Activity Report 2012

Team I4S

Statistical Inference for Structural Health Monitoring

RESEARCH CENTER
Rennes - Bretagne-Atlantique

THEME
Stochastic Methods and Models

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Team I4S

Keywords: Statistical Methods, Identification, Detection, Vibrations, Signal Processing, Numerical Methods

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2. Overall Objectives

2.1. Introduction

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

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 [33], [40]. 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 SVS (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), structural health monitoring and web integration (FP7 ISMS).
- 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

+ Prize : M. Döhler has received the Fundation of Rennes 1st Prize 2012 for his PhD.
+ The team was given the privilege to organize the next joint EWSHM and PHM conference in 2014 in Nantes together with IFSTTAR and Nantes University.

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 $(Z_0, ..., Z_N)$ 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 [34] :

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

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 $\widehat{\theta}_N$ 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

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 [31] that the residual is asymptotically Gaussian :

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

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 :

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

where

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

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 [29]. Here we only sketch two intuitively simple statistical nuisance elimination techniques, which proceed by projection and rejection, respectively.

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

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

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

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

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

The properties and relationships of these two types of tests are investigated in [28].

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 :

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

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

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 [39]. 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 $R_i \triangleq \mathbf{E}\left(Y_k\ Y_{k-i}^T\right)$ and:

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

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

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

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

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 [33]. 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 [37] 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 [37], [33].

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 [38]. 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 [30].

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"* [35]. 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 [32], [36], 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

With the help of former engineers, I4S team has developed and maintained a Scilab toolbox devoted to modal analysis and vibration monitoring of structures or machines subjected to known or ambient (unknown) excitation. This software (COSMAD 3.64) has been registered at the APP under the number

IDDN.FR.001.210011.002.S.A.2003.000.20700

A list of test-cases (simulators, laboratory test-beds, real structures) for which COSMAD has been used is available on I4S website. 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. Other services are

- *Output-only and Input/Ouptut subspace-based identification*,
- *Automated on-line identification package*,
- *Subspace-based identification through moving sensors data fusion*,
- *Damage detection and monitoring*,
- *Damage localization*,

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, and within the framework of bilateral contracts with SNECMA and SVS.

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

This Scilabtoolbox 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 undertake joint investigations with us. Just recently, SNECMA funded development for the Cosmad toolbox in 2010.

5.2. Prototypes

Three software have been deposed to the Agency of Program Protection, i.e.

- 1/ VIBRA-PARTICULAIRE : APP IDDN.FR.001.420016.000.S.P.2012.000.20700

They will be transferred to partners and industrial contracts when possible.

+ A new version of the COSMAD toolbox has been deposed at APP and concerns the transfer to SVS action.

6. New Results

6.1. identification of linear systems

6.1.1. Modular identification and damage detection for large structures

Participants: Michael Döhler, Laurent Mevel.

Subspace identification algorithms are efficient for output-only eigenstructure identification of linear MIMO systems. The problem of merging sensor data obtained from moving and nonsimultaneously recorded measurement setups under varying excitation is considered. To address the problem of dimension explosion, when retrieving the system matrices of the complete system, a modular and scalable approach is proposed. Adapted to a large class of subspace methods, observability matrices are normalized and merged to retrieve global system matrices [12].

6.1.2. Fast multi order subspace identification algorithm

Participants: Michael Döhler, Laurent Mevel.

Subspace methods have proven to be efficient for the identification of linear time-invariant systems, especially applied to mechanical, civil or aeronautical structures in operation conditions. Therein, system identification results are needed at multiple (over-specified) model orders in order to distinguish the true structural modes from spurious modes using the so-called stabilization diagrams. In this paper, new efficient algorithms are derived for this multi-order system identification with subspace-based identification algorithms and the closely related Eigensystem Realization Algorithm. It is shown that the new algorithms are significantly faster than the conventional algorithms in use. They are demonstrated on the system identification of a large-scale civil structure [11], [15].

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

Participants: Michael Döhler, 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. Uncertainty computation schemes have been developed.This approach has been validated on large scale examples[16].

6.1.4. Subspace methods in frequency domain

Participants: Philippe Mellinger, Michael Döhler, Laurent Mevel.

In Operational Modal Analysis (OMA) of large structures it is often needed to process output-only sensor data from multiple non-simultaneously recorded measurement setups, where some reference sensors stay fixed, while the others are moved between the setups. A standard approach to process the data together for global system identification is to transfer the data into frequency domain and merge it there. However, this only works if the unmeasured ambient excitation remains stationary throughout all setups. As the ambient excitation can be different from setup to setup, the amplitude of the measured data can be different as well and the data has to be normalized. Recently, a method has been developed for covariance- and data-driven Stochastic Subspace Identification (SSI) to automatically normalize and merge the data from multiple setups in order to obtain the global modal parameters (natural frequencies, damping ratios, mode shapes), instead of doing the SSI for each setup separately. In this paper, we adapt this approach to multi-setup SSI in frequency domain, where we use spectra data instead of time series data. We demonstrate the advantages of the new merging approach in the frequency domain and apply it to a relevant industrial large scale example, where we compare the estimation results of the modal parameters between the time and frequency domain approaches [24].

6.1.5. Subspace Identification for Linear Periodically Time-varying Systems

Participant: Ahmed Jhinaoui.

In this paper, an extension of the output-only subspace identification, to the class of linear periodically time-varying (LPTV) systems, is proposed. The goal is to identify a useful information about the system's stability using the Floquet theory which gives a necessary and sufficient condition for stability analysis. This information is retrieved from a matrix called the monodromy matrix, which is extracted by some simultaneous singular value decomposition (SVD) and from a resolution of a least squares criterion. The method is, finally, illustrated by a simulation of a model of a helicopter with hinged-blades rotor and a prototype of the same model. The method is then applied to data from a real wind turbine [22], [19], [20].

6.2. damage detection for mechanical structures

6.2.1. Damage detection and localisation

Participants: Michael Döhler, Luciano Marin, Laurent Mevel.

Mechanical systems under vibration excitation are prime candidate for being modeled by linear time invariant systems. Damage detection in such systems relates to the monitoring of the changes in the eigenstructure of the corresponding linear system, and thus reflects changes in modal parameters (frequencies, damping, mode shapes) and finally in the finite element model of the structure. Damage localization using both finite element information and modal parameters estimated from ambient vibration data collected from sensors is possible by the Stochastic Dynamic Damage Location Vector (SDDLV) approach. Damage is related to some residual derived from the kernel of the difference between transfer matrices in both reference and damage states and a model of the reference state. Deciding that this residual is zero is up to now done using some empirically defined threshold. In this paper, we show how the derivation of the uncertainty of the state space system can be used to derive uncertainty on the damage localization residuals and help to decide about the damage location [23].

6.2.2. 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 work 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 [17], [26].

6.2.3. Input-Output Subspace-Based Fault Detection

Participant: Laurent Mevel.

Subspace-based fault detection method using input-output information is developed in this paper. In some practical applications, the environment noise is the only input that excites the system. Although the statistical properties of the noise might be estimated, the value of the noise is not usually available at each time instance. The traditional subspace fault detection is already developed for such situations. In several other applications, measured inputs are applied to the system or even the stochastic noise might be measurable. While it is still possible to use the traditional output-only detection method, it is reasonable to expect that the application of extra input information together with the output data improves the detection. Several computation issues are discussed in this paper to include input data in the detection method, correctly. Simulation results show the efficiency of using the input information to improve the quality of fault detection [18].

6.2.4. Structural Reliability Updating with Stochastic Subspace Damage Detection Information

Participant: Michael Döhler.

Damage detection algorithms as a part of Structural Health Monitoring (SHM) are widely applied in research and industry and have shown their capabilities to efficiently detect structural damages. These algorithms usually compare a model from a safe reference state of a structure to vibration data from a possibly damaged state. For such a comparison, special properties of real vibration data introduce uncertainties, such as low signal-to-noise ratios, non-stationary or nonwhite ambient excitation, non-linear behavior and many more. Recently, statistical damage detection algorithms based on stochastic subspace identification have been proposed that take into account the uncertainties in the data. Building upon the uncertainty modeling, the next step in the view of the authors is to utilize damage detection algorithm information in the context of the structural reliability theory. Therefore, this paper introduces an approach for the updating of the structural reliability with damage detection algorithm information. Two steps are described namely the determination of a probability of detection (PoD) distribution function for damage detection algorithms accounting for the relevant uncertainties and the concept of Bayesian updating of the structural reliability. The introduced approaches are applied in generic examples. In this way the potential of the utilization of damage detection system information for more reliable structural systems are demonstrated [27].

6.3. Instability monitoring of aeronautical structures

6.3.1. Instability monitoring for LPTV systems

Participants: Laurent Mevel, Ahmed Jhinaoui.

Most subspace-based methods enabling instability monitoring are restricted to the linear time-invariant (LTI) systems. In this paper, a new subspace method of instability monitoring is proposed for the linear periodically time-varying (LPTV) case. For some LPTV systems, the system transition matrices may depend on some parameter and are also periodic in time. A certain range of values for the parameter leads to an unstable transition matrix. Early warning should be given when the system gets close to that region, taking into account the time variation of the system. Using the theory of Floquet, some symptom parameter of stability- or residual- is defined. Then, the parameter variation is tracked by performing a set of parallel cumulative sum (CUSUM) tests. Finally, the method is tested on a simulated model of a helicopter with hinged blades, for monitoring the ground resonance phenomenon [21]. It follows the work on linear systems for aircraft monitoring done previously [14].

6.3.2. Optimal input design for identification and detection

Participant: Laurent Mevel.

This paper considers the problem of auxiliary input design for subspace-based fault detection methods. In several real applications, particularly in the damage detection of mechanical structures and vibrating systems, environment noise is the only input to the system. In some applications, white noise produces low quality output data for the subspace-based fault detection method. In those methods, a residual is calculated to detect the fault based on the output information. However, some modes of the system may not influence the outputs and the residual appropriately if the input is not exciting enough for those modes. In this paper, the method of "rotated inputs" is implemented to excite the system modes. In addition to produce a residual more sensitive to the weak modes, it is possible to detect system order changes due to the fault using the rotated inputs. Simulation results demonstrate the efficiency of injecting the auxiliary input to improve the subspace-based fault detection methodology. [13]. This work is funded by FP7-NMP Large Scale Integrated Project IRIS.

7. Bilateral Contracts and Grants with Industry

7.1. Bilateral Contracts with Industry

7.1.1. Contracts with SVS

Participants: Laurent Mevel, Michael Döhler.

Annual agreement Inria-SVS 2381 + contract 4329

I4S is doing technology transfer towards SVS to implement I4S technologies into ARTEMIS Extractor Pro. This is done under a royalty agreement between Inria and SVS .

7.2. Bilateral Grants with Industry

7.2.1. PhD CIFRE with Dassault Aviation

Participants: Laurent Mevel, Philippe Mellinger.

Following the FliTE2 project, a joint PhD thesis between Inria and Dassault Aviation has been initiated. The thesis will pursue the work achieved in FliTE2 and started in June 2011 funded by Dassault Aviation and the CIFRE Agency.

8. Partnerships and Cooperations

8.1. National Initiatives

8.1.1. Pôle de Compétitivité ASTECH MODIPRO

Participants: Laurent Mevel, Meriem Zghal.

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. The project ended in October 2012.

8.1.2. Collaboration with IFSTTAR

Participant: Laurent Mevel.

I4S is related to the project FUI SIPRIS (Systèmes d'Instrumentation pour la prévention des risques), lead by Advitam. Work has just started with IFSTTAR.

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

Participants: Laurent Mevel, Meriem Zghal.

I4S has a 2 year collaboration with EPI ALEA on using particular filtering in vibration analysis. The output has been submitted for publication.

8.1.4. Collaboration with ISAE

Participants: Laurent Mevel, Ahmed Jhinaoui.

Ahmed Jhinaoui is finishing his 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. See also [25].

8.2. European Initiatives

8.2.1. FP7 Projects

8.2.1.1. FP7 ISMS

Type: PEOPLE

Instrument: Industry-Academia Partnerships and Pathway (IAPP)

Duration: September 2010 - August 2013

Coordinator: SVS (Structural Vibrations Solutions) (Denmark)

Others partners: University of British Columbia, Canada

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 has been spending 5 months in 2010-2011 in Danemark. Laurent Mevel spent 2 months in 2012 in Danemark. The mid term project has been well reviewed by the EC.

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

Type: Cooperation

Instrument: Collaborative project -Large Scale Integrating project

Duration: October 2008 - March 2012

Coordinator: VCE, Austria (Denmark)

Others partners: 40 partners

IIRIS (*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. I4S is involved in the online monitoring sub-project.

I4S is involved in the core consortium of this FP7-NMP Large Scale Integrated Project.

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.

The project ended in Spring 2012.

8.3. International Initiatives

8.3.1. Inria International Partners

8.3.1.1. 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.

SVS and I4S are investigating how to link the modal analysis software ARTeMIS of SVS and COSMAD. Through an annual agreement, I4S gets a license of ARTeMIS in exchange to offer support for integrating our damage detection software into SVS 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.

8.3.1.2. Collaboration on damage localization and monitoring with Boston University

This work is related to the thesis of Luciano Marin. The objective is the draft of an associated Inria team. Currently exchange of postdocs and joint PhD supervision have been done.

8.3.2. Participation In International Programs

8.3.2.1. Northeastern University

Participants: Laurent Mevel, Luciano Marin.

Program: International joint supervision of PhD agreement

Title: Design of fast statistical algorithms for monitoring of damage and uncertainties in civil and aeronautic structures

Inria principal investigator: Laurent MEVEL

Northeastern University (United States)

Duration: May 2011 - Apr 2014

This collaboration involves a new PhD student, Luciano Marin, and is involving Professor Bernal from University of Boston, USA.

8.4. International Research Visitors

8.4.1. Visits of International Scientists

Michael Döhler of Northeastern University has visited twice in June and September 2012 for a total of 4 weeks.

9. Dissemination

9.1. Scientific Animation

L. Mevel is part of the IOMAC organisation committee. He is also reviewer for numerous journals and conference boards. He is associate editor of Journal of Modelling and Simulation in Engineering. He is part of the local organizing committee of EWSHM 2014.

9.2. Teaching - Supervision - Juries

9.2.1. Supervision

PhD in progress : Ambient diagnosis and early instability monitoring for helicopter rotor : Ahmed Jhinaoui, ,since June 2010, L.Mevel and J. Morlier (ISAE)

PhD in progress : Algorithms for monitoring and localization of damage. Luciano Marin, since October 2010, L.Mevel and D. Bernal (University of NorthEastern, Boston, USA)

PhD in progress : Aeroelastic instability early detection methods in frequency domain. Philippe Mellinger, since June 2011, L. Mevel and C. Meyer (Dassault Aviation)

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