

INSTITUT NATIONAL DE RECHERCHE EN INFORMATIQUE ET EN AUTOMATIQUE

# Project-Team sisthem

# Statistical Inference for STructural HEalth Monitoring

Rennes - Bretagne Atlantique



# **Table of contents**

1.	Team	<mark>1</mark>			
2.	Overall Objectives1				
	2.1. Introduction	1			
	2.1.1. Context.	1			
	2.1.2. Objectives.	2			
	2.1.3. Industrial and academic relations.	2			
	2.2. Highlights of the year	2			
3.	Scientific Foundations	2			
	3.1. Introduction	2			
	3.2. Identification	3			
	3.3. Detection	3			
	3.4. Diagnostics	5			
	3.4.1. Isolation.	5			
	3.4.2. Diagnostics.	6			
	3.5. Subspace-based identification and detection	6			
	3.5.1. Covariance-driven subspace identification.	7			
	3.5.2. Model parameter characterization.	7			
	3.5.3. Residual associated with subspace identification.	8			
	3.5.4. Other uses of the key factorizations.	8			
4.	Application Domains	8			
	4.1. Introduction	8			
	4.2. Vibrations-based monitoring	9			
	4.3. Civil engineering	9			
	4.4. Aeronautics	10			
5.	Software	11			
6.	New Results				
	6.1. Eigenstructure identification	13			
	6.1.1. Properties of subspace identification methods.	13			
	6.1.2. Identification using filtering techniques.	13			
	6.1.3. Eigenstructure identification.	13			
	6.1.4. Improving subspace identification by modal basis change.	13			
	6.1.5. Robustness to data perturbation.	13			
	6.2. Change/damage detection and isolation	13			
	6.2.1. Variants of the subspace-based detection algorithm.	14			
	6.2.2. Model validation.	14			
	6.2.3. Frequency domain tests.	14			
	6.2.4. Handling nuisance parameters.	14			
	6.3. Flutter monitoring and onset detection	14			
	6.3.1. Online CUSUM tests.	15			
	6.3.2. Comparing identification and detection approaches to monitoring.	15			
	6.3.3. Robust flutter margins for flutter detection.	15			
	6.4. Handling the temperature effect	15			
	6.4.1. Damage detection for masonry structures.	16			
	6.4.2. Involving modal filters.	16			
7.	Contracts and Grants with Industry	16			
	7.1. Eurêka project FliTE2	16			
	7.2. FP7-NMP Large Scale IP IRIS	17			
	7.3. SNECMA	18			
	7.4. SVIBS	18			

8.	Othe	r Grants and Activities	18
	8.1.	SAMCO association	18
	8.2.	FWO Research Network ICCoS	19
	8.3.	Partnership with KU Leuven	19
	8.4.	International collaborations	19
9.	Dissemination		
	9.1.	Scientific animation	19
	9.2.	Conference and workshop committees, invited conferences	19
	9.	2.1. Committees.	19
	9.	2.2. Invited publications.	20
	9.3.	Visits and invitations	20
10.	Rib	liography	20

# 1. Team

#### Head of project-team

Michèle Basseville [ Research Director (DR) CNRS, HdR ]

#### **Administrative Assistant**

Laurence Dinh [ Secretary (SAR) Inria, shared with DistribCom, IPSO, S4 ]

#### Research Scientists (Inria)

Albert Benveniste [ Research Director (DR), part–time, HdR ] Maurice Goursat [ Research Director (DR), part–time, HdR ] Laurent Mevel [ Research Associate (CR) ]

#### Post-doctoral Fellow (Cnrs)

Fethi Bouziani [ from September 1, 2007 ]

#### **Technical staff (Inria)**

Simon Berger [ ingénieur expert, FliTE2 project, until June 30, 2007 ] Neil Babou [ ingénieur associé, from December 1, 2007 ]

#### Ph.D. Students

Gilles Canales [ U. Rennes I, MESR fellowship, from October 1, 2006 ] Rafik Zouari [ Inria grant, from October 1, 2005 ]

# 2. Overall Objectives

#### 2.1. Introduction

**Keywords:** aeronautics, change detection, civil engineering, diagnostics, monitoring, on-line identification and detection algorithms, optimal sensors placement, sensors fusion, statistical hypotheses testing, subspace-based algorithms, system identification, vibration-based structural analysis and damage detection and localization.

#### 2.1.1. Context.

Structural Health Monitoring (SHM) is the whole process of the design, development and implementation of techniques for the detection, localization and estimation of damages, for monitoring the integrity of structures and machines within the aerospace, civil and mechanical engineering infrastructures [46], [63]. In addition to these key driving application areas, SHM is now spreading over most transportation infrastructures and vehicles, within the naval, railway and automobile domains. Examples of structures or machines to be monitored include aircrafts, space crafts, buildings, bridges, dams, ships, offshore platforms, on-shore and off-shore wind farms (wind energy systems), turbo-alternators and other heavy machineries, ....

The emergence of stronger safety and environmental norms, the need for early decision mechanisms, together with the widespread diffusion of sensors of all kinds, result in a thorough renewal of sensor information processing problems. This calls for new research investigations within the sensor data (signal and image) information processing community. In particular, efficient and robust methods for structural analysis, non destructive evaluation, integrity monitoring, damage diagnosis and localization, are necessary for fatigue and aging prevention, and for condition-based maintenance. Moreover, multidisciplinary research, mixing information science, engineering science and scientific computing, is mandatory. However, most of the SHM research investigations are conducted within mechanical, civil and aeronautical engineering departments, with little involvement of advanced data information processing specialists.

#### 2.1.2. Objectives.

In this context, and based on our background and results on model-based statistical identification, change detection and vibration monitoring, our objectives are :

- Importing knowledge from engineering communities within our model-based information processing methods;
- Mixing statistical inference tools (identification, detection, rejection) with simplified models of aerodynamic effects, thermo-dynamical or other environmental effects;
- Involving nonlinearities in the models, algorithms and proofs of performances;
- Exporting our data processing algorithms within the SHM community, based on specific training actions, on a dedicated free Scilab toolbox, and an industrial software.

#### 2.1.3. Industrial and academic relations.

- Industrial projects: with SNECMA (F.) and SVIBS (DK).
- Multi-partners projects: at European level on exploitation of flight test data under natural excitation conditions (FliTE2 - Eurêka), on structural assessment, monitoring and control (SAMCO Association),
- Academic research: national project on monitoring civil engineering structures (CONSTRUCTIF

   ACI S&I), European network on system identification (FP5 TMR), FWO research network on identification and control.

# 2.2. Highlights of the year

- 1. *Research*: Thanks to a collaboration with the Acoustics & Vibration Research Group of Vrije Universiteit Brussel (VUB), we have been developing frequency methods for damage detection (see module 6.2) and for flutter monitoring (see module 6.3).
- 2. *Transfer*: The Scilab toolbox COSMAD has been transferred to SNECMA. The FliTE2 European project has undergone major steps (see module 7.1).

# 3. Scientific Foundations

# 3.1. Introduction

In this section, the main features for the key monitoring issues, namely identification, detection, and diagnostics, are provided, and a particular instantiation relevant for vibration monitoring is described.

It should be stressed that the foundations for identification, detection, and diagnostics, are fairly general, if not generic. Handling high order linear dynamical systems, in connection with finite elements models, which call for using subspace-based methods, is specific to vibration-based SHM. Actually, one particular feature of model-based sensor information data processing as exercised in SISTHEM, is the combined use of black-box or semi-physical models together with physical ones. Black-box and semi-physical models are, for example, eigenstructure parameterizations of linear MIMO systems, of interest for modal analysis and vibration-based SHM. Such models are intended to be identifiable. However, due to the large model orders that need to be considered, the issue of model order selection is really a challenge. Traditional advanced techniques from statistics such as the various forms of Akaïke criteria (AIC, BIC, MDL, ...) do not work at all. This gives rise to new research activities specific to handling high order models.

Our approach to monitoring assumes that a model of the monitored system is available. This is a reasonable assumption, especially within the SHM areas. The main feature of our monitoring method is its intrinsic ability to the early warning of small deviations of a system with respect to a reference (safe) behavior under usual operating conditions, namely without any artificial excitation or other external action. Such a normal behavior is summarized in a reference parameter vector  $\theta_0$ , for example a collection of modes and mode-shapes.

#### 3.2. Identification

Keywords: adaptive estimation, estimating function, recursive estimation.

See module 6.1.

The behavior of the monitored continuous system is assumed to be described by a parametric model  $\{\mathbf{P}_{\theta}, \theta \in \Theta\}$ , where the distribution of the observations  $(Z_0, ..., Z_N)$  is characterized by the parameter vector  $\theta \in \Theta$ . An *estimating function*, for example of the form:

$$\mathcal{K}_N(\theta) = 1/N \sum_{k=0}^{N} K(\theta, Z_k)$$

is such that  $\mathbf{E}_{\theta}[\mathcal{K}_N(\theta)] = 0$  for all  $\theta \in \Theta$ . In many situations,  $\mathcal{K}$  is the gradient of a function to be minimized: squared prediction error, log-likelihood (up to a sign), .... For performing model identification on the basis of observations  $(Z_0,...,Z_N)$ , an estimate of the unknown parameter is then [51]:

$$\widehat{\theta}_N = \arg \{ \theta \in \Theta : \mathfrak{K}_N(\theta) = 0 \}$$

Assuming that  $\theta^*$  is the true parameter value, and that  $\mathbf{E}_{\theta^*}[\mathcal{K}_N(\theta)] = 0$  if and only if  $\theta = \theta^*$  with  $\theta^*$  fixed (identifiability condition), then  $\widehat{\theta}_N$  converges towards  $\theta^*$ . Thanks to the central limit theorem, the vector  $\mathcal{K}_N(\theta^*)$  is asymptotically Gaussian with zero mean, with covariance matrix  $\Sigma$  which can be either computed or estimated. If, additionally, the matrix  $\mathcal{J}_N = -\mathbf{E}_{\theta^*}[\mathcal{K}_N'(\theta^*)]$  is invertible, then using a Taylor expansion and the constraint  $\mathcal{K}_N(\widehat{\theta}_N) = 0$ , the asymptotic normality of the estimate is obtained:

$$\sqrt{N} (\widehat{\theta}_N - \theta^*) \approx \mathcal{J}_N^{-1} \sqrt{N} \, \mathfrak{K}_N(\theta^*)$$

In many applications, such an approach must be improved in the following directions:

- Recursive estimation: the ability to compute  $\widehat{\theta}_{N+1}$  simply from  $\widehat{\theta}_N$ ;
- Adaptive estimation: the ability to track the true parameter  $\theta^*$  when it is time-varying.

#### 3.3. Detection

**Keywords:** local approach, residual evaluation, residual generation.

See module 6.3.

Our approach to on-board detection is based on the so-called asymptotic statistical local approach, which we have extended and adapted [6], [5], [2]. It is worth noticing that these investigations of ours have been initially motivated by a vibration monitoring application example. It should also be stressed that, as opposite to many monitoring approaches, our method does not require repeated identification for each newly collected data sample.

For achieving the early detection of small deviations with respect to the normal behavior, our approach generates, on the basis of the reference parameter vector  $\theta_0$  and a new data record, indicators which automatically perform:

- The early detection of a slight mismatch between the model and the data;
- A preliminary diagnostics and localization of the deviation(s);
- The tradeoff between the magnitude of the detected changes and the uncertainty resulting from the estimation error in the reference model and the measurement noise level.

These indicators are computationally cheap, and thus can be embedded. This is of particular interest in some applications, such as flutter monitoring, as explained in module 4.4.

As in most fault detection approaches, the key issue is to design a *residual*, which is ideally close to zero under normal operation, and has low sensitivity to noises and other nuisance perturbations, but high sensitivity to small deviations, before they develop into events to be avoided (damages, faults, ...). The originality of our approach is to:

- Design the residual basically as a parameter estimating function,
- Evaluate the residual thanks to a kind of central limit theorem, stating that the residual is asymptotically Gaussian and reflects the presence of a deviation in the parameter vector through a change in its own mean vector, which switches from zero in the reference situation to a non-zero value.

This is actually a strong result, which transforms any detection problem concerning a parameterized stochastic *process* into the problem of monitoring the mean of a Gaussian *vector*.

The behavior of the monitored system is again assumed to be described by a parametric model  $\{P_{\theta}, \theta \in \Theta\}$ , and the safe behavior of the process is assumed to correspond to the parameter value  $\theta_0$ . This parameter often results from a preliminary identification based on reference data, as in module 3.2.

Given a new N-size sample of sensors data, the following question is addressed: Does the new sample still correspond to the nominal model  $\mathbf{P}_{\theta_0}$ ? One manner to address this generally difficult question is the following. The asymptotic local approach consists in deciding between the nominal hypothesis and a close alternative hypothesis, namely:

(Safe) 
$$\mathbf{H}_0$$
:  $\theta = \theta_0$  and (Damaged)  $\mathbf{H}_1$ :  $\theta = \theta_0 + \eta/\sqrt{N}$  (1)

where  $\eta$  is an unknown but fixed change vector. A residual is generated under the form:

$$\zeta_N = 1/\sqrt{N} \sum_{k=0}^N K(\theta_0, Z_k) = \sqrt{N} \,\mathcal{K}_N(\theta_0) . \tag{2}$$

If the matrix  $\mathcal{J}_N = -\mathbf{E}_{\theta_0}[\mathcal{K}'_N(\theta_0)]$  converges towards a limit  $\mathcal{J}$ , then the central limit theorem shows [44] that the residual is asymptotically Gaussian :

$$\zeta_N \xrightarrow[N \to \infty]{} \left\{ \begin{array}{cc} & \mathcal{N}(0,\Sigma) & \text{ under } \mathbf{P}_{\theta_0} \ , \\ \\ & \mathcal{N}(\mathcal{J}\,\eta,\Sigma) & \text{ under } \mathbf{P}_{\theta_0+\eta/\sqrt{N}} \ , \end{array} \right.$$

where the asymptotic covariance matrix  $\Sigma$  can be estimated, and manifests the deviation in the parameter vector by a change in its own mean value. Then, deciding between  $\eta=0$  and  $\eta\neq 0$  amounts to compute the following  $\chi^2$ -test, provided that  $\mathcal J$  is full rank and  $\Sigma$  is invertible:

$$\chi^2 = \overline{\zeta}^T \mathbf{F}^{-1} \overline{\zeta} \geqslant \lambda . \tag{3}$$

where

$$\overline{\zeta} \stackrel{\Delta}{=} \mathcal{J}^T \Sigma^{-1} \zeta_N \text{ and } \mathbf{F} \stackrel{\Delta}{=} \mathcal{J}^T \Sigma^{-1} \mathcal{J}$$
 (4)

With this approach, it is possible to decide, with a quantifiable error level, if a residual value is significantly different from zero, for assessing whether a fault/damage has occurred. It should be stressed that the residual and the sensitivity and covariance matrices  $\mathcal{J}$  and  $\Sigma$  can be evaluated (or estimated) for the nominal model. In particular, it is *not* necessary to re-identify the model, and the sensitivity and covariance matrices can be pre-computed off-line.

### 3.4. Diagnostics

**Keywords:** diagnostics, isolation.

See modules 6.4 and 6.3.

A further monitoring step, often called *fault isolation*, consists in determining which (subsets of) components of the parameter vector  $\theta$  have been affected by the change. Solutions for that are now described. How this relates to diagnostics is addressed afterwards.

#### 3.4.1. Isolation.

The question: which (subsets of) components of  $\theta$  have changed?, can be addressed using either nuisance parameters elimination methods or a multiple hypotheses testing approach [41]. Here we only sketch two intuitively simple statistical nuisance elimination techniques, which proceed by projection and rejection, respectively.

The fault vector  $\eta$  is partitioned into an informative part and a nuisance part, and the sensitivity matrix  $\mathcal{J}$ , the Fisher information matrix  $\mathbf{F} = \mathcal{J}^T \Sigma^{-1} \mathcal{J}$  and the normalized residual  $\overline{\zeta} = \mathcal{J}^T \Sigma^{-1} \zeta_N$  are partitioned accordingly

$$\eta = \left( \begin{array}{c} \eta_a \\ \eta_b \end{array} \right) \; , \quad \mathcal{J} = \left( \begin{array}{ccc} \mathcal{J}_a & \mathcal{J}_b \end{array} \right) \; , \quad \mathbf{F} = \left( \begin{array}{ccc} \mathbf{F}_{aa} & \mathbf{F}_{ab} \\ \mathbf{F}_{ba} & \mathbf{F}_{bb} \end{array} \right) \; , \quad \overline{\zeta} = \left( \begin{array}{c} \overline{\zeta}_a \\ \overline{\zeta}_b \end{array} \right) \; .$$

A rather intuitive statistical solution to the isolation problem, which can be called *sensitivity* approach, consists in projecting the deviations in  $\eta$  onto the subspace generated by the components  $\eta_a$  to be isolated, and deciding between  $\eta_a = \eta_b = 0$  and  $\eta_a \neq 0$ ,  $\eta_b = 0$ . This results in the following test statistics:

$$t_a = \overline{\zeta}_a^T \mathbf{F}_{aa}^{-1} \overline{\zeta}_a , \qquad (5)$$

where  $\overline{\zeta}_a$  is the partial residual (score). If  $t_a \ge t_b$ , the component responsible for the fault is considered to be a rather than b.

Another statistical solution to the problem of isolating  $\eta_a$  consists in viewing parameter  $\eta_b$  as a nuisance, and using an existing method for inferring part of the parameters while ignoring and being robust to the complementary part. This method is called *min-max approach*. It consists in replacing the nuisance parameter component  $\eta_b$  by its least favorable value, for deciding between  $\eta_a=0$  and  $\eta_a\neq 0$ , with  $\eta_b$  unknown. This results in the following test statistics:

$$t_a^* = \overline{\zeta}_a^{*T} \mathbf{F}_a^{*-1} \overline{\zeta}_a^* , \qquad (6)$$

where  $\overline{\zeta}_a^* \stackrel{\Delta}{=} \overline{\zeta}_a - \mathbf{F}_{ab} \, \mathbf{F}_{bb}^{-1} \, \overline{\zeta}_b$  is the effective residual (score) resulting from the regression of the informative partial score  $\overline{\zeta}_a$  over the nuisance partial score  $\overline{\zeta}_b$ , and where the Schur complement  $\mathbf{F}_a^* = \mathbf{F}_{aa} - \mathbf{F}_{ab} \, \mathbf{F}_{bb}^{-1} \, \mathbf{F}_{ba}$  is the associated Fisher information matrix. If  $t_a^* \geq t_b^*$ , the component responsible for the fault is considered to be a rather than b.

The properties and relationships of these two types of tests are investigated in [37].

#### 3.4.2. Diagnostics.

In most SHM applications, a complex physical system, characterized by a generally non identifiable parameter vector  $\Phi$  has to be monitored using a simple (black-box) model characterized by an identifiable parameter vector  $\theta$ . A typical example is the vibration monitoring problem in module 4.2, for which complex finite elements models are often available but not identifiable, whereas the small number of existing sensors calls for identifying only simplified input-output (black-box) representations. In such a situation, two different diagnosis problems may arise, namely diagnosis in terms of the black-box parameter  $\theta$  and diagnosis in terms of the parameter vector  $\Phi$  of the underlying physical model.

The isolation methods sketched above are possible solutions to the former. Our approach to the latter diagnosis problem is basically a detection approach again, and not a (generally ill-posed) inverse problem estimation approach [4]. The basic idea is to note that the physical sensitivity matrix writes  $\mathcal{J}\mathcal{J}_{\Phi\theta}$ , where  $\mathcal{J}_{\Phi\theta}$  is the Jacobian matrix at  $\Phi_0$  of the application  $\Phi \mapsto \theta(\Phi)$ , and to use the sensitivity test (5) for the components of the parameter vector  $\Phi$ . Typically this results in the following type of directional test:

$$\chi_{\Phi}^{2} = \zeta^{T} \Sigma^{-1} \mathcal{J} \mathcal{J}_{\Phi\theta} \left( \mathcal{J}_{\Phi\theta}^{T} \mathcal{J}^{T} \Sigma^{-1} \mathcal{J} \mathcal{J}_{\Phi\theta} \right)^{-1} \mathcal{J}_{\Phi\theta}^{T} \mathcal{J}^{T} \Sigma^{-1} \zeta \geqslant \lambda . \tag{7}$$

It should be clear that the selection of a particular parameterization  $\Phi$  for the physical model may have a non negligible influence on such type of tests, according to the numerical conditioning of the Jacobian matrices  $\mathcal{J}_{\Phi\theta}$ .

As a summary, the machinery in modules 3.2, 3.3 and 3.4 provides us with a generic framework for designing monitoring algorithms for continuous structures, machines and processes. This approach assumes that a model of the monitored system is available. This is a reasonable assumption within the field of applications described in module 4.2, since most mechanical processes rely on physical principles which write in terms of equations, providing us with models. These important *modeling* and *parameterization* issues are among the questions we intend to investigate within our research program.

The key issue to be addressed within each parametric model class is the residual generation, or equivalently the choice of the *parameter estimating function*.

# 3.5. Subspace-based identification and detection

Keywords: Hankel matrix factorization, covariance-driven subspace-based algorithms.

See module 6.3.

For reasons closely related to the vibrations monitoring applications described in module 4.2, we have been investigating subspace-based methods, for both the identification and the monitoring of the eigenstructure  $(\lambda, \phi_{\lambda})$  of the state transition matrix F of a linear dynamical state-space system:

$$\begin{cases}
X_{k+1} = F X_k + V_{k+1} \\
Y_k = H X_k
\end{cases},$$
(8)

namely the  $(\lambda, \varphi_{\lambda})$  defined by :

$$\det (F - \lambda I) = 0, \quad (F - \lambda I) \phi_{\lambda} = 0, \quad \varphi_{\lambda} \stackrel{\triangle}{=} H \phi_{\lambda}$$
 (9)

The (canonical) parameter vector in that case is:

$$\theta \stackrel{\Delta}{=} \left( \begin{array}{c} \Lambda \\ \text{vec} \Phi \end{array} \right) \tag{10}$$

where  $\Lambda$  is the vector whose elements are the eigenvalues  $\lambda$ ,  $\Phi$  is the matrix whose columns are the  $\varphi_{\lambda}$ 's, and vec is the column stacking operator.

Subspace-based methods is the generic name for linear systems identification algorithms based on either time domain measurements or output covariance matrices, in which different subspaces of Gaussian random vectors play a key role [62]. A contribution of ours, minor but extremely fruitful, has been to write the output-only covariance-driven subspace identification method under a form that involves a parameter estimating function, from which we define a *residual adapted to vibration monitoring* [1]. This is explained next.

#### 3.5.1. Covariance-driven subspace identification.

Let  $R_i \stackrel{\Delta}{=} \mathbf{E} \left( Y_k \ Y_{k-i}^T \right)$  and:

$$\mathcal{H}_{p+1,q} \stackrel{\Delta}{=} \begin{pmatrix}
R_0 & R_1 & \vdots & R_{q-1} \\
R_1 & R_2 & \vdots & R_q \\
\vdots & \vdots & \vdots & \vdots \\
R_p & R_{p+1} & \vdots & R_{p+q-1}
\end{pmatrix} \stackrel{\Delta}{=} \operatorname{Hank}(R_i) \tag{11}$$

be the output covariance and Hankel matrices, respectively; and:  $G \stackrel{\Delta}{=} \mathbf{E}(X_k Y_k^T)$ . Direct computations of the  $R_i$ 's from the equations (8) lead to the well known key factorizations:

$$R_{i} = HF^{i}G$$

$$\mathcal{H}_{p+1,q} = \mathcal{O}_{p+1}(H,F) \,\mathcal{C}_{q}(F,G)$$
(12)

where:

$$\mathcal{O}_{p+1}(H,F) \stackrel{\Delta}{=} \left( \begin{array}{c} H \\ HF \\ \vdots \\ HF^p \end{array} \right) \quad \text{and} \quad \mathcal{C}_q(F,G) \stackrel{\Delta}{=} (G \ FG \ \cdots \ F^{q-1}G)$$

are the observability and controllability matrices, respectively. The observation matrix H is then found in the first block-row of the observability matrix O. The state-transition matrix F is obtained from the shift invariance property of O. The eigenstructure  $(\lambda, \phi_{\lambda})$  then results from (9).

Since the actual model order is generally not known, this procedure is run with increasing model orders.

#### 3.5.2. Model parameter characterization.

Choosing the eigenvectors of matrix F as a basis for the state space of model (8) yields the following representation of the observability matrix:

$$\mathfrak{O}_{p+1}(\theta) = \begin{pmatrix} \Phi \\ \Phi \Delta \\ \vdots \\ \Phi \Delta^p \end{pmatrix}$$
(13)

where  $\Delta \stackrel{\Delta}{=} \operatorname{diag}(\Lambda)$ , and  $\Lambda$  and  $\Phi$  are as in (10). Whether a nominal parameter  $\theta_0$  fits a given output covariance sequence  $(R_j)_j$  is characterized by [1]:

$$\mathcal{O}_{p+1}(\theta_0)$$
 and  $\mathcal{H}_{p+1,q}$  have the same left kernel space. (14)

This property can be checked as follows. From the nominal  $\theta_0$ , compute  $\mathcal{O}_{p+1}(\theta_0)$  using (13), and perform e.g. a singular value decomposition (SVD) of  $\mathcal{O}_{p+1}(\theta_0)$  for extracting a matrix U such that:

$$U^T U = I_s \text{ and } U^T \mathcal{O}_{p+1}(\theta_0) = 0$$
 (15)

Matrix U is not unique (two such matrices relate through a post-multiplication with an orthonormal matrix), but can be regarded as a function of  $\theta_0$ . Then the characterization writes:

$$U(\theta_0)^T \mathcal{H}_{p+1,q} = 0 \tag{16}$$

#### 3.5.3. Residual associated with subspace identification.

Assume now that a reference  $\theta_0$  and a new sample  $Y_1, \dots, Y_N$  are available. For checking whether the data agree with  $\theta_0$ , the idea is to compute the empirical Hankel matrix  $\widehat{\mathcal{H}}_{p+1,q}$ :

$$\widehat{\mathcal{H}}_{p+1,q} \stackrel{\Delta}{=} \operatorname{Hank}\left(\widehat{R}_i\right), \quad \widehat{R}_i \stackrel{\Delta}{=} 1/(N-i) \sum_{k=i+1}^N Y_k Y_{k-i}^T$$
 (17)

and to define the residual vector:

$$\zeta_N(\theta_0) \stackrel{\Delta}{=} \sqrt{N} \operatorname{vec} \left( U(\theta_0)^T \widehat{\mathcal{H}}_{p+1,q} \right)$$
 (18)

Let  $\theta$  be the actual parameter value for the system which generated the new data sample, and  $\mathbf{E}_{\theta}$  be the expectation when the actual system parameter is  $\theta$ . From (16), we know that  $\zeta_N(\theta_0)$  has zero mean when no change occurs in  $\theta$ , and nonzero mean if a change occurs. Thus  $\zeta_N(\theta_0)$  plays the role of a residual.

It is our experience that this residual has highly interesting properties, both for damage detection [1] and localization [4], and for flutter monitoring [8].

#### 3.5.4. Other uses of the key factorizations.

Factorization (3.5.1) is the key for a characterization of the canonical parameter vector  $\theta$  in (10), and for deriving the residual. Factorization (12) is also the key for :

- Proving consistency and robustness results [16];
- Designing an extension of covariance-driven subspace identification algorithm adapted to the presence and fusion of non-simultaneously recorded multiple sensors setups [7];
- Proving the consistency and robustness of this extension [9];
- Designing various forms of *input-output* covariance-driven subspace identification algorithms adapted to the presence of both known inputs and unknown excitations [10].

# 4. Application Domains

#### 4.1. Introduction

In this section, the problems we are faced with vibration-based monitoring and within our two major application domains are briefly described.

# 4.2. Vibrations-based monitoring

**Keywords:** mechanical structure, modal analysis, subspace–based method, vibrations.

See modules 3.5.

Detecting and localizing damages for monitoring the integrity of structural and mechanical systems is a topic of growing interest, due to the aging of many engineering constructions and machines and to increased safety norms. Many current approaches still rely on visual inspections or *local* non destructive evaluations performed manually. This includes acoustic, ultrasonic, radiographic or eddy-current methods; magnet or thermal field techniques, .... These experimental approaches assume an *a priori* knowledge and the accessibility of a neighborhood of the damage location. Automatic *global* vibration-based monitoring techniques have been recognized to be useful alternatives to those local evaluations [46]. However this has led to actual damage monitoring systems only in the field of rotating machines.

A common feature of the structures to be monitored (e.g. civil engineering structures subject to hurricanes or earthquakes, but also swell, wind and rain; aircrafts subject to strength and turbulences, ...) is the following. These systems are subject to both fast and unmeasured variations in their environment and small slow variations in their vibrating characteristics. The available data (measurements from e.g. strain gauges or accelerometers) do not separate the effects of the external forces from the effect of the structure. The external forces vary more rapidly than the structure itself (fortunately!), damages or fatigues on the structure are of interest, while any change in the excitation is meaningless. Expert systems based on a human-like exploitation of recorded spectra can hardly work in such a case: the changes of interest (1% in eigenfrequencies) are visible neither on the signals nor on their spectra. A global health monitoring method must rather rely on a model that will help in discriminating between the two mixed causes of the changes that are contained in the measurements.

Classical modal analysis and vibration monitoring methods basically process data registered either on test beds or under specific excitation or rotation speed conditions. However there is a need for vibration monitoring algorithms devoted to the processing of data recorded in-operation, namely during the actual functioning of the considered structure or machine, without artificial excitation, speeding down or stopping.

Health monitoring techniques based on processing vibration measurements basically handle two types of characteristics: the *structural parameters* (mass, stiffness, flexibility, damping) and the *modal parameters* (modal frequencies, and associated damping values and mode-shapes); see [59] and references therein. A central question for monitoring is to compute *changes* in those characteristics and to assess their *significance*. For the *frequencies*, crucial issues are then: how to compute the changes, to assess that the changes are significant, to handle *correlations* among individual changes. A related issue is how to compare the changes in the frequencies obtained from experimental data with the sensitivity of modal parameters obtained from an analytical model. Furthermore, it has been widely acknowledged that, whereas changes in frequencies bear useful information for damage *detection*, information on changes in (the curvature of) mode-shapes is mandatory for performing damage *localization*. Then, similar issues arise for the computation and the significance of the changes. In particular, assessing the significance of (usually small) changes in the mode-shapes, and handling the (usually high) correlations among individual mode-shape changes are still considered as open questions [59], [46].

Controlling the computational complexity of the processing of the collected data is another standard monitoring requirement, which includes a limited use of an analytical model of the structure. Moreover, the reduction from the analytical model to the experimental model (truncated modal space) is known to play a key role in the success of model-based damage detection and localization.

The approach which we have been developing, based on the foundations in modules 3.2–3.5, aims at addressing all the issues and overcoming the limitations above.

# 4.3. Civil engineering

See modules 3.5, 6.1, 6.2, 6.4, and 7.4.

Civil engineering is a currently renewing scientific research area, which can no longer be restricted to the single mechanical domain, with numerical codes as its central focus. Recent and significant advances in physics and physical chemistry have improved the understanding of the detailed mechanisms of the constitution and the behavior of various materials (see e.g. the multi-disciplinary general agreement CNRS-Lafarge). Moreover, because of major economical and societal issues, such as durability and safety of infrastructures, buildings and networks, civil engineering is evolving towards a multi-disciplinary field, involving in particular information sciences and technologies and environmental sciences.

These last ten years, monitoring the integrity of the civil infrastructure has been an active research topic, including in connected areas such as automatic control, for mastering either the aging of the bridges, as in America (US, Canada) and Great Britain, or the resistance to seismic events and the protection of the cultural heritage, as in Italy and Greece. The research effort in France seems to be more recent, maybe because a tendency of long term design without fatigue oriented inspections, as opposite to less severe design with planned mid-term inspections. One of the current thematic priorities of the Réseau de Génie Civil et Urbain (RGCU) is devoted to constructions monitoring and diagnostics. The picture in Asia (Japan, and also China) is somewhat different, in that the demand for automatic data processing for global SHM systems is much higher, because recent or currently built bridges are equipped with hundreds if not thousands of sensors, in particular the Hong Kong-Shenzen Western Corridor and Stonecutter Bridge projects.

Among the challenges for vibration-based bridges health monitoring, two major issues are the different kinds of (non measured) excitation sources and the environmental effects [60]. Typically the traffic on *and* under the bridge, the wind and also the rain, contribute to excite the structure, and influence the measured dynamics. Moreover, the temperature is also known to affect the eigenfrequencies and mode-shapes, to an extent which is significant w.r.t. the deviations to be monitored. This is addressed in module 6.4.

#### 4.4. Aeronautics

See modules 3.5, 6.1, 6.2, 6.3, 7.1 and 7.3.

The aging of aerospace structures is a major current concern of civilian and military aircraft operators. Another key driving factor for SHM is to increase the operation and support efficiency of an air vehicle fleet. A SHM system is viewed as a component of a global integrated vehicle health management (IVHM) system. An overview of the users needs can be found in [43].

Improved safety and performance and reduced aircraft development and operating costs are other major concerns. One of the critical design objectives is to clear the aircraft from unstable aero-elastic vibrations (flutter) in all flight conditions. This requires a careful exploration of the dynamical behavior of the structure subject to vibration and aero-servo-elastic forces. This is achieved via a combination of ground vibration tests and in-flight tests. For both types of tests, various sensors data are recorded, and modal analyses are performed. Important challenges of the in-flight modal analyses are the limited choices for measured excitation inputs, and the presence of unmeasured natural excitation inputs (turbulence). A better exploitation of flight test data can be achieved by using output-only system identification methods, which exploits data recorded under natural excitation conditions (e.g., turbulent), without resorting to artificial control surface excitation and other types of excitation inputs [10].

A crucial issue is to ensure that the newly designed airplane is stable throughout its operating range. A critical instability phenomenon, known under the name of "aero-elastic flutter, involves the unfavorable interaction of aerodynamic, elastic, and inertia forces on structures to produce an unstable oscillation that often results in structural failure" [52]. For preventing from this phenomenon, the airplane is submitted to a flight flutter testing procedure, with incrementally increasing altitude and airspeed. The problem of predicting the speed at which flutter can occur is usually addressed with the aid of identification methods achieving modal analysis from the in-flight data recorded during these tests. The rationale is that the damping coefficient reflects the rate of increase or decrease in energy in the aero-servo-elastic system, and thus is a relevant measure of stability. Therefore, while frequencies and mode-shapes are usually the most important parameters in structural analysis, the most critical ones in flutter analysis are the damping factors, for some critical modes. The mode-shapes are usually not estimated for flutter testing.

Until the late nineties, most approaches to flutter clearance have led to *data-based* methods, processing different types of data. A *combined data-based and model-based* method has been introduced recently under the name of flutterometer. Based on an aero-elastic state-space model and on frequency-domain transfer functions extracted from sensor data under controlled excitation, the flutterometer computes on-line a robust flutter margin using the  $\mu$ -method for analyzing the worst case effects of model uncertainty. In recent comparative evaluations using simulated and real data [45], [54], several data-based methods are shown to fail in accurately predicting flutter when using data from low speed tests, whereas the flutterometer turns out not to converge to the true flutter speed during envelope expansion, due to inherent conservative predictions.

Algorithms achieving the *on-line in-flight* exploitation of flight test data are expected to allow a more direct exploration of the flight domain, with improved confidence and reduced costs. Among other challenges, one important issue to be addressed on-line is the flight flutter monitoring problem, stated as the problem of monitoring some specific damping coefficients. On the other hand, it is known, e.g. from Cramer-Rao bounds, that damping factors are difficult to estimate accurately. For improving the estimation of damping factors, and moreover for achieving this in real-time during flight tests, one possible although unexpected route is to rely on detection algorithms able to decide whether some damping factor decreases below some critical value or not. The rationale is that detection algorithms usually have a much shorter response time than identification algorithms. This is addressed in module 6.3.

# 5. Software

# 5.1. COSMAD: Modal analysis and health monitoring Scilab toolbox

**Keywords:** Scilab, damage detection, damage localization, identification, input-output identification, modal diagnosis, optimal sensor positioning, output-only identification, sensor fusion, subspace-based identification, vibration monitoring.

Participants: Laurent Mevel [corresponding person], Neil Babou, Simon Berger, Maurice Goursat.

With the help of Yann Veillard, Auguste Sam and Simon Berger, former engineers, Laurent Mevel and Maurice Goursat have developed a Scilab toolbox devoted to modal analysis and vibration monitoring of structures or machines subjected to known or ambient (unknown) excitation [57], [56].

This software (COSMAD 3.64) has been registered at the APP under the number

IDDN.FR.001.210011.002.S.A.2003.000.20700

and can be down-loaded from <a href="http://www.irisa.fr/sisthem/cosmad/">http://www.irisa.fr/sisthem/cosmad/</a>. A list of test-cases (simulators, laboratory test-beds, real structures) for which COSMAD has been used is available from <a href="http://www.irisa.fr/sisthem/sisthem-testcases.pdf">http://www.irisa.fr/sisthem/sisthem-testcases.pdf</a>.

The toolbox has undergone heavy changes, performed by Simon Berger as a side project of the FliTE2 European project. COSMAD performs the following tasks:

- Output-only (O/O) subspace-based identification, working batch-wise, see modules 3.5, 6.1 and 7.1. The problem is to identify the eigenstructure (eigenvalues and observed components of the associated eigenvectors) of the state transition matrix of a linear dynamical system, using only the observation of some measured outputs summarized into a sequence of covariance matrices corresponding to successive time shifts. An overview of this method can be found in [3], and details in [48], [61] and [30], [31].
- Input-output (I/O) subspace-based identification, working batch-wise, see modules 3.5, 6.1 and 7.1. The problem is again to identify the eigenstructure, but now using the observation of some measured inputs and outputs summarized into a sequence of cross-covariance matrices. This method is described in [10].
- Automatic subspace-based modal analysis, a pre-tuned version of the O/O and I/O identification methods above. This is described in [57].

- Automated on-line identification package, see modules 3.2, 3.5 and 6.1. The main question is to react to non stationarities and fluctuations in the evolution of the modes, especially the damping. The developed package allows the extraction of such modes using a graphical interface allowing us to follow the evolution of all frequencies and damping over time and to analyze their stabilization diagram (from which they were extracted). Automated modal extraction is performed based on the automated analysis and classification of the stabilization diagram. For this method, see [14] and [58], [49].
- Automatic recursive subspace-based modal analysis, a sample point-wise version of the O/O and I/O identification algorithms above. For this method, see [47].
- Subspace-based identification through moving sensors data fusion, see modules 3.2 and 3.5. The problem is to identify the eigenstructure based on a joint processing of signals recorded at different time periods, under different excitations, and with different sensors pools. The key principles are described in [7] and a consistency result can be found in [9]. Further investigations, including automated mode extraction, can be found in [18], [19].
- Damage detection, working batch-wise, see modules 3.3, 3.5, and 4.2. Based on vibrations measurements processing, the problem is to perform early detection of small deviations of the structure w.r.t. a reference behavior considered as normal. Such an early detection of small deviations is mandatory for fatigue prevention. The algorithm confronts a new data record, summarized by covariance matrices, to a reference modal signature. The method is described in [1], [4].
- *Damage monitoring*, a sample point-wise version of the damage detection algorithm above. This is described in [55].
- On-line flutter onset detection, see modules 3.3, 3.5, 4.2 and 6.3. This algorithm detects that one damping coefficient crosses a critical value from above. For this method see [8] [14]. An extension to detect if some subset of the whole modal parameter vector varies with respect to a threshold value, applies directly to monitoring the evolution of a set of frequencies or a set of damping coefficients with respect to their reference values [40], [50].
- *Modal diagnosis*, working batch-wise, see modules 3.4, 3.5, and 4.2. This algorithm finds the modes the most affected by the detected deviation. For this method, see [4].
- *Damage localization*, see modules 3.4, 3.5 and 4.2. The problem is to find the part of the structure, and the associated structural parameters (e.g. masses, stiffness coefficients) that have been affected by the damage. We state and solve this problem as a detection problem, and not an (ill-posed) inverse estimation problem. This is explained in [4]. This module has been completely rewritten and is now much easier to use [12].
- Optimal sensor positioning for monitoring. At the design stage of the monitoring system, a criterion is computed, which quantifies the relevance of a given sensor number and positioning for the purpose of structural health monitoring. For this criterion, see the articles [38], [36].

The modules have been tested by different partners, especially the French industrial partners, EADS, Dassault and Sopemea, within the FliTE2 project (see module 7.1), by partners from the past CONSTRUCTIF project [30], [31], and within the framework of bilateral contracts with SNECMA and SVIBS (see modules 7.3 and 7.4).

Based on intensive internal evaluation of the toolbox, on both simulated and real data sets, EADS Space Transportation and CNES have been investigating how to use the toolbox for the exploitation of the next Ariane 5 flight data sets [53] [26].

This Scilab toolbox continues to play the role of a programming and development environment for all our newly designed algorithms. Moreover, offering a *maintained* Scilab platform turns out to be a crucial factor in convincing industrial partners to undergo joint investigations with us or to involve us within partnerships in FP6 integrated projects proposals, see module 8.1.

As from December 2007, Neil Babou, associate engineer, works on finalizing the next major version of COSMAD. This version is based on the work of Simon Berger during FliTE2 as described in module 7.1. Major code rewriting has been done to use the object oriented framework. Identification techniques used during FliTE2 have also been implemented. Neil Babou will finalize the toolbox and adapt the graphical interface code in Java to follow the migration of Scilab to this language.

# 6. New Results

# 6.1. Eigenstructure identification

**Keywords:** automated identification, input-output identification, modal analysis, output-only identification, subspace–based method.

Participants: Michèle Basseville, Albert Benveniste, Maurice Goursat, Laurent Mevel.

See modules 3.2, 3.5, 4.2, 7.1, 7.3 and 7.4.

#### 6.1.1. Properties of subspace identification methods.

The article proving general consistency theorems for subspace methods under non stationary excitation, within a general framework encompassing most subspace approaches (either output-only or input/output, should they be covariance, data or frequency driven), has been published in an IEEE journal [16].

### 6.1.2. Identification using filtering techniques.

Some filtering algorithms based on particle filtering theory have been designed [22]. The objective is to provide online confidence intervals for maximum likelihood identification. The work will end up in a filtering toolbox currently developed by F. Campillo and to be used and evaluated within SISTHEM.

#### 6.1.3. Eigenstructure identification.

Succesfull results have been obtained using multipatch methods for merging experiments measured at different times [18], [19]. This method has been tested on the Z24 bridge [55] allowing to get estimation results at once on all the 300 sensors, splitted into 9 setups. The methods did exhibit good capability to produce clean stabilization diagrams without spurious modes. Work is ongoing for improving the quality of the results with the help of SVIBS, see module 7.4.

#### 6.1.4. Improving subspace identification by modal basis change.

Improving subspace identification by changing the modal basis has been investigated with success [24]; see the 2006 activity report.

#### 6.1.5. Robustness to data perturbation.

The stability of the poles when artificial perturbation is added to the data - more precisely to the covariances - has been investigated. It has been shown that spurious modes are usually stable with respect to perturbation, which is a non obvious remark considering the definition of spurious poles for stabilization diagrams (spurious modes are considered to be unstable inside the diagram) [25].

#### 6.2. Change/damage detection and isolation

**Keywords:** change detection, earthquake monitoring, nuisance parameters, null space computation.

Participants: Michèle Basseville, Albert Benveniste, Gilles Canales, Maurice Goursat, Laurent Mevel.

See modules 3.3, 3.4, 6.3 and 6.4.

#### 6.2.1. Variants of the subspace-based detection algorithm.

Whereas the subspace-based residual has been initially introduced as in (18) with a parametric left null space  $U(\theta_0)$  computed as displayed in (15), in some cases it may be of interest to compute an empirical null space, based on a reference dataset only. Performing a SVD of the empirical Hankel matrix built on that dataset provides us with such an empirical kernel. When multiple reference datasets are available, as e.g. when handling the temperature effect, see module 6.4, a global empirical Hankel matrix is computed by averaging the empirical Hankel matrices corresponding to each reference dataset, and a global empirical left kernel can then be computed as above [11].

A FRF driven version of the test, where the covariance matrix results from averaging multiple repetitions of FRF data, has been successfully tested on cantilever data [27].

Bootstrap techniques for computing the residual covariance matrix, based on sub-sampling the residual sequence, have been tested successfully for processing earthquake data which are typically very short and highly nonstationary [17].

#### 6.2.2. Model validation.

The results obtained during the master thesis of Gilles Canales (see the 2006 activity report) on fast minimization of model validation criteria using the subspace damage detection test have been presented at IOMAC 07 [23]. An extension together with an application on a laboratory beam provided by LCPC has been performed.

#### 6.2.3. Frequency domain tests.

The first year of the PhD thesis of G. Canales has been focused on understanding and developing some detection tests in the frequency domain. Indeed, advances in engineering have led to the increase in monitoring capacities (number of sensors). This calls for developing new and more efficient approaches to the monitoring problem. One such approach was to try to work out a frequency domain damage detection test.

A new residual based on the polyreference Least Square Complex Frequency domain (LSCF) identification method has been proposed. Consistency and asymptotical normality of that residual have been proved. Using the local approach and assuming some small changes on the transfer function, a  $\chi_2$  test has been derived. Efficiency of the method for detecting variations in some frequency bands of interest, using the above mentioned model validation framework, has been demonstrated on some laboratory example from VUB, Belgium, see module 9.3.

#### 6.2.4. Handling nuisance parameters.

The investigation [42] of the handling of nuisance parameters in systems monitoring has been pursued. Parameter orthogonality, as expressed in the Fisher information matrix being block-diagonal, is known to be a key issue for investigating the coupling between two subsets of components of the parameter vector [37]. The extension of this orthogonality property, to the case of estimating functions other than in maximum likelihood, should play a role in nuisance parameter rejection [34].

### 6.3. Flutter monitoring and onset detection

Keywords: CUSUM test, aeronautical structure, flutter, modal analysis, subspace-based residual.

Participants: Michèle Basseville, Albert Benveniste, Fethi Bouziani, Maurice Goursat, Laurent Mevel, Rafik Zouari.

See modules 3.3, 3.5, 4.4 and 7.1.

Stating the flutter monitoring problem (see modules 4.4 and 7.1) as a statistical hypotheses testing problem, in [8] and [40] we have advocated for an on-line test built on a sample-wise temporal data-driven computation for the subspace-based residual (18), a non-local approximation for that residual, and the cumulative sum (CUSUM) test [5]. None of these approaches uses any model of the underlying physical phenomenon.

#### 6.3.1. Online CUSUM tests.

During the first year of his thesis, Rafik Zouari has investigated different ways to involve the coupling between two modes and mode-shapes within the framework of our on-line CUSUM test for flutter monitoring: flutter margin [32], modeshapes correlation [33]. The methods have been tested on a 2DOF aero-elastic model of two modes and a 2D airplane wing model.

The second year was focused on developing and enhancing the features of the CUSUM test for different usage conditions. Two versions of the test have been considered. The online computation of the Jacobian and covariance matrices removes the previous requirement of having data corresponding to the reference state. This is a progress for the design of flutter test because this reference data should have been as close as possible to the flutter [8], [14], which is unrealistic. Now the reference is only defined by the kernel matrix S. This matrix can be derived and computed from the SVD of a parametric observability matrix  $O_p$ , built using some value of the parameter assumed to be close to flutter. The previous remark implies that if any numerical aeroelastic model is available for the prediction of flutter speed, such a model can be used to give an estimate of the parameter close to flutter. Such an approach was tested on a 2DOF model with success. The lack of accurate models for realistic case studies yield to another formulation of the test.

Propagation of the inverse and or the half inverse covariance matrix has been investigated, using the inverse matrix lemma or a QR computation, respectively. The online computation of the covariance makes the test robust to changes in the excitation level. Another consequence is that the reference state is only present in the kernel matrix used in the residual: the availability of data corresponding to the reference state is no longer required, a crucial issue when it comes to a state preceding instability. This allows using numerical prediction for computing the flutter speed and updating the kernel. A prediction based on a complete numerical model has been investigated for a small structure [20]. Frequency-domain identification-based prediction is being investigated, thanks to a collaboration with the Acoustics & Vibration Research Group of Vrije Universiteit Brussel (VUB), see module 9.3.

Alternatively, a new empirical approach to kernel computation has been evaluated. It compares a recursive Hankel matrix computed online for each time instant t, with a recursive computation of its kernel. The kernel is representative of the modal state at some previous instant. If some brutal change arises, a discrepancy appears between the Hankel matrix and its kernel because of the delay between both computations. The test is not performing flutter detection but monitors the brutal variations of the monitored parameter, which will be the flutter phenomena if we assume that flutter corresponds to a brusque variation in the dynamics of the parameter.

#### 6.3.2. Comparing identification and detection approaches to monitoring.

A common monitoring approach views monitoring as an online *identification* problem. At each time step, the desired parameters must be re-identified from a data batch. A less standard monitoring approach views monitoring as an online *detection* problem. At each time step, the only issue addressed is whether the desired parameters have changed or not. An article introducing and comparing both subspace-based approaches for online in-flight vibration-based monitoring has been published in the special issue on *Applications of System Identification* of the *IEEE Control Systems Magazine* [14].

#### 6.3.3. Robust flutter margins for flutter detection.

Fethi Bouziani, CNRS postdoc, is focussing on developing new algorithms for flutter detection. He started by evaluating the merits of the  $\mu$  method developed by NASA for determining robust flutter margins. The objective is to formulate this approach in the context of statistics, and to derive some relevant statistical indicators.

# **6.4.** Handling the temperature effect

**Keywords:** civil engineering structures, modal analysis, temperature effect.

Participants: Michèle Basseville, Laurent Mevel.

See modules 3.4, 3.5 and 4.3.

The PhD thesis of Houssein Nasser completed last year has addressed the problem of rejecting the temperature effect when performing damage detection tests on civil structures. Because of the temperature effects, the test may not react to some damages, and conversely may be too sensitive to some ambient temperature changes. Three different methods have been proposed for overcoming these drawbacks. The first one [35] uses the simplified model of the temperature effect on the modal parameters, and rejects the temperature effect seen as a nuisance parameter. The second method assumes that the temperature (or any equivalent measure of the ambient state) is measured, involves the computation of a finite elements model (FEM) for updating the reference left kernel used in the computation of the test [39]. The third approach is based on the collection of varying reference temperature datasets, and on a reference kernel averaging all the temperature scenarios [11].

This year, the actual robustness to temperature changes of the proposed methods has been further investigated within LCPC by Dominique Siegert under the supervision of SISTHEM [31]. Different damage and temperature changes have been performed on a beam. The extreme reaction of the test to damages and its robustness to temperature changes have been shown.

#### 6.4.1. Damage detection for masonry structures.

Identification and damage detection under temperature changes have been performed on the Mogadouro clock tower and the San Jeronimo monastery church, two important historical monuments in Portugal [29]. It has been shown that subspace based damage detection methods as developed during H. Nasser's PhD thesis are robust to temperature changes. It has also been shown that online covariance computation is mandatory to get rid of false alarms due to seismic events as happened on the San Jeronimo church in 2007 during the measurement period. This work has been conducted in collaboration with Luis Ramos, from the University of Minho, Portugal.

#### 6.4.2. Involving modal filters.

We are collaborating with A. Deraemaeker from ULB to investigate the performance of a damage detection algorithm working on modal filters data instead of raw time series [28]. Typically, for a structure equipped with hundreds of sensors, the data reduction resulting from the modal filter algorithm consists in a number of distributed sensors equal to the number of modes in the frequency band of interest (generally 10 to 20).

# 7. Contracts and Grants with Industry

# 7.1. Eurêka project FliTE2

Participants: Michèle Basseville, Albert Benveniste, Simon Berger, Maurice Goursat, Laurent Mevel, Rafik Zouari

See modules 4.2, 4.4, 5.1, 6.1 and 6.3.

Contract INRIA — September 2005/August 2008.

We have been strongly contributing to the establishment, within the Eurêka framework, of a follow-up of the major cooperation FliTE for which a success story is available at

http://www.eureka.be/inaction/viewSuccessStory.do?docid=2684250.

The Eurêka project no 3341 FliTE2 («Flight Test Easy Extension») is devoted to improving the exploitation of flight test data, under natural excitation conditions (e.g. turbulence), enabling more direct exploration of the flight domain, with improved confidence and at reduced cost. It is coordinated by the industrial test laboratory Sopemea. As in FliTE the partners are Dassault–Aviation and EADS (AeroMatra Airbus) (France), LMS and KU Leuven (Belgium), Cracow University and the company PZL–Mielic (Poland), and INRIA. The partnership is extended to ONERA/CERT, to Lambert Aircraft Engineering, an SME building light aircrafts, and to the Dynamics and Aero-elasticity Group of Manchester University. Albert Benveniste helps Sopemea in the scientific coordination of the project.

In FliTE, the basis for novel techniques for in-flight test data structural analysis was developed, involving both controlled and uncontrolled (natural) excitations. The main objective of FliTE2 is the effective transfer of the results, algorithms, tools, and techniques of FliTE to aircraft manufacturers (Airbus. Dassault-Aviation) and vendors and service providers (LMS-International, SOPEMEA) members of the project. Domains covered by FliTE2 include:

- On-line and during flight processing of flight test data. This is part of flight tests and has two objectives:
  - flutter monitoring, that is, monitoring the risk that the aircraft enters into aeroelastic instability, possibly resulting in a loss of the aircraft; needed reaction time for flutter monitoring in about 1-10 seconds, depending on aircraft;
  - getting modal analysis of the aircraft in flight conditions; this analysis is then used to update the Finite Element model of the aircraft, and finalize fine tuning of various flight control algorithms.
- Ground Vibration Tests (GVT) and Environmental Tests. These are tests performed on ground, by properly shaking the structure. GVT is a major step in aircraft qualification, goal was to improve the quality and reduce the cost (use cheaper excitation techniques and faster modes of testing). Environmental tests are just qualification tests for structures subject to vibrations. Currently, the corresponding data are not exploited (since excitation forces are not measured in those tests). The goal is to exploit these data to perform modal analysis.

The project is structured into Working Groups, one for each major industrial user. This has facilitated the preparation of transfer, by properly adjusting to the specific requirements The WGs are driven by ONERA (with Airbus), Dassault-Aviation, SOPEMEA and LMS on ground vibration tests, and PZL and AGH on environmental tests. In addition, an extra WG, driven by Laurent Mevel (INRIA) and Jonathan Cooper (Manchester University), is devoted to research on aero-elastic flutter monitoring and prediction. Each of the academic partners is involved in several WGs.

Common algorithmic platforms have been developed and then customized for the different industrial users. The project also involves lots of advanced research, in both 1-second real-time modal analysis and flutter monitoring, leading to drastically new methods and algorithms. The project has created a unique tight network of academic and industrial partners over the years, which constitutes a significant competitive advantage in the considered sector. Of course, finalizing transfer until the flight test facilities of aircraft manufacturers will still require work beyond the end of Flite2. But FliTE2 will undoubtely be a big step forward in this area.

The project has attracted major interest as the following fact demonstrates. Due to late funding of the French partners, FliTE2 is closing by the end of 2007 for the Flamish and Polish partners. Still, at the last meeting in November 2007, they decided to continue working in FliTE2 with sustained manpower for the entire year 2008 (end of 2008 is the end of project for the French part).

In addition to and tightly connected with the involvment within the WGs mentioned above, the contribution of SISTHEM within FliTE2 is twofold. Rafik Zouari, during the second year of his thesis, has been developing several versions of the CUSUM test for flutter monitoring and instability prediction (see module 6.3). Simon Berger, engineer, has been working on transferring the subspace identification methods to ONERA. A Matlab prototype has been delivered this year for evaluation at ONERA. The prototype handles flight test records and performs automated online tracking of modes (frequency and damping coefficient) over time. The case study for this project asks for performing automated identification every one second and plotting frequencies and damping ratios for flutter monitoring. Automated model reduction techniques, as well as automated cluster analysis of stabilization diagrams have been implemented. A new object oriented framework have been used for implementing all those techniques in the COSMAD toolbox. Software packages have been delivered to ONERA for evaluation.

#### 7.2. FP7-NMP Large Scale IP IRIS

Participants: Michèle Basseville, Albert Benveniste, Maurice Goursat, Laurent Mevel.

See modules 4.2, 5.1.

Contract INRIA

SISTHEM is involved in the core consortium of the newly accepted FP7-NMP Large Scale Integrated Project IRIS (*Integrated European Industrial Risk Reduction System*). This project has been elaborated within the framework of the SAMCO association (see module 8.1). SISTHEM is involved in the online monitoring subproject.

#### **7.3. SNECMA**

Participants: Maurice Goursat, Laurent Mevel.

See modules 4.2, 4.4, 5.1, and 6.1.

Contract INRIA — January 2007/June 2007.

SISTHEM has investigated for SNECMA an identification case study on some undisclosed engine structure. Successfull results yield to the delivery of the COSMAD toolbox for internal evaluation at SNECMA. The end goal is the use of COSMAD in the industrial process of SNECMA.

# **7.4. SVIBS**

**Participants:** Maurice Goursat, Laurent Mevel.

See modules 4.2, 4.3, 5.1, 6.1, 6.2 and 6.4.

Annual agreement INRIA-SVIBS.

SVIBS (Structural Vibration Solutions A/S) is a company located in Aalborg, Denmark, having strong connections with the Department of Building Technology and Structural Engineering of Aalborg University (Prof. Rune Brincker).

SVIBS and SISTHEM are investigating how to link the modal analysis software ARTeMIS of SVIBS and COSMAD. Joint papers have been published [17], [18], [19]. Through an annual agreement, SISTHEM gets a license of ARTeMIS in exchange to offer support for integrating our damage detection software into SVIBS software and offerings.

# 8. Other Grants and Activities

#### 8.1. SAMCO association

Participant: Michèle Basseville.

See modules 4.2, 4.3 and 5.1.

The FP5 Growth thematic network SAMCO has been active from October 2001 until March 2006 within the framework of the Growth program. It has become a focal point of reference in the field of assessment, monitoring and control of civil and industrial structures, in particular the transportation infrastructure (bridges, etc.). The European Association for SAMCO was founded on April 2006. We are involved especially in the thematic group «Monitoring and Assessment». This turns out to be a useful complement to the diffusion of our knowledge and expertise in vibration monitoring.

Within this framework, we have offered Scilab as an open platform for the integration of the modules for algorithms and methods covering the objectives of automatic modal analysis, automatic modal and statistical damage detection methods. We have also offered the COSMAD toolbox, see module 5.1.

We are involved in the IRIS project proposal, dedicated to an *Integrated European Risk Reduction System*, submitted in the framework of the FP7 NMP-Large call, at the second stage.

#### 8.2. FWO Research Network ICCoS

Participants: Michèle Basseville, Albert Benveniste, Maurice Goursat, Laurent Mevel.

We participate to the Scientific Research Network «Identification and Control of Complex Systems» (ICCoS) launched by the Research Foundation of Flanders (FWO). This network is dedicated to national and international cooperation at postdoctoral level for the development of identification and control design methodologies.

## 8.3. Partnership with KU Leuven

Participant: Laurent Mevel.

Agreement INRIA-KU.Leuven

SISTHEM and Katholieke Universiteit Leuven (Guido de Roeck, Civil Engineering Department) are collaborating on the topic of confidence intervals for subspace-based estimates.

### 8.4. International collaborations

Participants: Michèle Basseville, Gilles Canales, Maurice Goursat, Laurent Mevel, Rafik Zouari.

This year, SISTHEM has been collaborating with the following universities and institutes:

- Aalborg University (DK), Civil Engineering Department [18], [19],
- The University of British Columbia (CA), Civil Engineering Department [17],
- Université Libre de Bruxelles (B), Active Structures Laboratory [28],
- Vrije Universiteit Brussel (B), Acoustics & Vibration Research Group, see module 9.3,
- Minho University (PT), Civil Engineering Department [29],
- Katholieke Universiteit Leuven (B), Civil Engineering Department [29],
- Harbin Institute of Technology (PRC), Civil Engineering Department [17],
- LCPC, Metrology and Instrumentation Division [30], [31].

# 9. Dissemination

#### 9.1. Scientific animation

M. Basseville is co-chair of the IFAC technical committee 6.4 «Fault Detection, Supervision and Safety of Technical Processes», within the coordinating committee 6 «Industrial Applications», and member of the technical committees 1.1 «Modeling, Identification and Signal Processing» and 1.4 «Stochastic Systems», within the coordinating committee 1 «Systems and Signals». She is associate editor for the IFAC journal «Automatica» and member of the editorial board of the IET journal «Control Theory and Applications». She is chair of the CNRS experts committee *Diagnostic et Sécurité*, and member of the Scientific Council of the research consortium (GIS) *Surveillance*, *Sûreté et Sécurité des Grands Systèmes* (3SGS).

A. Benveniste is associated editor at large (AEAL) for the journal IEEE *Transactions on Automatic Control*. He is member of the Strategic Advisory Council of the Institute for Systems Research, Univ. of Maryland, College Park, USA.

# 9.2. Conference and workshop committees, invited conferences

#### 9.2.1. Committees.

M. Basseville is associate editor within the IEEE Control Systems Society Conference Editorial Board, where she has been and still is in charge of the evaluation of papers submitted to ACC'07, CDC'07, and ACC'08.

L. Mevel has organized an invited session on *Identification uncertainty* for the International Operational Modal Analysis Conference (IOMAC'07), in Aalborg, Denmark, in April 2007. He is member of the IOMAC Scientific Committee.

#### 9.2.2. Invited publications.

The team has been involved in:

- The special issue on *Applications of System Identification* of the *IEEE Control Systems Magazine*. An article entitled «In-flight monitoring of aeronautical structures: vibration-based online automated identification versus detection» has been published [14];
- The special issue on *Advances in Subspace-Based Techniques for Signal Processing and Communications* of the *EURASIP Journal of Applied Signal Processing*. An article entitled «Subspace-based algorithms for structural identification, damage detection, and sensor data fusion» has been published [15];
- The Encyclopedia of SHM. An article entitled « Model-based statistical signal processing for change and damage detection», outlining the key concepts of the statistical model-based change detection methodology and its usefulness for addressing fault and damage detection problems, has been invited and accepted [13];
- A minisymposium on *Identification Methods in Structural Dynamics* organized for the *ECCOMAS Thematic Conference: 1st International Conference on Computational Dynamics and Earthquake Engineering (COMPDYN'07)* which took place in Rethymnon, Krete, Greece, on June 2007.

#### 9.3. Visits and invitations

Tim De Troyer, PhD student within the Acoustics & Vibration Research Group of the Vrije Universiteit in Brussel, visited us a couple of weeks during the summer. With Rafik Zouari, he has investigated how to link frequency identification methods and statistical detection tests. The objective is to use the prediction of flutter speed provided by his frequency identification methods for online tuning of the statistical CUSUM test. The latter method should help the former improving the flutter detection accuracy.

Laurent Mevel visited Palle Andersen, Managing Director of Structural Vibration Solutions A/S (SVIBS), Aalborg, Denmark, during a couple of days in May 2007. SVIBS is promoting ARTeMIS, a commercial modal identification software, and is interested in our know-how on damage detection and localization. The ongoing work consists in sharing real data, possibly coming from major places outside Europe, and comparing identification and detection results obtained with either ARTeMIS or COSMAD - see modules 5.1, 6.1, 6.2 and 7.4.

# 10. Bibliography

# Major publications by the team in recent years

- [1] M. BASSEVILLE, M. ABDELGHANI, A. BENVENISTE. Subspace–based fault detection algorithms for vibration monitoring, in "Automatica", vol. 36, n<sup>o</sup> 1, January 2000, p. 101–109, http://dx.doi.org/10.1016/S0005-1098(99)00093-X.
- [2] M. BASSEVILLE. On–board component fault detection and isolation using the statistical local approach, in "Automatica", vol. 34, n<sup>o</sup> 11, November 1998, p. 1391–1416, http://dx.doi.org/10.1016/S0005-1098(98)00086-7.

[3] M. BASSEVILLE, A. BENVENISTE, M. GOURSAT, L. HERMANS, L. MEVEL, H. VAN DER AUWERAER. Output—only subspace—based structural identification: from theory to industrial testing practice, in "ASME Journal of Dynamic Systems, Measurement, and Control", vol. 123, n<sup>o</sup> 4, December 2001, p. 668–676, http://dx.doi.org/10.1115/1.1410919.

- [4] M. BASSEVILLE, L. MEVEL, M. GOURSAT. Statistical model-based damage detection and localization: subspace-based residuals and damage-to-noise sensitivity ratios, in "Journal of Sound and Vibration", vol. 275, no 3-5, August 2004, p. 769-794, http://dx.doi.org/10.1016/j.jsv.2003.07.016.
- [5] M. BASSEVILLE, I. V. NIKIFOROV. *Detection of Abrupt Changes Theory and Applications*, Information and System Sciences Series, Prentice Hall, Englewood Cliffs, 1993, <a href="http://www.irisa.fr/sisthem/kniga/">http://www.irisa.fr/sisthem/kniga/</a>.
- [6] A. BENVENISTE, M. MÉTIVIER, P. PRIOURET. *Adaptive Algorithms and Stochastic Approximations*, Applications of Mathematics, vol. 22, Springer Verlag, New York, 1990.
- [7] L. MEVEL, M. BASSEVILLE, A. BENVENISTE, M. GOURSAT. *Merging sensor data from multiple measure-ment setups for nonstationary subspace–based modal analysis*, in "Journal of Sound and Vibration", vol. 249, n<sup>o</sup> 4, January 2002, p. 719–741, http://dx.doi.org/10.1006/jsvi.2001.3880.
- [8] L. MEVEL, M. BASSEVILLE, A. BENVENISTE. Fast in-flight detection of flutter onset: a statistical approach, in "AIAA Journal of Guidance, Control, and Dynamics", vol. 28, no 3, May 2005, p. 431-438, http://pdf.aiaa.org/jaPreview/JGCD/2005/PVJA6184.pdf.
- [9] L. MEVEL, A. BENVENISTE, M. BASSEVILLE, M. GOURSAT. Blind subspace-based eigenstructure identification under nonstationary excitation using moving sensors, in "IEEE Transactions on Signal Processing", vol. SP-50, no 1, January 2002, p. 41-48, http://dx.doi.org/10.1109/78.972480.
- [10] L. MEVEL, A. BENVENISTE, M. BASSEVILLE, M. GOURSAT, B. PEETERS, H. VAN DER AUWERAER, A. VECCHIO. *Input/output versus output-only data processing for structural identification - Application to in-flight data analysis*, in "Journal of Sound and Vibration", vol. 295, n<sup>o</sup> 3-5, August 2006, p. 531-552, http://dx.doi.org/10.1016/j.jsv.2006.01.039.

#### **Year Publications**

## Articles in refereed journals and book chapters

- [11] É. BALMÈS, M. BASSEVILLE, F. BOURQUIN, L. MEVEL, H. NASSER, F. TREYSSÈDE. Merging sensor data from multiple temperature scenarios for vibration-based monitoring of civil structures, in "Structural Health Monitoring", To appear, vol. 7, 2008.
- [12] É. BALMÈS, M. BASSEVILLE, L. MEVEL, H. NASSER, W. ZHOU. *Statistical model-based damage localization: a combined subspace-based and substructuring approach*, in "Structural Control and Health Monitoring", To appear Published online on Sept. 11, 2007, 2007, http://dx.doi.org/10.1002/stc.223.
- [13] M. BASSEVILLE. *Model-based statistical signal processing for change and damage detection*, in "Encyclopedia of Structural Health Monitoring, Chichester, UK", C. BOLLER, F.-K. CHANG, Y. FUJINO (editors), To appear, Wiley, 2008.

- [14] M. BASSEVILLE, A. BENVENISTE, M. GOURSAT, L. MEVEL. In-flight monitoring of aeronautic structures: vibration-based on-line automated identification versus detection, in "IEEE Control Systems Magazine, Special Issue on Applications of System Identification", vol. 27, n<sup>o</sup> 5, oct 2007, p. 27-42, http://dx.doi.org/10. 1109/MCS.2007.904652.
- [15] M. BASSEVILLE, A. BENVENISTE, M. GOURSAT, L. MEVEL. Subspace-based algorithms for structural identification, damage detection, and sensor data fusion, in "Journal of Applied Signal Processing, Special Issue on Advances in Subspace-Based Techniques for Signal Processing and Communications", Article ID 69136, vol. 2007, 2007, http://www.hindawi.com/GetArticle.aspx?doi=10.1155/2007/69136.
- [16] A. Benveniste, L. Mevel. *Nonstationary consistency of subspace methods*, in "IEEE Transactions on Automatic Control", vol. 52, n<sup>o</sup> 6, June 2007, p. 974-984, http://dx.doi.org/10.1109/TAC.2007.898970.

#### **Publications in Conferences and Workshops**

- [17] P. ANDERSEN, M. BASSEVILLE, L. MEVEL, C. VENTURA, W. ZHOU. Seismic damage assessment in structures using stochastic subspace-based algorithm, in "Proceedings of the 1st International Conference on Computational Dynamics and Earthquake Engineering (COMPDYN), Rethymno, Crete, GR", Paper 1060, ECCOMAS, June 2007.
- [18] P. Andersen, R. Brincker, M. Goursat, L. Mevel. *Automated modal parameter extraction of civil engineering structures*, in "Proceedings of the 2nd International Conference on Experimental Vibration Analysis for Civil Engineering Structures (EVACES), Porto, PT", Paper 160, U. Porto and LCPC, October 2007.
- [19] P. Andersen, R. Brincker, L. Mevel. *Automated modal parameter estimation for operational modal analysis*, in "Proceedings of the International Operational Modal Analysis Conference (IOMAC), Aalborg, DK", Paper 45, April 2007.
- [20] M. BASSEVILLE, A. BENVENISTE, L. MEVEL, R. ZOUARI. *On-line detection of aircraft instability precursors*, in "Proceedings of the 56th ISI session, Special Topics Contributed Paper Meeting on Changepoint detection and nonlinear filtering methods: applications, Lisbon, PT", International Statistical Institute, August 2007.
- [21] M. BASSEVILLE, L. MEVEL, H. NASSER. *Méthodes sous-espaces pour la surveillance vibratoire sous contraintes thermiques*, in "Proceedings of the 21st Colloque GRETSI, Troyes, F.", Paper 90, September 2007.
- [22] F. CAMPILLO, G. CANALES, L. MEVEL. *Particle based confidence intervals*, in "Proceedings of the International Operational Modal Analysis Conference (IOMAC), Aalborg, DK", Paper 131, April 2007.
- [23] G. CANALES, L. MEVEL. A quasi Newton based model validation procedure for improving parameter estimation, in "Proceedings of the International Operational Modal Analysis Conference (IOMAC), Aalborg, DK", Paper 136, April 2007.
- [24] M. GOURSAT, L. MEVEL. *Use of modal basis in two steps subspace identification procedure*, in "Proceedings of the 25th International Modal Analysis Conference (IMAC–XXV), Orlando, Fl.", Paper 92, SEM, Inc., February 2007.

[25] M. GOURSAT, L. MEVEL. Covariance subspace identification: numerical analysis of spurious mode stability, in "Proceedings of the 26th International Modal Analysis Conference (IMAC–XXVI), Orlando, Fl.", Paper 73 - To appear, SEM, Inc., February 2008.

- [26] V. LE GALLO, M. GOURSAT, LUC-OLIVIER. GONIDOU. Damping characterization and flight identification, in "Proceedings of the 25th International Modal Analysis Conference (IMAC–XXV), Orlando, Fl.", Paper 56, SEM, Inc., February 2007.
- [27] L. MEVEL, A. BENVENISTE, S. BERGER, M. SPLETZER, A. RAMAN. *Enhanced mass sensing using subspace identification in microcantilevers*, in "Proceedings of the 25th International Modal Analysis Conference (IMAC–XXV), Orlando, Fl.", Paper 97, SEM, Inc., February 2007.
- [28] H. NASSER, A. DERAEMAECKER, L. MEVEL, M. BASSEVILLE. *Modal filtering data reduction and subspace detection for handling the temperature effect in structural health monitoring*, in "Proceedings of the 2nd International Conference on Experimental Vibration Analysis for Civil Engineering Structures (EVACES), Porto, PT", Paper 027, U. Porto and LCPC, October 2007.
- [29] L. RAMOS, L. MEVEL, PAULO B. LOURENÇO, G. DE ROECK. *Dynamic monitoring of historical masonry structures for damage identification*, in "Proceedings of the 26th International Modal Analysis Conference (IMAC–XXVI), Orlando, Fl.", Paper 63 To appear, SEM, Inc., February 2008.
- [30] D. SIEGERT, L. DIENG, M. GOURSAT. *Frequency monitoring of stay-cables*, in "Proceedings of the 25th International Modal Analysis Conference (IMAC–XXV), Orlando, Fl.", Paper 150, SEM, Inc., February 2007.
- [31] D. SIEGERT, L. MEVEL, M. GOURSAT. *Experimental validation of damage monitoring techniques in variable temperature conditions*, in "Proceedings of the 26th International Modal Analysis Conference (IMAC–XXVI), Orlando, Fl.", Paper 96 To appear, SEM, Inc., February 2008.
- [32] W. Zhou, S. Maalej, R. Zouari, L. Mevel. *Flutter monitoring with the statistical subspace method for the 2-D structure*, in "Proceedings of the 25th International Modal Analysis Conference (IMAC–XXV), Orlando, Fl.", Paper 93, SEM, Inc., February 2007.
- [33] R. ZOUARI, L. MEVEL, M. BASSEVILLE. *Mode-shapes correlation and CUSUM test for on-line flutter monitoring*, in "Proceedings of the 17th IFAC Symposium on Automatic Control in Aerospace (ACA), Toulouse, F.", Paper 55, IFAC, June 2007.

#### **Internal Reports**

[34] M. BASSEVILLE. *Traitement des paramètres de nuisance : orthogonalité et insensibilité*, Technical report, n<sup>o</sup> 1860, IRISA, July 2007, http://hal.inria.fr/inria-00165485/fr/.

#### References in notes

[35] É. BALMÈS, M. BASSEVILLE, L. MEVEL, H. NASSER. Handling the temperature effect in vibration-based monitoring of civil structures: a combined subspace-based and nuisance rejection approach, in "Proceedings of the 6th Symposium on Fault Detection, Supervision and Safety of Technical Processes (SAFEPROCESS), Beijing, China", IFAC/IMACS, August 2006, p. 655-660.

- [36] M. BASSEVILLE. On sensor positioning for structural health monitoring, in "Proceedings of the 2nd European Workshop on Structural Health Monitoring, Munich, FRG", July 2004.
- [37] M. BASSEVILLE. *Information criteria for residual generation and fault detection and isolation*, in "Automatica", vol. 33, n<sup>o</sup> 5, May 1997, p. 783–803, http://dx.doi.org/10.1016/S0005-1098(97)00004-6.
- [38] M. BASSEVILLE, A. BENVENISTE, B. GACH-DEVAUCHELLE, M. GOURSAT, D. BONNECASE, P. DOREY, M. PREVOSTO, M. OLAGNON. *Damage monitoring in vibration mechanics: issues in diagnostics and predictive maintenance*, in "Mechanical Systems and Signal Processing", vol. 7, n<sup>o</sup> 5, 1993, p. 401–423, http://dx.doi.org/10.1006/mssp.1993.1023.
- [39] M. BASSEVILLE, F. BOURQUIN, L. MEVEL, H. NASSER, F. TREYSSÈDE. *Handling the temperature effect in SHM: combining a subspace-based statistical test and a temperature-adjusted null space*, in "Proceedings of the 3rd European Workshop on Structural Health Monitoring, Granada, S.", July 2006, p. 759-766.
- [40] M. BASSEVILLE, M. GOURSAT, L. MEVEL. *Multiple CUSUM tests for flutter monitoring*, in "Proceedings of the 14th Symposium on System Identification (SYSID), Newcastle, Aus.", IFAC / IFORS, March 2006, p. 624-629.
- [41] M. BASSEVILLE, I. V. NIKIFOROV. *Fault isolation for diagnosis : nuisance rejection and multiple hypotheses testing*, in "Annual Reviews in Control", vol. 26, n<sup>o</sup> 2, December 2002, p. 189–202, http://dx.doi.org/10.1016/S1367-5788(02)00029-9.
- [42] M. BASSEVILLE, I. V. NIKIFOROV. *Handling nuisance parameters in systems monitoring*, in "Proceedings of the 44th IEEE Conference on Decision and Control and European Control Conference (CDC-ECC'05), Seville, Spain", IEEE & EUCA, December 2005.
- [43] C. BOLLER. Ways and options for aircraft structural health management, in "Proceedings of the European COST F3 Conference on System Identification and Structural Health Monitoring, Madrid, Spain", June 2000, p. 71–82.
- [44] B. DELYON, A. JUDITSKY, A. BENVENISTE. On the relationship between identification and local tests, Publication Interne, no 1104, IRISA, May 1997, ftp://ftp.irisa.fr/techreports/1997/PI-1104.ps.gz.
- [45] G. DIMITRIADIS, J. E. COOPER. *Flutter prediction from flight flutter test data*, in "Journal of Aircraft", vol. 38, n<sup>o</sup> 2, 2001, p. 355–367.
- [46] C. R. FARRAR, S. W. DOEBLING, D. NIX. *Vibration-based structural damage identification*, in "The Royal Society, Philosophical Transactions: Mathematical, Physical and Engineering Sciences", vol. 359, n<sup>o</sup> 1778, 2001, p. 323–345.
- [47] I. GOETHALS, L. MEVEL, A. BENVENISTE, B. DE MOOR. *Recursive output-only subspace identification for in-flight flutter monitoring*, in "Proceedings of the 22nd International Modal Analysis Conference (IMAC–XXII), Dearborn", SEM, Inc., January 2004.
- [48] M. GOURSAT, L. MEVEL. An example of analysis of thermal effects on modal characteristics of a mechanical structure using Scilab, in "Scilab Research, Development and Applications, Beijing, China", S.-Y. QIN, B. HU, S. LI, C. GOMEZ (editors), Tsinghua University Press Springer, 2005, p. 241–256.

[49] M. GOURSAT, L. MEVEL. *On-line monitoring of Bradford stadium*, in "Proceedings of the 23rd International Modal Analysis Conference (IMAC–XXIII), Orlando, FL.", SEM, Inc., January 2005.

- [50] M. GOURSAT, L. MEVEL. Scilab tools for simulation of systems with non stationary modal parameters, in "Proceedings of the 8th International Middle Eastern Simulation Multiconference, Alexandria, Egypt", August 2006, p. 193–199.
- [51] C. C. HEYDE. Quasi-Likelihood and its Applications, Springer Series in Statistics, Springer-Verlag, Berlin, 1997.
- [52] M. KEHOE. A historical overview of flight flutter testing, Technical Memorandum, n<sup>o</sup> NASA TM-4720, NASA Dryden, October 1995.
- [53] V. LE GALLO, M. GOURSAT, L. GONIDOU. Damping characterization and flight identification, in "Proceedings of the 57th International Astronautical Congress (IAC 2006), Valencia, S.", International Academy of Astronautics, October 2006.
- [54] R. LIND. Flight test evaluation of flutter prediction methods, in "Journal of Aircraft", vol. 40, n<sup>o</sup> 5, 2003, p. 964–970.
- [55] L. MEVEL, M. GOURSAT, M. BASSEVILLE. Stochastic subspace-based structural identification and damage detection and localization — Application to the Z24 bridge benchmark, in "Mechanical Systems and Signal Processing", vol. 17, n<sup>o</sup> 1 (Special issue on COST F3 Benchmarks), January 2003, p. 143–151, http://dx.doi. org/10.1006/mssp.2002.1552.
- [56] L. MEVEL, M. GOURSAT, M. BASSEVILLE. *Detection for in-operation structures : a Scilab toolbox use of the GUI for the localization*, in "Proceedings of the 22nd International Modal Analysis Conference (IMAC–XXII), Dearborn", SEM, Inc., January 2004.
- [57] L. MEVEL, M. GOURSAT. A complete Scilab toolbox for output—only identification, in "Proceedings of the 22nd International Modal Analysis Conference (IMAC–XXII), Dearborn", SEM, Inc., January 2004.
- [58] L. MEVEL, M. GOURSAT, A. SAM. *Automated on-line monitoring during a flight*, in "Proceedings of the 22nd International Modal Analysis Conference (IMAC–XXII), Dearborn", SEM, Inc., January 2004.
- [59] H. G. NATKE, C. CEMPEL. Model-Aided Diagnosis of Mechanical Systems: Fundamentals, Detection, Localization, Assessment, Springer-Verlag, Berlin, 1997.
- [60] B. PEETERS, J. MAECK, G. DE ROECK. Vibration-based damage detection in civil engineering: excitation sources and temperature effects, in "Smart Materials and Structures", vol. 10, no 3, 2001, p. 518-527.
- [61] D. SIEGERT, S. STAQUET, G. CUMUNEL, M. GOURSAT, F. TOUTLEMONDE. *Vibration based structural health monitoring of prebended steel-VHPC beams*, in "Proceedings of the SEM Annual Conference, Saint Louis, MI", Paper 302, June 2006.
- [62] P. VAN OVERSCHEE, B. DE MOOR. Subspace Identification for Linear Systems, Kluwer Academic Publishers, Boston, 1996.

[63] H. VAN DER AUWERAER, B. PEETERS. *International research projects on structural health monitoring : an overview*, in "Structural Health Monitoring", vol. 2, n<sup>o</sup> 4, December 2003, p. 341–358.