Traitement statistique de signaux

pour la Surveillance d'Intégrité de Structures

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Traitement statistique

de l'information multi-capteurs

sur la base de modèles physiques

pour la surveillance et le diagnostic

de systèmes dynamiques complexes

Problématique privilégiée :

surveillance de systèmes soumis à des vibrations

Problème : surveillance en fonctionnement

- The excitation is typically:
  - natural, not controlled.
  - not measured:
    - buildings, bridges, offshore structures,
    - rotating machinery (e.g. steam flowing),
    - cars, trains, aircrafts.
  - nonstationary (e.g., turbulent).
- The data contain slow and fast non-stationarities
- How to merge multiple measurements setups e.g. in case of moving sensors?
- How to detect and localize small damages ?

Model-based statistical approach - Key issues

Vibrations : problème de structure propre

FE model:
$$\begin{cases} M\ \ddot{\mathcal{Z}}(s) + C\ \dot{\mathcal{Z}}(s) + K\ \mathcal{Z}(s) &= \nu(s) \\ Y(s) &= L\ \mathcal{Z}(s) \end{cases}$$

$$(M\mu^2 + C\mu + K)\ \Psi_\mu = 0\ ,\quad \psi_\mu = L\ \Psi_\mu$$

State space:
$$\begin{cases} X_{k+1} &= F\ X_k + V_k \\ Y_k &= H\ X_k \end{cases}$$

$$F\ \varphi_\lambda = \lambda\ \varphi_\lambda\ ,\quad \phi_\lambda \triangleq H\ \varphi_\lambda$$

Parameter:
$$\underbrace{e^{\delta\mu} = \lambda}_{\text{modes}}\ ,\quad \underbrace{\psi_\mu = \phi_\lambda}_{\text{mode shapes}}\ ;\ \theta \triangleq \begin{pmatrix} \Lambda \\ \text{vec}\ \Phi \end{pmatrix}$$

Vibrations : problème ARMA non-stationnaire

$$\begin{cases} X_{k+1} &= F\ X_k + V_k \\ Y_k &= H\ X_k \end{cases}$$

$$Y_k = \sum_{i=1}^{p} A_i\ Y_{k-i} + \sum_{j=0}^{q} B_j(k)\ V_{k-j},\quad H\ F^p = \sum_{i=1}^{p} A_i\ H\ F^{p-i}$$

- Monitor AR part, with nonstationary MA part.
- Modal changes not visible on spectra (1%).
- Likelihood : no hope !

Output-only covariance-driven subspace identification

$$\begin{cases} X_{k+1} &= F\ X_k\ +\ V_k \\ Y_k &= H\ X_k \end{cases}\qquad G \triangleq \mathbf{E}\left(X_k\ Y_k^T\right),\quad \underbrace{R_i \triangleq \mathbf{E}\left(Y_k\ Y_{k-i}^T\right)}_{\text{ok if stationary !}}$$

$$\mathcal{H} \triangleq \begin{pmatrix} R_0 & R_1 & R_2 & \dots \\ R_1 & R_2 & R_3 & \dots \\ R_2 & R_3 & R_4 & \dots \\ \vdots & \vdots & \ddots & \vdots \end{pmatrix},\ \mathcal{O} \triangleq \begin{pmatrix} H \\ HF \\ HF^2 \\ \vdots \end{pmatrix},\ \mathcal{C} \triangleq \begin{pmatrix} G & FG & F^2G & \dots \end{pmatrix}$$

$$R_i = H\ F^i\ G \Longrightarrow \mathcal{H} = \mathcal{O}\ \mathcal{C}$$

$$\mathcal{H} \longrightarrow \mathcal{O} \longrightarrow (H, F) \longrightarrow (\lambda, \varphi_\lambda)$$

Implementation

$$\underbrace{\hat{R}_i \triangleq 1/N \sum_{k=1}^{N} Y_k\ Y_{k-i}^T}_{\text{ok when nonstationary !}}\ ,\qquad \hat{\mathcal{H}} = \begin{pmatrix} \hat{R}_0 & \hat{R}_1 & \hat{R}_2 & \dots \\ \hat{R}_1 & \hat{R}_2 & \hat{R}_3 & \dots \\ \hat{R}_2 & \hat{R}_3 & \hat{R}_4 & \dots \\ \vdots & \vdots & \ddots & \vdots \end{pmatrix}$$

$$\hat{\mathcal{H}} \approx \hat{\mathcal{O}}\ \hat{\mathcal{C}}$$

$$\text{SVD}(\hat{\mathcal{H}}) + \text{truncation} \longrightarrow \hat{\mathcal{O}} \longrightarrow (\hat{H}, \hat{F}) \longrightarrow (\hat{\lambda}, \hat{\varphi}_\lambda)$$

$$\hat{\mathcal{H}} = U\ \Delta\ W^T = U \begin{pmatrix} \Delta_1 & 0 \\ 0 & \Delta_0 \end{pmatrix} W^T\ ;\ \hat{\mathcal{O}} = U\ \Delta_1^{1/2}$$

$$\mathcal{O}_p^{\uparrow}(H, F) = \mathcal{O}_p(H, F)\ F$$

$$\det(F - \lambda\ I) = 0\ ,\quad F\ \Phi_\lambda = \lambda\ \Phi_\lambda,\quad \varphi_\lambda = H\ \Phi_\lambda$$

Model-based statistical approach - Key issues

- Modelling
- Output-only covariance-driven subspace identification
- Merging multiple measurements setups
- Robustness to nonstationary excitation
- Structural monitoring: damage detection and diagnostics

Examples: Z24 bridge & flutter monitoring

Free toolbox

Merging multiple measurements setups (1)

$$\underbrace{\begin{bmatrix} Y_k^{(0,1)} \\ Y_k^{(1)} \end{bmatrix}}_{\text{Record 1}} \quad \underbrace{\begin{bmatrix} Y_k^{(0,2)} \\ Y_k^{(2)} \end{bmatrix}}_{\text{Record 2}} \quad \cdots \quad \underbrace{\begin{bmatrix} Y_k^{(0,J)} \\ Y_k^{(J)} \end{bmatrix}}_{\text{Record J}}$$

$$\begin{cases} X_{k+1}^{(j)} = F\ X_k^{(j)} + V_k^{(j)} & \\ Y_k^{(0,j)} = H_0\ X_k^{(j)} & \text{(the reference)} \\ Y_k^{(j)} = H_j\ X_k^{(j)} & \text{(sensor pool n}^o j\text{)} \end{cases}$$

$$R_i^{0,j} \triangleq \mathrm{E}\ Y_k^{(0,j)}\ Y_{k-i}^{(0,j)\,T}\ , \quad R_i^j \triangleq \mathrm{E}\ Y_k^{(j)}\ Y_{k-i}^{(0,j)\,T}$$

$\mathrm{E}\ Y_k^{(j)}\ Y_{k-i}^{(j)\,T}$ not used, $\mathrm{E}\ Y_k^{(j')}\ Y_{k-i}^{(j)\,T}$ $(j \neq j')$ not available

Merging multiple measurements setups (2)

Stationary excitation

$$\mathrm{cov} V_k^{(j)} = Q\ , \quad G \triangleq \mathrm{E}\ X_k^{(j)}\ Y_k^{(0,j)\,T}$$

$$R_i^{0,j} = H_0\ F^i\ G \ \triangleq\ R_i^0\ , \quad R_i^j = H_j\ F^i\ G$$

$$R_i^{\pi} \triangleq \begin{bmatrix} R_i^0 \\ R_i^1 \\ \vdots \\ R_i^J \end{bmatrix} = H\ F^i\ G\ , \quad H \triangleq \begin{bmatrix} H_0 \\ H_1 \\ \vdots \\ H_J \end{bmatrix}$$

Nonstationary excitation

$$\mathrm{cov} V_k^{(j)} = Q_j\ , \quad G_j \triangleq \mathrm{E}\ X_k^{(j)}\ Y_k^{(0,j)\,T}$$

$$R_i^{0,j} = H_0\ F^i\ G_j\ , \quad R_i^j = H_j\ F^i\ G_j$$

Hint: right renormalization of the covariances.

Merging multiple measurements setups (3)

Reference sensors: using the redundancy

$$R_i^{0,j} = H_0\ F^i\ G_j\ , \quad G \triangleq (\, G_1\ \ G_2\ \ \ldots\ \ G_J \,)$$

$$R_i^0 \triangleq (\, R_i^{0,1}\ \ R_i^{0,2}\ \ \ldots\ \ R_i^{0,J} \,) = H_0\ F^i\ G$$

$$\mathcal{H}_0 \triangleq \begin{pmatrix} R_0^0 & R_1^0 & R_2^0 & \ldots \\ R_1^0 & R_2^0 & R_3^0 & \ldots \\ R_2^0 & R_3^0 & R_4^0 & \ldots \\ \vdots & \vdots & \ddots & \vdots \end{pmatrix} = \mathcal{O}(H_0, F)\ \mathcal{C}(F, G) \longrightarrow \mathcal{C}(F, G_j)$$

Merging multiple measurements setups (4)

Moving sensors: normalizing the data

$$R_i^j = H_j \; F^i \; G_j \, , \quad \mathcal{H}_j \triangleq \begin{pmatrix} R_0^j & R_1^j & R_2^j & \dots \\ R_1^j & R_2^j & R_3^j & \dots \\ R_2^j & R_3^j & R_4^j & \dots \\ \vdots & \vdots & \ddots & \vdots \end{pmatrix} = \mathcal{O}(H_j, F) \; \mathcal{C}(F, G_j)$$

$$\bar{\mathcal{H}}_j \triangleq \mathcal{H}_j \; \left(\mathcal{C}^T(F, G_j) \; \left(\mathcal{C}(F, G_j) \; \mathcal{C}^T(F, G_j) \right)^{-1} \; \mathcal{C}(F, G_1) \right)$$

$$\bar{\mathcal{H}}_j \; \leftrightarrow \; \bar{R}_i^j \triangleq H_j \; F^i \; G_1 \quad (1 \leq j \leq J)$$

$$\bar{R}_i \triangleq \begin{pmatrix} \bar{R}_i^0 \\ \bar{R}_i^1 \\ \vdots \\ \bar{R}_i^J \end{pmatrix} , \quad \bar{R}_i^0 \triangleq R_i^{0,1} = H_0 \; F^i \; G_1$$

$$\bar{\mathcal{H}} \triangleq \begin{pmatrix} \bar{R}_0 & \bar{R}_1 & \bar{R}_2 & \dots \\ \bar{R}_1 & \bar{R}_2 & \bar{R}_3 & \dots \\ \bar{R}_2 & \bar{R}_3 & \bar{R}_4 & \dots \\ \vdots & \vdots & \ddots & \vdots \end{pmatrix} = \mathcal{O}(H, F) \; \mathcal{C}(F, G_1)$$

Merging multiple measurements setups (5)

- Build the J Hankel matrices $\mathcal{H}_{0,j} = \mathrm{Hank}(R_i^{(0,j)})$
- $\mathcal{H}_0 \triangleq$ interleaving the block-columns of the $\mathcal{H}_{0,j}$'s
- SVD $(\mathcal{H}_0)$ + truncation $\longrightarrow$ $\mathcal{C}(F, G) \triangleq \mathcal{C}$
- Partition $\mathcal{C} = (\; \mathcal{C}_1 \;\; \mathcal{C}_2 \;\; \dots \;\; \mathcal{C}_J \;)$
- Compute $(\mathcal{C}_j^T \; (\mathcal{C}_j \, \mathcal{C}_j^T \,)^{-1} \; \mathcal{C}_1)$
- Build the J Hankel matrices $\mathcal{H}_j \; = \; \mathrm{Hank}(R_i^j)$
- Renormalize: $\bar{\mathcal{H}}_j \triangleq \mathcal{H}_j \; (\mathcal{C}_j^T \; (\mathcal{C}_j \, \mathcal{C}_j^T \,)^{-1} \; \mathcal{C}_1)$; $\bar{\mathcal{H}}_0 \triangleq \mathcal{H}_{0,1}$
- $\bar{\mathcal{H}} \triangleq$ interleaving the block-rows of the $(J+1)$ $\bar{\mathcal{H}}_j$'s
- Apply the subspace algorithm to $\bar{\mathcal{H}}$.

Model-based statistical approach - Key issues

- Modelling
- Output-only covariance-driven subspace identification
- Merging multiple measurements setups
- Robustness to nonstationary excitation
- Structural monitoring: damage detection and diagnostics

Examples: Z24 bridge & flutter monitoring

Free toolbox

Robustness to nonstationary excitation

Approximate factorization of covariances : $\widehat{R}_i \;\approx\; H \; F^i \; \widehat{G}$

Consistency : $T^{-1} \; \widehat{F} \; T \to F, \quad \widehat{H} \to H; \quad (\widehat{\lambda}, \widehat{\varphi}_\lambda) \to (\lambda, \varphi_\lambda)$

Holds true when merging multiple setups as well.

Theory and experience show that the combination of:

- the key factorization property of the covariances,
- the averaging operation in their computation,

allows to cancel out nonstationarities in the excitation

Model-based statistical approach - Key issues

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Structural monitoring : Eigenstructure monitoring

$$\begin{cases} X_{k+1} = F\ X_k + V_k \\ Y_k = H\ X_k \end{cases} \qquad F\ \varphi_\lambda = \lambda\ \varphi_\lambda, \quad \phi_\lambda \triangleq H\ \varphi_\lambda$$

Canonical parameter : $\theta \triangleq \begin{pmatrix} \Lambda \\ \text{vec}\,\Phi \end{pmatrix}$ modes / mode shapes

Observability in modal basis : $\mathcal{O}_{p+1}(\theta) = \begin{pmatrix} \Phi \\ \Phi\Delta \\ \vdots \\ \Phi\Delta^p \end{pmatrix}$

System parameter characterization:

$\mathcal{H}_{p+1,q}$ and $\mathcal{O}_{p+1}(\theta)$ have the same left kernel.

Eigenstructure monitoring - Contd

θ_0 : reference parameter, known (or identified)

Y_k: N-size sample of new measurements

Test statistics $\zeta_N(\theta_0)$: Which estimating function ?

Local approach (small deviations)

Test $\quad \mathrm{H}_0 : \ \theta = \theta_0 \quad$ against $\quad \mathrm{H}_1 : \ \theta = \theta_0 + \delta\theta/\sqrt{N}$

Eigenstructure monitoring - Contd

Fresh data $\longrightarrow \hat{R}_i \longrightarrow \hat{\mathcal{H}} = \begin{pmatrix} \hat{R}_0 & \hat{R}_1 & \hat{R}_2 & \dots \\ \hat{R}_1 & \hat{R}_2 & \hat{R}_3 & \dots \\ \hat{R}_2 & \hat{R}_3 & \hat{R}_4 & \dots \\ \vdots & \vdots & \ddots & \vdots \end{pmatrix}$

Nominal model : $\mathcal{O}(\theta_0) = \begin{pmatrix} \Phi \\ \Phi\Delta \\ \Phi\Delta^2 \\ \vdots \end{pmatrix}$ Observability in modal basis

! $\mathcal{H} = \mathcal{O}\ \mathcal{C}$! $\qquad \ker \hat{\mathcal{H}}^T \stackrel{?}{=} \ker \mathcal{O}^T(\theta_0)$

Eigenstructure monitoring - Contd

System parameter characterization:

$\mathcal{H}_{p+1,q}$ and $\mathcal{O}_{p+1}(\theta)$ have the same left kernel.

$$\exists\ S, \quad S^T\ S = I_s, \qquad S^T\ \mathcal{O}_{p+1}(\theta_0) = 0; \quad \text{say } S(\theta_0)$$

$$\theta_0 \leftrightarrow (R_i^0)_i \ \text{ characterized by: } \ S^T(\theta_0)\ \hat{\mathcal{H}}^0_{p+1,q} = 0$$

The subspace-based residual $\zeta_N(\theta_0)$:

$$\zeta_N(\theta_0) \triangleq \sqrt{N}\ \text{vec}\left(\ S^T(\theta_0)\ \hat{\mathcal{H}}_{p+1,q}\ \right)$$

The test statistics is asymptotically Gaussian

Mean sensitivity (Jacobian) $\mathcal{J}(\theta_0)$ and covariance $\Sigma(\theta_0)$

$$\zeta_N(\theta_0) \ \rightarrow \ \begin{cases} \mathcal{N}(\ 0,\ \Sigma(\theta_0)) & \text{under} \quad \mathbf{P}_{\theta_0} \\ \mathcal{N}(\ \mathcal{J}(\theta_0)\ \delta\theta,\ \Sigma(\theta_0)) & \text{under} \quad \mathbf{P}_{\theta_0+\frac{\delta\theta}{\sqrt{N}}} \end{cases}$$

(GLR) χ^2-test for modal monitoring

$$\zeta_N^T\ \Sigma^{-1}\ \mathcal{J}\ (\mathcal{J}^T\ \Sigma^{-1}\ \mathcal{J})^{-1}\ \mathcal{J}^T\ \Sigma^{-1}\ \zeta_N \ \geq h$$

(GLR) Directional χ^2-test for modal diagnosis

$$\zeta_N^T\ \Sigma^{-1}\ \mathcal{J}_i\ (\mathcal{J}_i^T\ \Sigma^{-1}\ \mathcal{J}_i)^{-1}\ \mathcal{J}_i^T\ \Sigma^{-1}\ \zeta_N \ \geq h$$

Model-based monitoring - Generalization

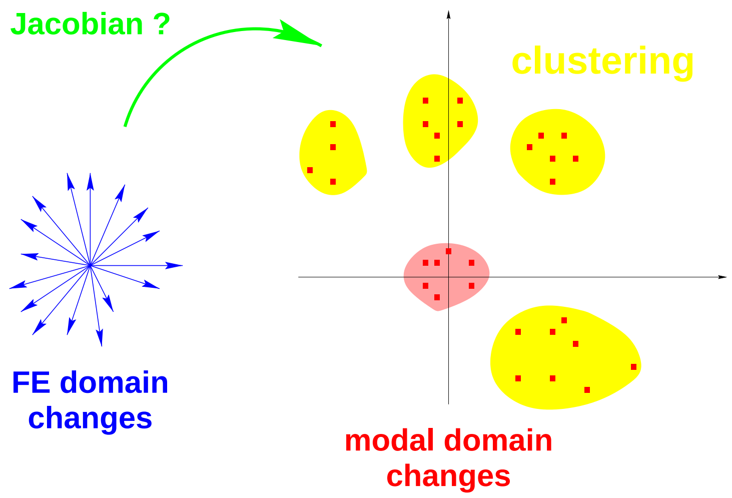
Any estimating function can play the role of a residual

Warning:

The prediction error is OK for sensor faults,

NOT for structural damages !

On-board damage diagnostics: projecting changes



Damage diagnostics: (local) sensitivity approach

$$\zeta \sim \mathcal{N}(\mathcal{J}\ \delta\theta,\quad \Sigma), \qquad \delta\theta = \mathcal{I}\ \mathcal{J}_{(M_0^\star, K_0^\star)} \begin{pmatrix} \delta M \\ \delta K \end{pmatrix}$$

$(M_0^\star, K_0^\star)$: design model

Jacobian : $(\delta M, \delta K) \xrightarrow{\mathcal{J}_{(M_0^\star, K_0^\star)}} (\delta\mu, \delta\psi_\mu)$

Reduction: $\mathcal{I}$ matching computed/identified modes

Problem : $\dim \begin{pmatrix} M \\ K \end{pmatrix} \gg \dim \theta$

Hint: **Cluster** the vectors $(\delta\mu, \delta\psi_\mu)$ using the χ^2-metric

Examples

- Example 1 - Z24 bridge
- Example 2 - Beam within thermal chamber
- Example 3 - Aircraft flutter monitoring
- Test cases processed so far
  http://www.irisa.fr/sisthem/sisthem-testcases.pdf

Processed test cases (1) - Simulators and laboratory test-beds

Task	Structure	Our algos tested at	Partner
I & D	18 masses & springs	Sisthem	CNEXO
I & D	Rotating shaft	Sisthem	EDF
I	Triangular structure	AS&I Dataid	
I & D	In-flight rocket	Sisthem	Ecole Centrale P.
I & D	Steelquake simulator	Sisthem	
I & D	Flutter simulator	Sisthem	V.U.Brussels
I & D	In-flight data	Sisthem	Airbus France
I	Launcher	EADS L.V.	CNES
I & D	Bridge deck	Sisthem	Ecole Centrale P.
I & D	Cantilever beam	Sisthem	EDF
I & D	Clamped & free aluminum beam	LMS	
I & D	Steel frame breadboard model	LMS	
I & D	Sport car scale model	LMS	
I & D	Steelquake model	Sisthem	COST F3
I & D	Composite plate	U. Siegen	
I & D	Reticular structure	LMS	
I & D	Pre-stressed beam	Sisthem	LCPC
I	Large scale pre-flexed beam	LCPC, Sisthem	
I & D	Aircraft model	Sisthem	U. Liège
I & D	Composite plastic engine oil pan	LMS, Sisthem	

Processed test cases (2) - Real structures

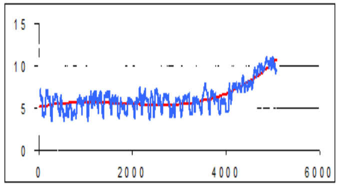
Task	Structure	Our algos tested at	Partner
I & D	Offshore platforms	CNEXO, Sisthem	Elf Norway
I & D	Turbo-alternator	Sisthem	EDF
I	Subway carrying bogies	AS&I Dataid	Ratp
I	Washing machine	AS&I Dataid	
I & D	Paris MS760 aircraft	Sopemea, Sisthem	
I & D	Sport car	LMS	
I	Helicopter	PZL-Swidnik	
I & D	Z24 bridge	LMS, Sisthem	COST F3
I & D	Slat track	LMS	
I & D	Ariane5 launcher, ground tests	Sisthem	EADS L.V.
I & D	Ariane5, flights 501 & 502	CNES, Sisthem	EADS L.V.
I	Launcher	EADS Launch Vehicles	CNES
I	Airbus A320 - In-flight	Airbus France, Sisthem	Airbus Fr.
I	Airbus A340 - In-flight	Sisthem	Airbus Fr.
I	Rafale - Ground tests	Sopemea, Sisthem	Dassault
I	Rafale - In-flight	Sopemea, Dassault, Sisthem	Dassault
I	Falcon - In-flight	Sopemea, Dassault, Sisthem	Dassault
I	Bradford stadium	Sisthem	U.Sheffield
I	Manchester stadium	Sisthem	U.Sheffield

Example 1 - Z24 bridge

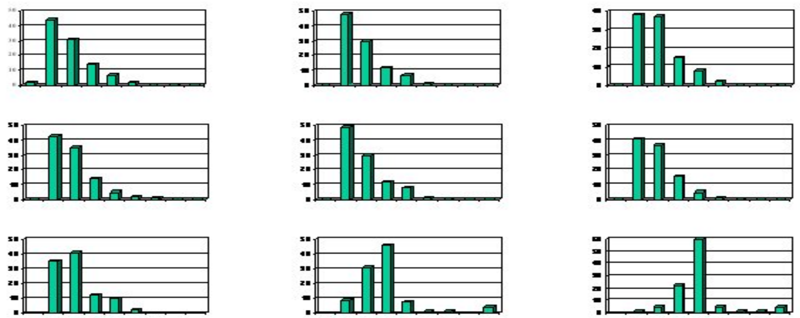
- A benchmark of the BRITE/EURAM project SIMCES and of the European COST action F3
- Response to traffic excitation under the bridge measured over one year in 139 points
- Two damage scenarios (DS1 and DS2): pier settlements of 20mm and 80mm.

Identified first four natural frequencies / Test values
(Results with four sensors)

	Mode	1	2	3	4	χ^2
Safe	Freq.(Hz)	3.88	5.01	9.80	10.30	8.80·10e2
Dam. DS1	Freq.(Hz)	3.87	5.06	9.79	10.32	8.00·10e5
Dam. DS2	Freq.(Hz)	3.76	4.93	9.74	10.25	3.96·10e6



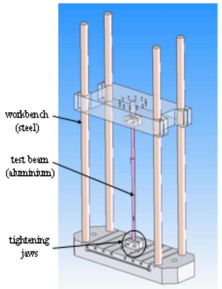
Test values over nine months (log-scale).

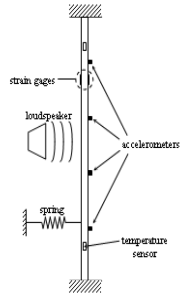


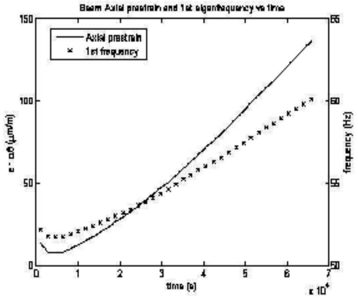
Histograms of the test values for each of the nine months.

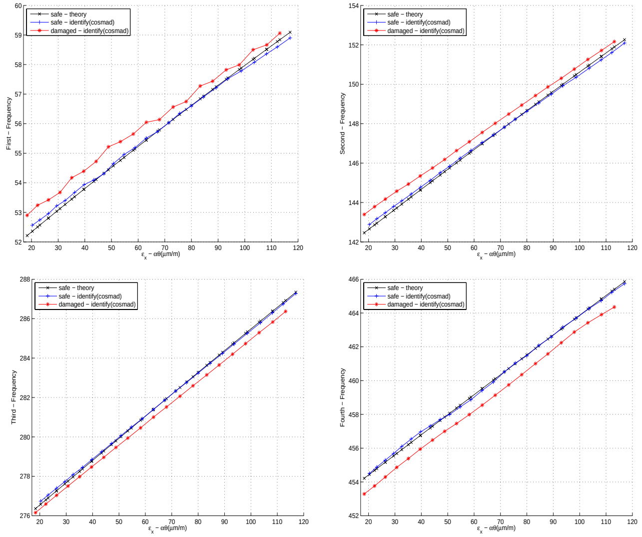
Example 2 - Beam within thermal chamber

- A laboratory test-case provided by LCPC
- Vertical clamped beam, subject to increasing temperatures
- Local damage: horizontal clamped spring attached to the beam, with tunable stiffness and height
- Thermal effect modelling, analytical computations for temperature updated modal parameters







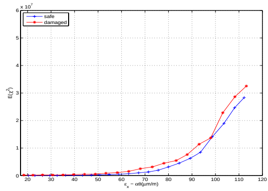


First 4 frequencies vs. thermal constraint.
Computed (black) and identified (blue: safe, red: damaged)

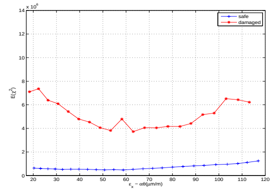
Robustness to temperature effects

New results - 3 solutions

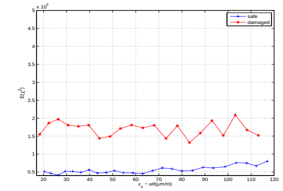
- Empirical kernel, merging many temperature conditions
- Simplified model of the temperature effect
  Analytical kernel updating
- Simplified model of the temperature effect
  Statistical nuisance rejection techniques



Original χ^2-test



After empirical merging



After kernel updating

Safe (blue) and damaged (red)

Example 3 - Aircraft flutter monitoring

- Aero-elastic flutter: critical unstability phenomenon
- Flight flutter testing procedure
- Objective: on-line in-flight exploitation of test data
- On-line flight flutter monitoring problem:
  monitoring some specific damping coefficient
- Decide whether $\rho < \rho_c$, critical value

Monitoring on-line a damping coefficient

- Write the subspace-based test-statistics ζ
  as a cumulative sum
- Test $\rho \geq \rho_c$ against $\rho < \rho_c$
  Non local ! Use a different asymptotics for ζ
- Introduce a minimum change magnitude
  (actual change magnitude unknown)
- Run two CUSUM tests in parallel
  (actual change direction unknown)

Monitoring a damping coefficient - Details

$$\overline{\zeta}_n(\rho_0) \triangleq \mathcal{J}(\rho_0)^T\ \Sigma(\theta_0)^{-1}\ \zeta_n(\theta_0) \ = \ \sum_{k=q}^{n-p} Z_k(\rho_0)\ /\sqrt{n}$$

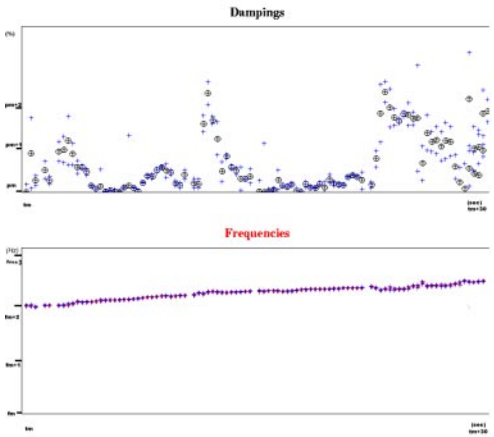
$$Z_k(\rho_0) \triangleq \mathcal{J}(\rho_0)^T\ \Sigma(\theta_0)^{-1}\ \text{vec}\left(U(\theta_0)^T\ \mathcal{Y}_{k,p+1}^{+}\ \mathcal{Y}_{k,q}^{-\ T}\right)$$

$Z_k \sim \mathcal{N}(\nu,.)$, Z_k's independent

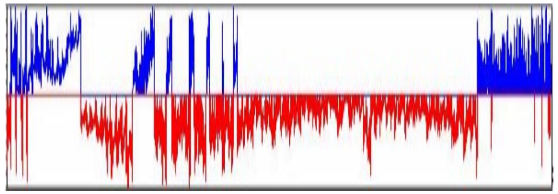
$\widetilde{\mathrm{H}}_0 : \ \nu \geq +\ \nu_m/2$ and $\widetilde{\mathrm{H}}_1 : \ \nu < -\ \nu_m/2$

Monitoring a damping coefficient - Details - Contd

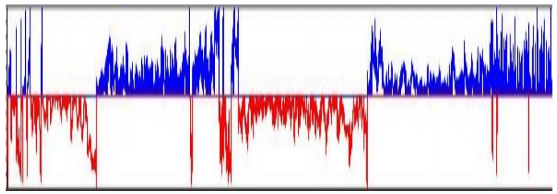
Decreasing mean	Increasing mean
$S_n^{(-)} \triangleq \overline{\Sigma}^{-1/2} \sum_{k=q}^{n-p}(Z_k + \nu_m)$	$S_n^{(+)} \triangleq \overline{\Sigma}^{-1/2} \sum_{k=q}^{n-p}(Z_k - \nu_m)$
$T_n^{(-)} \triangleq \max_{q \leq k \leq n-p} S_k^{(-)}$	$T_n^{(+)} \triangleq \min_{q \leq k \leq n-p} S_k^{(+)}$
$g_n^- \triangleq T_n^{(-)} - S_n^{(-)}$	$g_n^+ \triangleq S_n^{(+)} - T_n^{(+)}$
$g_n^- \geq \gamma^-$	$g_n^+ \geq \gamma^+$



Ariane booster launcher during a launch scenario on the ground
Automatic identification. Each symbol: processing 5 sec. data.



Test for $\rho_c = \rho_c^{(1)}$.



Test for $\rho_c = \rho_c^{(2)} < \rho_c^{(1)}$.

Bottom: $-g_n^-$ reflects $\rho < \rho_c$. Top: g_n^+ reflects $\rho > \rho_c$.

Toolbox COSMAD

COvariance Subspace Modal Analysis and Diagnosis

http://www.irisa.fr/sisthem/cosmad/

A toolbox to be used within Scilab

a free matrix computing environment

with support of Eurêka projects SINOPSYS and FliTE

Functions

- Output-only subspace-based identification
- Input-output subspace-based identification
- Automated subspace modal analysis and tracking
- Automated recursive subspace modal analysis
- Subspace-based moving sensors data fusion
- Damage detection
- Damage monitoring
- Modal diagnosis
- Damage localization
- Optimal sensors positioning for monitoring

Experimented for and/or within

- LMS International
- EADS Space Transportation and CNES
- Dassault Aviation
- Eurocopter
- SOPEMEA (Test Lab.)
- LCPC/SMI (Civil Eng. Inst. / Metrology dept.)

Current research topics and developments

- Flutter monitoring (aircrafts)
- Rejecting temperature effects (civil eng.)

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