Habilitation à diriger les recherches

mention mathématiques et applications

Identification and detection of stochastic systems application in structural monitoring

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22 Octobre 2008 / IRISA

Outline

A bit of history
SISTHEM team past and present

- Past works from M. Basseville, A. Benveniste, M. Goursat
- 1980 - 1991 : Research (4PhD theses)
  - collaboration with IFREMER and EDF
  - BR and IV methods for subspace identification
  - IV damage detection
- 1996-1999 : European project Eureka SINOPSYS :
  - subspace damage detection foundations (Basseville et al.)
  - 1998 : I'm here
- 2000-2008 : new research problems in civil engineering and aircraft monitoring

Hidden Markov chains

publications from PhD Thesis + postdoc

We will not talk about this.

1. Basic properties of the projective product, with application to products of column-allowable nonnegative matrices, Mathematics of Control, Signals and Systems, 2000. with F. LeGland.
2. Exponential forgetting and geometric ergodicity in hidden Markov models, Mathematics of Control, Signals and Systems, 2000. with F. LeGland.
3. Asymptotical statistics of misspecified hidden Markov models, IEEE Transactions on Automatic Control, 2004. with L. Finesso.

Applications

Monitoring of integrity and stability

We worked on these structures.

$$\mathbf{M}x''(t) + \mathbf{C}x'(t) + \mathbf{K}x(t) = f(t)$$

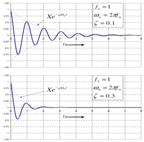
$$\left\{ \begin{array}{rcl} X_{k+1} & = & A\, X_k + V_{k+1} \\ Y_k & = & C\, X_k \end{array} \right.$$

$$\det(A - \lambda I) = 0, \;\; (A - \lambda I)\, \Phi_\lambda = 0$$

Mechanical engineers talk also about frequency and damping:

$$x(t) = \exp^{\gamma t}, \text{with } \gamma = \omega(-\zeta \pm \sqrt{\zeta^2 - 1})$$

$$\left\{ \begin{array}{l} \omega = \sqrt{k/m} \text{ and } f = \omega/(2 * \pi) \\ \zeta = c/(2 * \sqrt{k * m}) \end{array} \right.$$



Why structural health monitoring is important ?

- Civil and aeronautical structures are ageing very fast
- Human inspection is most of the time impractical or non reasonable
- Non all structural behaviour can be predicted by design (e.g. damping)
- Some parameters are critical and need to be monitored (e.g. damping)

Applications
context

- Non stationary excitation (turbulence) : unknown, uncontrolled, non measured
- Civil engineering
    - Slow varying structure
    - Large number of sensors
    - Main concern is damage due to ageing
    - Main nuisance is temperature variation
- Aeronautical structures
    - Fast transient structure
    - Large number of modes
    - Main concern is stability and flutter
    - Main nuisance is aeroelasticity interaction

Identification vs detection

- Identification : what is the system state ?
  - a system is described by a reduced set of features
  - goal : estimate the features.
  - many methods
- Detection : has the system changed ??
  - much simpler goal - provide a simple alarm
  - less precise information on the system state
  - information can be good enough for many applications
- 2 types of structures / 2 types of approaches

Outline

Subspace identification
model

$$\left\{ \begin{array}{lllllll} x_k & = & Ax_{k-1} & + & Bu_k & + & K(k)\nu_k \\ y_k & = & Cx_{k-1} & + & Du_k & + & L(k)\nu_k \end{array} \right.$$

where

$$\begin{bmatrix} K(k) \\ L(k) \end{bmatrix} \begin{bmatrix} K^T(k) & L^T(k) \end{bmatrix}$$

is the noise covariance matrix corresponding to the excitation varying in time.

The problem here is the identification of the pair (C, A).

Subspace identification
model

$$R_i(N) \triangleq \frac{1}{s_N} \langle Y_i, Z_0 \rangle_N \text{ (covariance) or}$$

$$R_i(N) \triangleq \frac{1}{s_N} \mathrm{E}_N(Y_i \mid Z_0) \text{ (data driven)}$$

$$\mathcal{H}_p(N) \triangleq \begin{bmatrix} R_1(N) \\ \vdots \\ R_p(N) \end{bmatrix} = \mathcal{O}_p \times G(N) \text{ and } \mathcal{O}_p \triangleq \begin{bmatrix} C \\ \vdots \\ CA^{p-1} \end{bmatrix}$$

- Akaike (1974), Verhaegen (1993), Deistler (1995), Moore (1996), Viberg (1997), Bauer (2000), Ljung (2002), Chiuso (2004), and Benveniste and Fuchs (1985)

Applications

A few examples - monitoring of Ariane 5 booster launch - EADS/CNES

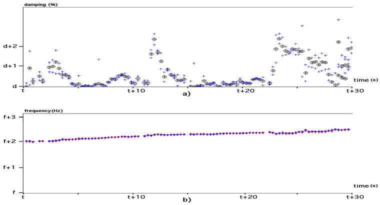


Figure: Parameters change during launch period - low uncertainty on frequency - damping is both critical and difficult to estimate

Applications

A few examples - soccer match in Bradford stadium

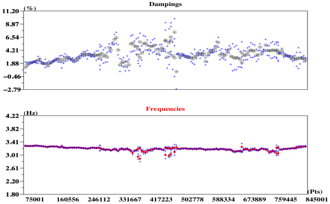


Figure: Sensors on stadium stand. Monitoring of crowd excitation. Jumps in parameter values : goals

Some output-only subspace algorithms

- Covariance driven subspace identification

$$Z_{0,M} = \begin{bmatrix} Y_0 \\ \vdots \\ Y_{-M} \end{bmatrix}$$

$$R_i(N) = \langle Y_i, Z_{0,M} \rangle_N,$$

$$\mathcal{Y}^+_{k,p} = \begin{pmatrix} Y_k \\ \vdots \\ Y_{k+p} \end{pmatrix},$$

$$\mathcal{H}_p(N) = \langle \mathcal{Y}^+_{0,p}, \mathcal{Y}^-_{0,M} \rangle_N$$

- Data driven subspace algorithms

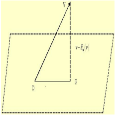
$$\mathcal{Y}^-_{k,p} = \begin{pmatrix} Y_k \\ \vdots \\ Y_{k-p} \end{pmatrix}.$$

$$\mathcal{H}_p(N) = \mathrm{E}_N(\mathcal{Y}^+_{0,p} \mid \mathcal{Y}^-_{0,M})$$

Some input/output subspace algorithms

- Using projected past input and output as instruments

$$\mathcal{H}_p = \langle \mathcal{Y}^+_{0,p}, Z_{0,M} \rangle_N \ ,$$



$$Z_i \triangleq \mathrm{E}_N \left(W_i \,\middle|\, \left(\mathcal{U}^+_{0,M} \right)^{\perp} \right) \quad \text{, where} \quad W_i \triangleq \begin{bmatrix} U_i \\ Y_i \end{bmatrix}$$

- Using projected inputs as instruments

$$\mathcal{H}_p = \mathrm{E}_N(\mathcal{Y}^+_{0,p} \mid Z_{0,M}),$$

where $Z_{0,M}$ is defined by $Z_i \triangleq \mathrm{E}_N \left(U_i \,\middle|\, \left(\mathcal{U}^+_{0,M} \right)^{\perp} \right)$

- Many more : CVA, MOESP, N4SID, ...

Subspace identification and Instruments

"instrument z_k depends on observable quantities" :

z_k is measurable wrt the σ algebra $\sigma(u_j : j \in \mathbb{Z}) \vee \sigma(y_l : l \leq k)$

"instrument has sustainable energy" :

$$\lim_{N\to\infty} s_N = \infty, \text{ where } s_N \triangleq \sum_{k=-M}^{N-1} \|z_k\|^2$$

"instrument is not much correlated to the inputs" :

$$\left\langle \begin{bmatrix} B \\ D \end{bmatrix} U_j, Z_0 \right\rangle_N = o(s_N) \text{ for } j > 0$$

"instrument is well correlated to the state" :

$$\liminf_{N\to\infty} \sigma_n \left(\frac{1}{s_N} \langle X_0, Z_0 \rangle_N \right) > 0$$

Subspace identification
a few comments

- Most subspace methods fit this "instrument" framework
- Non stationary excitation : coherency with applications

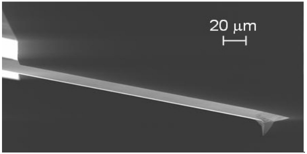
Theorem (consistent estimator)

$(C(N), A(N))$ derived from $\mathcal{H}_p(N)$ is a consistent estimator of (C, A)

Nonstationary consistency of subspace methods, IEEE Transactions on Automatic Control, 2007.
with A. Benveniste.

Outline

A few applications
nano MEMS particle detection



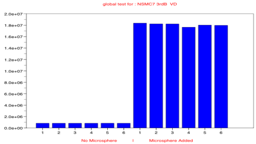


Figure: Mass detection (1 particle nano) on cantilever beam by detection. Repeatability over 6 different nano beams is checked. Collaboration with Purdue University

Damage detection

Residual definition

$$E_\theta H(\theta_*, Y) = 0 \text{ if } \theta = \theta_*$$

and

$$E_\theta H(\theta_*, Y) \neq 0 \text{ if } \theta \neq \theta_*$$

Now define a time-normalized residual

$$\zeta_N(\theta) = \frac{1}{\sqrt{N}} \sum_{t=1}^{N} H(\theta, Y_t)$$

Detection of Abrupt Changes - Theory and Applications - Basseville and Nikiforov (1993).

Damage detection
The local approach

$$\theta - \theta_* = \frac{1}{\sqrt{N}}\,\delta\ , \ \text{with } \delta \text{ independent of } N$$

What it means ??

- In Theory : we can obtain central limit theorems for the "damaged" scenario
- In Practice : the more samples we have, the smallest change we can detect
- With respect to others : it is a simple way to infer about the damaged state, without assuming too much about it

Damage detection

Statistical convergence

Theorem (central limit theorem for local approach)

$$\begin{cases} \zeta_N(\theta_*, \theta) & \longrightarrow & \mathcal{N}\left(0, \Sigma\left(\theta_*, \theta\right)\right) & \text{if } \theta = \theta_* \\ \zeta_N(\theta_*, \theta) & \longrightarrow & \mathcal{N}\left(-\mathbf{J}(\theta_*, \theta)\delta, \Sigma\left(\theta_*, \theta\right)\right) & \text{if } \theta = \theta_* + \frac{\delta}{\sqrt{N}} \end{cases}$$

$$\begin{aligned} \mathbf{J}(\theta_*, \theta) &= -\mathbf{E}_\theta \left(\frac{\partial H}{\partial \theta_*}(\theta_*, Y(\theta)) \right) \\ \Sigma(\theta_*, \theta) &= \lim_{N \to +\infty} Cov_\theta \left(\zeta_N(\theta_*, \theta)\right) \end{aligned}$$

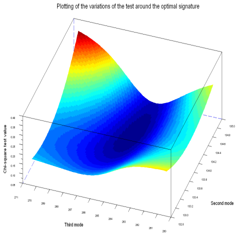
The change detection problem consists in answering the following question: do we still have $\theta = \theta_*$?

This task is achieved by computing the following χ^2 test

$$\chi^2(\theta_*, \theta) = \bar{\zeta}_N^T(\theta_*, \theta)\mathbf{K}^{-1}(\theta_*, \theta)\bar{\zeta}_N(\theta_*, \theta)$$

with

$$\bar{\zeta}_N^T(\theta_*, \theta) = \mathbf{J}^T(\theta_*, \theta)\Sigma^{-1}(\theta_*, \theta)\zeta_N(\theta_*, \theta)$$



and the Fisher matrix information as follows

$$\mathbf{K}(\theta_*, \theta) = \mathbf{J}^T(\theta_*, \theta)\Sigma^{-1}(\theta_*, \theta)\mathbf{J}(\theta_*, \theta)$$

Estimation of **K** is a very tricky problem (very slow convergence).

An application where **K** computation is critical

Painter Street Overstrass - California - collaboration with University of Vancouver, Ca and University of Aalborg, DK

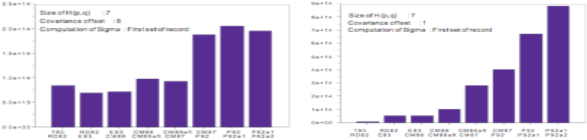


Figure: Damage detection. Very few samples (seismic data) - bootstrap methods.

Damage detection
Subspace

$$\zeta_N(\widehat{\theta}_*, \theta) = \sqrt{N}\, vec(S(\widehat{\theta}_*)^T \mathcal{H}_p)$$

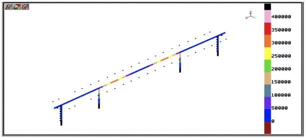
$$\left.\begin{array}{r} S(\widehat{\theta}_*)^T \mathcal{O}_p(\widehat{\theta}_*) = 0 \\ S(\widehat{\theta}_*)^T \mathcal{H}_p = 0 \end{array}\right\} \Leftarrow \mathcal{H}_p = \mathcal{H}_p(N) = \mathcal{O}_p(\theta) \times \mathcal{C}_p$$

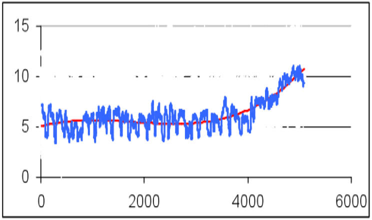
Subspace-based algorithms for structural identification, damage detection, and sensor data fusion, Journal of Applied Signal Processing. with M. Basseville, A. Benveniste, M. Goursat. 2007

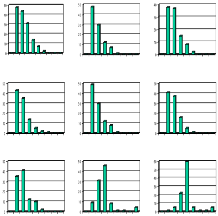
Outline

Damage localization

Bridge Z24. Eureka SINOPSYS project. Collaboration with LMS







Damage Localization

A few comments

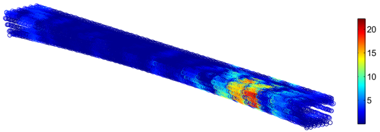
$$\mathbf{J}(\theta_*, \theta) \quad = \quad -\mathbf{E}_\theta \left(\frac{\partial H}{\partial \theta_*}(\theta_*, Y(\theta)) \right)$$

What it means ??

- The jacobian infers on the sensitivity with respect to any parameterization
- FEM parameterization for localization
- $size(\theta) \approx 100 << size(FEM) \approx 20k$

Damage Localization

A few plots



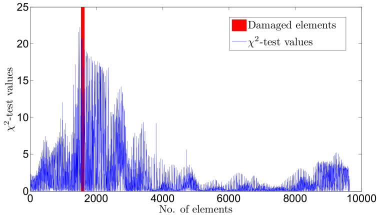


Figure: Damage Localization on bridge deck from ECP.

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Collaboration with LCPC/ECP/SDTOOLS and HIT, China

1. Statistical model-based damage detection and localization subspace-based residuals and damage-to-noise sensitivity ratios, Journal of Sound and Vibration, 2004.
2. Statistical model-based damage localization : a combined subspace-based and substructuring approach, Structural Control and Health Monitoring, 2008.

Outline

A few applications

Roberval bridge - France

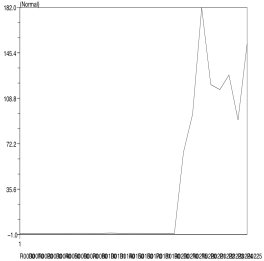

Figure: Damage detection on the Roberval bridge - Summer/Winter effect. Collaboration LCPC/KUL

Temperature modelling

$$M_{\text{struc}}\ddot{X} + C\dot{X} + (K_{\text{struc}} + K_T)X = V$$

$$A = \begin{bmatrix} 0 & I \\ -M_{\text{struc}}^{-1}(K_{\text{struc}} + K_T) & -M_{\text{struc}}^{-1}C \end{bmatrix}$$

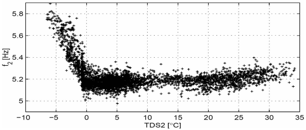

Figure: Frequency evolution on Bridge Z4 (KUL)

if T changes, reference model is wrong and has to be corrected

Temperature rejection
State of Art

- Analytical model based methods
  [Cawley 97],[Moorty 1992]
- Subspace identification (regression ARX)
  [Peeters & De Roeck 2000]
- Factor analysis [Kullaa 2002], modal filters [Deraemaeker & al 2006]
- Subspace detection (database of scenarios # T)
  [Fritzen & al 2003]
- PCA
  [Yan & al, 2004]

Temperature rejection

ACI CONSTRUCTIF - methods of rejection

- Correct the reference model by a thermal model
  $T \rightarrow (M, K_T) \rightarrow S(\theta_T)$
- Learn the reference by averaging scenarios at differents T
  $\bar{H} = \sum_i H_i \rightarrow S$
- Give the good direction (only works for small changes) : Minmax rejection of the temperature as a nuisance (skipped in this talk)

Temperature rejection
ACI CONSTRUCTIF - LCPC experiment in climate chamber

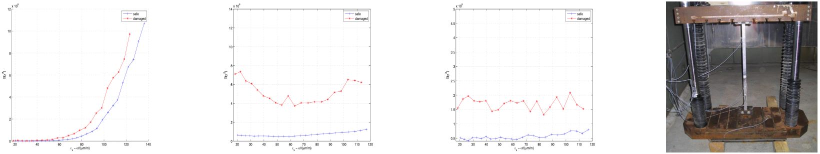

Figure: LCPC beam in climate chamber : 1/ empirical method by merging scenarios 2/ model based correction

Temperature rejection on civil structures

Jeronimo church - Portugal

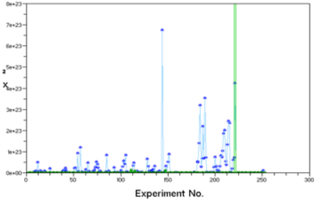

Figure: Blue : no temperature rejection. Green : temperature rejection. Green peak : seism detection. Collaboration with Minho University and KUL

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Collaboration Ecole Centrale De Paris / LCPC

PhD Houssein Nasser

1. Merging sensor data from multiple temperature scenarios for vibration-based monitoring of civil structures, Structural Health Monitoring, 2008.
2. Handling the temperature effect in vibration-based monitoring of civil structures : a combined subspace-based and nuisance rejection approach, Control Engineering Practice, 2008.

Outline

Flutter detection

Flutter : dynamic aero-elastic instability of a surface exposed to wind

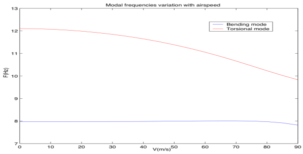
- **Flight Flutter Testing : Design the flutter free flight envelope for ensuring the aircraft stability**
  $\Rightarrow$ Very expensive and time consuming process
- Flutter : loss of stability leads to mechanical wreckage

- Project Eureka Flite and Flite 2 with Onera, Airbus, Dassault Aviation, Sopemea, LMS, VUB and KUL

Flutter detection
Aeroelasticity modelling

$$M\ddot{X} + C\dot{X} + KX = U^2 DX + UEX + V$$

$$A = \begin{bmatrix} 0 & I \\ -M_{\text{struc}}^{-1}(K_{\text{struc}} - U^2 D) & -M_{\text{struc}}^{-1}(C_{\text{struc}} - UE) \end{bmatrix}$$



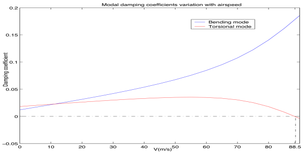


Figure: Frequency and damping evolution

Flutter detection

State of art

Current Flutter speed prediction algorithms using vibration data

- damping fit method
- Flutter margin (Zimmerman-Weissenburger)
- envelope function method
- Nissim-Gilyard method
- Flutterometer (Nasa)

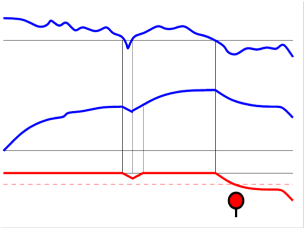
Flutter speed prediction using aerodynamic theory

- numerical fluid-structure interaction algorithms
- the k method and the $p - k$ method
- the μ method

Flutter detection

Methodology - R. Zouari - PhD thesis

- Statistical detection - realtime / robust to noise / simple
- Objective : early detection of "flutter"
- CUSUM test built on the foundations of the local approach
- Detect instant of flutter



Flutter detection
Cusum algorithm

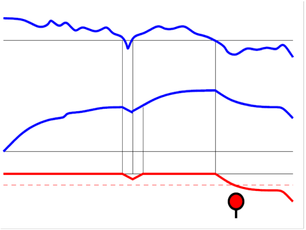
$$\overline{\zeta}_n(\theta_*) \triangleq \mathcal{J}_n(\theta_*,\theta)^T \; \Sigma_n^{-1}(\theta_*,\theta) \; vec(S(\theta_*)^T 1/n \sum_{i=p}^{n-p} \mathcal{Y}_{i,p}^{+} \mathcal{Y}_{i,p}^{-T})$$

$$Z_n(\theta_*) \triangleq \mathcal{J}_n(\theta_*,\theta)^T \Sigma_n^{-1}(\theta_*,\theta) \mathrm{vec}(S(\theta_*)^T \mathcal{Y}_{n,p}^{+} \mathcal{Y}_{n,p}^{-T})$$

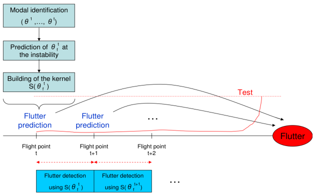
$$R_n(d) \triangleq \sum_k \overline{\Sigma}_k(d)^{-1/2} \, Z_k(d)$$

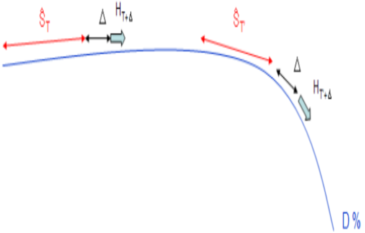
$$T_n(d) \triangleq \max_k R_k(d)$$

$$g_n(d) \triangleq R_n(d) - T_n(d)$$



Flutter detection
Model vs Empirical methods - collaboration VUB





- Model : predicted flutter point : combined data/model approach

$$det(Ms^2 + (C + UB)s + (K + U^2 D)) = 0$$

- Empirical : predict instant of critical drop

Flutter detection

Collaboration ONERA/AIrbus/AGH - PoLand

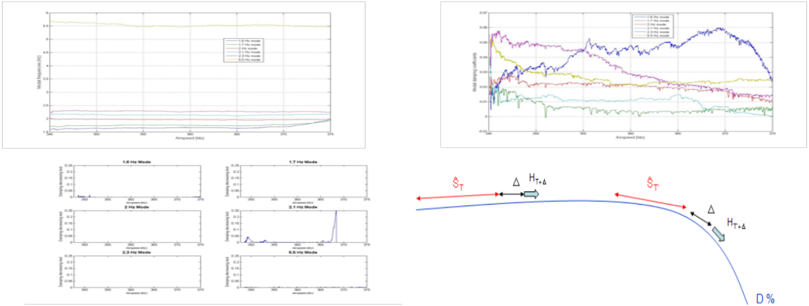


Figure: Simulated two engines aircraft in transient acceleration phase

Flutter detection

Flite 1 and Flite 2 projects publications

1. Fast in-flight detection of flutter onset : a statistical approach, AIAA Journal of Guidance, Control, and Dynamics, 2005.
2. In-flight monitoring of aeronautic structures : vibration-based on-line automated identification versus detection, IEEE Control Systems Magazine, Special Issue on Applications of System Identification, 2007.

PhD Rafik Zouari

An adaptive statistical approach to flutter detection, in Proceedings of the 17th IFAC World Congress, 2008.

Comments

- Both problems were approached using some heavy modelling (LCPC/ECP for temperature, VUB for flutter)
- Empirical methods : robust, efficient, automated, black box
- Both problems rely on correcting/adapting the reference / to physical parameter
  - Temperature for civil structure is a nuisance
  - Aeroelasticity for aircrafts is not a nuisance, it has to be detected
- Both problems have different challenges ahead
  - For flutter, aeroelasticity equations can be avoided - just watch the damping drop - but transient effects, system size, turbulence make the problem hard to solve
  - For temperature rejection, the system is quite stationary and small, but the thermal effects are complex - it is not even sure, the assumptions are correct

Outline

Frequency domain

Why ?

- A large activity in frequency domain identification
  - Polymax
  - Transmissibility
  - OMAX
  - FDD
- Some advantages for large scale systems
  - Focus on frequency band
  - Not quadratic with sensor
- G. Canales PhD thesis

Frequency domain

Polymax - Polyreference LSCF

$$\mathbf{B}(\omega) = \mathbf{H}(\omega)\mathbf{A}(\omega) + \mathbf{V}(\omega)\ , H - H_0 = \frac{1}{\sqrt{K}}\widetilde{H}\ ,$$

$$\zeta_K^N(\mathbf{B}_{k,0}^N, \mathbf{A}_{k,0}^N, \omega) = \frac{1}{\sqrt{K}}\sum_{k=1}^{K}\left(\mathbf{B}_{k,0}^N(\omega) - \mathbf{H}(\omega)\mathbf{A}_{k,0}^N(\omega)\right)\left(\mathbf{A}_{k,0}^N(\omega)\right)^H$$

Theorem (polymax damage detection)

$$\zeta_K^N(\mathbf{B}_{k,0}^N, \mathbf{A}_{k,0}^N, \omega) \sim \mathcal{N}\left(-\widetilde{\mathbf{H}}(\omega)S_0^{aa}(\omega), S_0^{aa}(\omega)S_0^{vv}(\omega)\right)$$

$$\chi_K^N(\mathbf{B}_{k,0}^N, \mathbf{A}_{k,0}^N, \omega) = \frac{\zeta_K^N(\mathbf{B}_{k,0}^N, \mathbf{A}_{k,0}^N, \omega)\left(\zeta_K^N(\mathbf{B}_{k,0}^N, \mathbf{A}_{k,0}^N, \omega)\right)^H}{\widehat{S}_0^{aa}(\omega)\widehat{S}_0^{vv}(\omega)}$$

Frequency domain

Polymax - Polyreference LSCF - Eureka project Flite1

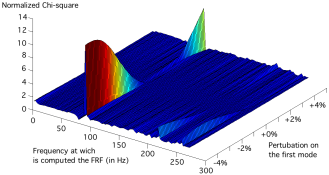


Figure: Polyreference LSCF detection on non specified aircraft from an unspecified french aircraft manufacturer

PhD Gilles Canales

A polyreference least squares complex frequency domain based statistical test for damage detection, in Proceedings of the 17th IFAC World Congress, 2008.

Discussion

- Identification/Detection : theory AND applications
- Real applications transfer on large scale systems
  - Scilab COSMAD Toolbox used by partners (2001-)
  - identification methods : SNECMA, EADS, ONERA, ...
  - detection methods : LCPC, SVIBS, ...
- Ongoing collaborations
  - academic : KUL, VUB, HIT, UBC, LCPC, ECP, Minho
  - industrial : LMS, SVIBS, SDTOOLS, SNECMA, EADS, ONERA, Dassault

Discussion

- Past works have focused on
  - time series and subspace methods
  - long stationary sequences
  - small systems
- What has been neglected
  - frequency domain methods
  - confidence intervals and FEM recalage
  - transient events (seismic events and buildings)
  - large systems
- Time of laboratory and academic experiments belong to the past : collaboration with industrials and academic partners is critical

Real scale implementation

From the bridge Z4 up to now

Figure: Bridge Z24 -1999

Figure: Bridge monitoring project under way funded by Canada government - 2009 - technology transfer - SVIBS DK

Thanks to

all members of the SISTHEM team

and all who supported me up to now