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Team i4s

Inference for Structures

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Theme : Stochastic Methods and Models

Activity Report

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2. Overall Objectives

2.1. Introduction

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 [38], [56]. In addition to these key driving application areas, SHM is now spreading over most transportation infrastructures and vehicles, within the naval, railway and automobile domains. Examples of structures or machines to be monitored include aircrafts, space crafts, buildings, bridges, dams, ships, offshore platforms, on-shore and off-shore wind farms (wind energy systems), turbo-alternators and other heavy machineries, ...

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

2.1.2. Objectives.

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

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

2.1.3. Industrial and academic relations.

- Industrial projects: with SNECMA (F.) and SVIBS (DK).
- Multi–partners projects at European level: on exploitation of flight test data under natural excitation conditions (FliTE2 - Eurêka), on structural assessment, monitoring and control (SAMCO Association), on industrial risk reduction (IRIS CP-IP).
- Academic research: national project on monitoring civil engineering structures (CONSTRUCTIF - ACI S&I), French Pôle de compétitivité ASTECH MODIPRO, European network on system identification (FP5 TMR), FWO research network on identification and control.

2.2. Highlights of the year

1. *Research :* Thanks to a collaboration with the research group at LMS (BE), we have been developing output-only large scale methods for damage detection (see module 6.3).
2. *Research :* Thanks to a collaboration with KUL (BE) and FEUP (PT), we have been testing on large scale bridges data fusion techniques for identification.
3. *Transfer :* The Scilab toolbox COSMAD has been transferred to SNECMA. Strong evaluation of this toolbox for in-house usage by SNECMA has been performed. A modified version is currently developped for transfer.
4. *Transfer :* In house Subspace algorithms for identification have been licenced to SVIBS (DK).

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 I4S, 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 Akaike criteria (AIC, BIC, MDL, ...) do not work at all. This gives rise to new research activities specific to handling high order models.

Our approach to monitoring assumes that a model of the monitored system is available. This is a reasonable assumption, especially within the SHM areas. The main feature of our monitoring method is its intrinsic ability to the early warning of small deviations of a system with respect to a reference (safe) behavior under usual operating conditions, namely without any artificial excitation or other external action. Such a normal behavior is summarized in a reference parameter vector θ_0, for example a collection of modes and mode-shapes.

3.2. Identification

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 [43] :

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

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 $\widehat{\theta}_N$ converges towards θ^*. Thanks to 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 $\mathcal{K}_N(\widehat{\theta}_N) = 0$, the asymptotic normality of the estimate is obtained :

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

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

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

3.3. Detection

See module 6.5.

Our approach to on-board detection is based on the so-called asymptotic statistical local approach, which we have extended and adapted [5], [4], [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 [36] that the residual is asymptotically Gaussian :

$$\zeta_N \xrightarrow[N \to \infty]{} \begin{cases} \mathcal{N}(0, \Sigma) & \text{under } \mathbf{P}_{\theta_0}\ , \\[2ex] \mathcal{N}(\mathcal{J}\,\eta, \Sigma) & \text{under } \mathbf{P}_{\theta_0+\eta/\sqrt{N}}\ , \end{cases} \tag{3}$$

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 :

$$\chi^2 = \bar{\zeta}^T\,\mathbf{F}^{-1}\,\bar{\zeta} \gtrless \lambda\ . \tag{4}$$

where

$$\bar{\zeta} \triangleq \mathcal{J}^T\,\Sigma^{-1}\,\zeta_N \quad \text{and} \quad \mathbf{F} \triangleq \mathcal{J}^T\,\Sigma^{-1}\,\mathcal{J} \tag{5}$$

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

See modules 6.6 and 6.5.

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 [32]. 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 $\mathfrak{J}$, the Fisher information matrix $\mathbf{F} = \mathfrak{J}^T\,\Sigma^{-1}\,\mathfrak{J}$ and the normalized residual $\overline{\zeta} = \mathfrak{J}^T\,\Sigma^{-1}\,\zeta_N$ are partitioned accordingly

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

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 :

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

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 :

$$t_a^* = \overline{\zeta}_a^{\,*\,T}\;\mathbf{F}_a^{*-1}\;\overline{\zeta}_a^{\,*} \;, \tag{7}$$

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

The properties and relationships of these two types of tests are investigated in [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 [3]. The basic idea is to note that the physical sensitivity matrix writes $\mathfrak{J}\,\mathfrak{J}_{\Phi\theta}$, where $\mathfrak{J}_{\Phi\theta}$ is the Jacobian matrix at Φ_0 of the application $\Phi \mapsto \theta(\Phi)$, and to use the sensitivity test (6) for the components of the parameter vector Φ. Typically this results in the following type of directional test :

$$\chi^2_\Phi = \zeta^T \, \Sigma^{-1} \, \mathcal{J} \, \mathcal{J}_{\Phi\theta} \, (\mathcal{J}^T_{\Phi\theta} \, \mathcal{J}^T \, \Sigma^{-1} \, \mathcal{J} \, \mathcal{J}_{\Phi\theta})^{-1} \, \mathcal{J}^T_{\Phi\theta} \, \mathcal{J}^T \, \Sigma^{-1} \, \zeta \gtrless \lambda \ . \tag{8}$$

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

See module 6.5.

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 (λ, ϕ_λ) of the state transition matrix F of a linear dynamical state-space system :

$$\left\{ \begin{array}{rcl} X_{k+1} & = & F \ X_k + V_{k+1} \\ Y_k & = & H \ X_k \end{array} \right. , \tag{9}$$

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

$$\det \ (F - \lambda \ I) = 0, \quad (F - \lambda \ I) \ \phi_\lambda = 0, \quad \varphi_\lambda \triangleq H \ \phi_\lambda \tag{10}$$

The (canonical) parameter vector in that case is :

$$\theta \triangleq \begin{pmatrix} \Lambda \\ \mathrm{vec}\Phi \end{pmatrix} \tag{11}$$

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 [55]. A contribution of ours, minor but extremely fruitful, has been to write the output-only covariance-driven subspace identification method under a form that involves a parameter estimating function, from which we define a *residual adapted to vibration monitoring* [1]. This is explained next.

3.5.1. Covariance-driven subspace identification.

Let $R_i \triangleq \mathbf{E} \left(Y_k \ Y^T_{k-i} \right)$ and:

$$\mathcal{H}_{p+1,q} \triangleq \begin{pmatrix} R_0 & R_1 & \vdots & R_{q-1} \\ R_1 & R_2 & \vdots & R_q \\ \vdots & \vdots & \vdots & \vdots \\ R_p & R_{p+1} & \vdots & R_{p+q-1} \end{pmatrix} \triangleq \mathrm{Hank}\left(R_i\right) \tag{12}$$

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 (9) lead to the well known key factorizations :

$$\begin{aligned} R_i &= HF^iG \\ \mathcal{H}_{p+1,q} &= \mathcal{O}_{p+1}(H,F)\ \mathcal{C}_q(F,G) \end{aligned} \tag{13}$$

where:

$$\mathcal{O}_{p+1}(H,F) \triangleq \begin{pmatrix} H \\ HF \\ \vdots \\ HF^p \end{pmatrix} \quad \text{and} \quad \mathcal{C}_q(F,G) \triangleq (G\ FG\ \cdots\ F^{q-1}G) \tag{14}$$

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 (λ, ϕ_λ) then results from (10).

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

$$\mathcal{O}_{p+1}(\theta) = \begin{pmatrix} \Phi \\ \Phi\Delta \\ \vdots \\ \Phi\Delta^p \end{pmatrix} \tag{15}$$

where $\Delta \triangleq \mathrm{diag}(\Lambda)$, and Λ and Φ are as in (11). Whether a nominal parameter θ_0 fits a given output covariance sequence $(R_j)_j$ is characterized by [1]:

$$\mathcal{O}_{p+1}(\theta_0) \ \text{ and } \ \mathcal{H}_{p+1,q} \ \text{ have the same left kernel space.} \tag{16}$$

This property can be checked as follows. From the nominal θ_0, compute $\mathcal{O}_{p+1}(\theta_0)$ using (15), and perform e.g. a singular value decomposition (SVD) of $\mathcal{O}_{p+1}(\theta_0)$ for extracting a matrix U such that:

$$U^T\ U = I_s \ \text{ and } \ U^T\ \mathcal{O}_{p+1}(\theta_0) = 0 \tag{17}$$

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:

$$U(\theta_0)^T \ \mathcal{H}_{p+1,q} = 0 \tag{18}$$

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 $\widehat{\mathcal{H}}_{p+1,q}$:

$$\widehat{\mathcal{H}}_{p+1,q} \triangleq \text{Hank}\left(\widehat{R}_i\right), \quad \widehat{R}_i \triangleq 1/(N-i) \sum_{k=i+1}^{N} Y_k \ Y_{k-i}^T \tag{19}$$

and to define the residual vector:

$$\zeta_N(\theta_0) \triangleq \sqrt{N} \ \text{vec}\left(U(\theta_0)^T \ \widehat{\mathcal{H}}_{p+1,q}\right) \tag{20}$$

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 (18), 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 [3], 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 (11), and for deriving the residual. Factorization (13) is also the key for :

- Proving consistency and robustness results [6];
- Designing an extension of covariance-driven subspace identification algorithm adapted to the presence and fusion of non-simultaneously recorded multiple sensors setups [7];
- Proving the consistency and robustness of this extension [9];
- Designing various forms of *input-output* covariance-driven subspace identification algorithms adapted to the presence of both known inputs and unknown excitations [10].

4. Application Domains

4.1. Introduction

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

4.2. Vibrations-based monitoring

See modules 3.5.

Detecting and localizing damages for monitoring the integrity of structural and mechanical systems is a topic of growing interest, due to the aging of many engineering constructions and machines and to increased safety norms. Many current approaches still rely on visual inspections or *local* non destructive evaluations performed manually. This includes acoustic, ultrasonic, radiographic or eddy-current methods; magnet or thermal field techniques, ... These experimental approaches assume an *a priori* knowledge and the accessibility of a neighborhood of the damage location. Automatic *global* vibration-based monitoring techniques have been recognized to be useful alternatives to those local evaluations [38]. However this has led to actual damage monitoring systems only in the field of rotating machines.

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

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

Health monitoring techniques based on processing vibration measurements basically handle two types of characteristics: the *structural parameters* (mass, stiffness, flexibility, damping) and the *modal parameters* (modal frequencies, and associated damping values and mode-shapes); see [50] and references therein. A central question for monitoring is to compute *changes* in those characteristics and to assess their *significance*. For the *frequencies*, crucial issues are then: how to compute the changes, to assess that the changes are significant, to handle *correlations* among individual changes. A related issue is how to compare the changes in the frequencies obtained from experimental data with the sensitivity of modal parameters obtained from an analytical model. Furthermore, it has been widely acknowledged that, whereas changes in frequencies bear useful information for damage *detection*, information on changes in (the curvature of) mode-shapes is mandatory for performing damage *localization*. Then, similar issues arise for the computation and the significance of the changes. In particular, assessing the significance of (usually small) changes in the mode-shapes, and handling the (usually high) correlations among individual mode-shape changes are still considered as open questions [50], [38].

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, 6.6, and 7.7.

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 [51]. 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 6.6.

4.4. Aeronautics

See modules 3.5, 6.1, 6.3, 6.5, 7.1 and 7.6.

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 [33].

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

A crucial issue is to ensure that the newly designed airplane is stable throughout its operating range. A critical instability phenomenon, known under the name of *“aero-elastic flutter, involves the unfavorable interaction of aerodynamic, elastic, and inertia forces on structures to produce an unstable oscillation that often results in structural failure”* [44]. 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 [37], [45], 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 6.5 .

5. Software

5.1. COSMAD: Modal analysis and health monitoring Scilab toolbox

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

With the help of Yann Veillard, Auguste Sam and Simon Berger, former engineers, Laurent Mevel and Maurice Goursat have developed a Scilab toolbox devoted to modal analysis and vibration monitoring of structures or machines subjected to known or ambient (unknown) excitation [48], [47].

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

IDDN.FR.001.210011.002.S.A.2003.000.20700

and can be down-loaded from http://www.irisa.fr/i4s/cosmad/. A list of test-cases (simulators, laboratory test-beds, real structures) for which COSMAD has been used is available from http://www.irisa.fr/i4s/cases.pdf.

COSMAD performs the following tasks :

- *Output-only (O/O) subspace-based identification*, working batch-wise, see modules 3.5, 6.1 and 7.1. The problem is to identify the eigenstructure (eigenvalues and observed components of the associated eigenvectors) of the state transition matrix of a linear dynamical system, using only the observation of some measured outputs summarized into a sequence of covariance matrices corresponding to successive time shifts. An overview of this method can be found in [29], and details in [40], [54], [52] and [53].
- *Input-output (I/O) subspace-based identification*, working batch-wise, see modules 3.5, 6.1 and 7.1. The problem is again to identify the eigenstructure, but now using the observation of some measured inputs and outputs summarized into a sequence of cross-covariance matrices. This method is described in [10].
- *Automatic subspace-based modal analysis*, a pre-tuned version of the O/O and I/O identification methods above. This is described in [48].
- *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 [30] and [49], [41].

- *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 [39].
- *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], [3].
- *Damage monitoring*, a sample point-wise version of the damage detection algorithm above. This is described in [46].
- *On-line flutter onset detection*, see modules 3.3, 3.5, 4.2 and 6.5. This algorithm detects that one damping coefficient crosses a critical value from above. For this method see [8] [30]. 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 [31], [42].
- *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 [3].
- *Damage localization*, see modules 3.4, 3.5 and 4.2.

  The problem is to find the part of the structure, and the associated structural parameters (e.g. masses, stiffness coefficients) that have been affected by the damage. We state and solve this problem as a detection problem, and not an (ill-posed) inverse estimation problem. This is explained in [3].
- *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 [28], [26].

The modules have been tested by different partners, especially the French industrial partners, EADS, Dassault and Sopemea, within the FliTE2 project (see module 7.1), by partners from the past CONSTRUCTIF project [52] and [53], and within the framework of bilateral contracts with SNECMA and SVIBS (see modules 7.6 and 7.7).

This Scilab toolbox continues to play the role of a programming and development environment for all our newly designed algorithms. Moreover, offering a *maintained* Scilab platform turns out to be a crucial factor in convincing industrial partners to undergo joint investigations with us or to involve us within partnerships in FP7 integrated projects proposals, see module 8.1.

As from December 2007, Neil Babou, associate engineer, has worked on finalizing the next major version of COSMAD. Identification techniques used during FliTE2 have also been implemented by F. Queyroi. Porting COSMAD to Scilab 5 has been done. A specific version for use within SNECMA is currently under way.

6. New Results

6.1. Eigenstructure identification

Participants: Michael Döhler, Maurice Goursat, Laurent Mevel.

See modules 3.2, 3.5, 4.2, 7.1, 7.6 and 7.7.

6.1.1. Improving subspace identification : slight modifications of the algorithm

There are numerous ways to implement the covariance subspace identification method. The variants relate to the choice of parameters, which have to be tuned by the user. Such tuning is only reliably done by the mechanical engineer, when the parameter has a physical meaning. From the data to the results there are 4 main steps in the covariance subspace identification method. In this paper [19], we are concerned with the computation of the decomposition of the Hankel matrix and the mean square estimation of the transition matrix. We compare different cases for the algorithms related to these steps: how to choose the parameters and what are the corresponding perturbations on the results for the different basic numerical algorithms. The conclusion is that with some modifications we can easily obtain more precise and reliable results. The idea is also to minimize the number of parameters to be tuned by the user. With a matrix normalization and some approximation scheme we get an implementation being a very efficient and stable identification procedure. All these algorithms are theoretically equivalent, but in practice some give much better results. These new schemes have been validated on different concrete cases (civil structure, aircraft, space launcher). Improvements in damping stability is the main output of this work. Implementation of this work in COSMAD (see module 5.1) and for transfer to SNECMA and SVIBS (see modules 7.6 and 7.7) has been done in 2009.

6.1.2. Monitoring of aerospace rockets

We revisit the problem of the modal analysis of space launchers. We consider the Ariane 5 launcher with its usual equipment during a commercial flight under the natural unknown excitation. The case of space launchers is a typical example of a complex structure with sub-structures strongly and quickly varying in time. This issue becomes especially important in e.g. estimation of damping of aerospace vehicles. The eigenfrequencies are also sliding during the flight but the modeshapes are more stable. Recently, a new implementation of the subspace identification method has been proposed, leading to cleaner and more stable stabilization diagrams. We monitor the behavior of estimated modal parameters by applying this crystal clear implementation of the data driven and the covariance driven Stochastic Subspace Identification algorithms. We show the importance of crystal clear to monitor successfully frequencies and damping estimates over time in such a non stationary case. This work will be presented in [18].

6.2. Large structures identification - Data fusion

Participants: Michael Döhler, Laurent Mevel.

See modules 3.2, 3.5, 4.2, and 7.7.

In Operational Modal Analysis (OMA) of large structures we often need to process sensor data from multiple non simultaneously recorded measurement setups. These setups share some sensors in common, the so-called reference sensors that are fixed for all the measurements, while the other sensors are moved from one setup to the next. To obtain the modal parameters of the investigated structure, it is necessary to process the data of all the measurement setups and normalize it as the unmeasured background excitation of each setup might be different. For this we compare three different approaches which differ in the order of the data merging, normalization and system identification step: The classical PoSER (identification-normalization-merging), the PoGER (merging-identification-normalization) and the PreGER (normalization-merging-identification). Special care was taken with the PreGER method and its efficiency has been tested with respect to the two other methods. The system identification is done with the SSI-cov/ref method. We apply these methods to the extraction of the modal parameters (natural frequencies, damping ratios and mode shapes) of the Luiz I arch bridge in Porto, Portugal, compare them and evaluate the different methods [17].

A variant of this approach has been derived to handle different subspace approaches such as the UPC data driven approach. It has been tested on a building in Vancouver and presented in [16]. This is part of M. Döhler thesis and related to SVIBS agreement.

6.3. Change/damage detection and isolation in the frequency domain

Participants: Gilles Canales, Laurent Mevel.

See modules 3.3, 3.4, and 6.5.

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

A new residual based on the polyreference Least Square Complex Frequency domain (LSCF) identification method has been proposed and described in the 2007 report. It has been presented at [34].

In the second year of Gilles Canales thesis, different frequency domain damage detection residuals have been derived for the transmissibility frequency domain method. It has been presented at [14] and has been submitted to SYSID 09 [15].

Consistency and asymptotical normality of that residual have been proved. We monitor some small changes in the transmissibility equation, where the transmissibility is the ratio between output and input in the frequency domain. Assuming a single force is applied to the system, this leads to an output only frequency domain method, a relaxing hypothesis with respect to last year [34].

Other frequency domain methods under investigation include OMAX, Maximum likelihood and frequency domain decomposition methods. Residuals for such techniques have been evaluated. G. Canales is currently writing his thesis.

6.4. Composite structures

Participants: Michael Döhler, Maurice Goursat, Laurent Mevel.

See modules 3.4, 3.5 and 4.3.

A comparison of three different damage detection methods is made on three identical glass reinforced composite panels, similar to the load carrying laminate in a wind turbine blade. Sensor data were recorded in the healthy state and after the introduction of damage by means of a four point bending quasi static test. Acceleration sensors, PZT transducers and the piezoelectric excited Lamb waves were used for the measurements of the panels. All three methods are based on the comparison of the healthy and damaged structure. The first method is statistical covariance driven damage detection using a subspace based algorithm, where one damage indicator for all three panels was computed. The second method is based on PZT transducers and the A0 mode of Lamb waves propagating in the panel, making use of the reflection of the signal at damage in the panel. The third method is based on the estimation of modal parameters of the intact and damaged panel using pLSCF and following their deviations. The results from these three damage detection methods are compared and discussed. This work will be presented in [20] and [21].

6.5. Flutter monitoring and onset detection

Participants: Michèle Basseville, Laurent Mevel, Rafik Zouari.

See modules 3.3, 3.5, 4.4 and 7.1.

Stating the flutter monitoring problem (see modules 4.4 and 7.1) as a statistical hypotheses testing problem, in [8] and [30] we have advocated for an on–line test built on a sample-wise temporal data-driven computation for the subspace–based residual (20), a non-local approximation for that residual, and the cumulative sum (CUSUM) test [4]. None of these approaches uses any model of the underlying physical phenomenon.

6.5.1. *Adaptive online CUSUM tests.*

A new empirical approach to kernel computation has been evaluated and presented at the IFAC World Congress [57]. It compares a recursive Hankel matrix computed online for each time instant t, with a recursive computation of its kernel. The kernel is representative of the modal state at some previous instant. If some brutal change arises, a discrepancy appears between the Hankel matrix and its kernel because of the delay between both computations. The test is not performing flutter detection but monitors the brutal variations of the monitored parameter, which will be the flutter phenomena if we assume that flutter corresponds to a brusque variation in the dynamics of the parameter. An application to a large scale simulated aircraft has been performed during the FliTE2 project and presented at EWSHM in Poland. This was done in collaboration with AGH [58]. It involves mixing wavelet filtering and the above CUSUM test. Wavelet filtering allows reducing model order of the monitored system, which help reducing false alarms.

Work is currently ongoing to publish this work.

6.5.2. Subspace based damping monitoring

Tracking the evolutions of modal parameters is not an easy task. In fact, even for stationary systems, identification is a complex task, notwithstanding the computation of confidence intervals. For non stationary systems, such as an aircraft in operation, reaction time and system variability render most identification methods difficult to implement. The CUSUM technique is reused to handle monitoring of slight in-operation modal variations over time. Application to simulation data shows the relevance of the new approach to track damping coefficients of critical modes. The methods involves the computation of a parametrized reference kernel for the CUSUM test, tuned with some signature representative of some predefined threshold corresponding to a confidence interval for the monitored damping. Minmax rejection allows the rejection of the effect of the frequency evaluation due to the mismatch between the modal model defined by the parameterized kernel and the current model associated with the data, resulting from the interaction with the aeroelasticity model. This method of tracking modal parameter variations by a change detection technique defined by some predefined adaptive threshold has been validated on both academic examples and some realistic simulation of an aircraft under acceleration phase provided by Dassault Aviation. This work has been presented at [24].

6.6. Handling the temperature effect

Participants: Michael Döhler, Maurice Goursat, Laurent Mevel.

See modules 3.4, 3.5 and 4.3.

The PhD thesis of Houssein Nasser completed in 2006 has addressed the problem of rejecting the temperature effect when performing damage detection tests on civil structures. Because of the temperature effects, the test may not react to some damages, and conversely may be too sensitive to some ambient temperature changes.

Some approach is based on the collection of varying reference temperature datasets, and on a reference kernel averaging all the temperature scenarios [25]. This is the topic of the following case studies.

6.6.1. Temperature rejection : case study on a bridge

After the work on a beam under temperature and damages changes in I4S and LCPC [53], this year, the actual robustness to temperature changes of the proposed methods has been further investigated within LCPC by Dominique Siegert under the supervision of I4S [23]. The extreme reaction of the test to summer/winter and its robustness to small temperature changes have been shown. This work presents the processing methods and the analysis results of ambient vibration data recorded during a six-month period on a highway bridge, the Roberval bridge in France. Data analysis was focused on the variations of the modal parameter related to the accuracy of the estimates and to the temperature effects. The first flexural and torsional modes were estimated with their variance from short acceleration time series records using stochastic covariance driven subspace identification techniques. The frequency variation estimates were compared to the variations induced by structural modifications simulated with a finite element model for assessing the detection threshold level. Subsequently the temperature induced variations in the measured frequencies were analysed. The effectiveness of the temperature robust version of Houssein Nasser Phd thesis was investigated with the available data records. Results of the damage detection test show the response to the temperature effects. Significant increases in the variance of the parameter estimates were also detected by the test. Confidence intervals based on analytical derivation of the subspace equation were compared with the evolution of the damage detection test with success, in collaboration with Katholieke Universiteit Leuven.

6.6.2. *Temperature rejection : case study on a bridge mock up*

Small localized damages are hardly detected by global monitoring methods. The effectiveness of vibration based detection depends on the accuracy of the modal parameter estimates and is limited by the low sensitivity of the modal parameters to a local stiffness reduction. A local reduction of stiffness related to frequency changes less than 1% was successfully detected on a 10 meter span composite UHPFRC - FRP reinforced timber beam bridge loaded in laboratory conditions up to the serviceability limit state (SLS). Such a small decrease in the stiffness was not detected by the monitoring of the static load-deflection measurements but was confirmed by non-linear local strain measurements. Statistical subspace-based damage detection successfully detected the change of the modal parameters of the investigated structure. Further analysis with a finite element model was conducted for assessing the consistency of the expected location and extent of the damaged elements. Work will be presented in [22].

7. Contracts and Grants with Industry

7.1. Eurêka project FliTE2

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

See modules 4.2, 4.4, 5.1, 6.1 and 6.5.

Contract INRIA — September 2005/November 2008.

We have been strongly contributing to the establishment, within the Eurêka framework, of a follow-up of the major cooperation FliTE for which a success story is available at
http://www.eurekanetwork.org/.

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.

This project is finished, but work is still going on for publishing results of Rafik zouari thesis. A new FP7 project proposal is under consideration.

7.2. FP7-NMP CP-IP 213968-2 IRIS

Participants: Michael Döhler, Laurent Mevel, Xuan Binh Lam.

See modules 4.2, 5.1.

Contract INRIA 3947

I4S is involved in the core consortium of FP7-NMP Large Scale Integrated Project IRIS (*Integrated European Industrial Risk Reduction System*), which helds its kick off meeting in October 2008. This project has been elaborated within the framework of the SAMCO association (see module 8.1). I4S is involved in the online monitoring sub-project.

A new PhD student, Xuan Binh Lam, has started from November 1st, 2008, willing to work on safety related work for risk control, especially for monitoring of transient events.

The FP7 IRIS project about Risk assessment involves 40 partners and is headed by Helmut Wenzel, VCE (Austria). INRIA is involved in Group 3 about Structural Health Monitoring. I4S works with Sheffield University and BAM (Germany) for development of tools for structural damage detection for bridges and wind farms. Laurent Mevel is also member of the core IRIS Vision group, and is responsible of the scientific coherency of the project.

7.3. SIMS

Participant: Laurent Mevel.

See modules 4.2, 4.3, 5.1, 6.1. 6.2, and 6.6.

SIMS, Canada : I4S has signed a collaborative agreement with SVIBS. This leads to SVIBS bringing INRIA into a 12 year long SHM project in Canada with ambitious objectives of producing some full internet based structural health monitoring project with potential applications to buildings, hospitals and of course, the collection of bridges monitored by the Ministry of Transportation of British Columbia. This project is also related to TPV, a startup in civil engineering, whose objectives is to valuate our methods in North America.

This project is monitored by University of British Columbia, under contract with Ministry of Transportation, BC. This work is performed with help of DDS, Belgium and SVIBS, DK. This will implement INRIA algorithms in a SHM system, and will provide a large scale outdoor demonstration for I4S.

7.4. PhD CIFRE with Dassault Aviation

Participant: Laurent Mevel.

See modules 3.3, 3.4, 6.3, 6.5, and 7.1.

Following the FliTE2 project, discussions are under way about a joint PhD thesis between INRIA and Dassault Aviation. The thesis will pursue the work achieved in FliTE2 and starts in Fall 2010 funded by Dassault Aviation.

7.5. Pôle de Compétitivité ASTECH MODIPRO

Participants: Maurice Goursat, Laurent Mevel.

See modules 3.3, 3.4, 6.3, 6.5, and 7.1.

Contract INRIA 4162

I4S is implied in a national project for aircraft SHM starting Fall 2009. This project will improve on monitoring procedures developed in previous projects to provide some algorithms for use in Dassault Aviation aircraft monitoring procedures.

7.6. SNECMA

Participants: Neil Babou, Maurice Goursat, Laurent Mevel.

See modules 4.2, 4.4, 5.1, and 6.1.

Contract INRIA to be signed December 2009.

In 2007, I4S has investigated for SNECMA an identification case study on some undisclosed engine structure. Successfull results yield to the delivery of the COSMAD toolbox for internal evaluation at SNECMA. The end goal is the use of COSMAD in the industrial process of SNECMA. Internal evaluation of COSMAD has been performed inhouse by SNECMA in 2008. A contract has been signed and some software package will be developed to suit SNECMA needs in 2010. Work on the SNECMA prototype has been performed in 2009.

7.7. SVIBS

Participant: Laurent Mevel.

See modules 4.2, 4.3, 5.1, 6.1, and 6.6.

Annual agreement INRIA-SVIBS 2381 + contract 4329

SVIBS (Structural Vibration Solutions A/S) is a company located in Aalborg, Denmark, having strong connections with the Department of Civil Engineering of University of British Columbia, CA (Prof. Carlos Ventura).

SVIBS and I4S are investigating how to link the modal analysis software ARTeMIS of SVIBS and COSMAD. Through an annual agreement, I4S gets a license of ARTeMIS in exchange to offer support for integrating our damage detection software into SVIBS software and offerings. A contract has been signed, where I4S provides algorithms and expertise for integration within a damage detection structural health monitoring system and SVIBS does the implementation. This technology transfer has been funded by the ministry of transportation of British Columbia, Canada. The work is supervised by UBC, CA. The end product will be a web based structural health monitoring system for in operation bridges.

I4S is doing technology transfer towards SVIBS to implement I4S technologies into ARTEMIS Extractor Pro. This is done under a royalty agreement between INRIA and SVIBSḞirst achievements include the implementation of the so called Crystal Clear SSI, a subspace variant, with much lower signal to noise ratio, and whose interest in the mechanical engineering community is very high. Other I4S algorithms are currently under review to be integrated within ARTEMIS. SVIBS and I4S are also related in the related IAPP proposal and the SIMS project.

8. Other Grants and Activities

8.1. SAMCO association

See modules 4.2, 4.3 and 5.1.

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

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

We are involved in the IRIS project proposal, elaborated in this framework, see module 7.2.

8.2. FWO Research Network ICCoS

Participants: Albert Benveniste, Laurent Mevel.

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

8.3. Partnership with KU Leuven

Participants: Maurice Goursat, Laurent Mevel.

Agreement INRIA-KU.Leuven

I4S and Katholieke Universiteit Leuven (Guido de Roeck, Civil Engineering Department) are collaborating on the topic of confidence intervals for subspace-based estimates [23]. Collaboration has also occurred on the topic of data fusion for subspace experiments [17].

8.4. Marie Curie FP7-PEOPLE-2009-IAPP ISMS

Participants: Michael Döhler, Laurent Mevel.

See modules 4.2, 4.3, 5.1, 6.6, and 7.7.

A proposal has been submitted with SVIBS, University of British Columbia and I4S to develop a framework for handling structural health monitoring methods. This proposal implies some long stay of the concerned people, Laurent Mevel and Michael Döhler for I4S abroad. Palle Andersen from SVIBS is assumed to stay 4 months at INRIA, for tighten integration of COSMAD and ARTEMIS software.

8.5. International collaborations

Participants: Michael Döhler, Maurice Goursat, Laurent Mevel.

This year, I4S has been collaborating with the following universities and institutes :

- The University of British Columbia (CA), Civil Engineering Department,
- Vrije Universiteit Brussel (B), Acoustics & Vibration Research Group, [59], [35],
- Minho University (PT), Civil Engineering Department [12],
- Katholieke Universiteit Leuven (B), Civil Engineering Department [12],
- LCPC, Metrology and Instrumentation Division [53],
- Faculty of Engineering of University of Porto [17].

9. Dissemination

9.1. Scientific animation

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

9.2. Conference and workshop committees, invited conferences

9.2.1. Committees.

L. Mevel is member of the IOMAC (International Operational Modal Analysis Conference) Scientific Committee, held in Italy, in May 2009. He is also scientific supervisor of the IRIS FP7 project.

9.2.2. Invited publications.

The team has been involved in:

- A special session on *Flight Flutter Testing and Analysis* at the *International Conference on Noise and Vibration Engineering* in Troyes, BE, in June 2009 [13].

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Major publications by the team in recent years

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