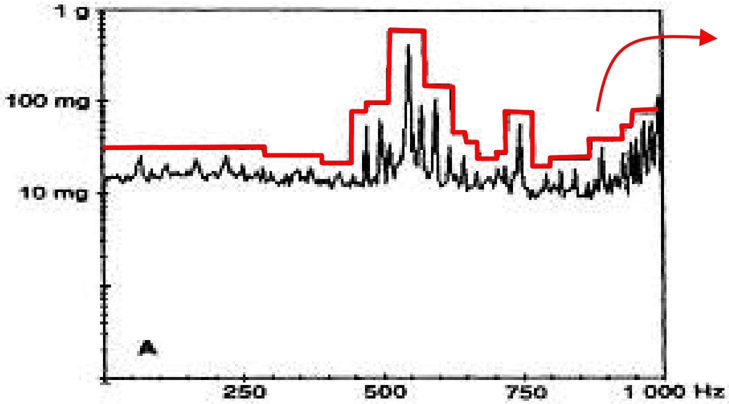
Machine Condition Monitoring (Example)

Monitoring of the indicators by comparison with an envelope

The envelope is determined from a reference spectrum (« vibratory signature ») obtained in good operating conditions.

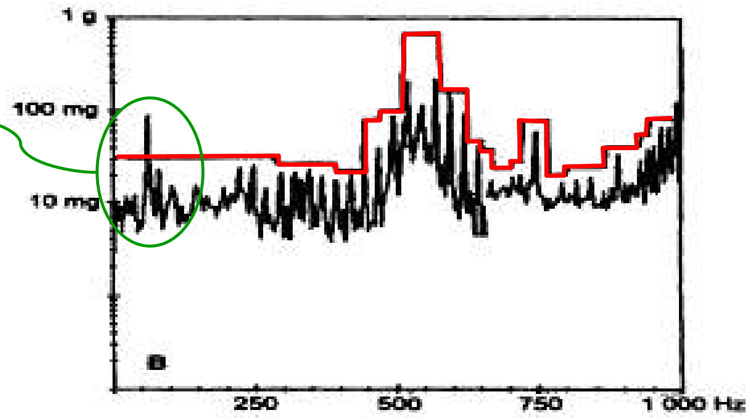
Example

Vibration signature
at the bearing
(normal state)



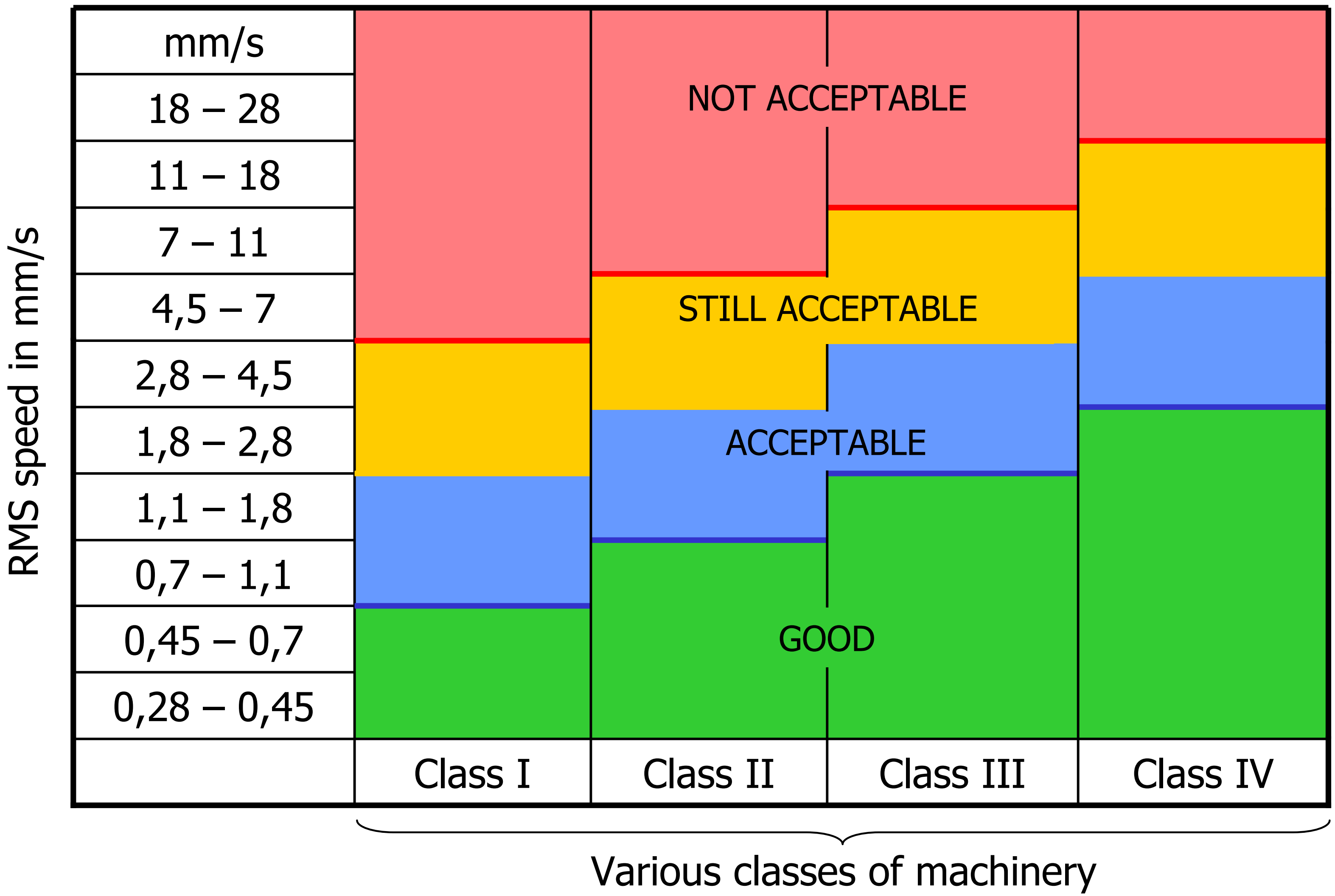
Envelope

Overshoot



Vibration signature
at the bearing
(after occurrence
of a defect)

ISO Guidelines for Machinery Vibration Severity



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Recent Methods

For

Structural Health Monitoring

Some definitions

Structural Health Monitoring (SHM)

Process of implementing a damage detection strategy for aerospace, civil and mechanical engineering structures.

Damage

Changes to the material and/or geometric properties which affect the performance of the system.

Problem of detection

Damage is detected through changes in some carefully selected structural features (e.g. modal parameters)

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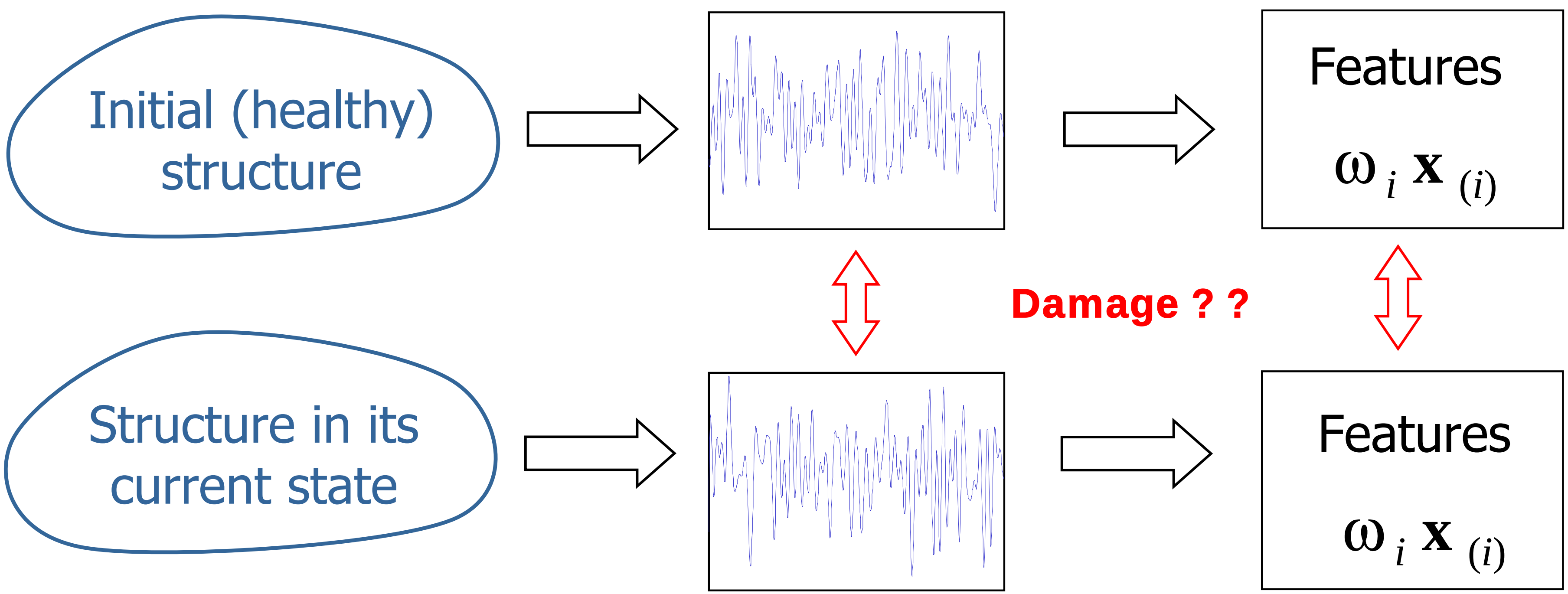
Structural Health Monitoring Process

The SHM process involves three steps:

- the observation of a system over time using periodically sampled dynamic measurements from an array of sensors,
- the extraction of damage-sensitive features from these measurements,
- the statistical analysis of these features to determine the current state of system health.



Damage Problem

The damage state of a system can be described as a five-step process (Rytter, 1993) to answer the following questions.

- Level 1: ***Existence***. Is there damage in the system?
- Level 2: ***Location***. Where is the damage in the system?
- Level 3: ***Type***. What kind of damage is present?
- Level 4: ***Extent***. How severe is the damage?
- Level 5: ***Prognosis***. How much useful life remains?

Some Difficulties

Categories of false indications of damage

- False-positive damage indication = indication of damage when none is present.
- False-negative damage indication = no indication of damage when damage is present.

→ Use of statistical procedures to increase robustness

Classification of SHM methods

Model-based techniques

Updating of structural parameters or matrices (inverse problem)

Non-model based techniques

Identification of modal parameters

- non-supervised methods (statistics)
- supervised methods (pattern recognition, neural networks, …)

Structural Dynamics Problem

Homogeneous equation of motion

Inertia forces — **Restoring forces**

$$\mathbf{M}\,\ddot{\mathbf{x}} + \mathbf{K}\,\mathbf{x} = 0 \quad \text{where} \quad \mathbf{x} = \begin{Bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{Bmatrix}$$

Mass matrix — **Stiffness matrix**

Structural Dynamics Problem

The general solution of the equation of motion is of the form

$$\mathbf{x} = \mathbf{x}_{(i)} \cos \omega_i t \qquad (i = 1, 2, \ldots, n)$$

mode-shape vector n° *i*

natural frequency n° *i*

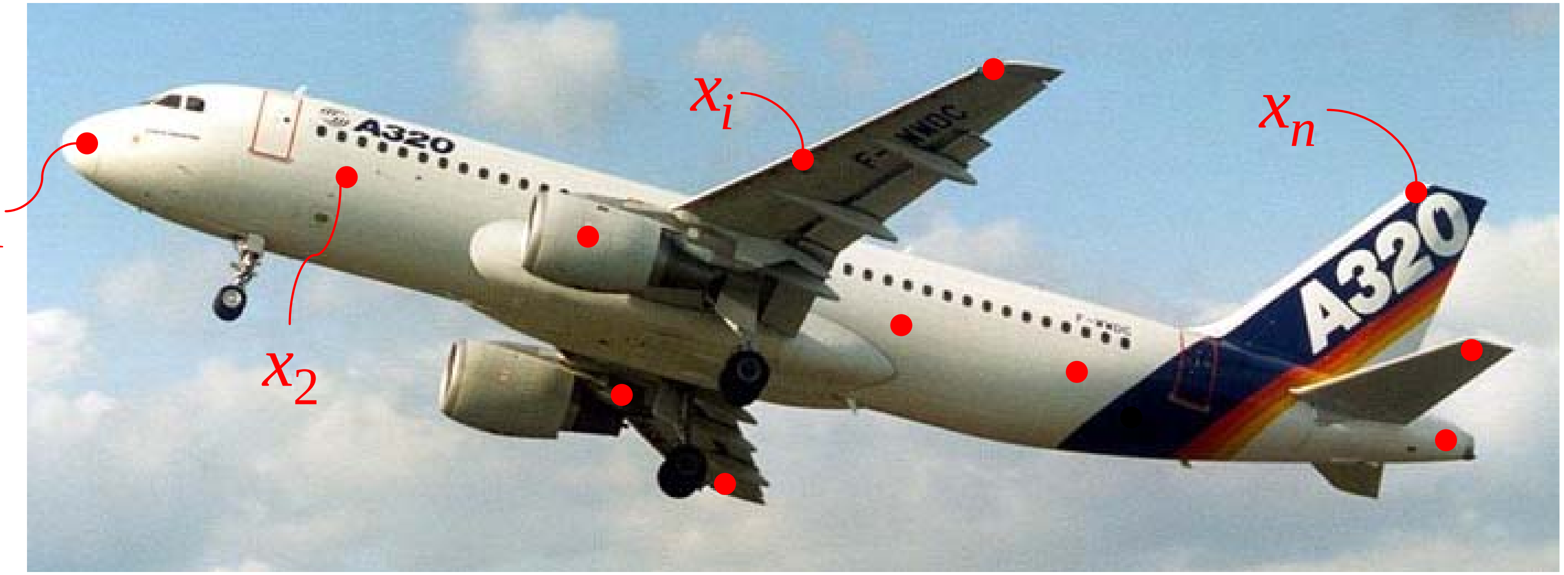
→ the dynamic behavior of a structure is completely characterized by its modal parameters

(i.e. the natural frequencies ω_i and mode-shapes $\mathbf{x}_{(i)}$).

Principal Component Analysis (PCA)

Principal Component Analysis (PCA)

Instrumented structure



N snapshots

Observation matrix:

$$\mathbf{X} = \begin{bmatrix} x_1(t_1) & \cdots & x_1(t_N) \\ \vdots & \ddots & \vdots \\ x_n(t_1) & \cdots & x_n(t_N) \end{bmatrix}$$

n measurement co-ordinates

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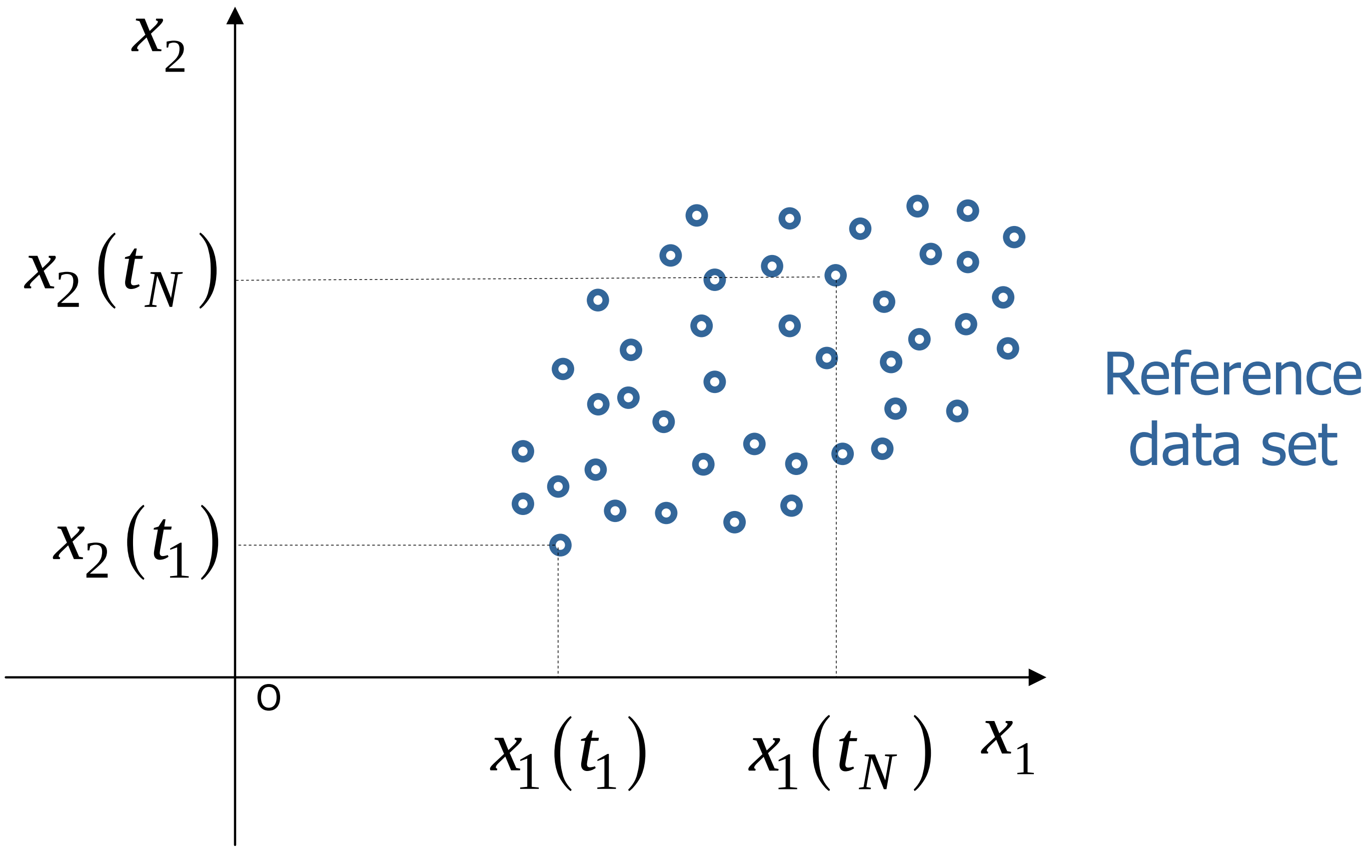
Principal Component Analysis (PCA)

PCA in 2D-space

$$\mathbf{X} = \begin{bmatrix} x_1(t_1) & x_1(t_2) & \cdots & x_1(t_N) \\ x_2(t_1) & x_2(t_2) & \cdots & x_2(t_N) \end{bmatrix}$$

Geometric interpretation



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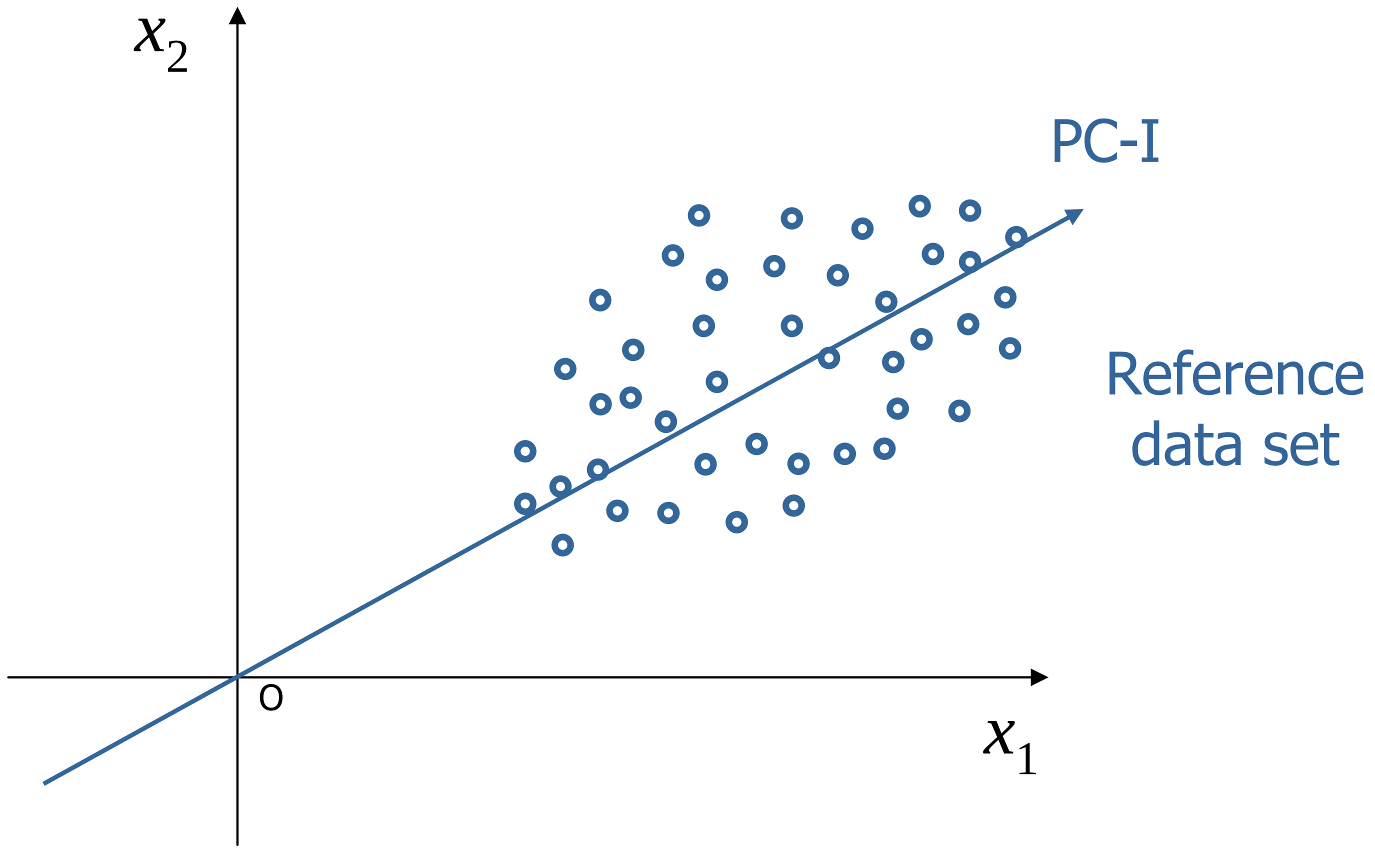
Principal Component Analysis (PCA)

Geometric interpretation

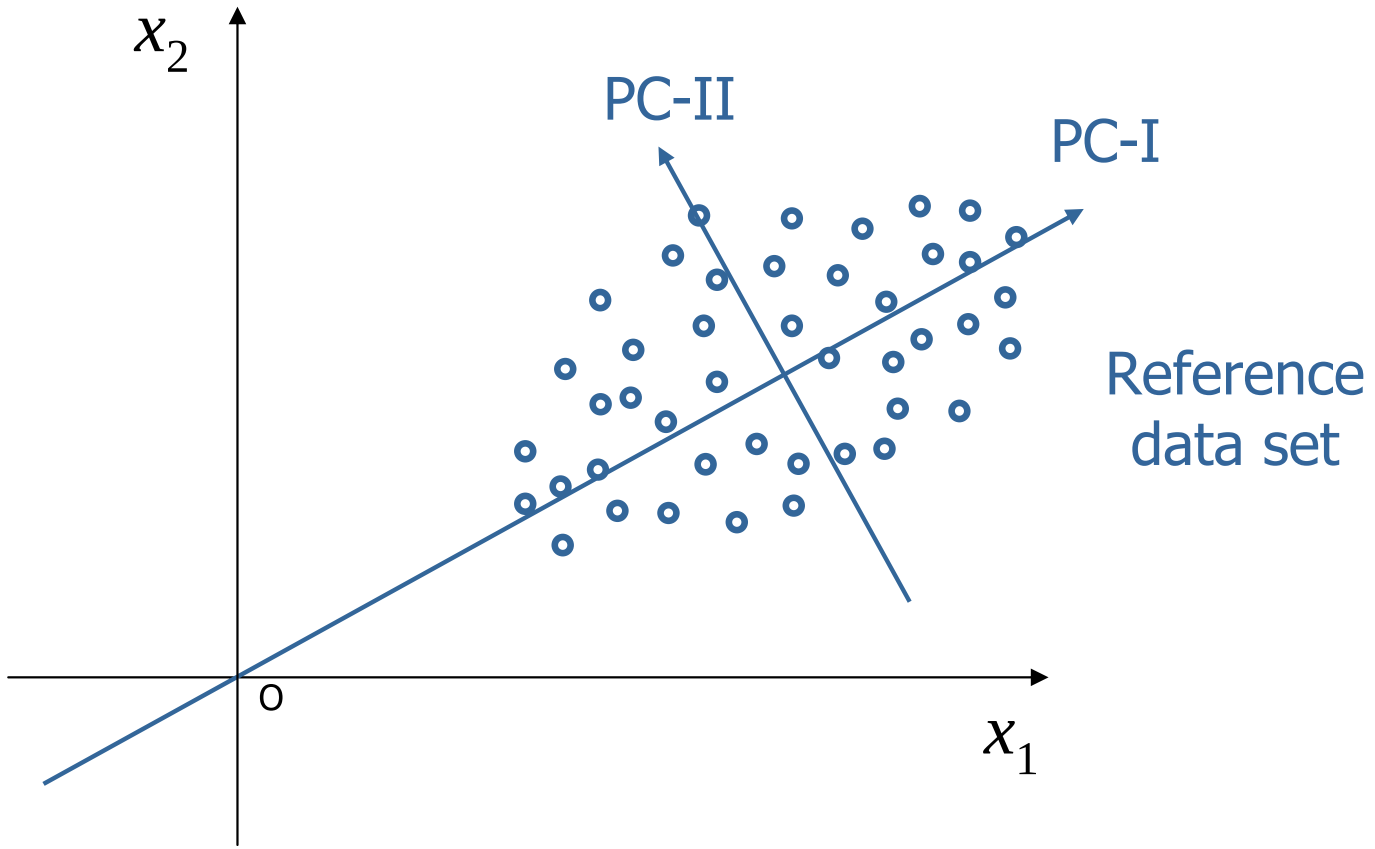
PCA in 2D-space



Structural Damage Detection Problem

Geometric interpretation

PCA in 2D-space



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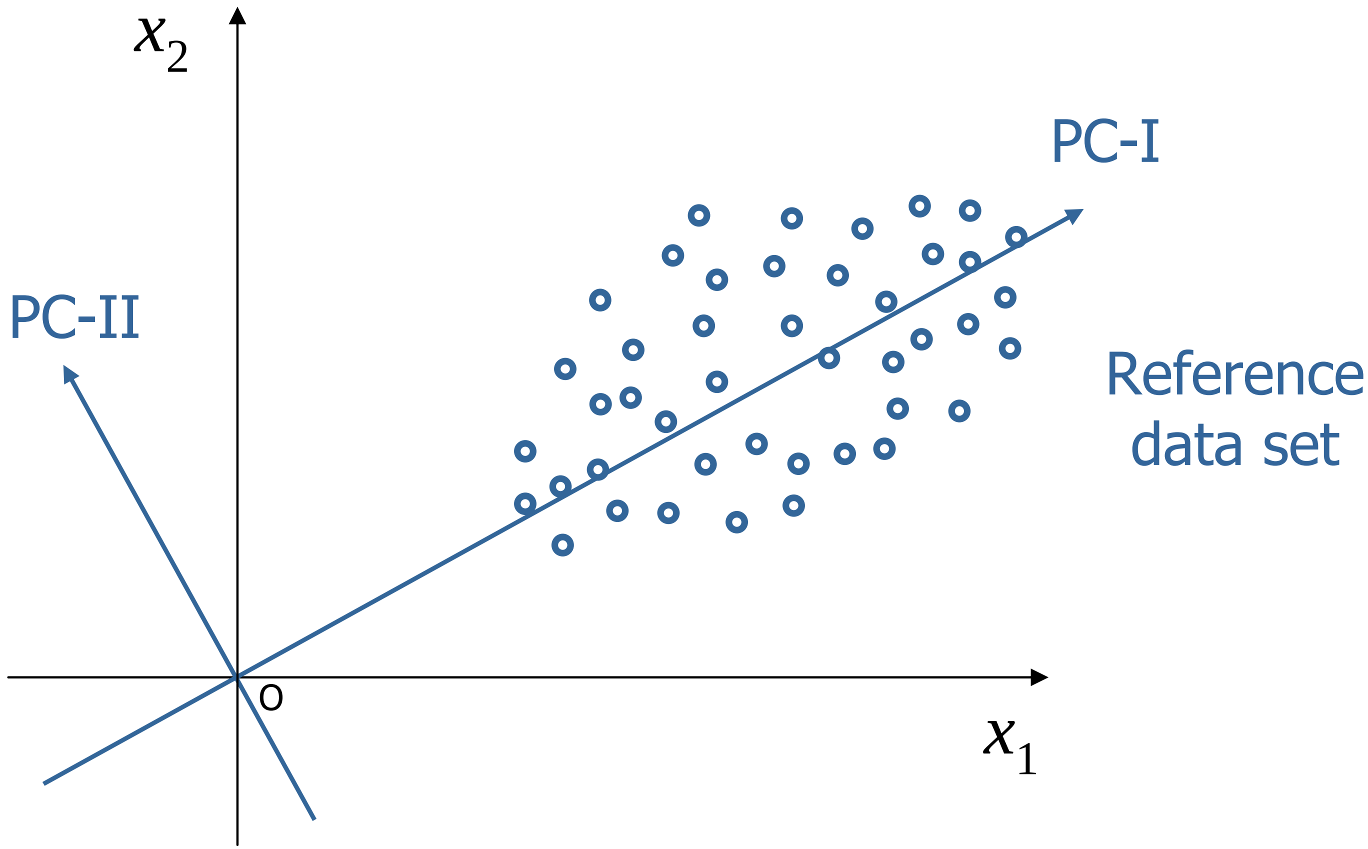
Principal Component Analysis (PCA)

Geometric interpretation

PCA in 2D-space



Structural Damage Detection Problem

Concept of Subspace Angle (Golub-Van Loan)

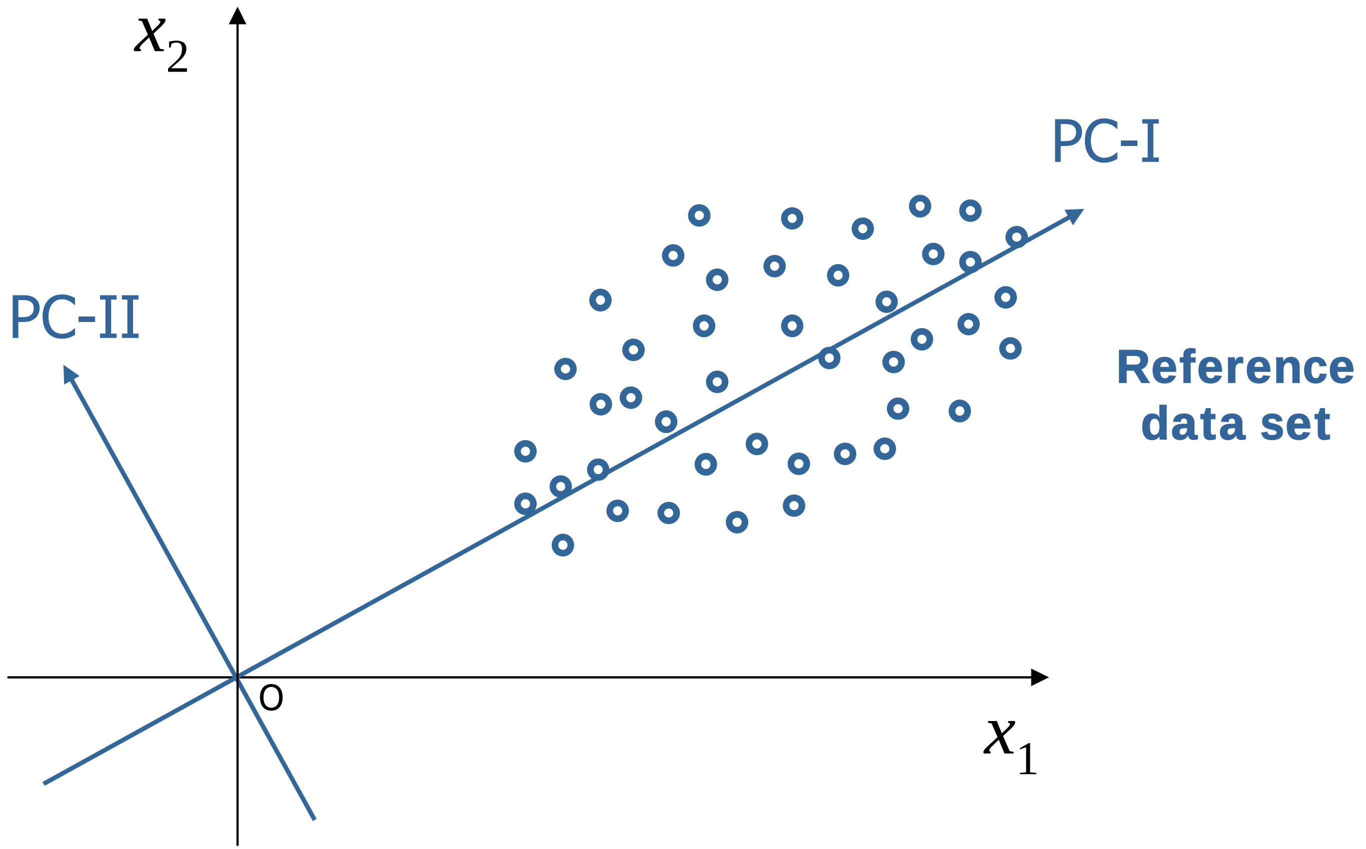
Key idea

- Use PCA to extract the structural response subspace (PC-I, PC-II)
- Use the concept of subspace angles to compare the hyperplanes associated with the reference (undamaged) state and with the current (possibly damaged?) state of the structure.

Structural Damage Detection Problem

Geometric interpretation

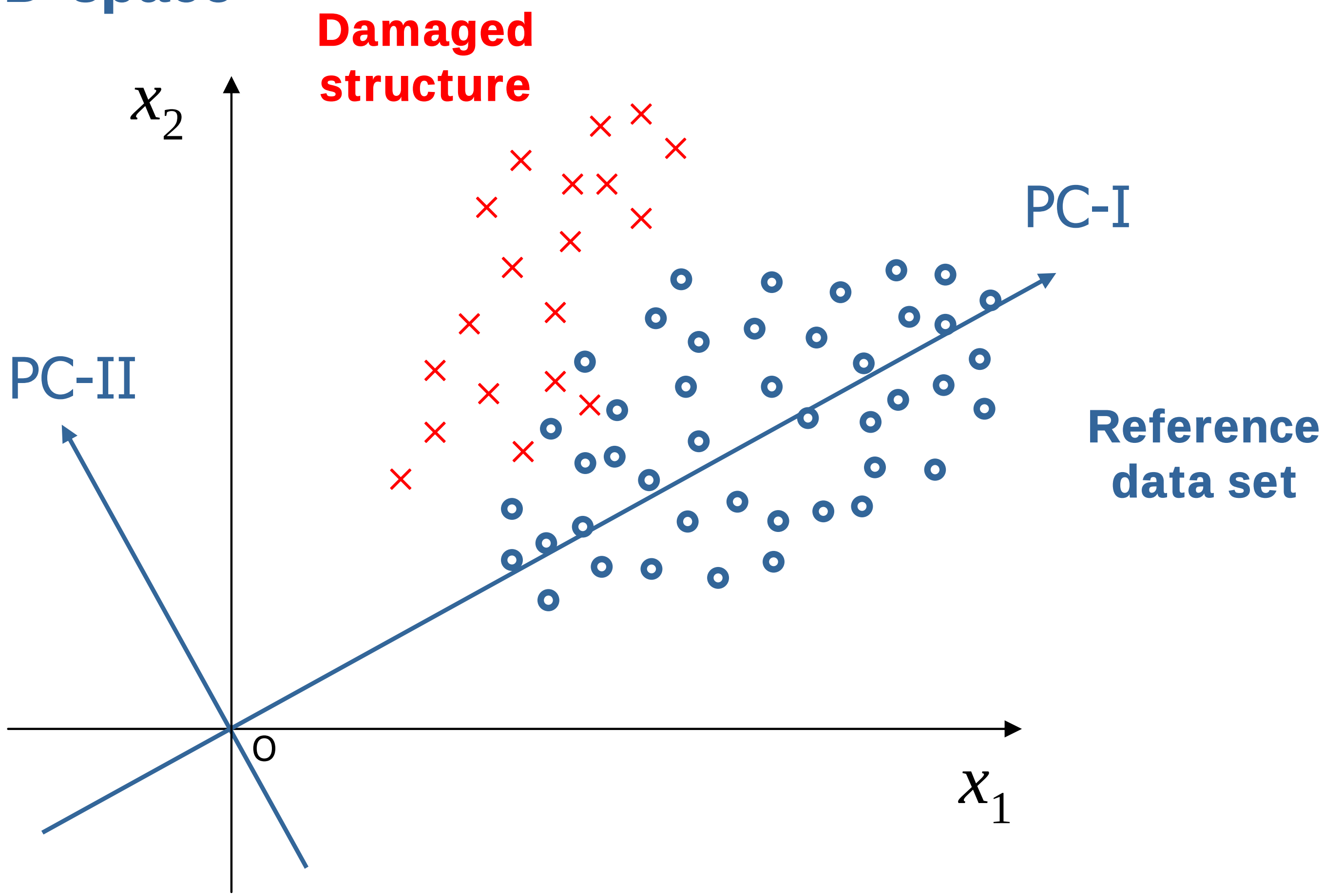
PCA in 2D-space



Structural Damage Detection Problem

Geometric interpretation

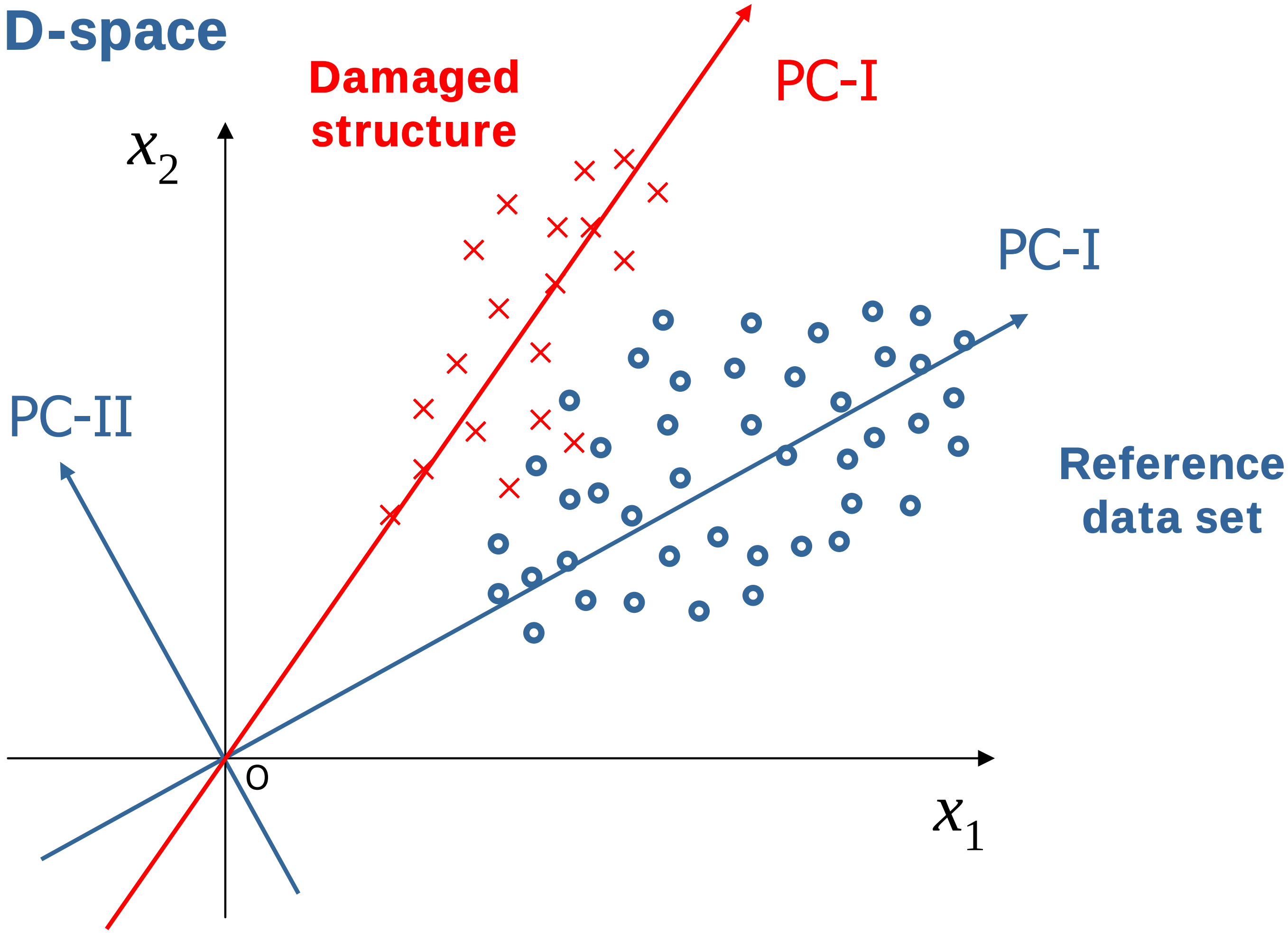
PCA in 2D-space



Structural Damage Detection Problem

Geometric interpretation

PCA in 2D-space



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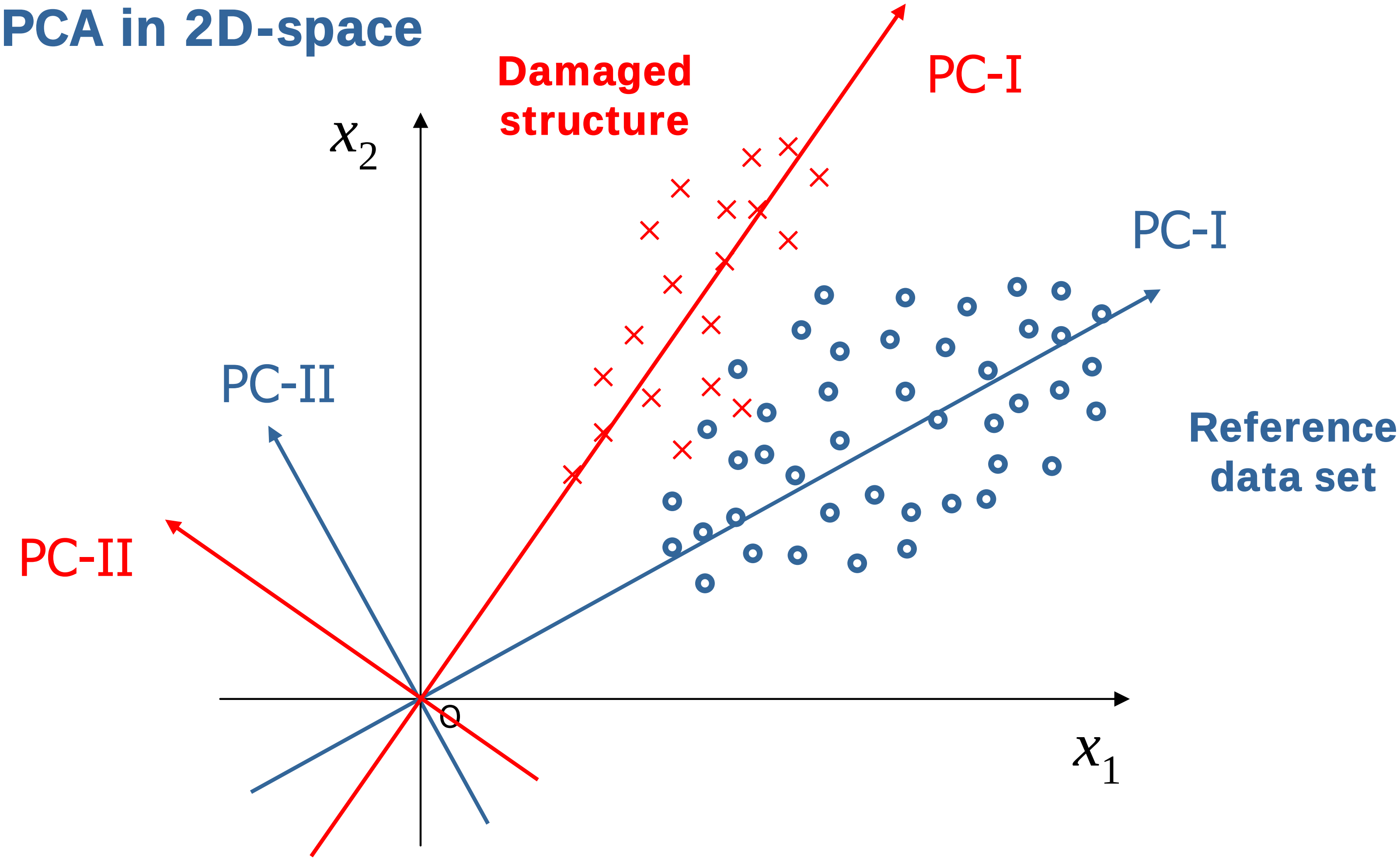
Structural Damage Detection Problem

Geometric interpretation

PCA in 2D-space



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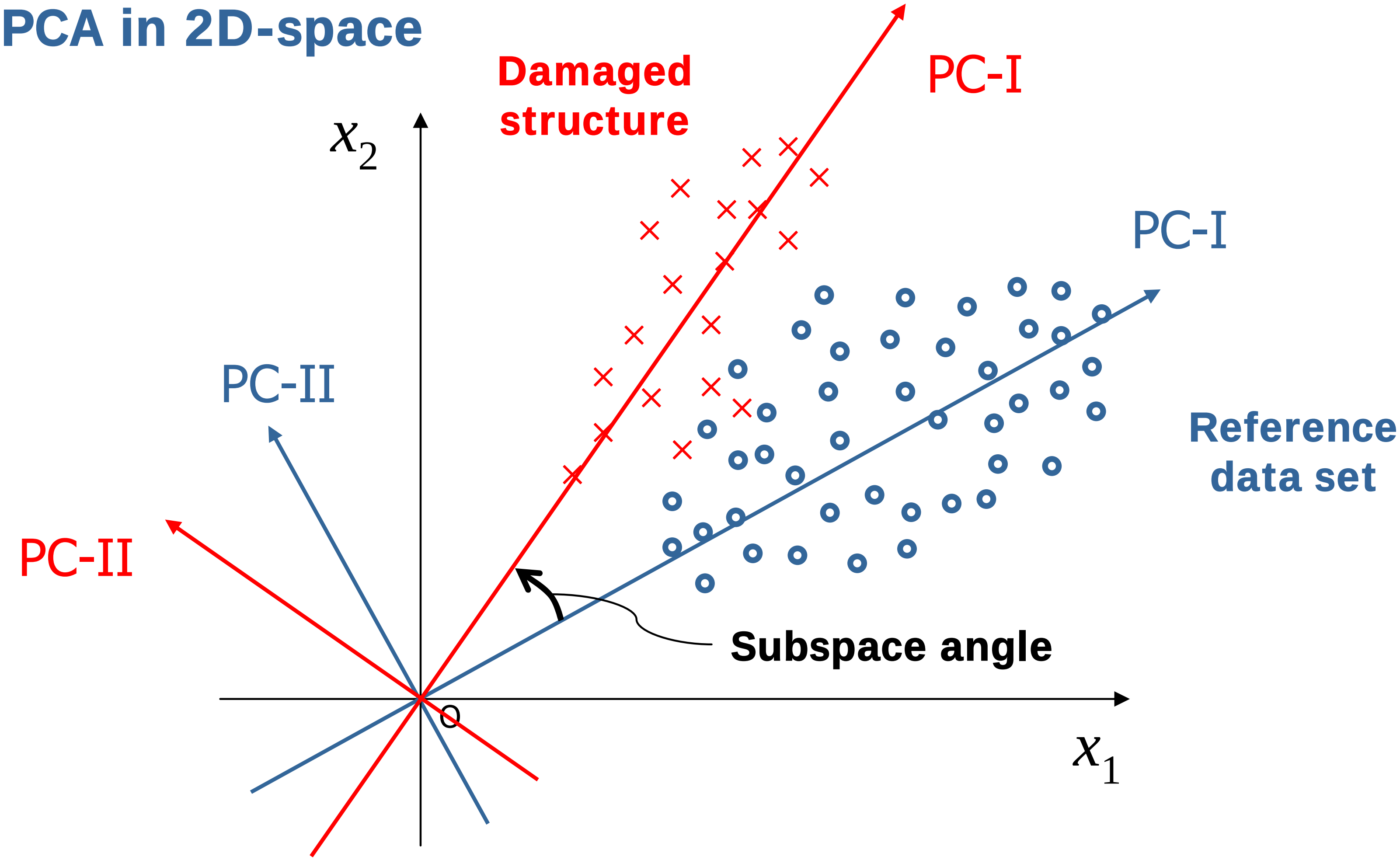
Structural Damage Detection Problem

Geometric interpretation

PCA in 2D-space



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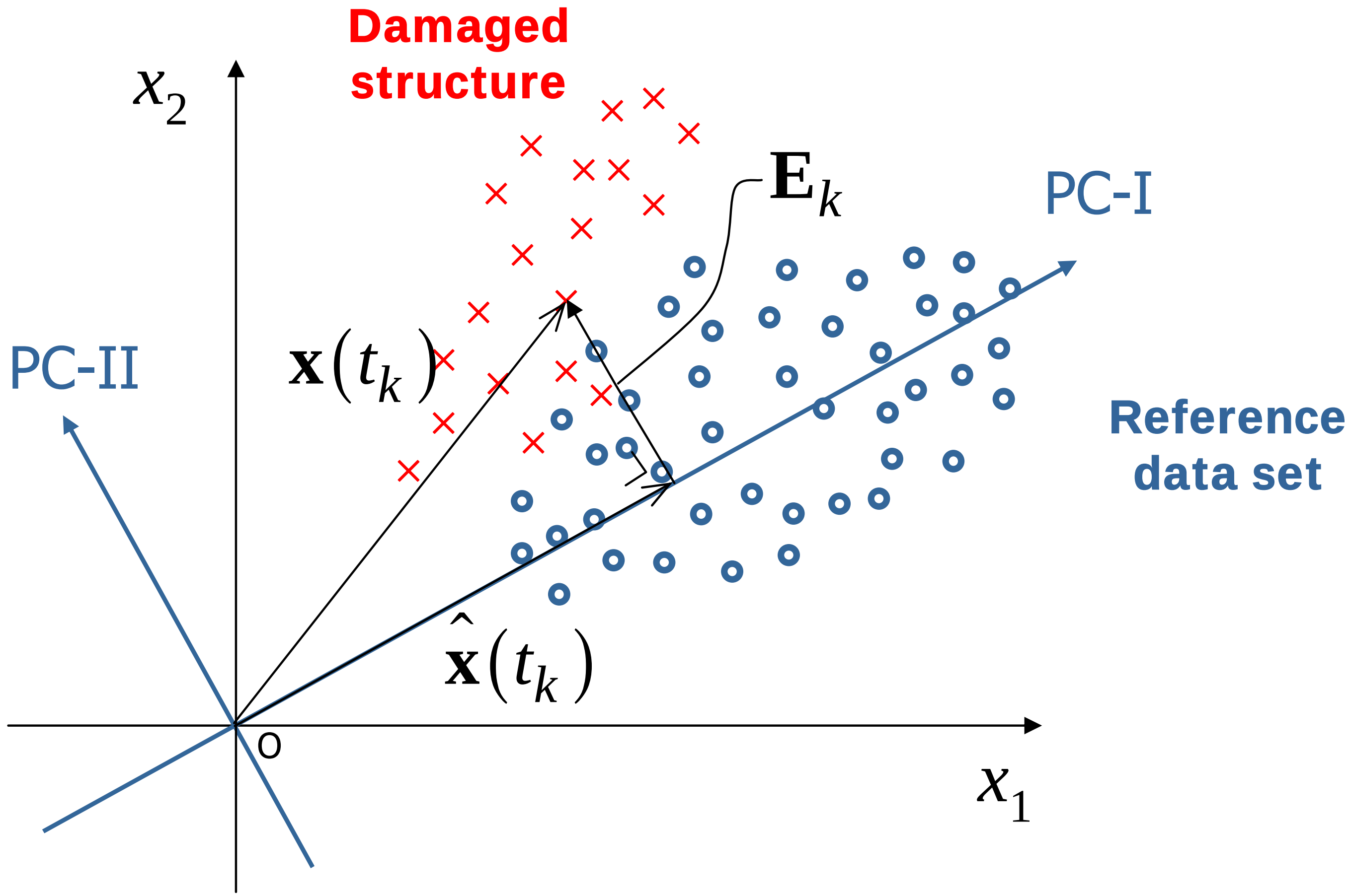
Structural Damage Detection Problem

Novelty Analysis

The aim is to build a prediction model using the principal components of reference.



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Structural Damage Detection Problem

Definition of the Novelty Index

Residual error matrix : $\mathbf{E} = \mathbf{X} - \widehat{\mathbf{X}}$

Euclidean norm : $NI_k^E = \left\| \mathbf{E}_k \right\|$

→ prediction error vector at time t_k

Statistical tool : $CL = \overline{NI} + 3\,\sigma$

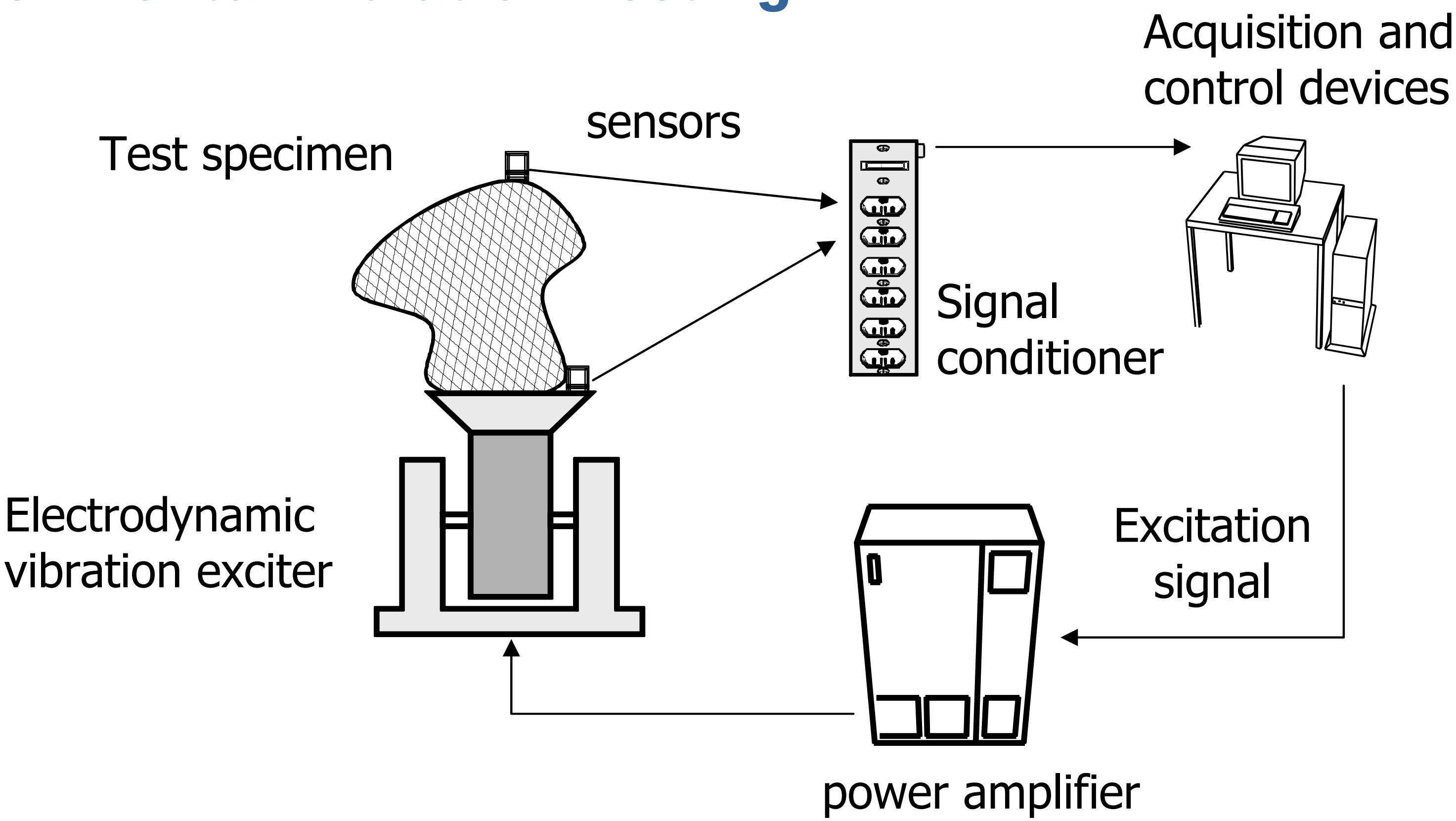
mean value ($\overline{NI}$)

standard deviation (σ)

(Upper Control Limit at 99.7 % confidence interval)

Example of Damage Detection

Environmental Vibration Testing



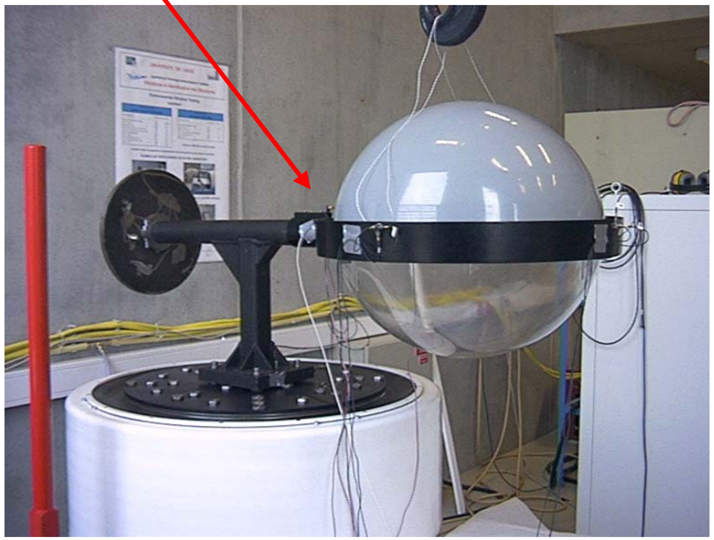
Detection of damages usually by visual inspection or by comparison of frequency spectra before and after the test.

Objective : to be able to detect damage as soon as it appears.

Example of Damage Detection

Fatigue testing of a street lighting device

Control accelerometer



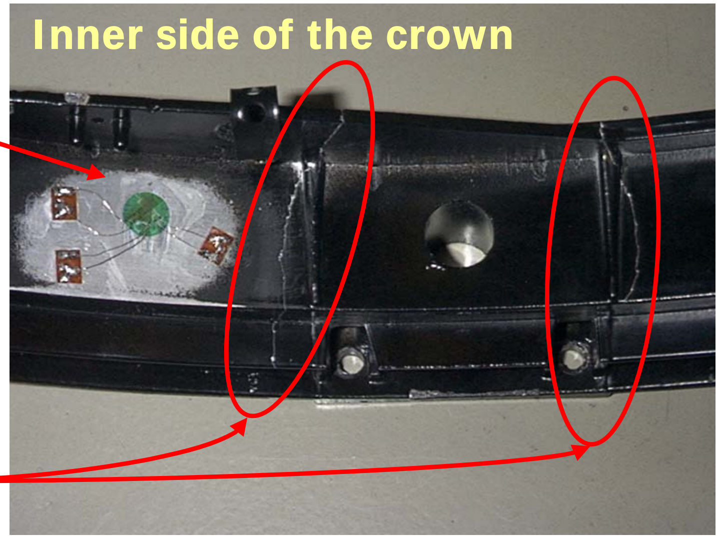
+ 10 measurement accelerometers

Vibration specifications

- Sine excitation at the first resonance frequency (~ 12,4 Hz) during 1 hour.
- Acceleration level of 0,5 g at the fixation.

Total test duration: ~ 4 hours

Strain gauges



Mode of failure of the crown

Crack initiation and propagation

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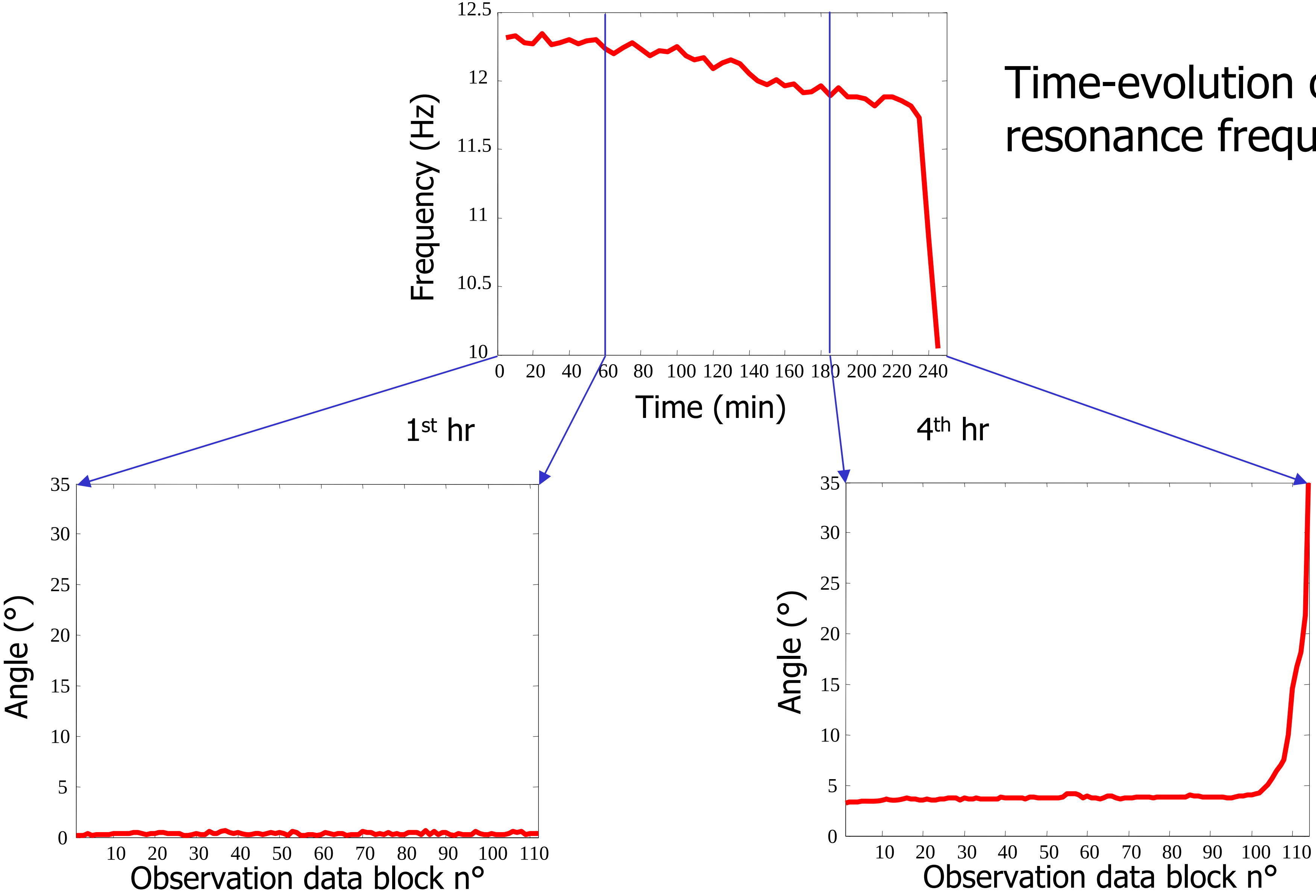
Damage Detection (Results)



Time-evolution of the resonance frequency

Time-evolution of the angle

Principal Component Analysis (PCA)

Limitation of the PCA-based method

The number of sensors must be larger than the number of active modes → it can be solved using the concept of null-subspace of the Hankel matrices of responses.

Null Subspace Analysis (NSA)

Aim : to replace the observation matrix $\mathbf{X}$ by a "dynamic" response matrix (i.e. the Hankel matrix)

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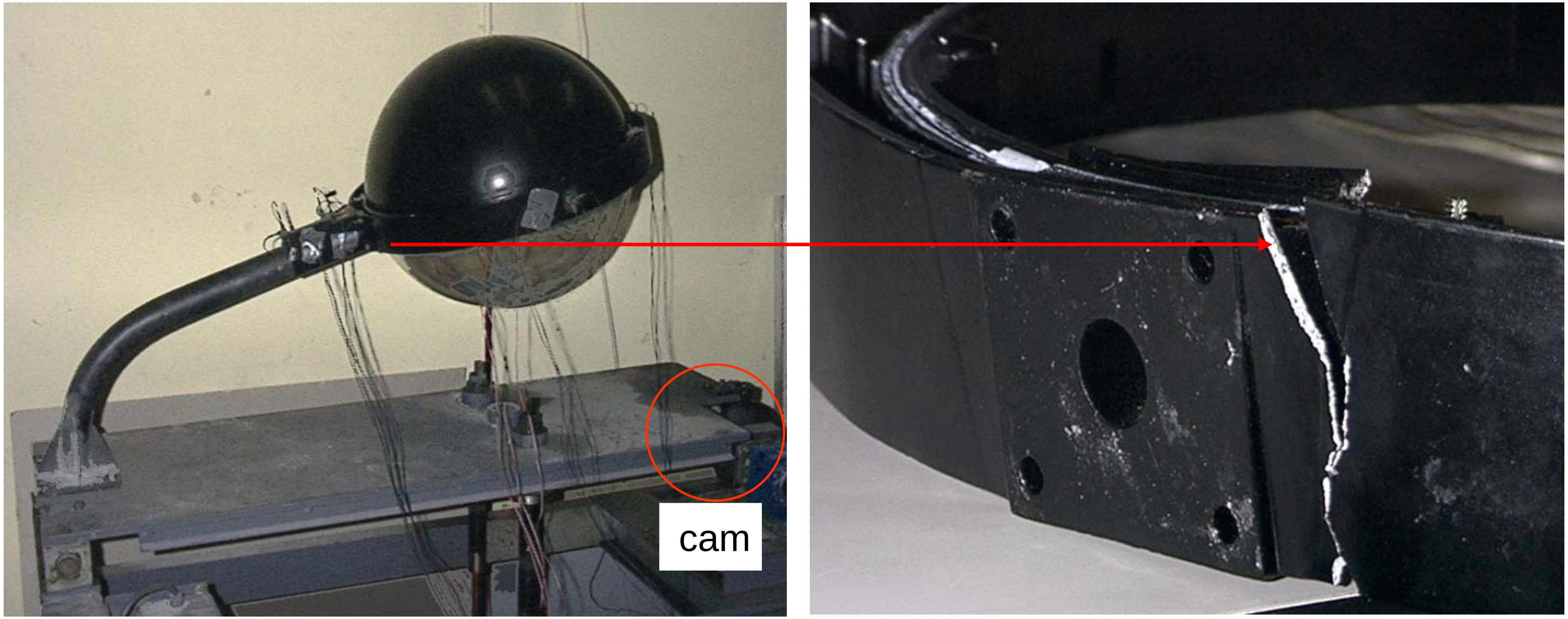
Null Subspace Analysis (NSA)

- **Definition of the data-driven Hankel matrix**

$$\mathbf{H}_{1,2i} = \begin{bmatrix} \mathbf{x}_1 & \mathbf{x}_2 & \dots & \dots & \mathbf{x}_j \\ \mathbf{x}_2 & \mathbf{x}_3 & \dots & \dots & \mathbf{x}_{j+1} \\ \dots & \dots & \dots & \dots & \dots \\ \mathbf{x}_i & \mathbf{x}_{i+1} & \dots & \dots & \mathbf{x}_{i+j-1} \\ \hline \mathbf{x}_{i+1} & \mathbf{x}_{i+2} & \dots & \dots & \mathbf{x}_{i+j} \\ \mathbf{x}_{i+2} & \mathbf{x}_{i+3} & \dots & \dots & \mathbf{x}_{i+j+1} \\ \dots & \dots & \dots & \dots & \dots \\ \mathbf{x}_{2i} & \mathbf{x}_{2i+1} & \dots & \dots & \mathbf{x}_{2i+j-1} \end{bmatrix} \equiv \begin{pmatrix} \mathbf{X}_p \\ -- \\ \mathbf{X}_f \end{pmatrix} \equiv \frac{\text{"}\,past\,\text{"}}{\text{"}\,future\,\text{"}}$$

where 2i is the (user-defined) number of row blocks, each row block contains m terms (number of measurement sensors), j is number of columns (in practice, j = N-2i+1, N is the number of sampling points)

Null Subspace Analysis (NSA)



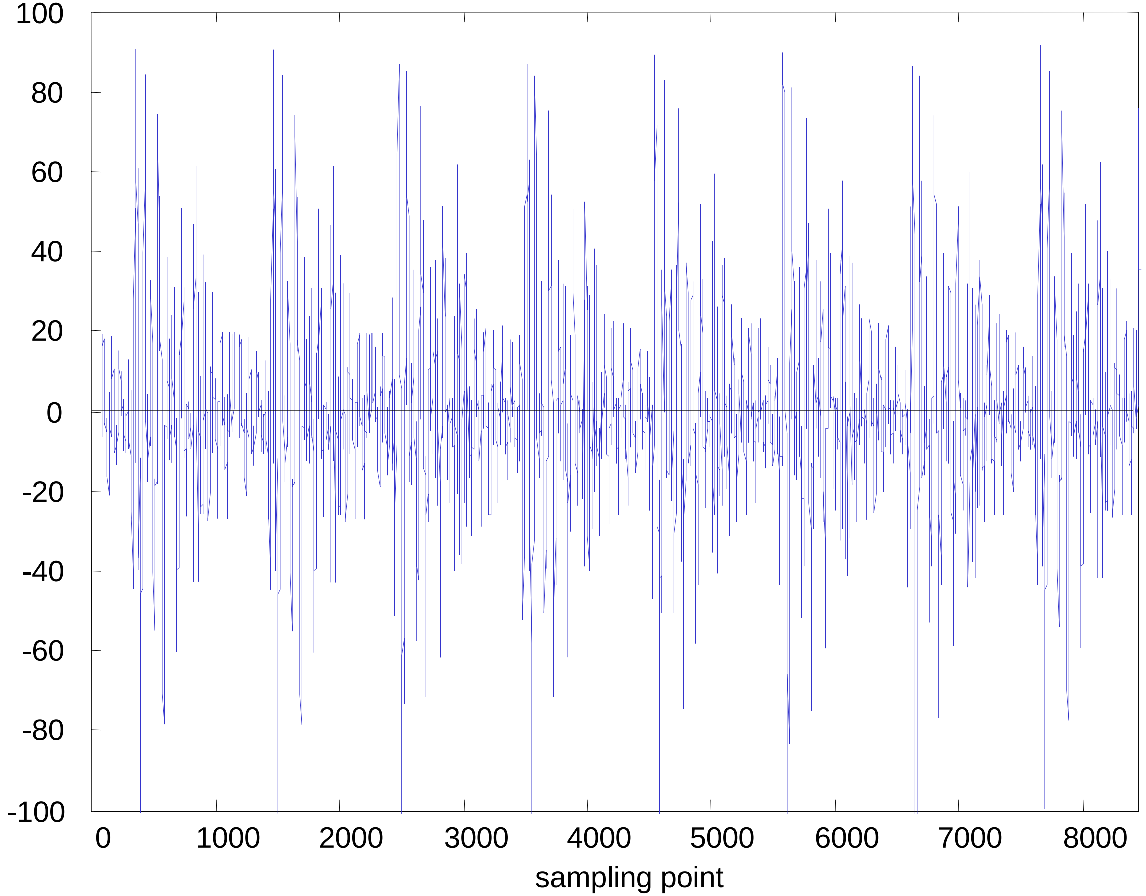
→ The street-lighting device is excited by a shock applied every 2 sec. by a cam mechanism.

→ Accelerometers and strain-gauges measure the structural responses with a sampling frequency of 528 Hz.

→ Test duration : 2 hrs 38 min with a failure in the frame close to the fixation.

Null Subspace Analysis (NSA)

Example of the system response under repeated impulsions



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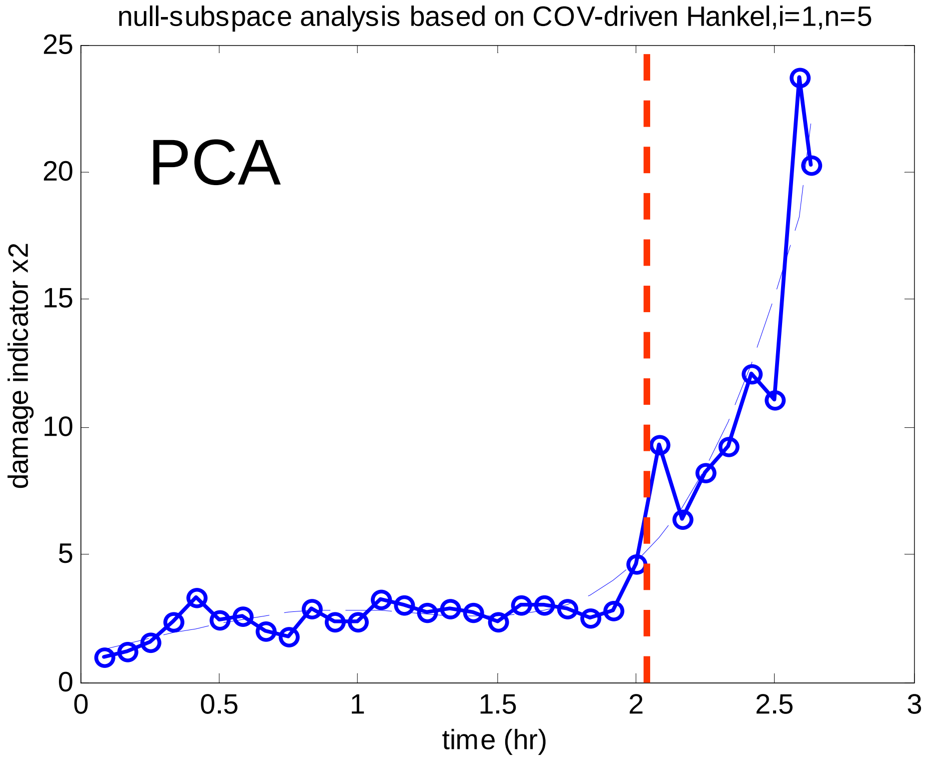
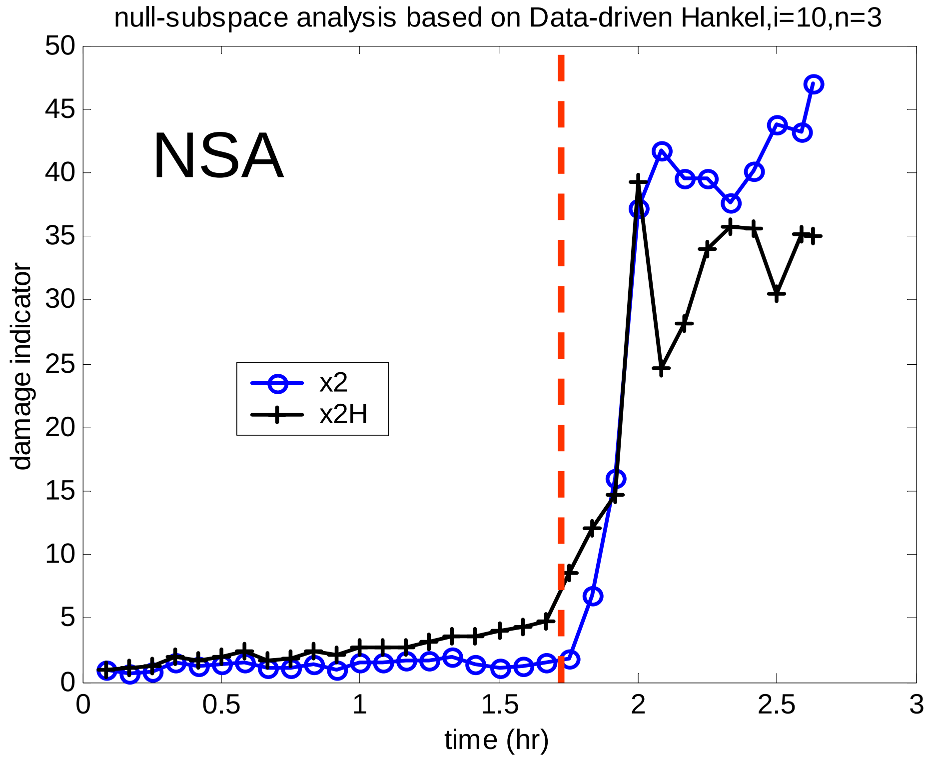
Null Subspace Analysis (NSA)

On-line monitoring: the NSA-based method indicates obvious damage development earlier than the PCA-based method





Kernel Principal Component Analysis (KPCA)

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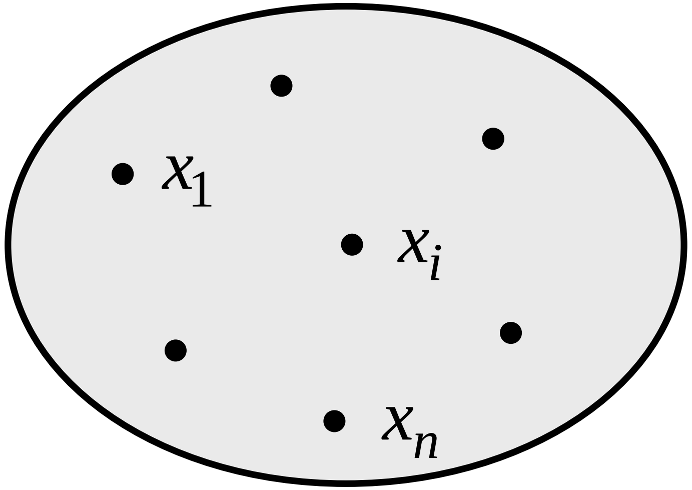
Kernel Principal Component Analysis (KPCA)



n measurement co-ordinates

N time samples

$$\mathbf{X} = \begin{bmatrix} x_1(t_1) & \cdots & x_1(t_N) \\ \vdots & \ddots & \vdots \\ x_n(t_1) & \cdots & x_n(t_N) \end{bmatrix}$$

Key idea

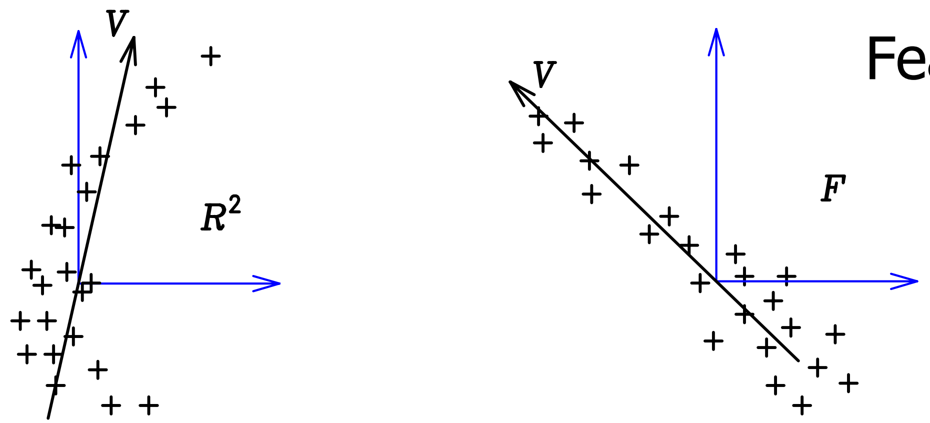
- Create a map $\mathbf{x}(t_k) \mapsto \Phi(\mathbf{x}(t_k))$ which defines a high dimensional feature space F
- Apply PCA in space F

Kernel Principal Component Analysis (KPCA)

The eigenvectors identified in the feature space F can be considered as kernel principal components (KPCs), which characterize the dynamical system in each working state.

Input space

Feature space



a) Linear PCA

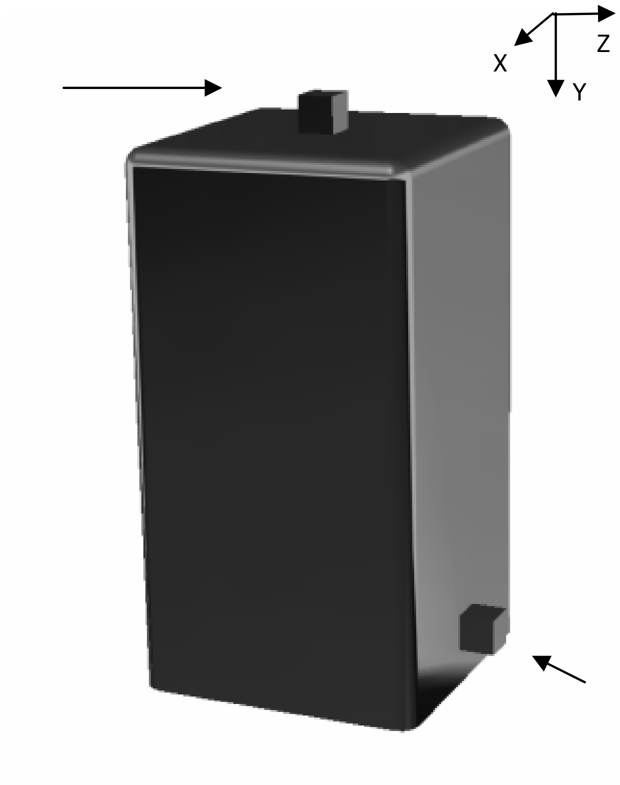
b) Kernel PCA

Examples of Fault Detection in Industrial Systems

Fault Detection in Industrial Systems

Example 1: Quality tests on electro-mechanical devices at the end of the assembly line

Top monoaxial accelerometer



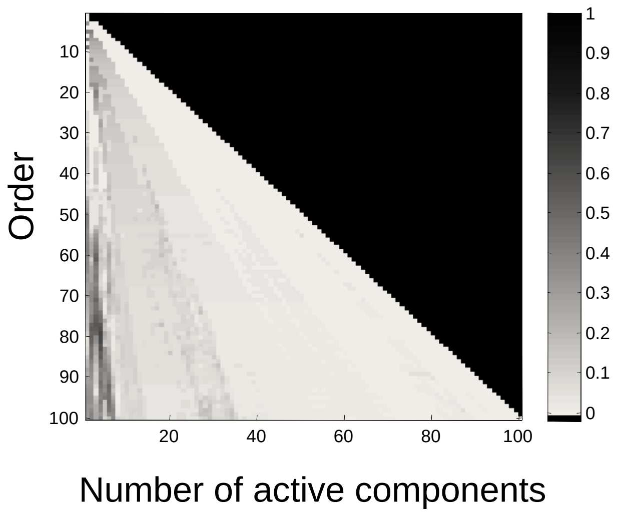
Instrumented device

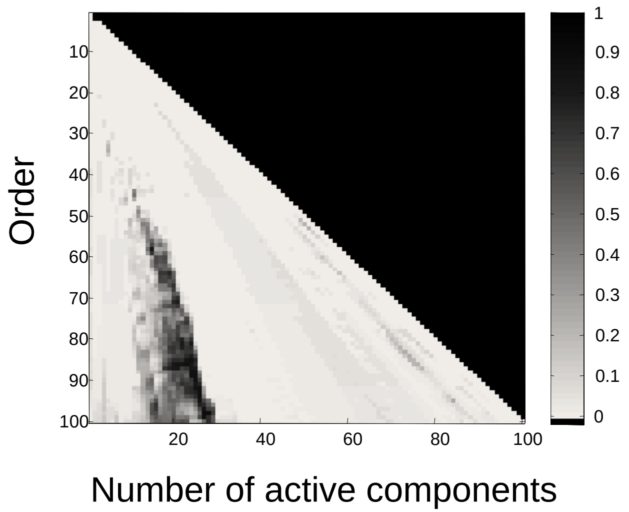
Flank triaxial accelerometer

Fault Detection in Industrial Systems

NSA-based detection method

Mapping of the space [number of PCs, system order]





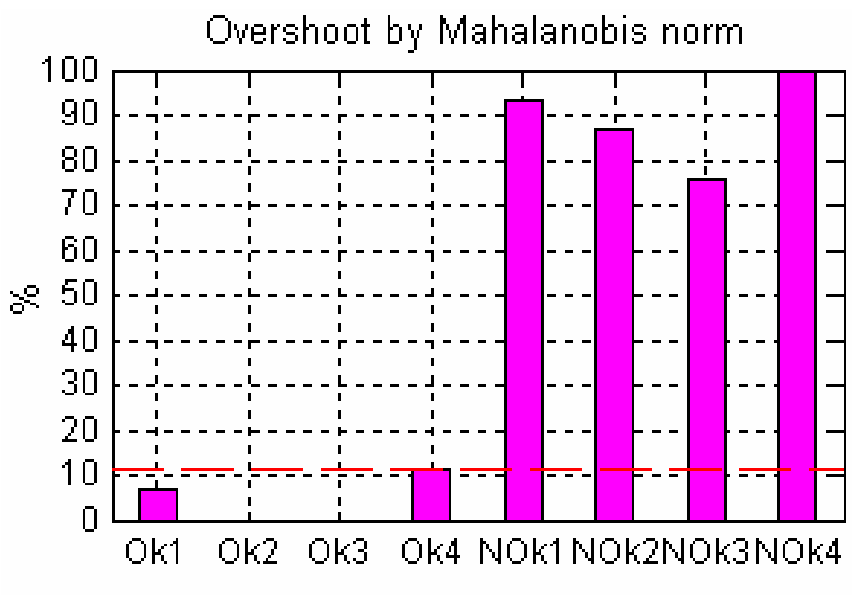
Mapping of a healthy component in the X direction using 6σ–limit

Mapping of a damaged component in the X direction using 6σ-limit

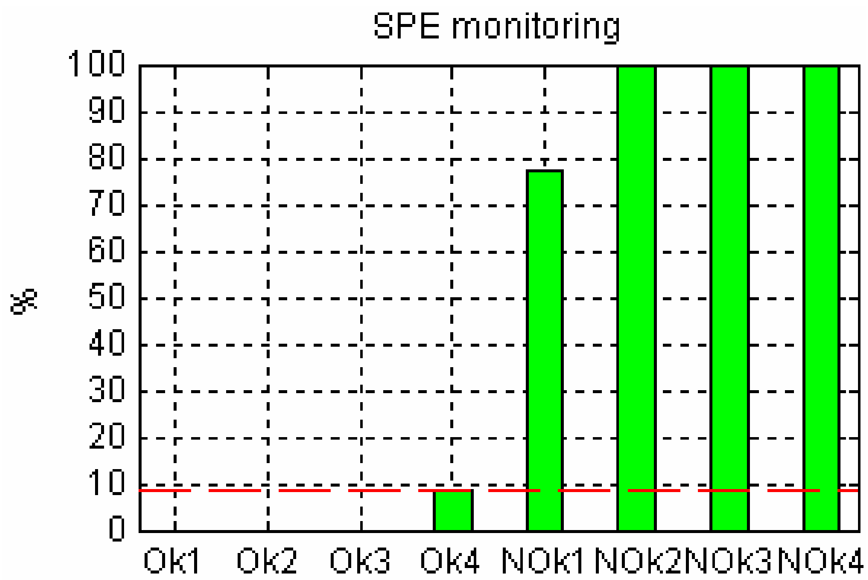
Damage indicator based on the reconstruction error (Novelty index)

Fault Detection in Industrial Systems

Damage detection by NSA and KPCA methods based on statistics – (the dashed horizontal line correspond to the maximal value for good devices)

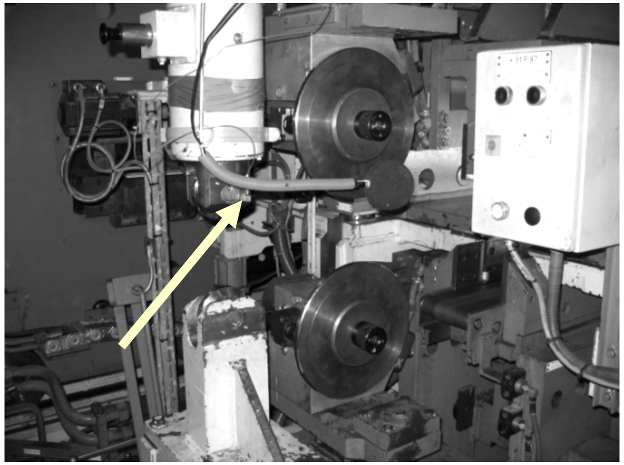


NSA based - detection



KPCA based - detection

Example 2: Quality control of welded joints

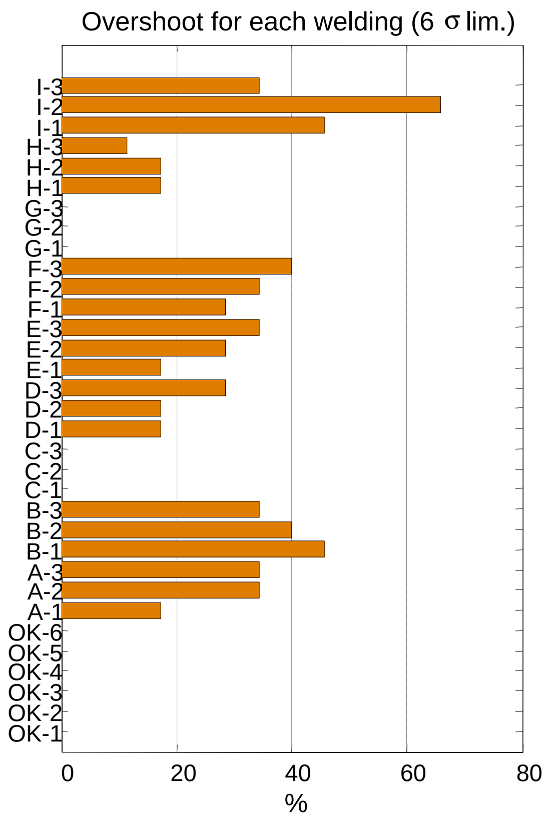


Name	Modified parameter	Weld quality
Welding A	-33% covering	Acceptable
Welding B	-66% covering	Bad
Welding C	-33% compensation	Good
Welding D	-66% compensation	Acceptable
Welding E	-10% current	Acceptable
Welding F	-20% current	Bad
Welding G	-10% forging pressure	Good
Welding H	+5% forging pressure	Acceptable
Welding I	-66% covering and compensation	Bad

Welds realized with modified parameters (with respect to the nominal parameters)

Fault Detection in Industrial Systems

Fault detection based on Null subspace analysis (NSA), using the Novelty Index (NI) based on the Mahalanobis norm

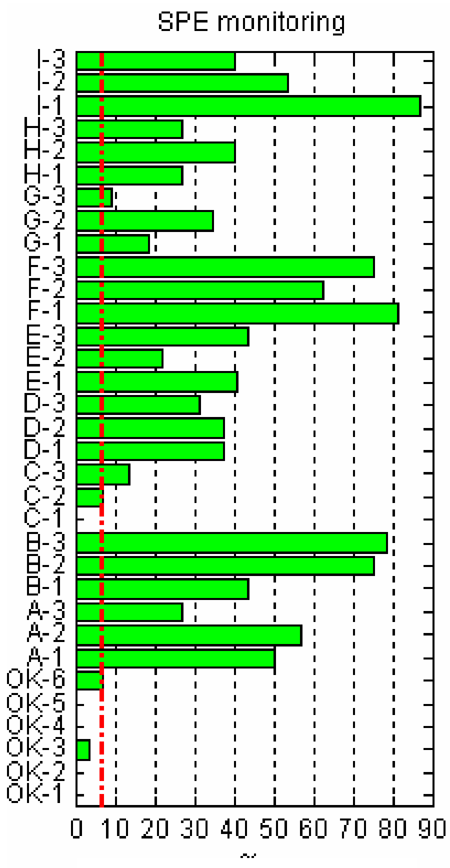


$$NI_{\lim} = \overline{NI} + 6\sigma$$

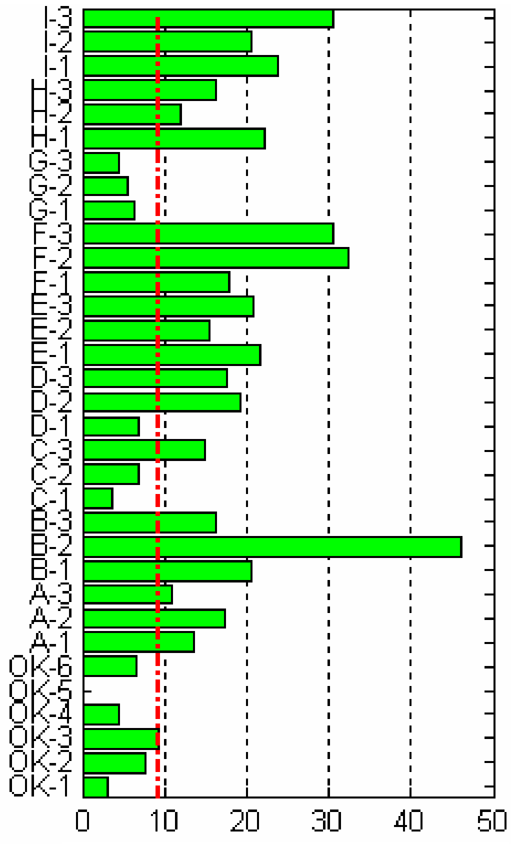
standard deviation of *NI* for the reference test

Fault Detection in Industrial Systems

Fault detection based on KPCA



Statistics



Subspace angle

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Conclusion

- Analyse vibratoire est un outil puissant et complexe
- Pas simple à mettre en place, demande réflexion
- Coût important d'une maintenance vibratoire

  => machine stratégique

Further readings

- Christian Boller, Fu-Kuo Chang, Yozo Fujino,

  Encyclopedia of Structural Health Monitoring (5 volumes),

  Wiley, 2009

- Nguyen Viet Ha,

  Damage Detection and Fault Diagnosis in Mechanical Systems Using Vibration Signals,

  University of Liege, PhD thesis, 2010

Thank you for your attention.