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Team i4s

*Statistical Inference for Structural Health
Monitoring*

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R *eport*

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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

- Transfer : the multi measurements setup merging developed within M. Döhler PhD thesis has been transferred to SVS, DK for inclusion in Artemis Pro 2011.
- Transfer : COSMAD toolbox has been transferred to SNECMA for in operation use.
- Research : ISMS, a Marie Curie project (FP7 People program for mobility) has been started.

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

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, \dots, 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, \dots, Z_N) , an estimate of the unknown parameter is then [43] :

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

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^* . 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 $\mathcal{K}_N(\hat{\theta}_N) = 0$, 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

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}_{θ_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 :

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

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

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

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 :

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

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 :

$$\chi^2 = \bar{\zeta}^T \mathbf{F}^{-1} \bar{\zeta} \geq \lambda . \quad (4)$$

where

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

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

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 [34]. 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 $\bar{\zeta} = \mathcal{J}^T \Sigma^{-1} \zeta_N$ are partitioned accordingly

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

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 :

$$t_a = \bar{\zeta}_a^T \mathbf{F}_{aa}^{-1} \bar{\zeta}_a, \quad (6)$$

where $\bar{\zeta}_a$ 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 :

$$t_a^* = \bar{\zeta}_a^{*T} \mathbf{F}_a^{*-1} \bar{\zeta}_a^*, \quad (7)$$

where $\bar{\zeta}_a^* \triangleq \bar{\zeta}_a - \mathbf{F}_{ab} \mathbf{F}_{bb}^{-1} \bar{\zeta}_b$ is the effective residual (score) resulting from the regression of the informative partial score $\bar{\zeta}_a$ over the nuisance partial score $\bar{\zeta}_b$, 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 [29].

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 $\mathcal{J} \mathcal{J}_{\Phi\theta}$, 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 (6) for the components of the parameter vector Φ . Typically this results in the following type of directional test :

$$\chi_{\Phi}^2 = \zeta^T \Sigma^{-1} \mathcal{J} \mathcal{J}_{\Phi\theta} (\mathcal{J}_{\Phi\theta}^T \mathcal{J}^T \Sigma^{-1} \mathcal{J} \mathcal{J}_{\Phi\theta})^{-1} \mathcal{J}_{\Phi\theta}^T \mathcal{J}^T \Sigma^{-1} \zeta \geq \lambda . \quad (8)$$

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

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 :

$$\begin{cases} X_{k+1} = F X_k + V_{k+1} \\ Y_k = H X_k \end{cases} , \quad (9)$$

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

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

The (canonical) parameter vector in that case is :

$$\theta \triangleq \begin{pmatrix} \Lambda \\ \text{vec}\Phi \end{pmatrix} \quad (11)$$

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 $R_i \triangleq \mathbf{E} (Y_k Y_{k-i}^T)$ and:

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

be the output covariance and Hankel matrices, respectively; and: $G \triangleq \mathbf{E}(X_k Y_k^T)$. Direct computations of the R_i 's from the equations (9) lead to the well known key factorizations :

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

where:

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

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:

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

where $\Delta \triangleq \text{diag}(\Lambda)$, 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]:

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

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:

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

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:

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

3.5.3. Residual associated with subspace identification.

Assume now that a reference θ_0 and a new sample Y_1, \dots, Y_N are available. For checking whether the data agree with θ_0 , the idea is to compute the empirical Hankel matrix $\widehat{\mathcal{H}}_{p+1,q}$:

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

and to define the residual vector:

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

Let θ be the actual parameter value for the system which generated the new data sample, and \mathbf{E}_θ 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

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

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.

4.4. Aeronautics

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 [35].

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.

5. Software

5.1. COSMAD : Modal analysis and health monitoring Scilab toolbox

Participants: Laurent Mevel [corresponding person], 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*, 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 [31], and details in [40], [54], [52] and [53].
- *Input-output (I/O) subspace-based identification*, 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*, 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 [32] 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*, 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,

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*, This algorithm detects that one damping coefficient crosses a critical value from above. For this method see [8] [32]. 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 [33], [42].
- *Modal diagnosis*, working batch-wise, This algorithm finds the modes the most affected by the detected deviation. For this method, see [3].
- *Damage localization*,
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 [30], [28].

The modules have been tested by different partners, especially the French industrial partners, EADS, Dassault and Sopemea, within the FLiTE2 project, by partners from the past CONSTRUCTIF project [52] and [53], and within the framework of bilateral contracts with SNECMA and SVIBS (see modules 7.4 and 7.5).

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.

6. New Results

6.1. identification of linear systems

6.1.1. Multi measurement setup merging

Participants: Michael Döhler, Laurent Mevel.

In Operational Modal Analysis (OMA) of large structures it is often needed to process sensor data from multiple non-simultaneously recorded measurement setups. As the ambient unmeasured excitation can be different from setup to setup, the amplitude of the measured data can be different as well. So the data from all the setups has to be normalized, merged and processed together. With this so-called "PreGER" multisetup system identification, the modal parameters of a structure are obtained, where the covariance- and datadriven Stochastic Subspace Identification (SSI) is used. Furthermore, the uncertainty of the obtained modal parameters is evaluated. See [13] and [17]. These algorithms have been tested in the IRIS project in collaboration with University of Tokyo, Japan in [18] on the S101 bridge, a benchmark of the CE.

6.1.2. Fast multi order subspace identification algorithm

Participants: Michael Döhler, Laurent Mevel.

Stochastic subspace identification methods are an efficient tool for system identification of mechanical systems in Operational Modal Analysis (OMA), where modal parameters are estimated from measured vibrational data of a structure. System identification is usually done for many successive model orders, as the true system order is unknown and identification in results at different model orders need to be compared to distinguish true structural modes from spurious modes in so-called stabilization diagrams. An algorithm to estimate the system matrices at multiple model orders has been derived. See [24].

6.1.3. Evaluation of confidence intervals and computation of sensitivities for subspace methods

Participants: Michael Döhler, Xuan Lam, Laurent Mevel.

In Operational Modal Analysis, the modal parameters (natural frequencies, damping ratios and mode shapes) obtained from Stochastic Subspace Identification (SSI) of a structure, are afflicted with statistical uncertainty. Algorithms that automatically compute the confidence intervals of modal parameters allow comparing the quality of covariance- and data-driven SSI. see [22] in collaboration with Harbin Institut of Technology, China and [14]. A variant of this approach has been derived for the Eigenvalue-Realization-Algorithm (ERA) [27].

6.1.4. Automated monitoring of vibration characteristics

Participants: Michael Döhler, Xuan Lam, Laurent Mevel.

Hongguang Zhu master SISAE, helped Michael Döhler implementing algorithms for confidence interval computation and turning the code into an efficient implementation after some recent development in this field, then able to handle a significant higher model order in the algorithm with a faster computation. This is a delivery of the IRIS FP7 project as well as source of potential collaborations [22].

6.2. damage detection for mechanical structures

6.2.1. Damage detection and temperature rejection

Participants: Michael Döhler, Xuan Lam, Laurent Mevel.

Previous works on damage detection, already detailed in the 2009 activity report have been published. See [21] and [11] in collaboration with LCPC, and [20] in collaboration with LMS, Be and the RISOE lab in Poland. Finally, see [12] in collaboration with Harbin Institute of China.

6.2.2. Modular identification and damage detection for large structures

Participants: Michael Döhler, Laurent Mevel.

In Operational Modal Analysis (OMA) of large structures it is often needed to process sensor data from multiple non-simultaneously recorded measurement setups, especially in the case of large structures.. In this work [16], a new efficient variant of the PreGER algorithm is presented that avoids the numerical explosion of the calculation by using a modular approach, where the data from the measurement setups is processed setup by setup and not at the same time. Furthermore, a new efficient variant of the subspace-based stochastic damage detection for multiple measurement setups is presented. See [15].

6.2.3. Robust subspace damage detection

Participants: Michael Döhler, Laurent Mevel.

Subspace methods enjoy some popularity, especially in mechanical engineering, where large model orders have to be considered. In the context of detecting changes in the structural properties and the modal parameters linked to them, some subspace based fault detection residual has been recently proposed and applied successfully. However, most works assume that the unmeasured ambient excitation level during measurements of the structure in the reference and possibly damaged condition stays constant, which is not possible in any application. This paper addresses the problem of robustness of such fault detection methods. A subspace-based fault detection test is derived that is robust to excitation change but also to numerical instabilities that could arise easily in the computations. See [25].

6.3. Instability monitoring of aeronautical structures

6.3.1. Ground resonance monitoring for hinged-blades helicopters

Participants: Ahmed Jhinaoui, Laurent Mevel.

Works on the problem of helicopter ground resonance and the prediction of related instability zones relay generally on online modal analysis, neglecting thus the problem of model's uncertainties. In this work, an on-line algorithm of detection, built on the CUSUM test, is proposed. A numerical application to simulation data is then reported. A mechanical model is used for simulation and is extended to the class of helicopters with damped structures. See [26].

6.3.2. Crystal clear SSI for automated monitoring of aerospace engines

Participants: Maurice Goursat, Michael Döhler, Laurent Mevel.

We revisit the problem of the modal analysis of space launchers Ariane 5. 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. Recently, a new implementation of the subspace identification method has been proposed, leading to cleaner and more stable stabilization diagrams (licenced to SVIBS, DK). See [19].

6.3.3. Optimal input design for identification and detection

Participants: Alireza Esna Ashari, Laurent Mevel, Albert Benveniste.

Output only techniques rely on the presence on unknown turbulence, which may or may not be enough to excite the system. A new approach for applying artificial input to the system for maximizing detection and identifiability has been developed.

7. Contracts and Grants with Industry

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

Participants: Michael Döhler, Laurent Mevel, Xuan Lam.

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 holds its kick off meeting in October 2008. This project has been elaborated within the framework of the SAMCO association. I4S is involved in the online monitoring sub-project.

The FP7 IRIS project about Risk assessment involves 40 partners and is headed by Helmut Wenzel, VCE (Austria), a SME company. 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.

7.2. SIMS

Participants: Laurent Mevel, Michael Döhler.

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 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. I4S is subcontractor of SVS. Contract has to be signed.

7.3. PhD CIFRE with Dassault Aviation

Participant: Laurent Mevel.

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 January 2011 funded by Dassault Aviation.

7.4. SNECMA

Participants: Maurice Goursat, Laurent Mevel.

Contracts INRIA signed in December 2009 (2009-alloc 4589) and July 2010 (2010-alloc 5110).

In 2007, I4S has investigated for SNECMA an identification case study on some undisclosed engine structure. Successful 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 and 2010.

7.5. SVIBS

Participants: Laurent Mevel, Michael Döhler.

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 SVIBS . First 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 ISMS and the SIMS project.

8. Other Grants and Activities

8.1. Regional Initiatives

Participants: Laurent Mevel, Michael Döhler.

I4S is working together with LCPC, Nantes on the problem of temperature rejection for civil structure monitoring[21]. Many different initiatives are on going.

8.2. National Initiatives

8.2.1. *Pôle de Compétitivité ASTECH MODIPRO*

Participants: Maurice Goursat, Laurent Mevel.

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. I4S works together with Qinghua Zhang of INRIA Rocquencourt, project team SISYPHE, on this topic.

8.2.2. Collaboration with LCPC

Participant: Laurent Mevel.

I4S is related to the forthcoming project FUI SIPRIS (Systèmes d'Instrumentation pour la prévention des risques), lead by Advitam.

8.2.3. Collaboration with ALEA, EPI Team at Inria Bordeaux Center

Participants: Laurent Mevel, Meriem Zghal.

I4S has started a 2 year collaboration with EPI ALEA on using particular filtering in vibration analysis. A new engineer has been hired for that task, starting October 2010.

8.2.4. Collaboration with ISAE

Participants: Laurent Mevel, Ahmed Jhinaoui.

A new PhD student, Ahmed Jhinaoui has started a new thesis on helicopter instability. This thesis is codirected by professor Morlier from ISAE, France. This thesis is funded by FP7-NMP Large Scale Integrated Project IRIS.

8.3. European Initiatives

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

Participants: Michael Döhler, Laurent Mevel, Xuan Lam.

I4S is involved in the core consortium of FP7-NMP Large Scale Integrated Project IRIS (*Integrated European Industrial Risk Reduction System*), which held its kick off meeting in October 2008. This project has been elaborated within the framework of the SAMCO association. I4S is involved in the online monitoring sub-project. PhD student, Xuan Binh Lam, is finishing his thesis on uncertainty quantification for system identification. PhD student, Michael Döhler is also deeply involved in that project.

Two visits lasting each one week occurred in 2010. Falk Hille from BAM visited us to work with M. Döhler on topics relevant to IRIS. Bijaya Jaishi from Sheffield University visited us in Spring 2010 on the same topics. M. Döhler visited University of Tokyo, department of Civil Engineering in November 2010.

8.3.2. ISMS, FP7 Marie Curie IAPP

Participants: Michael Döhler, Laurent Mevel.

In 2009, a proposal has been submitted with SVS, 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 and one of its engineer from SVS are assumed to stay 9 months at INRIA, for tighten integration of COSMAD and ARTEMIS software. The proposal has been rated 88/100 and ranked A in the final selection procedure. The project has been signed on August 1st 2010 and has been running from September 1st. Michael Döhler is spending 5 months in 2010-2011 in Denmark.

8.4. International Initiatives

8.4.1. SIMS, Canada

Participants: Michael Döhler, Laurent Mevel.

A new project called SIMS is currently ongoing on vibration analysis and monitoring in Canada. This project is funded by Ministry of Transport, British Columbia, Canada. It implies deep collaboration with University of British Columbia, Canada. This project has connexions with partners of IRIS project, including University of Tokyo, Japan.

8.4.2. *Collaboration on damage localization and monitoring with Boston University*

Participants: Michael Döhler, Laurent Mevel, Luciano Gallegos.

This collaboration involves a new PhD student, Luciano Gallegos, and is involving Professor Bernal from University of Boston, USA. Professor Bernal visited us for one week in 2010.

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