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Activity Report 2013

Project-Team I4S

Statistical Inference for Structural Health Monitoring

RESEARCH CENTER
Rennes - Bretagne-Atlantique

THEME
Optimization and control of dynamic systems

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Project-Team I4S

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

Creation of the Team: 2009 April 01, *updated into Project-Team:* 2013 January 01.

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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. Resume

The objective of this team is the intrinsic coupling of statistics and thermo-aeroelastic coupling modeling for the development of robust and autonomous structural health monitoring solutions of mechanical structures. The emphasis of the team is the handling of very large systems such as the recent wind energy converters currently being installed in Europe, building on the expertise acquired by the proposed team on bridges as an example of civil engineering structure, and for aircrafts and helicopters in the context of aero elastic instability monitoring. The necessity of system identification and damage detection systems robust to environmental variations and being designed to handle a very large model dimension motivates us. As examples, the explosion in the installed number of sensors and the robustness to temperature variation will be the main focus of the team. This implies new statistical and numerical technologies as well as improvements on the modeling of the underlying physical models. Many techniques and methods originate from the mechanical community and thus exhibit a very deep understanding of the underlying physics and mechanical behavior of the structure. On the other side, system identification techniques developed within the control community are more related to data modeling and take into account the underlying random nature of measurement noise. Bringing these two communities together is the objective of this joint team between Inria and IFSTTAR. It will results hopefully in methods numerically robust, statistically efficient and also mixing modeling of both the uncertainties related to the data and the associated complex physical models related to the laws of physics and finite element models.

Damage detection in civil structures has been a main focus over the last decade. Still, those techniques need to be matured to be operable and installed on structures in operation, and thus be robust to environmental nuisances. Then, damage localization, quantification and prognosis should be in that order addressed by the team. To be precise and efficient, it requires correct mixing between signal processing, statistical analysis, Finite Elements (FEM) Models updating and a yet to be available precise modeling of the environmental effects such as temperature through 3D field reconstruction.

Theoretical and practical questions are more and more complex. For example, in civil engineering, from handling hundreds of sensors automatically during some long period of time to localize and quantify damage with or without numerical models. Very large heavily instrumented structures are yet to come and they will ask for a paradigm in how we treat them from a renewed point of view. As the structures become large and complex, also the thermal and aeroelastic (among other) modeling becomes complex. Bridges and aircraft have been the main focus of our research of the past and still will be our concern. Opening our expertise on new applications topics such as helicopters and wind energy converters is also part of our priorities.

2.1.1.1. Objectives

The main objectives of the team are first to pursue current algorithmic research activities, in order to accommodate still-to-be-developed complex physical models. More precisely, we want successively

- To develop statistical algorithms robust to noise and variation in the environment
- Handle transient and highly varying systems under operational conditions
- To consider the impact of uncertainties on the current available identification algorithms and develop efficient, robust and fast implementation of such quantities
- To consider relevant non trivial thermal models for usage in rejection based structural health monitoring and more generally to mix numerical model, physical modeling and data
- To develop theoretical and software tools for monitoring and localization of damages on civil structures or instability for aircrafts
- To explore new paradigms for handling of very large and complex structures heavily instrumented with new challenges (distributed computing)
- To consider society concerns (damage quantification and remaining life prognosis)

2.1.2. Introduction to physics driven dynamical models in the context of civil engineering elastic structures

The design and maintenance of flexible structures subject to noise and vibrations is an important topic in civil and mechanical engineering. It is an important component of comfort (cars and buildings) and contributes significantly to the safety related aspects of design and maintenance (aircrafts, aerospace vehicles and payloads, long-span bridges, high-rise towers...). Requirements from these application areas are numerous and demanding.

Detailed physical models derived from first principles are developed as part of system design These models involve the dynamics of vibrations, sometimes complemented by other physical aspects (fluid-structure interaction, aerodynamics, thermodynamics).

Laboratory and in-operation tests are performed on mock-up or real structures, in order to get so-called modal models, ie to extract the modes and damping factors (these correspond to system poles), the mode shapes (corresponding eigenvectors), and loads. These results are used for updating the design model for a better fit to data, and sometimes for certification purposes (e.g. in flight domain opening for new aircrafts, reception for large bridges).

The monitoring of structures is an important activity for the system maintenance and health assessment. This is particularly important for civil structures. Damaged structures would typically exhibit often very small changes in their stiffness due to the occurrence of cracks, loss of prestressing or post tensioning, chemical reactions, evolution of the bearing behavior and most importantly scour. A key difficulty is that such system characteristics are also sensitive to environmental conditions, such as temperature effects (for civil structures), or external loads (for aircrafts). In fact these environmental effects usually dominate the effect of damage. This is why, for very critical structures such as aircrafts, detailed active inspection of the structures is performed as part of the maintenance. Of course, whenever modal information is used to localize a damage, the localization of a damage should be expressed in terms of the physical model, not in terms of the modal model used in system identification. Consequently, the following elements are encountered and must be jointly dealt with when addressing these applications: design models from the system physics, modal models used in structural identification, and, of course, data from sensors. Corresponding characteristics are given now: Design models are Finite Element models, sometimes with tens or hundreds of thousands elements, depending on professional habits which may vary from one sector to another. These models are linear if only small vibrations are considered; still, these models can be large if medium-frequency spectrum of the load is significant. In addition, nonlinearities enter as soon as large vibrations or other physical effects (aerodynamics, thermodynamics, ..) are considered. Moreover stress-strain paths and therefore the response (and load) history comes into play.

Sensors can range from a handful of accelerometers or strain gauges, to thousands of them, if NEMS (Nano Electro Mechanical Structures), MEMS (Microelectromechanical systems) or optical fiber sensors are used. Moreover, the sensor output can be a two-dimensional matrix if electro magnet (IR (infrared), SAR, shearography ...) or other imaging technologies are used.

2.1.2.1. Multi-fold thermal effects

The temperature constitutes an often dominant load because it can generate a deflection as important as that due to the self-weight of a bridge. In addition, it sometimes provokes abrupt slips of bridge spans on their bearing devices, which can generate significant transient stresses as well as a permanent deformation, thus contributing to fatigue.

But it is also well-known that the dynamic behavior of structures under monitoring can vary under the influence of several factors, including the temperature variations, because they modify the stiffness and thus the modes of vibration. As a matter of fact, depending on the boundary conditions of the structure, possibly uniform thermal variations can cause very important variations of the spectrum of the structure, up to 10%, because in particular of additional prestressing, not forgetting pre strain, but also because of the temperature dependence of the characteristics of materials. As an example, the stiffness of elastomeric bearing devices vary considerably in the range of extreme temperatures of moderate countries. Moreover, eigenfrequencies and modal shapes do not depend monotonically with temperature. Abrupt dynamical behavior may show up due to a change of boundary conditions e.g. due to limited expansion or frost bearing devices. The temperature can actually modify the number of contact points between the piles and the main span of the bridge. Thus the environmental effects can be several orders of magnitude more important than the effect of true structural damages. It will be noted that certain direct methods aiming at detecting local curvature variations stumble on the dominating impact of the thermal gradients. In the same way, the robustness and effectiveness of model-based structural control would suffer from any unidentified modification of the vibratory behavior of the structure of interest. Consequently, it is mandatory to cure dynamic sensor outputs from thermal effects before signal processing can help with a diagnostics on the structure itself, otherwise the possibility of reliable ambient vibration monitoring of civil structures remains questionable. Despite the paramount interest this question deserves, thermal elimination still appears to challenge the SHM community.

2.1.2.2. Toward a multidisciplinary approach

Unlike previously mentioned blind approaches, successful endeavours to eliminate the temperature from subspace-based damage detection algorithms prove the relevance of relying on predictive thermo-mechanical models yielding the prestress state and associated strains due to temperature variations. As part of the CONSTRUCTIF project supported by the Action Concertée Incitative Sécurité Informatique of the French Ministry for Education and Research, very encouraging results in this direction were obtained and published. they were substantiated by laboratory experiments of academic type on a simple beam subjected to a known uniform temperature. Considering the international pressure toward reliable methods for thermal elimination, these preliminary results pave the ground to a new SHM paradigm. Moreover, for one-dimensional problems, it was shown that real time temperature identification based on optimal control theory is possible provided the norm of the reconstructed heat flux is properly chosen. Finally, thermo-mechanical models of vibrating thin structures subject to thermal prestress, prestrain, geometric imperfection and damping have been extensively revisited. This project led by Inria involved IFSTTAR where the experiments were carried out. The project was over in July 2006. Note that thermo-mechanics of bridge piles combined with an *ad hoc* estimation of thermal gradients becomes of interest to practicing engineers. Thus, I4S's approach should suit advanced professional practice. Finite element analysis is also used to predict stresses and displacements of large bridges in Hong-Kong bay .

Temperature rejection is the primary focus and obstacle for SHM projects I4S participates in civil engineering, like SIMS project in Canada, ISMS in Danemark or SIPRIS in France.

2.1.2.3. Models for monitoring under environmental changes - scientific background

We will be interested in studying linear stochastic systems, more precisely, assume at hand a sequence of observations Y_n measured during time,

$$\left\{ \begin{array}{ccc} X_{n+1} & = & AX_n + V_n \\ Y_n & = & HX_n \end{array} \right. \tag{1}$$

where V_n is a zero mean process, A is the transition matrix of the system, H is the observation matrix between state and observation, and X_n the process describing the monitored system. X_n can be related to a physical process (for example, for a mechanical structure, the collection of displacements and velocities at different points). Different problems arise

1/ identify and characterize the structure of interest. It may be possible by matching a parametric model to the observed time series Y_n in order to minimize some given criterion, whose minimum will be the best approximation describing the system,

2/ decide if the measured data describe a system in a so called "reference" state (the term "reference" is used in the context of fault detection, where the reference is considered to be safe) and monitor its deviations with respect of its nominal reference state.

Both problems should be addressed differently if

1/ we consider that the allocated time to measurement is large enough, resulting in a sequence Y_n whose size tends to infinity, a requirement for obtaining statistical convergence results. It corresponds to the identification and monitoring of a dynamical system with slow variations. For example, this description is well suited to the long-term monitoring of civil structures, where records can be measured during relatively (to sampling rate) large periods of time (typically many minutes or hours).

2/ we are interested in systems, whose dynamic is fast with respect to the sampling rate, most often asking for reaction in terms of seconds. It is, for example, the case for mission critical applications such as in-flight control or real-time security and safety assessment. Both aeronautics and transport or utilities infrastructures are concerned. In this case, fast algorithms with sample-by-sample reaction are necessary.

The monitoring of mechanical structures can not be addressed without taking into account the close environment of the considered system and their interactions. Typically, monitored structures of interest do not reside in laboratory but are considered in operational conditions, undergoing temperature, wind and humidity variations, as well as traffic, wind, water flows and other natural or man-made loads. Those variations do imply a variation of the eigenproperties of the monitored structure, variations to be separated from the damage/instability induced variations.

For example, in civil engineering, an essential problem for in operation health monitoring of civil structures is the variation of the environment itself. Unlike laboratory experiments, civil structure modal properties change during time as temperature and humidity vary. Traffic and comparable transient events also influence the structures. Thus, structural modal properties are modified by slow low variations, as well as fast transient non stationarities. From a damage detection point of view, the former has to be detected, whereas the latter has to be neglected and not perturb the detection. Of course, from a structural health monitoring point of view the knowledge of the true load is in itself of paramount importance.

In this context, the considered perturbations will be of two kinds, either

1/ the influence of the temperature on civil structures, such as bridges or wind energy converters : as we will notice, those induced variations can be modeled by a additive component on the system stiffness matrix depending on the current temperature, as

$$K = K_{struct} + K_T \ .$$

We will then have to monitor the variations in K_{struct} independently of the variations in K_T, based on some measurements generated from a system, whose stiffness matrix is K.

2/ the influence of the aeroelastic forces on aeronautical structures such as aircrafts or rockets and on flexible civil structures such as long-span bridges : we will see as well that this influence implies a modification of the usual mechanical equation (2) as

$$M\ddot{Z} + C\dot{Z} + KZ = V \tag{2}$$

where (M, C, K) are the mass, damping and stiffness matrices of the system and Z the associated vector of displacements measured on the monitored structure. In a first approximation, those quantities are related by (2). Assuming U is the velocity of the system, adding U dependent aeroelasticity terms, as in (3), introduces a coupling between U and (M, C, K).

$$M\ddot{Z} + C\dot{Z} + KZ = U^2DZ + UE\dot{Z} + V \tag{3}$$

Most of the research at Inria since 10 years has been devoted to the study of subspace methods and how they handle the problems described above.

Model (2) is characterized by the following property (we formulate it for the single sensor case, to simplify notations): Let $y_{-N} \cdots y_{+N}$ be the data set, where N is large, and let M, P sufficiently smaller than N for the following objects to make sense: 1/ define the row vectors $Y_k = (y_k \cdots y_{k-M}), |k| \leq P$; 2/ stack the Y_k on top of each other for $k = 0, 1, \cdots, P$ to get the data matrix $\mathcal{Y}_+$ and stack the column vectors Y_k^T for $k = 0, -1, \cdots, -P$ to get the data matrix $\mathcal{Y}_-$; 3/ the product $\mathcal{H} = \mathcal{Y}_+ \mathcal{Y}_-$ is a Hankel matrix. Then, matrix $\mathcal{H}$ on the one hand, and the observability matrix $\mathcal{O}(H, F)$ of system (2) on the other hand, possess almost identical left kernel spaces, asymptotically for M, N large. This property is the basis of subspace identification methods. Extracting $\mathcal{O}(H, F)$ using some Singular Value Decomposition from $\mathcal{H}$ then (H, F) from $\mathcal{O}(H, F)$ using a Least Square approach has been the foundation of the academic work on subspace methods for many years. The team focused on the numerical efficiency and consistency of those methods and their applicability on solving the problems above.

There are numerous ways to implement those methods. This approach has seen a wide acceptance in the industry and benefits from a large background in the automatism literature. Up to now, there was a discrepancy between the a prior efficiency of the method and some not so efficient implementations of this algorithm. In practice, for the last ten years, stabilization diagrams have been used to handle the instability and the weakness with respect to noise, as well as the poor capability of those methods to determine model orders from data. Those methods implied some engineering expertise and heavy post processing to discriminate between model models and noise. This complexity has leads the mechanical community to adopt preferably frequency domain methods such as Polyreference LSCF over the years. Our focus has been on improving the numerical stability of the subspace algorithms by studying how to compute the least square solution step in this algorithm. This yields to a very efficient noise free algorithm, which in the past year has provided a renewed acceptance in the mechanical engineering community for the subspace algorithms. In the past years we focused on improving speed and robustness of those algorithms.

Subspace methods can also be used to test whether a given data set conforms a model: just check whether this property holds, for a given pair {data, model}. Since equality holds only asymptotically, equality must be tested against some threshold ε; tuning ε relies on so-called *asymptotic local* approach for testing between close hypotheses on long data sets — this method was introduced by Le Cam in the 70s. By using the Jacobian between pair (H, F) and the modes and mode shapes, or the Finite Element Model parameters, one can localize and assess the damage.

In oder to discriminate between damage and temperature variations, we need to monitor the variations in K_{struct} while keeping blind to the variations in K_T in statistical terms, we must detect and diagnose changes in K_{struct} while rejecting nuisance parameter K_T. Several techniques were explored in the thesis of Houssein Nasser, from purely empirical approaches to (physical) model based approaches. Empirical approaches do work, but model based approaches are the most promising and a focus of our future researches. This approach requires a physical model of how temperature affects stiffness in various materials. This is why a large part of our future research is devoted to the modeling of such environmental effect.

This approach has been used also for flutter monitoring in the thesis of Rafik Zouari for handling the aeroelastic effect.

2.2. Highlights of the Year

- Prize Bretagne Jeune Chercheur 2013 for Michael Doehler.
- PEGASE 2 launch

3. Research Program

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 [31] :

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

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 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 :

$$\text{(Safe) } \mathbf{H}_0 : \ \theta = \theta_0 \quad \text{and} \quad \text{(Damaged) } \mathbf{H}_1 : \ \theta = \theta_0 + \eta/\sqrt{N} \tag{4}$$

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

$$\zeta_N = 1/\sqrt{N} \sum_{k=0}^{N} K(\theta_0, Z_k) = \sqrt{N}\, \mathcal{K}_N(\theta_0) \ . \tag{5}$$

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 [30] that the residual is asymptotically Gaussian :

$$\zeta_N \xrightarrow[N \to \infty]{} \begin{cases} \mathcal{N}(0, \Sigma) & \text{under } \mathbf{P}_{\theta_0} \ , \\ \\ \mathcal{N}(\mathcal{J}\,\eta, \Sigma) & \text{under } \mathbf{P}_{\theta_0 + \eta/\sqrt{N}} \ , \end{cases} \tag{6}$$

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 :

$$\chi^2 = \overline{\zeta}^{\,T}\, \mathbf{F}^{-1}\, \overline{\zeta} \gtrless \lambda \ . \tag{7}$$

where

$$\overline{\zeta} \triangleq \mathcal{J}^T\, \Sigma^{-1}\, \zeta_N \quad \text{and} \quad \mathbf{F} \triangleq \mathcal{J}^T\, \Sigma^{-1}\, \mathcal{J} \tag{8}$$

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.

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].

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 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 for the components of the parameter vector Φ. Typically this results in the following type of directional test :

$$\chi^2_\Phi = \zeta^T\,\Sigma^{-1}\,\mathcal{J}\,\mathcal{J}_{\Phi\theta}\,(\mathcal{J}^T_{\Phi\theta}\,\mathcal{J}^T\,\Sigma^{-1}\,\mathcal{J}\,\mathcal{J}_{\Phi\theta})^{-1}\,\mathcal{J}^T_{\Phi\theta}\,\mathcal{J}^T\,\Sigma^{-1}\,\zeta \gtrless \lambda\ . \tag{9}$$

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 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, 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 :

$$\left\{\begin{array}{rcl} X_{k+1} & = & F\ X_k + V_{k+1} \\ Y_k & = & H\ X_k \end{array}\right. , \tag{10}$$

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

$$\det\ (F - \lambda\ I) = 0, \quad (F - \lambda\ I)\ \phi_\lambda = 0, \quad \varphi_\lambda \triangleq H\ \phi_\lambda \tag{11}$$

The (canonical) parameter vector in that case is :

$$\theta \triangleq \begin{pmatrix} \Lambda \\ \mathrm{vec}\Phi \end{pmatrix} \tag{12}$$

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 [32]. 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:

$$\mathcal{H}_{p+1,q} \triangleq \begin{pmatrix} R_0 & R_1 & \vdots & R_{q-1} \\ R_1 & R_2 & \vdots & R_q \\ \vdots & \vdots & \vdots & \vdots \\ R_p & R_{p+1} & \vdots & R_{p+q-1} \end{pmatrix} \triangleq \mathrm{Hank}\,(R_i) \tag{13}$$

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 (10) lead to the well known key factorizations :

$$\begin{array}{rcl} R_i & = & H F^i G \\ \mathcal{H}_{p+1,q} & = & \mathcal{O}_{p+1}(H,F)\ \mathcal{C}_q(F,G) \end{array} \tag{14}$$

where:

$$\mathcal{O}_{p+1}(H,F) \triangleq \begin{pmatrix} H \\ HF \\ \vdots \\ HF^p \end{pmatrix} \quad \text{and} \quad \mathcal{C}_q(F,G) \triangleq (G\ FG\ \cdots\ F^{q-1}G) \tag{15}$$

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 (11).

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

$$\mathcal{O}_{p+1}(\theta) = \begin{pmatrix} \Phi \\ \Phi\Delta \\ \vdots \\ \Phi\Delta^p \end{pmatrix} \tag{16}$$

where $\Delta \triangleq \mathrm{diag}(\Lambda)$, and Λ and Φ are as in (12). Whether a nominal parameter θ_0 fits a given output covariance sequence $(R_j)_j$ is characterized by [1]:

$$\mathcal{O}_{p+1}(\theta_0) \text{ and } \mathcal{H}_{p+1,q} \text{ have the same left kernel space.} \tag{17}$$

This property can be checked as follows. From the nominal θ_0, compute $\mathcal{O}_{p+1}(\theta_0)$ using (16), and perform e.g. a singular value decomposition (SVD) of $\mathcal{O}_{p+1}(\theta_0)$ for extracting a matrix U such that:

$$U^T\, U = I_s \text{ and } U^T\, \mathcal{O}_{p+1}(\theta_0) = 0 \tag{18}$$

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:

$$U(\theta_0)^T\, \mathcal{H}_{p+1,q} = 0 \tag{19}$$

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

$$\widehat{\mathcal{H}}_{p+1,q} \triangleq \mathrm{Hank}\left(\widehat{R}_i\right), \quad \widehat{R}_i \triangleq 1/(N-i) \sum_{k=i+1}^{N} Y_k\, Y_{k-i}^T \tag{20}$$

and to define the residual vector:

$$\zeta_N(\theta_0) \triangleq \sqrt{N}\ \mathrm{vec}\left(U(\theta_0)^T\, \widehat{\mathcal{H}}_{p+1,q}\right) \tag{21}$$

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 (19), 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 (12), and for deriving the residual. Factorization (14) 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].

3.5.5. Research program

The research will first focus on the extension and implementation of current techniques as developed in I4S and IFSTTAR. Before doing any temperature rejection on large scale structures as planned, we need to develop good and accurate models of thermal fields. We also need to develop robust and efficient versions of our algorithms, mainly the subspace algorithms before envisioning linking them with physical models. Briefly, we need to mature our statistical toolset as well as our physical modeling before mixing them together later on.

3.5.5.1. Direct vibration modeling under temperature changes

This task builds upon what has been achieved in the CONSTRUCTIF project, where a simple formulation of the temperature effect has been exhibited, based on relatively simple assumptions. The next step is to generalize this modeling to a realistic large structure under complex thermal changes. Practically, temperature and resulting structural prestress and pre strains of thermal origin are not uniform and civil structures are complex. This leads to a fully 3D temperature field, not just a single value. Inertia effects also forbid a trivial prediction of the temperature based on current sensor outputs while ignoring past data. On the other side, the temperature is seen as a nuisance. That implies that any damage detection procedure has first to correct the temperature effect prior to any detection.

Modeling vibrations of structures under thermal prestress does and will play an important role in the static correction of kinematic measurements, in health monitoring methods based on vibration analysis as well as in durability and in the active or semi-active control of civil structures that by nature are operated under changing environmental conditions. As a matter of fact, using temperature and dynamic models the project aims at correcting the current vibration state from induced temperature effects, such that damage detection algorithms rely on a comparison of this thermally corrected current vibration state with a reference state computed or measured at a reference temperature. This approach is expected to cure damage detection algorithms from the environmental variations.

I4S will explore various ways of implementing this concept, notably within the FUI SIPRIS project.

3.5.5.2. Damage localization algorithms (in the case of localized damages such as cracks)

During the CONSTRUCTIF project, both feasibility and efficiency of some damage detection and localization algorithms were proved. Those methods are based on the tight coupling of statistical algorithms with finite element models. It has been shown that effective localization of some damaged elements was possible, and this was validated on a numerical simulated bridge deck model. Still, this approach has to be validated on real structures.

On the other side, new localization algorithms are currently investigated such as the one developed conjointly with University of Boston and tested within the framework of FP7 ISMS project. These algorithms will be implemented and tested on the PEGASE platform as well as all our toolset.

When possible, link with temperature rejection will be done along the lines of what has been achieved in the CONSTRUCTIF project.

3.5.5.3. Uncertainty quantification for system identification algorithms

Some emphasis will be put on expressing confidence intervals for system identification. It is a primary goal to take into account the uncertainty within the identification procedure, using either identification algorithms derivations or damage detection principles. Such algorithms are critical for both civil and aeronautical structures monitoring. It has been shown that confidence intervals for estimation parameters can theoretically be related to the damage detection techniques and should be computed as a function of the Fisher information matrix associated to the damage detection test. Based on those assumptions, it should be possible to obtain confidence intervals for a large class of estimates, from damping to finite elements models. Uncertainty considerations are also deeply investigated in collaboration with Dassault Aviation in Mellinger PhD thesis or with Northeastern University, Boston, within Gallegos PhD thesis.

4. Software and Platforms

4.1. COSMAD

Participants: Michael Doehler, Laurent Mevel.

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.

4.2. PEGASE

Participants: Vincent Le Cam, Mathieu Le Pen, Laurent Mevel.

We have developed a generic wireless platform that can be considered as the a result of redundant needs in wireless monitoring especially applied to civil engineering monitoring applications. This platform includes software and hardware bricks and aims at being generic by its native implementation of sober components, the worldwide TCP/IP protocol (802.11g), a signal processor, a small GPS receiver, and a micro embedded operating system (uClinux).

Since 2009, this platform -named PEGASE - is subject of an industrial transfer that has generated some tens of indivudual sales. A set of pluggable boards (that integrate the application specific sensing operation) offers a ready-to-use panel of wireless sensing solutions for developing specific applications as well as they can be seen as prototyping boards for further electronic developments.

As PEGASE platform reached a mature level of dissemination, LCPC recent efforts are now leaded with the goal of improving its wireless capacities. Those works concern energy saving while keeping a high level of embedded processing, of sampling rate or time-synchronization.

As software layers are mainly written in standard C language under Linux OS, those pragmatic solutions could easily be re-used by even radically different systems. The focus will specifically be pointed on: an algorithm that allows PEGASE wireless boards to be synchronized up to some uS using a GPS technique while keeping the GPS receiver OFF most of the time; a description of how the use of an operating system such as uClinux allows a full and remotely update of wireless sensors; the hardware and software strategies that have been developed to make PEGASE fully autonomous using solar cells.

The main characteristics of PEGASE feature are the following:

- Use of TCP/IP/WiFi as the wireless protocol: reliable, low-cost, scalable (IP is the worldwide protocol). Turned OFF when PEGASE doesn't communicate.
- Use of the Analog Device low-power Blackfin BF537 as core processor (Digital Signal Processor): 16 bits processor able of complex operations.
- Implementation of a small and low-power GPS receiver to ensure localization and, first of all, absolute time synchronization up to few μS GMT.
- uClinux as the embedded operating system: allows high level of abstraction while PEGASE algorithms are then programmed using standard ANSI C language.

Since its first version on january 2008, PEGASE has been used in various configurations where its properties fitted specific needs. Since a third-party partner (A3IP company) has been licensed by LCPC, PEGASE has been sold in hundreds of specimens and implemented in various configurations. This dissemination proved the capacity of wireless systems to really answer a large spectrum of applications. Developments in progress have the goal to increase this panoply. Even if uClinux and WiFi integration could be considered as *heavy*, the result is a great ability for developers or customers to achieve their own applications. The genericity of C language and the worldwide IP protocol make them ubiquitous. A quite expert job has been leaded to develop specific embedded drivers under uClinux OS in order to get specific behaviors for time synchronization, quartz drift auto-training and correction. This specific and dynamic correction takes temperature effects into account and the result is an absolute time synchronisation better that 4 μS. Even if technologies evolve (components, processor, batteries...), generic principle could be extracted independently from technological choices. Those main principles are: daughter/mother boards, Linux integration, a ready to use c-object library, a boost circuit linked to a MPPT algorithm, GPS synchronization and quartz correction. Most of the improvements can be reused and applied to other wireless platforms even using drastically different electronic implementations.

m Porting of subspace modal analysis algorithms is currently under way on the PEGASE platform.

5. New Results

5.1. identification of linear systems

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

Participants: Michael Doehler, Laurent Mevel.

Stochastic Subspace Identification methods have been extensively used for the modal analysis of mechanical, civil or aeronautical structures for the last ten years. So-called stabilization diagrams are used, where modal parameters are estimated at successive model orders, leading to a graphical procedure where the physical modes of the system are extracted and separated from spurious modes. Recently an uncertainty computation scheme has been derived allowing the computation of uncertainty bounds for modal parameters at some given model order. In this paper, two problems are addressed. Firstly, a fast computation scheme is proposed reducing the computational burden of the uncertainty computation scheme by an order of magnitude in the model order compared to a direct implementation. Secondly, a new algorithm is proposed to derive the uncertainty bounds for the estimated modes at all model orders in the stabilization diagram. It is shown that this new algorithm is both computationally and memory efficient, reducing the computational burden by two orders of magnitude in the model order[14].

5.1.2. Subspace methods in frequency domain

Participants: Philippe Mellinger, Michael Doehler, Laurent Mevel.

In this paper a combined subspace algorithm and a way to quantify uncertainties of its resulting identified modal parameter has been presented. Even if the algorithm is data-driven, it was proven that uncertainties can still be quantified by using the square subspace matrix without any modification neither on the identified modal parameters or on the stabilization diagrams. A comparison between uncertainty quantification based on this data-driven combined subspace algorithm and the well-known covariance-driven stochastic subspace algorithm shows good results on this new method. Both values and confidence intervals are similar. However combined algorithm gives better results considering spurious modes. [27].

5.1.3. Subspace Identification for Linear Periodically Time-varying Systems

Participants: Laurent Mevel, Ahmed Jhinaoui.

Many systems such as turbo-generators, wind turbines and helicopters show intrinsic time-periodic behaviors. Usually, these structures are considered to be faithfully modeled as Linear Time-Invariant (LTI). In some cases where the rotor is anisotropic, this modeling does not hold and the equations of motion lead necessarily to a Linear Periodically Time-Varying (referred to as LPTV in the control and digital signal field or LTP in the mechanical and nonlinear dynamics world) model. Classical modal analysis methodologies based on the classical time-invariant eigenstructure (frequencies and damping ratios) of the system no more apply. This is the case in particular for subspace methods. For such time-periodic systems, the modal analysis can be described by characteristic exponents called Floquet multipliers. The aim of this paper is to suggest a new subspace-based algorithm that is able to extract these multipliers and the corresponding frequencies and damping ratios. The algorithm is then tested on a numerical model of a hinged-bladed helicopter on the ground. [22], [23], [18].

5.2. damage detection for mechanical structures

5.2.1. Damage detection and localisation

Participants: Michael Doehler, Luciano Gallegos, 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 an empirically defined threshold. In this paper, we show how the uncertainty in the estimates of the state space system can be used to derive uncertainty bounds on the damage localization residuals to decide about the damage location with a hypothesis test.[13], [21], [26].

5.2.2. *Robust subspace damage detection*

Participants: Michael Doehler, Laurent Mevel.

The detection of changes in the eigenstructure of a linear time invariant system by means of a subspace-based residual function has been proposed previously. While enjoying some success in its applicability in particular in the context of vibration monitoring, the robustness of this framework against changes in the noise properties has not been properly addressed yet. In this paper, a new robust residual is proposed and the robustness of its statistics against changes in the noise covariances is shown. The complete theory for hypothesis testing for fault detection is derived and a numerical illustration is provided[16].

5.2.2.1. *Feasibility of reflectometry techniques for non destructive evaluation of external post-tensioned cables*

Participant: Qinghua Zhang.

Nowadays a considerable number of bridges is reaching an age when renovating operations become necessary. For some bridges, external post-tension is realized with cables protected in ducts, with the residual internal space imperfectly filled with a fluid cement grout. Detecting the problems of injection in the ducts is visually impossible from the outside. Through a collaboration with the SISYPHE project-team, the feasibility of reflectometry techniques for cable health monitoring is investigated via numerical simulations and laboratory experiments. The main idea consists in adding electrically conductive tapes along a duct so that the duct and the added tapes can be treated as an electrical transmission line. It is then possible to apply advanced reflectometry methods developed by the SISYPHE project-team, initially for true electric cables.

6. Bilateral Contracts and Grants with Industry

6.1. Bilateral Contracts with Industry

6.1.1. *Contracts with SVS*

Participants: Laurent Mevel, Michael Doehler.

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 .

6.2. Bilateral Grants with Industry

6.2.1. *PhD CIFRE with Dassault Aviation*

Participants: Laurent Mevel, Philippe Mellinger.

contract 7843.

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.

6.3. Bilateral Grants with Industry

6.3.1. *Collaboration with Bruel and Kjaer*

Participants: Laurent Mevel, Ivan Gueguen.

Collaboration has started on analysis on wind turbines data.

7. Partnerships and Cooperations

7.1. National Initiatives

7.1.1. Collaboration with ADVITAM

Participants: Laurent Mevel, Dominique Siegert, Ivan Gueguen.

contract 6841.

I4S is related to the project FUI SIPRIS (Systèmes d'Instrumentation pour la prévention des risques), lead by Advitam. Dominique Siegert and Ivan Gueguin handled instrumentation of a portique structure in Nantes for testing in scilab, matlab and lab view of modal analysis algorithms. Link with PEGASE platform have been done, testing and damage simulation have been performed. Internal report has been produced.

7.1.2. Collaboration with STX

Participants: Dominique Siegert, Ivan Gueguen.

Collaboration happened with STX during Fondeol project for the monitoring of foundation of wind turbine.

7.1.3. 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.

7.2. European Initiatives

7.2.1. FP7 Projects

7.2.1.1. FP7 ISMS

Participants: Laurent Mevel, Michael Doehler.

Type: PEOPLE

Instrument: Industry-Academia Partnerships and Pathway (IAPP)

Duration: September 2010 - August 2014

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 Doehler 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 Doehler has been spending 5 months in 2010-2011 in Denmark. Laurent Mevel spent 2 months in 2012 in Denmark. Palle Andersen was in Rennes in 2013 for 3 months. The mid term project has been well reviewed by the EC.

7.2.1.2. MODRIO Project

Participant: Qinghua Zhang.

MODRIO: Model Driven Physical Systems Operation. This ITEA 2 (Information Technology for European Advancement) project is joined by partners from Austria, Belgium, Finland, France, Germany, Italy and Sweden. See the complete of list of partners on the MODRIO page of the ITEA call website (https://itea3.org/all-projects/call-14.html).

To meet the evermore stringent safety and environmental regulations for power plants and transportation vehicles, system operators need new techniques to improve system diagnosis and operation. Open standards are necessary for different teams to cooperate by sharing compatible information and data. The objective of the MODRIO project is to extend modeling and simulation tools based on open standards from system design to system diagnosis and operation.

7.3. International Initiatives

7.3.1. Inria International Partners

7.3.1.1. SIMS, Canada

Participants: Michael Doehler, 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. 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.

7.3.1.2. Collaboration on damage localization and monitoring with Boston University

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

7.3.2. Participation In International Programs

7.3.2.1. Northeastern University

Participants: Laurent Mevel, Michael Doehler, Luciano Gallegos.

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 PhD student, Luciano Gallegos, and is involving Professor Bernal from University of Boston, USA. The thesis has been defended in 2013.

7.4. International Research Visitors

7.4.1. Visits of International Scientists

Participants: Koen Tiels, Palle Andersen.

Palle Andersen was here for 3 months within ISMS project.

Koen Tiels from VUB in Bruxelles has visited us for 2 months in 2013.

8. Dissemination

8.1. 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 co-head of the local organizing committee of EWSHM 2014.

V. LeCam is head of the local organizing committee of EWSHM 2014 (http://www.ewshm2014.com).

8.2. Teaching - Supervision - Juries

8.2.1. Supervision

PhD : Luciano Gallegos, Algorithms for monitoring and localization of damage. Luciano Gallegos, Université de Rennes 1, 08/10/13, L. Mevel and D. Bernal.

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

8.2.2. Juries

Laurent Mevel was examinator in the jury of Jérémy Vayssettes at University of Poitiers in November 2013.

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