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Statistical Inference for STructural HEalth Monitoring

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2. Overall Objectives

2.1. Overall Objectives

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 [50], [66]. 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 machinery, ...

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 diagnostics 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.

- 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 - FP5 Growth),
- 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.

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 raise 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 θ_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 [54] :

$$\hat{\theta}_N = \arg\{\theta \in \Theta \, : \, \mathcal{K}_N(\theta) = 0\}$$

Assuming that θ^* is the true parameter value, and that $\mathbf{E}_{\theta^*}[\mathcal{K}_N(\theta)] = 0$ if and only if $\theta = \theta^*$ with θ^* fixed (identifiability condition), then $\hat{\theta}_N$ converges towards θ^*. From the central limit theorem, the vector $\mathcal{K}_N(\theta^*)$ is asymptotically Gaussian with zero mean, with covariance matrix Σ 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 $\mathcal{K}_N(\hat{\theta}_N) = 0$, the asymptotic normality of the estimate is obtained :

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

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

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

3.3. Detection

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

See module 6.4.

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 θ_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 $\{\mathbf{P}_\theta\,,\ \theta \in \Theta\}$, and the safe behavior of the process is assumed to correspond to the parameter value θ_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 :

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

where η 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 [48] that the residual is asymptotically Gaussian :

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

where the asymptotic covariance matrix Σ 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 χ^2-test, provided that $\mathcal{J}$ is full rank and Σ is invertible :

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

where

$$\overline{\zeta} \triangleq \mathcal{J}^T\,\Sigma^{-1}\,\zeta_N \quad \text{and} \quad \mathbf{F} \triangleq \mathcal{J}^T\,\Sigma^{-1}\,\mathcal{J} \tag{4}$$

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 Σ 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 6.5 and 6.4.

A further monitoring step, often called *fault isolation*, consists in determining which (subsets of) components of the parameter vector θ 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 θ have changed ?*, can be addressed using either nuisance parameters elimination methods or a multiple hypotheses testing approach [45]. Here we only sketch two intuitively simple statistical nuisance elimination techniques, which proceed by projection and rejection, respectively.

The fault vector η 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

$$\eta = \begin{pmatrix} \eta_a \\ \eta_b \end{pmatrix} \ , \quad \mathcal{J} = \begin{pmatrix} \mathcal{J}_a & \mathcal{J}_b \end{pmatrix} \ , \quad \mathbf{F} = \begin{pmatrix} \mathbf{F}_{aa} & \mathbf{F}_{ab} \\ \mathbf{F}_{ba} & \mathbf{F}_{bb} \end{pmatrix} \ , \quad \overline{\zeta} = \begin{pmatrix} \overline{\zeta}_a \\ \overline{\zeta}_b \end{pmatrix} \ .$$

A rather intuitive statistical solution to the isolation problem, which can be called *sensitivity* approach, consists in projecting the deviations in η onto the subspace generated by the components η_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 :

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

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

Another statistical solution to the problem of isolating η_a consists in viewing parameter η_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 η_b by its least favorable value, for deciding between $\eta_a = 0$ and $\eta_a \neq 0$, with η_b unknown. This results in the following test statistics :

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

where $\overline{\zeta}_a^{\,*} \triangleq \overline{\zeta}_a - \mathbf{F}_{ab} \, \mathbf{F}_{bb}^{-1} \, \overline{\zeta}_b$ 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 [43].

3.4.2. Diagnostics.

In most SHM applications, a complex physical system, characterized by a generally non identifiable parameter vector Φ has to be monitored using a simple (black-box) model characterized by an identifiable parameter vector θ. 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 θ and diagnosis in terms of the parameter vector Φ 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 Φ_0 of the application $\Phi \mapsto \theta(\Phi)$, and to use the sensitivity test (5) for the components of the parameter vector Φ. Typically this results in the following type of directional test :

$$\chi^2_\Phi = \zeta^T\,\Sigma^{-1}\,\mathcal{J}\,\mathcal{J}_{\Phi\theta}\,(\mathcal{J}^T_{\Phi\theta}\,\mathcal{J}^T\,\Sigma^{-1}\,\mathcal{J}\,\mathcal{J}_{\Phi\theta})^{-1}\,\mathcal{J}^T_{\Phi\theta}\,\mathcal{J}^T\,\Sigma^{-1}\,\zeta \gtrless \lambda \ . \tag{7}$$

It should be clear that the selection of a particular parameterization Φ 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 6.4.

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 $(\lambda,\varphi_\lambda)$ of the state transition matrix F of a linear dynamical state-space system :

$$\left\{ \begin{array}{rcl} X_{k+1} & = & F\ X_k + V_{k+1} \\ Y_k & = & H\ X_k \end{array} \right. , \tag{8}$$

namely the (λ,ϕ_λ) defined by :

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

The (canonical) parameter vector in that case is :

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

where Λ is the vector whose elements are the eigenvalues λ, Φ is the matrix whose columns are the ϕ_λ'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 [65]. A contribution of ours, minor but extremely fruitful, has been to write the output-only covariance-driven subspace identification method under a form which 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 $R_i \triangleq \mathbf{E}\left(Y_k\ Y_{k-i}^T\right)$ and:

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

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

$$\begin{aligned} R_i &= HF^iG \\ \mathcal{H}_{p+1,q} &= \mathcal{O}_{p+1}(H,F)\ \mathcal{C}_q(F,G) \end{aligned} \tag{12}$$

where:

$$\mathcal{O}_{p+1}(H,F) \triangleq \begin{pmatrix} H \\ HF \\ \vdots \\ HF^p \end{pmatrix} \quad \text{and} \quad \mathcal{C}_q(F,G) \triangleq (G\ FG\ \cdots\ F^{q-1}G)$$

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

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

where $\Delta \triangleq \text{diag}(\Lambda)$, and Λ and Φ are as in (10). Whether a nominal parameter θ_0 fits a given output covariance sequence $(R_j)_j$ is characterized by [1]:

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

This property can be checked as follows. From the nominal θ_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:

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

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 θ_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* θ_0 *and a new sample* $Y_1, \cdots, Y_N$ *are available.* For checking whether the data agree with θ_0, the idea is to compute the empirical Hankel matrix $\hat{\mathcal{H}}_{p+1,q}$:

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

and to define the residual vector:

$$\zeta_N(\theta_0) \triangleq \sqrt{N}\ \text{vec}\left(U(\theta_0)^T\ \hat{\mathcal{H}}_{p+1,q}\right) \tag{18}$$

Let θ 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 θ. From (16), we know that $\zeta_N(\theta_0)$ has zero mean when no change occurs in θ, 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 θ in (10), and for deriving the residual. Factorization (12) is also the key for :

- Proving consistency and robustness results [14];
- 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 [15].

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, 6., 7.1 and 8.1.

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 [50]. 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 which 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 [63] 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 opened questions [63], [50].

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, 6.5 and 8.1.

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 [64]. 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 6.5.

4.4. Aeronautics

See modules 3.5, 6.1, 6.4 and 7.1.

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 [47].

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 input (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 [15].

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”* [55]. 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 μ-method for analyzing the worst case effects of model uncertainty. In recent comparative evaluations using simulated and real data [49], [56], 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 6.4.

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], Simon Berger, Maurice Goursat.

With the help of Yann Veillard and Auguste Sam, 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 [59], [58].

This software (COSMAD 3.1.1) has been registered at the APP under the number

IDDN.FR.001.210011.000.S.A.2003.000.20700

and can be down-loaded from http://www.irisa.fr/sisthem/cosmad/. The toolbox is currently undergoing heavy changes. The work is done by Simon Berger as a side project of the FliTE2 European project. Parts of this work will be made available after it is finished and approved by the FliTE2 partners. See module 7.1 for more details.

This toolbox 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].
- *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 [15].
- *Automatic subspace-based modal analysis*, a pre-tuned version of the O/O and I/O identification methods above. This is described in [59].

- *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 [60], [61], [53].
- *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 [52].
- *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].
- *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 [57].
- *On-line flutter onset detection*, see modules 3.3, 3.5, 4.2 and 6.4. This algorithm detects that one damping coefficient crosses a critical value from above. For this method see [8]. 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 [22], [24].
- *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), which 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 by Wensong Zhou and is now much easier to use [17], [34].
- *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 [44], [42].

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 within the CONSTRUCTIF project (see module 8.1) [32], [31] and bilateral contracts. Based on intensive internal evaluation of the toolbox, on both simulated and real data sets, EADS Space Transportation and CNES are currently investigating how to use the toolbox for the exploitation of the next Ariane 5 flight data sets [26], [30].

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.

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.

6.1.1. Improving subspace identification by modal basis change.

Usually subspace identification is a one step procedure working on user selected time series. Without prior knowledge, sensors with little to no information about the desired modes do not bring information to the identification procedure. They may even degrade the identification results, especially for damping estimates. The idea of this work is to use the result of a first step identification to obtain raw mode-shapes estimates. Then, the mode-shape matrix allows us to project the data in modal basis, allowing to obtain a set of time series with - a priori - more pertinent information. Then, the subspace identification is applied to the projected time series. Early results show improvements in the identification of the modes, provided that the estimation of the mode-shapes in the first step is good enough. The work will be presented at IMAC'07 [25].

6.1.2. Properties of subspace identification methods.

The article describing and comparing output-only and input/output covariance-driven subspace identification methods (see 2005 activity report) has been published [15].

The article describing the general framework encompassing most well known subspace approaches (either output-only or input/output, should they be covariance, data or frequency driven), and proving general consistency theorems for subspace methods under non stationary excitation, has been accepted for publication in an IEEE journal [14].

6.1.3. Automated modal analysis.

Different case studies have been performed to test the capacity and robustness of the on-line monitoring method implemented in the COSMAD toolbox, see module 5.1. The results of the analysis of long datasets from different scenarios in the Bradford Stadium (international benchmark) [23] have been submitted to a special issue of an international journal.

6.1.4. Time series simulation.

Being able to generate large time series is critical for many of our applications. Extensions and variants of our time series simulator (see 2004 and 2005 activity reports) encompass the crudest linear recursion white noise simulator up to a FRF driven time series simulator. This simulator is a key tool for many application cases, including flutter case generation, time series simulation from FRF at specific temperatures [67], and time series simulation for model validation [28].

A time series simulator has been programmed and will be included in the Scilab toolbox when the GUI is completed.

Further work on time series simulation is reported in module 6.4.

6.2. Change/damage detection, isolation, and diagnostics

Keywords: *CUSUM algorithms*, *change detection*, *nuisance parameters*, *null space computation*.

Participants: Michèle Basseville, Albert Benveniste, Simon Berger, Maurice Goursat, Laurent Mevel, Houssein Nasser, Wensong Zhou.

See modules 3.3, 3.4, 6.4 and 6.5.

6.2.1. Null space computation for subspace-based detection.

The subspace-based residual has been initially introduced as in (18), namely with a parametric left kernel $U(\theta_0)$ computed as displayed in (15).

6.2.1.1. QR computation.

In Nasser's PhD thesis, a new computation scheme has been proposed for the subspace-based residual. This computation is based on a QR factorization of the matrix built by putting together the observability matrix corresponding to the reference model and the Hankel matrix built from the fresh data. The QR factorization ensures that the left kernel U is strictly orthogonal to the reference observability even in the presence of noise. The triangular form of the QR factorization allows also the resulting residual to be of smaller size, which is critical, for the damage detection procedure.

Both the Jacobian and covariance matrices associated with this residual are also of smaller dimensions, reducing the computational burden of the algorithm. Experimentally, this algorithm has been shown to exhibit a better behavior than the previous algorithm, especially in validation problems where less correlations seem to be required in order to achieve sufficient contrast between the reference and the "damaged" states.

6.2.1.2. Empirical null space.

It turns out that it some cases it may be of interest to compute an empirical left kernel, based only on a reference dataset, and not on a reference signature. Performing a SVD of the empirical Hankel matrix built on the reference dataset provides us with such an empirical kernel. Such an approach is used e.g. in [51], [68].

When multiple reference datasets are available, as e.g. when handling the temperature effect, see module 6.5, 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 [21], [36].

This approach has been applied to data of different types, in addition to the two test-cases investigated within CONSTRUCTIF, see modules 6.5 and 8.1. The results obtained while processing data from two new application areas, seismic and MEMS, respectively, are explained below.

6.2.2. FRF driven subspace-based detection.

In [67], the damage detection test was adapted to handle the (common) case where the available inputs are frequency response functions (FRF), and not time series data. The residual (18) was computed by simulating time series and correlation matrices were derived from impulse response functions (IRF), which result from the inverse Fourier transform of the FRF.

A new version of the test has been proposed this year. The covariance matrix is now the result of the averaging of multiple repetitions of FRF measurements. This method has been successfully tested on cantilever data [27], this is explained below.

6.2.3. New application areas.

This year, we have been involved in investigations regarding two applications in domains which we never investigated before. The first one was known to us to be a relevant test case for the methods we design, the second one is a bit more surprising.

6.2.3.1. Earthquake monitoring.

Earthquake data are typically very short and highly non stationary. The small sample size does not guarantee a good identification, and does not ensure that the usual computation scheme of the residual covariance works. It implies that the test fails to detect damage in that problem. To compensate for poor identification, the empirical kernel technique described above has been used. As for the computation of the covariance matrix, the classical scheme cuts the signal in different parts, computes a residual on each of those parts, and averages the different residuals. For earthquake data, not enough residuals can be obtained to get a good estimate of the covariance.

Bootstrap techniques have been investigated and tested successfully. Sub-sampling of the residual sequence is performed. Experimentally, it has been shown that the computation of the residual covariance matrix is improved, and that higher contrast is obtained for detecting the evolving damage of the soil under earthquake pressure. This work has been submitted to the Mini-symposium on *Identification Methods in Structural Dynamics* organized for the *ECCOMAS Thematic Conference: 1st International Conference on Computational Dynamics and Earthquake Engineering*, which we have been invited to participate to.

6.2.3.2. MEMS.

Micro-electro-mechanical systems (MEMS) has brought both opportunities and challenges to the field of structural dynamics in a different scale, owing primarily to its interdisciplinary nature of research and extremely small feature size. An application of the MEMS is to detect a target mass particle attached eccentrically to a microcantilever by measuring three-dimensional modes in the microcantilever vibration spectrum. A technique of current interest is the use of scanning probe microcantilevers, initially developed for imaging purposes in scanning force microscopy, for sensing applications. Recent studies have shown that microcantilevers can be fabricated which have sensitivities into the attogram regime. A major objective is to detect the variation in mass on such structures. It has been shown that the addition of a target mass particle can be detected by measuring multiple three dimensional modes in the micro cantilever spectrum. Our objective is to apply subspace identification and detection techniques to the MEMS structures. One particular feature of this application lies in the fact that only direct FRF (frequency domain) measurements are collected.

For the cantilever data, multiple measurements were performed on "similar" structures. The new FRF method described above exhibited good capabilities to average the modal structures of these "similar" cantilevers [27]. As opposed to [67], the new approach is based on the computation of the empirical kernel, and requires neither the identification of some model nor the simulation of the corresponding data.

6.2.4. Handling nuisance parameters.

The investigation [45], [46] 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 [43]. The extension of this orthogonality property, to the case of estimating functions other than in maximum likelihood, is an insensitivity property expressed with the aid of sub-matrices of the sensitivity matrix of the considered estimating function. This sensitivity matrix, rather than the Fisher information matrix, should play a role in nuisance parameter rejection.

6.2.5. Handling FEM for damage localization.

The aim of the post-doctoral sojourn of Wensong Zhou has been to improve the computation and clustering of the sensitivities $\mathcal{J}_{\Phi\theta}$ in (7), based in particular on sub-structuring techniques of common use within the FEM community. Actually, the damage localization tests are obtained by plugging aggregated sensitivities of the modes and mode-shapes w.r.t. FEM structural parameters.

The technique has been tested on the numerical bridge of É. Balmes used in H. Nasser's PhD thesis. This simulation involves approximately 10000 elements. The technique was able to detect the damage correctly. This work implied to rewrite the Jacobian by removing the influence of the damping coefficients from the computation of the sensitivities.

Moreover, considering the large number of physical elements and the small number of sensors and modes, an identifiability problem appears. Some elements are indistinguishable from others from the point of view of the test. Macro clusters have to be considered. An evaluation of the geometrical relevance of the statistical clustering operation has been done. It has been shown that the clusters tend to be convex and that they aggregate when the desired size of the cluster rises [17], [34].

6.3. Model validation

Keywords: *modal analysis*, *model validation*, *subspace–based method*.

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

See modules 3.3, 3.5, 4.2.

The main problem for identification techniques in general is to obtain confidence intervals and more generally to assess information about some previous identification techniques output. This problem is also known as the model validation problem. It can be seen as a first step before doing any damage detection test, because damage detection techniques, should they be identification driven or (better) model driven, need to be fed with a reference signature, which must be as close as possible to the reference data. So, obtaining the best identified signature is required both as the output of the identification procedure and as the input of any damage detection procedure.

In [28], it has been shown that damage detection technique can be used to check if some given signature corresponds to some record. The method has been shown to work well but suffers from heavy computational task. This year, using the QR factorization of H. Nasser's thesis and a Quasi-Newton approach, a validation algorithm has been developed to perform the search for the identified model best matching the given record. The QR approach, by forcing the orthogonalization of the different terms of the damage detection residual, reduces the effect of noise and thus does not require as much correlation as the classical SVD driven factorization. The Quasi-Newton approach ensures that no exhaustive search is done and that the best path from the initial condition to the optimal point is obtained in a minimal number of steps. The function to minimize is the result of the statistical test for a candidate modal parameter with the reference model in input. The gradient is computed by finite-difference formula. The inverse of the Hessian matrix is approximated by an iterative formula at each step of the minimization algorithm, namely the BFGS formula. The linear search performed at each step of the minimization algorithm was done with the Goldstein-Price criteria, for it does not require to compute the gradient at each step.

Since computing the value of the statistical test is very time consuming, special care was taken to avoid redundant computing, especially regarding quantities depending only on the reference data. The original algorithms were thus cleaned and rewritten for the purpose of this model validation algorithm. This work was the subject of Gilles Canales's Master Thesis. The second problem in the model validation setup is to obtain confidence intervals from both the record and the identified model. In [18], [40], some formulae has been proposed for obtaining these confidence intervals using the Jacobian and the covariance matrices from the damaged detection procedure, linking both identification and detection problems, see module 3.5. Experimental results on that matter have been reported in [29] and [13]. The tricky part of this work was to avoid ill conditioning in the computation of the covariance matrix.

6.4. Flutter monitoring and onset detection

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

Participants: Michèle Basseville, Albert Benveniste, Maurice Goursat, Laurent Mevel, Wensong Zhou, Rafik Zouari.

See modules 3.3, 3.5, 4.4 and 7.1.

In a previous study, we have investigated the flutter monitoring problem, see modules 4.4 and 7.1, stated as a statistical hypotheses testing problem regarding a specified damping coefficient which crosses a critical value from above. In [8], 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 (different from the local approximation in module 3.4), and the cumulative sum (CUSUM) test [5], see also module 6.2.

6.4.1. Different criteria for flutter monitoring.

The more realistic problem of monitoring two pairs of eigenfrequencies and damping coefficients subject to specific time variations has been addressed in [22]. From the physics of the flutter phenomenon, it may be assumed indeed that two modes evolve until super-imposition at an unknown time instant, and monitoring the difference in the two frequencies has been shown to be relevant as well. The real challenge of this parameterization is the lack of any calibration data corresponding to the (unknown) modal state associated to the crossing scenario. It has been experimentally shown that, when calibrated to react to a given crossing scenario, the test also reacts correctly to other crossing scenarios, even if the two frequencies cross each other at another position in the frequency domain.

None of these approaches uses any model of the underlying physical phenomenon. The aim of the doctoral thesis of Rafik Zouari is to investigate the use of (reduced) aero-servo-elastic models for the design of flutter detection tests, and calibrate the trade-off between complexity, efficiency and robustness of the resulting algorithm. This is done within the framework of FliTE2, in particular in collaboration with J. Cooper, U. Manchester, see module 7.1.

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. A new flutter criterion has been proposed based on the classical flutter margin theory. This criterion involves both the frequency and damping coefficient of the two considered modes, by forcing some 4th order equation to remain stable (Rough-Hurwitz criterion). From this so-called flutter margin, two expressions of a new Jacobian matrix have been proposed. One is computed from the continuous modes, the second uses the discrete modes as input. Both methods have been tested on a 2DOF aero-elastic model of two modes. These two flutter criterions are based on the monitoring of the frequency and damping coefficient as the source of flutter.

Other approaches consider that the mode shapes exhibit some specific behavior when flutters occurs. A new criterion based on the MAC, the correlation between mode shapes, has been developed. The MAC criterion has been tested on a 2D airplane wing model. Successful results of flutter monitoring and comparison with both the analytical modes and flutter margin criterion built on identification results have been published in [35], [33].

6.4.2. Simulation of flutter phenomena.

Rafik Zouari has developed a 2DOF model of the flutter phenomenon, in order to test the flutter algorithms on simulated time series exhibiting a realistic flutter phenomenon. During the master thesis of Sirine Maalej, a 2D airplane wing has been developed, with the help of Wensong Zhou. This simulator is able to generate multi-sensor time series and will be our in-house benchmark for testing the flutter monitoring algorithms.

6.4.3. 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, and a possible deviation with respect to a reference parameter vector is tested.

An article introducing and comparing subspace-based identification and detection algorithms for online in-flight vibration-based monitoring is currently under revision for publication in a special issue on *Applications of System Identification* for the *IEEE Control Systems Magazine*.

6.5. Handling the temperature effect

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

Participants: Michèle Basseville, Maurice Goursat, Laurent Mevel, Houssein Nasser.

See modules 3.4, 3.5, 4.3 and 8.1.

This work is performed within the framework of the CONSTRUCTIF project, see module 8.1.

The PhD thesis of Houssein Nasser addresses 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.

6.5.1. Three approaches.

Three different methods have been proposed for overcoming these drawbacks. The first one [62] [19], [16] uses the simplified temperature model relating the modal parameter of interest with the ambient temperature developed last year. The method consists in computing the Jacobian of the modal parameters with respect to the ambient temperature, and considering the temperature as a nuisance parameter. Thus, the damage detection test monitors the structural damage under the hypothesis that the temperature is a nuisance parameter.

The second method involves the computation of a finite elements model (FEM) and assumes that the temperature (or any equivalent measure of the ambient state) is measured. Then, knowing the ambient state and a reference signature at some reference ambient state, and modifying the stiffness according to the temperature model embedded in the FEM, we got the values of the computed modes at the ambient state. Then, the damage detection test can be performed with respect to this temperature dependent safe hypothesis [20].

The third approach is based on the collection of varying reference temperature datasets, and on the computation of the Hankel matrix and its kernel associated to all the datasets. This provides us with a reference kernel averaging all the temperature scenarios [21], [36]. Method 2 and Method 3 have been tested successfully on a bridge deck simulation case provided by E. Balmes (MSSMat, ECP). Validation on the data from the laboratory test beam provided by F. Treyssède (LCPC) was performed this year.

6.5.2. Link between modal filters and temperature rejection.

With the new advances in sensors and network technologies, the amount of data that can be collected in real time is increasing. For vibration-based damage detection, many algorithms are not suited to deal with hundreds or thousands of sensors. It is therefore necessary to reduce this huge amount of data, keeping only the relevant information about the damage to be detected.

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. 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 (i.e. generally 10 to 20). This is much less than the total of number of sensors and a number much more consistent with the computational requirements of our damage detection test.

In order to study the effect of the data reduction, we use data from a simulated model of a bridge. This model was used at ULB in the past to investigate the possibility of removing the effects of environment from the measurements. The bridge is equipped with a large number of sensors, and subject to different temperature changes (which affect its structural behavior through temperature dependent materials). Data are available for the undamaged as well as the damaged case, and for a large number of temperature cases. The damage detection procedure is applied with and without data reduction. The environmental effects are removed by techniques described in Nasser's thesis. The investigation of the effects of the data reduction is currently under way.

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 6.4.

Contract INRIA — SEPTEMBER 2005/AUGUST 2008.

We have been strongly contributing to the establishment of a follow-up of a major cooperation within the Eurêka framework. 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 of FliTE to aircraft manufacturers. To this end, the project has been structured into working groups addressing transfer to each industrial and driven by them, e.g. WGs are driven by ONERA (with Airbus), Dassault-Aviation, SOPEMEA and LMS on ground vibration tests, and PZL and AGH on environmental tests. A selected subset of academic partners is involved in each WG. 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. This new organization is effective from January 2006.

7.2. SAMCO network and association

Participant: Michèle Basseville.

See modules 4.2, 4.3 and 5.1.

Contract CNRS 500232 — FEBRUARY 2002/MARCH 2006.

The FP5 Growth thematic network SAMCO has been launched in October 2001 within the framework of the Growth program. It aims at becoming 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.). Several partners of the network have proposed our participation, and we became a participating member, 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 Scilab modal analysis modules, see module 5.1.

This year, we have been involved in the final workshop on the achievements and the future of the network [37]. During that workshop, the European Association for SAMCO was founded.

7.3. EADS Space Transportation

Participants: Maurice Goursat, Laurent Mevel.

See modules 4.2, 4.4 and 5.1.

Collaboration with EADS is going on. A case study investigated by EADS using our COSMAD software has been the topic of two joint conference papers [26], [30].

We have been contacted for participating into the Aerospace IDF pole. In this framework, we have applied for being involved and funded in two investigations. The first one is concerned with the use of output-only subspace-based identification methods for improving the models of spatial vehicles obtained by processing flight test data.

The second one, stated as a PhD subject, addresses the issues of quantifying the uncertainty in estimates from flight test data and validating the resulting models.

8. Other Grants and Activities

8.1. Ministry grant CONSTRUCTIF

Participants: Michèle Basseville, Maurice Goursat, Laurent Mevel, Houssein Nasser, Wensong Zhou.

See modules 4.2, 4.3, 5.1, 6.2 and 6.5.

Contract INRIA 1 03 C 1559 — 16 JULY 2003/15 JULY 2006.

This project, within the framework of the ACI Sécurité & Informatique, is coordinated by Laurent Mevel. Our partners are LMSSMat (Laboratoire de Mécanique des Sols, Structures et Matériaux, École Centrale de Paris and CNRS), LCPC/SMI (Laboratoire Central des Ponts et Chaussées, Service Métrologie et Instrumentation, Paris and Nantes), and the INRIA project-team MACS (Rocquencourt).

The objectives of the project are, on the one hand, the intrinsic coupling of statistical models of sensor data with fine models of the physical phenomena governing the instrumented structures, and, on the other hand, the mixing of statistical inference, data assimilation, finite element model updating and optimization methods for structural dynamics. The investigation of potential mutual benefits of criteria used for different purposes by various methods designed in different scientific communities, is the central axis of the project. The main object of the study is the intrinsic involvement of the temperature effect, which is a generic issue for vibration monitoring of civil engineering structures.

Expanding on the joint paper with Dominique Chapelle (MACS) [62], we have proposed three methods to handle the temperature effect in damage detection. Those methods are presented in module 6.5. Collaboration has been enforced between CONSTRUCTIF partners. Étienne Balmès (MSSMat) has provided us with a simulated bridge deck FEM with embedded temperature variation. Fabien Treyssède (LCPC/SMI) has progressed on a laboratory beam experiment to test the proposed techniques and has also developed some temperature models for structural structures and especially beam structures. The case studies and the temperature models have been considered by Houssein Nasser and are part of his PhD thesis, as part of either his methods or the validation datasets.

Our damage localization method sketched in module 3.4 builds on the computation and clustering of the sensitivities $\mathcal{J}_{\Phi\theta}$ in (7). This method suffers from some limitations: some finite elements may be impossible to separate from a statistical point of view. During his post-doctoral sojourn, Wensong Zhou has investigated macro-classes generation by designing an update of the classification approach to model reduction proposed in [44]. The results obtained on a realistic bridge deck simulator provided by Étienne Balmès have been encouraging [17], [34].

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. This year, we have been invited to deliver a tutorial talk - see module 9.2.

9. Dissemination

9.1. Scientific animation

M. Basseville is member of the evaluation committee of the Security and Computer Science program (ANR SetIn) launched by the National Agency for Research.

She 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».

A. Benveniste is associated editor at large (AEAL) for the journal IEEE *Transactions on Automatic Control* and member of the editorial board of the journal *Proceedings of the* IEEE. 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'06, CDC'06, and ACC'07. She has been member of the international program committee of SYSID'06, Safeprocess'06 and CIFA'06.

She has organized an invited session on *System Identification and Detection for Flight Test Data Analysis*, for the *14th IFAC/IFORS Symposium on Identification and System Parameter Estimation - SYSID'06*, in Newcastle, Australia, in March 2006.

9.2.2. Invited publications and submissions.

The team has been invited to submit a paper to:

- 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» is under review;
- 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 accepted [12];
- A special session on *Validation Approaches for Structural Health Monitoring* at the *24th International Modal Analysis Conference* which took place in Saint Louis, MI, in January 2006. A tutorial paper has been presented [18];
- A special session on *Spatial Distribution of Damage* at the *4th World Conference on Structural Control and Monitoring* in San Diego, CA, in July 2006 [17];
- A special session on *Flight Flutter Testing and Analysis* at the *International Conference on Noise and Vibration Engineering* in Leuven, B., in September 2006 [35].

9.2.3. Invited presentations.

In addition to presentations with a publication in the proceedings, members of the SISTHEM project–team have also given the following presentations.

We have been invited to deliver a tutorial talk during the FWO Research Network ICCoS Workshop [40].

Albert Benveniste has been invited speaker at the event in honor of the 60th birthday of Lennart Ljung [13].

Michèle Basseville has presented Sisthem's views on advanced sensor data processing for structural health monitoring during the final workshop of the Growth network SAMCO as part of the research agenda [37].

Technical details on these issues have been presented at the working group on safety, monitoring, and supervision of the French GDR MACS [39].

The joint handling of physical models and statistical concepts has been explained with in a seminar at the Brittany extension of ENS Cachan [38].

9.3. Visits and invitations

Palle Andersen, Managing Director of Structural Vibration Solutions A/S (SVIBS), Aalborg, Denmark, visited us a couple of days in March 2006. 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 and 6.2.

Souha Bahlous, teaching assistant at the Institut Supérieur des Technologies de l'Environnement de l'Urbanisme et du Bâtiment (ISTEUB), and member of the Laboratoire de Systèmes et de Mécanique Appliquée (LASMAP), visited us during half a week in May 2006. She has given a seminar on her PhD work about modal filtering and statistical approach to structural damage diagnostics from ambiant vibration data.

Arnaud Deraemaecker, FNRS Postdoctoral Researcher in the Active Structures Laboratory (ASL) of Université Libre de Bruxelles (ULB), spent a couple of days with us in May 2006, with the objective of establishing a cooperation between our two groups. One topic of joint interest is the investigation of the potential benefit of the use of spatial filters as a forefront for reducing huge amount of data before applying our subspace-based damage detection algorithms. The application example for this investigation is a laboratory test-case available at ASL, and subject to a varying temperature environment. See module 6.5 for more details. Houssein Nasser will spend one year there as a post-doc on this topic.

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