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Statistical Inference for STructural HEalth Monitoring

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1. Team

Head of the project–team
Michèle Basseville [DR CNRS]

Administrative assistant
Huguette Béchu [TR INRIA, shared with ASPI, DistribCom, S4, until November 15]
Myriam David [TR INRIA, shared with DistribCom, S4, Triskell, from November 15]

Research scientists (INRIA)
Albert Benveniste [DR, part–time]
Maurice Goursat [DR, part–time]
Laurent Mevel [CR]

Project technical staff (INRIA)
Auguste Sam [ingénieur expert, until February 29]

Ph.D. student
Houssein Nasser [MENRT ACI S&I grant]

2. 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 [35][44]. 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, spacecrafts, 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 aerodynamical effects, thermodynamical 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 EADS Launch Vehicles on modal analysis of a launch vehicle,
- Multi–partners projects: at European level on exploitation of flight test data under natural excitation conditions (FliTE - 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).

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 [36] :

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

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 6.2.

Our approach to on-board detection is based on the so-called asymptotic statistical local approach, which we have extended and adapted [4][3][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 :

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

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

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

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 [33] that the residual is asymptotically Gaussian :

$$\zeta_N \xrightarrow[N \to \infty]{} \begin{cases} \mathcal{N}(0, \Sigma) & \text{under } \mathbf{P}_{\theta_0}\ , \\[2mm] \mathcal{N}(\mathcal{J}\,\eta, \Sigma) & \text{under } \mathbf{P}_{\theta_0 + \eta/\sqrt{N}}\ , \end{cases}$$

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 :

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

where $\overline{\zeta} \triangleq \mathcal{J}^T\,\Sigma^{-1}\,\zeta_N$ and $\mathbf{F} \triangleq \mathcal{J}^T\,\Sigma^{-1}\,\mathcal{J}$.

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 6.3 and 6.2.

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 [30]. 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 :

$$t_a = \overline{\zeta}_a^{\,T} \, \mathbf{F}_{aa}^{-1} \, \overline{\zeta}_a \;, \tag{4}$$

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 :

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

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 [27].

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 [7]. 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 (4) for the components of the parameter vector Φ. Typically this results in the following type of directional test :

$$\chi_\Phi^2 = \zeta^T \, \Sigma^{-1} \, \mathcal{J} \, \mathcal{J}_{\Phi\theta} \, (\mathcal{J}_{\Phi\theta}^T \, \mathcal{J}^T \, \Sigma^{-1} \, \mathcal{J} \, \mathcal{J}_{\Phi\theta})^{-1} \, \mathcal{J}_{\Phi\theta}^T \, \mathcal{J}^T \, \Sigma^{-1} \, \zeta \gtrless \lambda \;. \tag{6}$$

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 6.2.

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 :

$$\begin{cases} X_{k+1} & = & F & X_k + V_{k+1} \\ Y_k & = & H & X_k \end{cases},$$ (7)

namely the (λ, ϕ_λ) defined by :

$$\det \quad (F - \lambda \quad I) = 0, \qquad (F - \lambda \quad I) \quad \varphi_\lambda = 0, \qquad \phi_\lambda \triangleq H \quad \varphi_\lambda$$ (8)

The (canonical) parameter vector in that case is :

$$\theta \triangleq \begin{pmatrix} \Lambda \\ \mathrm{vec}\, \Phi \end{pmatrix}$$ (9)

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 [43]. 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 $R_i \triangleq \mathbf{E} \begin{pmatrix} Y_k & Y_{k-i}^T \end{pmatrix}$ and:

$$\mathcal{H}_{p+1,q} \triangleq \begin{pmatrix} R_0 & R_1 & \vdots & R_{q-1} \\ R_1 & R_2 & \vdots & R_q \\ \vdots & \vdots & \vdots & \vdots \\ R_p & R_{p+1} & \vdots & R_{p+q-1} \end{pmatrix} \triangleq \mathrm{Hank}\,(R_i)$$ (10)

be the output covariance and Hankel matrices, respectively; and: $G \triangleq \mathbf{E} \begin{pmatrix} X_k Y_k^T \end{pmatrix}$ Direct computations of the R_i's from the equations (7) lead to the well known key factorizations :

$$R_i \quad = \quad H F^i G$$ (11)

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

where:

$$\mathcal{O}_{p+1}(H, F) \triangleq \begin{pmatrix} H \\ HF \\ \vdots \\ HF^p \end{pmatrix} \qquad \text{and} \qquad \mathcal{C}_q(F, G) \triangleq \begin{pmatrix} G & FG & \cdots & F^{q-1}G \end{pmatrix} \tag{13}$$

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 (8).

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 (7) yields the following representation of the observability matrix:

$$\mathcal{O}_{p+1}(\theta) = \begin{pmatrix} \Phi \\ \Phi\Delta \\ \vdots \\ \Phi\Delta^p \end{pmatrix} \tag{14}$$

where $\Delta \triangleq \operatorname{diag}(\Lambda)$, and Λ and Φ are as in (9). Whether a nominal parameter θ_0 fits a given output covariance sequence $(R_j)_j$ is characterized by [1]:

$$\mathcal{O}_{p+1}(\theta_0) \qquad \text{and} \qquad \mathcal{H}_{p+1,q} \qquad \text{have the same left kernel space.} \tag{15}$$

This property can be checked as follows. From the nominal θ_0, compute $\mathcal{O}_{p+1}(\theta_0)$ using (14), and perform e.g. a singular value decomposition (SVD) of $\mathcal{O}_{p+1}(\theta_0)$ for extracting a matrix U such that: $U^T U = I_s$ and $U^T \mathcal{O}_{p+1}(\theta_0) = 0$. 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 $\hat{\mathcal{H}}_{p+1,q}$:

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

and to define the residual vector:

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

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 [7], and for flutter monitoring [8].

3.5.4. Other uses of the key factorizations.

Factorization (12) is the key for a characterization of the canonical parameter vector θ in (9), and for deriving the residual. Factorization (11) is also the key for :

- Proving consistency and robustness results [31];

- Designing an extension of covariance-driven subspace identification algorithm adapted to the presence and fusion of non-simultaneously recorded multiple sensors setups [5];

- Proving the consistency and robustness of this extension [6];

- Designing various forms of *input-output* covariance-driven subspace identification algorithms adapted to the presence of both known inputs and unknown excitations [25].

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 [35]. 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 [41] 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 [41][35].

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, 6.3 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 [42]. 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 6.3.

4.4. Aeronautics

See modules 3.5, 6.1, 6.2 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 [32].

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 [25].

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"* [37]. 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 [34][38], 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 6.2.

5. Software

5.1. COSMAD: Modal analysis and health monitoring Scilab toolbox

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

Participants: Laurent Mevel [corresponding person], Maurice Goursat, Auguste Sam.

With the help of Yann Veillard and Auguste Sam, 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 [20][18].

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

and can be downloaded from http://www.irisa.fr/sisthem/cosmad/. 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 [29].

- *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 [25].

- *Automatic subspace-based modal analysis*, a pre-tuned version of the O/O and I/O identification methods above. This is described in [39] [20].

- *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 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 [21][22][15][13].

- *Automatic recursive subspace-based modal analysis*, a point-wise version of the O/O and I/O identification algorithms above. For this method, see [12].

- *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 registered at different time periods, and under different excitations. The key principles are described in [5] and a consistency result can be found in [6].

- *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][7].

- *Damage monitoring*, a point-wise version of the damage detection algorithm above. This is described in [40].

- *On-line flutter onset detection*, see modules 3.3, 3.5, 4.2 and 6.2. This algorithm detects that one damping coefficient crosses a critical value from above. For this method see [8][16]. An extension to detect if some subset of the whole modal parameter data vector varies with respect to a threshold value, applies directly to monitoring the evolution of a set of frequencies or a set of damping with respect to their reference values [19].

- *Modal diagnosis*, 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 [7].

- *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 [7].

- *Optimal sensor positioning for monitoring*, see module 6.4. 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 [28] and [10].

The modules have been tested by different partners, especially the French industrial partners, EADS and Dassault, within the FliTE project, see module 7.1, and bilateral contracts. Based on intensive internal evaluation of the toolbox, EADS and CNES are currently investigating how to use the toolbox for the exploitation of the next Ariane 5 flight data sets.

This Scilab toolbox will continue 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 parternships in FP6 integrated projects proposals, see module 7.2.

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 Mével.

See modules 3.2, 3.5, 4.2, 7.1.

6.1.1. Input/output versus output-only subspace identification.

Theoretical and experimental investigations have been conducted for both output-only and input/output covariance subspace methods. On the theoretical side, robustness to nonstationary excitation and convergence of input/output covariance subspace have been investigated. On the experimental side, different studies have been conducted to evaluate the merits of input/output and output-only approaches. It has been shown that output-only approach efficiency do tend to get close to input/output methods when the sample size increases and/or when the stabilization diagram extraction of modes is performed with care [25][15][13].

6.1.2. Automated modal analysis.

Different case study has been performed to test the capacity and robustness of the online monitoring method implemented in COSMAD toolbox within the framework of FLite. In particular, a 4 hours long on-line monitoring of the Bradford Stadium has been conducted [15]. The results of this analysis will be submitted as a journal paper to be part of a special issue. On the other end, multiple case studies have shown the robustness of the approach for online monitoring of aircraft in flight situations [21][22][13].

Concurrently to the flutter monitoring approach validation by simulations, automated on-line monitoring have been performed to validate both the flutter detection technique and one in-house simulator (developed this year) for vibrational data [17][19].

Extensions and modifications of the automated approach are considered to handle the challenge of Flite2 Eureka project, including fast estimation and fast extraction of modes.

6.1.3. EM-based identification.

A tentative has been done to use likelihood-based EM estimation technique to increase the quality of subspace algorithms as a post-processing. It means that subspace algorithms were used to initialize the EM estimate. The algorithm has shown promising qualities, especially in its capacity in handling high order models on both simulation and real test cases. Nonetheless, it has not shown any valuable quality increase in the final estimate. Further work will be necessary.

6.1.4. Tracking via filtering techniques.

Ongoing work is done to enhance last year results on varying parameter tracking using likelihood-based recursive algorithms [12]. This type of algorithms has been shown to be able to adapt to parameter change on a sample-wise level. The objective of the current work is to extend previous work on high order models from realistic civil aeronautic structures. This work is jointly done with Fabien Campillo from ASPI project–team.

6.1.5. Data Simulation.

Work has progressed to obtain a realistic time series data simulator, in order to obtain long time series corresponding to high model order time varying modal structures. Both ODE resolution and discrete linear system evolution were considered. Application of such a simulator allows us to realistically test our identification and detection techniques. This work has been possible using an early time series simulator from VUB, Belgium.

6.2. 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.

See modules 3.3, 3.5, 4.4 and 7.1.

We have pursued the investigation of a first solution to the problem of monitoring a damping coefficient, which results from the flutter monitoring problem, see modules 4.4 and 7.1. The idea is to use the subspace–based residual (18), and to design a unilateral test statistics for detecting that a given damping coefficient crosses a critical value from above (decreases towards zero). Because fast reaction is seeked, the test involves a sample-wise temporal data-driven computation for the residual. Since the detection problem is no longer a *local* hypotheses testing problem, we have used a different asymptotic for the residual (different from the local approximation in module 3.4), combined with the cumulative sum (CUSUM) test built on the residual. The CUSUM test is of common use in quality control [3]. This algorithm works on–line [16][8][19].

Whereas in [8][16] the test is experimented on a real dataset, further numerical investigations have been pursued on simulated data [19]. The flutter online technique has been shown to work for any mode parameter (frequency or damping). It has also been extended to handle globally multiple modes monitored simultaneously. This new multi dimensional test is considered to better handle the inter relations between modes. It has also been shown that modes do tend to influence each others (tests on constant modes do react whenever close modes change), but it has also been shown that this reaction is less than test reaction on really changing modes. It has also been shown to be a non factor with respect to the capability of the test on the parameter of interest to track variations in change. Experimental study on the effect of tuning parameter has also been done.

6.3. Handling the temperature effect

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

Participants: Laurent Mevel, Houssein Nasser.

See modules 3.4, 3.5, 4.3 and 8.1.

This work is done in cooperation with Dominique Chapelle (MACS project–team, Rocquencourt) within the framework of the CONSTRUCTIF project, see module 8.1. This year, a simplified temperature model relating the modal parameter of interest with the ambient temperature has been developed.

Beam theories are frequently used to model civil engineering structures. They are applicable to structures for which two characteristic dimensions are much smaller than the third (namely, structures thin in two directions), and they provide solutions which are good approximations of reference solutions obtained with a 3D formulation.

We use here the Timoshenko beam theory which – unlike the Navier-Euler-Bernoulli theory – allows for shear deformations. We restrict our framework to small ("infinitesimal") displacements, and we assume that the beam is straight – positioned along the x-axis – and deforms in the (x, z) plane. The kinematical

assumption underlying the Timoshenko theory states that a beam section – orthogonal to the x-axis in the original configuration – undergoes a global translation u along z, and a rotation β around the vector $-\overrightarrow{j}$. We point out that translations along x can also be modeled, but in practice such translations are much smaller than transverse displacements, and the corresponding equations decouple from those describing u and β. When the structure undergoes a temperature variation $\Delta T = (T - T_0)$, if the boundary conditions are such that the length variation ΔL is constrained (typically $\Delta L = 0$) a pre-stress field arises. The major component of this pre-stress field is σ_{xx} which is homogeneous in the beam and given by (for an isotropic material)

$$\sigma_{xx} = E \left[\frac{\Delta L}{L} - \alpha \overline{\Delta T} \right], \quad \text{with} \quad \overline{\Delta T} = \frac{1}{L} \int_0^L \Delta T dx.$$

A simple argument similar to linear stability analysis then leads to the following stiffness variation

$$\Delta K_T = \int_0^L A \sigma_{xx} \frac{\partial u}{\partial x} \frac{\partial \tilde{u}}{\partial x} dx, \tag{19}$$

a bilinear form which operates on two displacements functions $(u, \tilde{u})$. Of course, it is straightforward to compute the corresponding (discrete) matrix form. We see in Eq. (19) how an increase in the temperature can lead to a decrease in the stiffness (a negative σ_{xx} gives a negative ΔK_T). We see in Eq. (19) how an increase in the temperature can lead to a decrease in the stiffness (a negative σ_{xx} gives a negative ΔK_T).

This year, we have developed the simplified temperature model. Extensions to anisotherm conditions will be also investigated. Obtaining the temperature model is only the first step and maybe the easiest one. Understanding how to link statistical tests and temperature sensitivity is the tricyk part of the study, and where we will focus the future works. Handling the temperature as a nuisance parameter seems at first an easy objective considering we have now the sensibilities of the modal parameters with respect to the temperature. The challenging part comes from the fact that the temperature does not satisfy the local asymptotic approach (changes in the temperature can be very high), so we can not assume that the necessary jacobian and covariance matrices have only to be computed on a safe reference structure once, but now at all steps on a "corrected" safe structure (the correction being made knowing both the reference structure and the variation of temperature). This implies also to compute reference modes, before testing any possibly damaged time data patch, from the FE model. All these considerations do imply large modifications in the processing of the test and its structure as it has been explained previously.

6.4. Optimal sensor positioning

Keywords: *Fisher information*, *observability*, *scalar functions of matrices*, *sensor positioning*.

Participant: Michèle Basseville.

See module 4.2.

Determining the best number and positions of sensors to be used for SHM is of crucial importance for costs and efficiency reasons. Different types of criteria have been used for quantifying the relevance of the number and the positions of sensors in a given set, and they have been optimized for selecting the best possible sets. Various matrix criteria, such as observability and controllability matrices, Fisher information matrix, modal assurance criterion matrix, are of interest for this purpose. One important issue, then, is to define which scalar function of the selected matrix should be optimized. Several scalar functions of matrices have been proposed, such as determinant, trace, extremal eigenvalues, off-diagonal terms, ... Another possibility is to exploit a Kullback distance between matrices, which gives rise to scalar functions of potential interest, with different invariance properties [10].

7. Contracts and Grants with Industry

7.1. Eurêka project FliTE

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

See modules 4.4, 5.1, 6.1 and 6.2.
Contract INRIA 2 02 C 0040 — May 2001/April 2004.

We have been strongly contributing to the establishment and coordination of a major cooperation within the Eurêka framework. The Eurêka project FliTE («Flight Test Easy») 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. 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 FliTE project aims at a better exploitation of flight test data, exploiting data recorded under natural excitation conditions (e.g., turbulent), without resorting to artificial control surface excitation and other types of excitation inputs. A second objective of FliTE is an improvement of the flight test procedures themselves.

Our expertise in output–only system identification methods, for modal analysis of vibrating structures under ambient and non-stationary excitation, and thus under unknown inputs, is central in the project [29] [5][6]. The involved INRIA project–teams are responsible for the task «development of algorithms and associated methods», and for the corresponding task reports. Moreover, Albert Benveniste helps Sopemea in the scientific coordination of the project.

The achievements of this year have been the following.

- An exhaustive experimental study of damping estimation in the specific case of an in-operation large aircraft dataset modal analysis. The work has been focused on the evaluation of merits of input/output versus output-only methods for damping estimations [13].

- We have pursued the investigation of a first solution [16][8] to the problem of monitoring a damping coefficient, which results from the flutter monitoring problem, see module 6.2. Numerous experiments have confirmed the relevance of the proposed on-line detection algorithm. A first attempt at elaborating a multi-dimensional flutter monitoring approach has been made [19], in preparation of (and in accordance with) FliTE2 objectives.

- An ongoing validation of the on-line identification monitoring approach on different civil structures [17][13][15].

- The start of the collaboration with EADS Launch vehicles on the validation of the COSMADToolbox in industrial environments. Even if this is not strictly related to FliTE this work has strong repercussion on SISTHEM objectives for FliTE2.

Recursive subspace identification and automated modal extraction has been the focus of the visit of Ivan Goethals (KU Leuven/SISTA) in the framework of FliTE, see module 9.4. Different clustering techniques, either heuristic, or statistically based have been tested. Adaptation of the damage detection clustering technique has been performed to obtain a fast and efficient automated modal extraction procedure.

From an experimental point of view, this project has provided lots of opportunities for testing and improving our identification and detection techniques, for both controlled/observed and uncontrolled/unobserved input excitation. On the identification front, large aircraft datasets have been successfully investigated using our online identification monitoring toolbox, for both full and recursive subspace algorithms [13]. On the detection side, massive progress have been achieved in flutter monitoring using our new detection scheme [19]. It allows us to successfully track damping values (the only really fluctuating part of the modes) without re–identifying the modes. This feature speeds up the process tremendously. Notice that both identification techniques and detection techniques have been tested on the same datasets (real aircraft in [13] and simulator [19]) and gave results cross–validating the methods.

In FliTE, the basis for novel techniques for in-flight test data structural analysis was developed, involving both controlled and uncontrolled (natural) excitations. Since the results of FliTE have been positively

evaluated, the partners have agreed with the national funding agencies to submit a follow-up project, FliTE2, which partnership is extended to ONERA/CERT. The main objective of FliTE2 is the effective transfer of the results of FliTE to aircraft manufacturers. This main effort will be combined with the continuation of research on improving the methods, algorithms, and software, in particular regarding fast detection algorithms for the flutter monitoring problem. The lengthy process of Eureka submission with DPAC funding is under progress and should be completed fall 2004.

7.2. FP5 Growth thematic network SAMCO

Participant: Michèle Basseville.

See modules 4.2, 4.3 and 5.1. Contract CNRS 500232 — February 2002/September 2005.

The 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 been involved in several FP6 IP proposals submitted in March 2004 within the NMP framework, of which unfortunately none have been accepted. 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.

8. Other Grants and Activities

8.1. ACI Sécurité & Informatique - Project CONSTRUCTIF

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

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

This project is coordinated by Laurent Mevel. Our partners are MSSMat (Laboratoire de Mécanique des Sols, Structures et Matériaux, École Centrale de Paris and CNRS), Laboratoire Central des Ponts et Chaussées (Service Métrologie et Instrumentation), 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.

The achievements of this year have been focused on the beginning of the PhD Thesis of Houssein Nasser. In collaboration with Dominique Chapelle (MACS), a simplified temperature model relating the modal parameter of interest with the ambient temperature has been developed, see module 6.1. We have shown that the stiffness matrix varies under temperature change and thus an analytical form can be derived to obtain the variation in stiffness for a specified temperature change. Its integration within the general framework of damage detection described in module 3.5 has been described [23]. In that damage detection method, we have proposed to reject the temperature as a nuisance parameter. Experimental validation has yet to come thanks to the experimental setup of LCPC/SMI within the context of this ACI project.

9. Dissemination

9.1. Scientific animation

M. Basseville is member of the steering committee of the GDR ISIS (Information, Signal, Images), member of the steering committee of the RTP24 «Mathématiques de l'information, des signaux et des systèmes». She is member of (the board of) the scientific committee of the Computer Security program launched by the French Ministry of Research (ACI «Sécurité & Informatique»).

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 also member of the MFPT (Machinery Failure Prevention Technology) Society technical committee on *Structural Health Management*.

She is associate editor for the IFAC journal «Automatica», for the journal «Mechanical Systems and Signal Processing», and within the IEEE Control Systems Society Conference Editorial Board, where she has been in charge of the evaluation of papers submitted to ACC'04, CDC'04 and ACC'05. She has been member of the international program committee of CIFA'04.

A. Benveniste is member of the editorial board of the journals «European Journal of Control», «Discrete Event Dynamic Systems» and «Proceedings of the IEEE».

9.2. Teaching

M. Basseville teaches «Statistical methods for in–situ monitoring» within the module «Tools for diagnostics», of the «Automatic Control and Industrial Computing» option, at École des Mines de Nantes.

9.3. Participation in workshops, seminars, lectures, etc.

In addition to presentations with a publication in the proceedings, and which are listed at the end of the document, members of the SISTHEM project–team have also given the following presentations.

During the *Journées de la STAtistique Rennaise*, Michèle Basseville has presented [26] the statistical foundations of the team activities, with an emphasis on the subspace-based estimating function (2) and the exploitation, for processing non-stationary data sets, of the factorization property (11).

9.4. Visits and invitations

Ivan Goethals, a PhD student of Bart De Moor at KU Leuven/SISTA has visited us during two weeks in August 2004, in the framework and with the support of the FliTE project, see module 7.1.

Recursive subspace identification and automated modal extraction has been the focus of this visit. Different clustering techniques, either heuristic, or statistically based have been tested. Adaptation of the damage detection clustering technique has been performed to obtain a fast and efficient automated modal extraction procedure.

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