Project-Team sigma2

Signaux, modèles et algorithmes

Rennes

THEME 4A

Activity Report

2003

Table of contents

1. Team

Head of the project–team
François Le Gland [DR INRIA]

Administrative assistant
Huguette Béchu

Research scientist (inria)
Albert Benveniste [DR, part–time]
Fabien Campillo [CR]
Frédéric Cérou [CR]
Éric Fabre [CR]
Stefan Haar [CR]
Laurent Mevel [CR]
Aline Roumy [CR]
Qinghua Zhang [DR]

Research scientist (cnrs)
Michèle Basseville [DR]

Faculty member (université de Rennes 1)
Jean–Jacques Fuchs [professor]

Faculty member (université de Rennes 2)
Arnaud Guyader [assistant professor]

Project technical staff (inria)
Bruno Marquié [ingénieur expert]
Jacques Palicot [spécialiste industriel, until September 30, 2003]
Auguste Sam [ingénieur expert]

Post–doctoral fellow (inria)
Mutlu Koca [since February 15, 2003]

Ph.D. student
Samy Abbes [MENRT grant]
Natacha Caylus [MENRT grant]
Houssein Nasser [ACI Sécurité grant, since October 1, 2003]
Sébastien Maria [MENRT grant, since October 1, 2003]
Olivier Perrin [CIFRE grant, Renault]

2. Overall Objectives

Key words: *identification*, *monitoring*, *diagnosis*, *subspace method*, *local approach*, *hidden Markov model (HMM)*, *particle filtering*, *distributed system*, *discrete event system (DES)*, *Petri net*, *partially stochastic model*, *automobile*, *aeronautics*, *civil engineering*, *vibration*, *modal analysis*, *telecommunication network*, *fault management*, *turbo–code*, *joint source–channel decoding*.

The objectives of the SIGMA2 project–team are the design, analysis, and implementation of statistical model–based algorithms, for identification, monitoring and diagnosis of complex industrial systems. The models considered are on one hand the stochastic state space models of automatic control, with increasing emphasis on nonlinear models, and on the other hand some partially stochastic models (HMM, Petri nets, nets of automata, etc.) on discrete structures (trees, graphs, etc.), e.g. to model distributed discrete events systems. The major methodological contributions of the project–team, which make the scientific background for the current research activities, consist of the use of the local asymptotic approach for monitoring and diagnosis of continuous systems, the design of particle filters for the statistical inference of HMM with general state

space, and the design of distributed Viterbi–like state reconstruction algorithms, for monitoring and diagnosis of distributed discrete events systems. The main applications considered are monitoring and diagnosis of vibrating mechanical structures (automobile, aerospace, civil engineering), monitoring and diagnosis of automobile subsystems, and fault diagnosis in telecommunication networks.

2.1.1. Research themes

- observers and filters for monitoring and diagnosis of nonlinear dynamical systems,
- subspace methods for modal analysis and monitoring,
- statistics of HMM with general state space, and associated particle methods,
- monitoring and diagnosis of distributed discrete events systems,
- approximate state estimation algorithms in graphical models and Bayesian networks, and application to turbo algorithms.

2.1.2. Industrial and academic relations

- industrial projects : with Renault on monitoring and diagnosis of automobile subsystems, with Alcatel Space Industry on turbo–estimation for satellite communications, with EADS Launch Vehicles on modal analysis of a launch vehicle,
- multi–partners projects : at national level on fault management in telecommunication networks (RNRT), on video transmission over IP channels (RNRT), and at european level on exploitation of flight test data under natural excitation conditions (Eurêka), on structural assessment, monitoring and control (Growth), on distributed control and stochastic analysis of hybrid systems (IST),
- academic research networks : at national level on hidden Markov chains and particle filtering (MathSTIC), on particle methods (AS–STIC), and at european level on system identification (TMR), on statistical methods for dynamical stochastic models (IHP).

3. Scientific Foundations

3.1. Introduction

The SIGMA2 project–team is concerned with modeling issues, from physical principles and from observation data. Hence the main problems considered are parametric estimation and identification, as well as model validation, hypotheses testing and diagnosis, which allow one to detect and to explain a possible disagreement between the assumed model and the observation data. These issues are addresssed for different classes of dynamical systems : linear, nonlinear, and more recently, distributed discrete event dynamical systems. We have chosen to give a detailed presentation of three points, where the project–team has had important contributions, and which form the scientific and methodological foundations for the current research activities.

3.2. Asymptotic local approach to monitoring and diagnostics of continuous dynamical systems

See module 6.2.

Key words: *fault detection*, *identification*, *local approach*, *fault diagnostics*, *intelligent alarms*.

Glossary

Local test Statistical technique for comparing two different models to the same data sample, when the sample size N grows towards infinity. In order to avoid singular situations, the deviation between the two models is normalized and stated proportional to $1/\sqrt{N}$. Results similar to the central limit theorem show that the test statistics for deciding between these models is asymptotically gaussian distributed with a different mean according to the model which the data has been sampled from

Condition–based maintenance As opposite to systematic inspection, the purpose is to continuously monitor the considered plant, structure or machine, based on data recorded by sensors, in order to prevent from the occurrence of a malfunctioning or a damage, before it might have had too severe consequences.

Intelligent alarms Fault indicators, carrying information useful for diagnostics, under the form of the components the most likely responsible of the detected fault. These indicators automatically perform the tradeoff between tha magnitude of the detected changes and the identification accuracy of the reference model on the one hand, and the measurement noise level on the other hand. These indicators are computationnally cheap, and thus can be embedded.

We have developed a general statistical method for confronting a model to data measured on a process, and performing the early detection of a slight mismatch between the model and the data. Making such a decision requires the comparison of the predicted effect of a slight deviation in the process with the measurements uncertainty. The so–called « asymptotic local » approach, introduced in the seventies by Le Cam [104][113], which we have extended and adapted [5][3], is the foundation of our general approach to monitoring [2][6].

This activity is in line with the earlier activity of the team on change detection. The major contribution is the develpment of a general and original approach to monitoring based on the statistical local approach. This monitoring approach is strengthened by the increasing interest in condtion–based maintenance, fatigue prevention and aided control in a number of industrial applications. The proposed approach consists in the eatrly detection of small deviations with respect to a reference behavior considered as normal, under usual working conditions, namely without artificial excitation, speeding down or stopping the monitored process or machine. The key principle is to design a « residual », ideally zero under normal functioning mode, with low sensitivity to noises and perturbations, and high sensitivity to small deviations (faults, damages, ...).

The behavior of the monitored system is assumed to be described by a parametric model $\{\mathbb{P}_\theta \, , \, \theta \in \Theta\}$, and the safe behavior of the process is assumed to correspond to the parameter value θ_0. This parameter value may either represent a typical normalized behavior for the considered system, or arise from a preliminary identification step based on reference data, for example:

$$\theta_0 = \arg\{\theta \in \Theta \, : \, U_N(\theta) = 0\} \ ,$$

where the « estimating function »

$$U_N(\theta) = \frac{1}{N} \sum_{n=0}^{N} H(\theta, Z_n) \ ,$$

is such that $\mathbb{E}_\theta[U_N(\theta)] = 0$ for all $\theta \in \Theta$. Given a new sequence of observations continuously registered at the ourput of sensors, the following questions are addressed :

- Does the new sample still correspond to the nominal model $\mathbb{P}_{\theta_0}$?

- If not, what are the components of the parameter vector θ the most affected by this change ? In case where the parameter θ has a physical meaning, answering this question allows to perform a diagnostic about the origin of the change in the behavior.

3.2.1. Detection

The asymptotic local approach allows a generic reduction of the validation problem for a « dynamical system » into a universal and « static » detection problem for the mean of a Gaussian random « vector ». Given a N–size sample, the problem is to decide between the nominal hypothesis $\theta = \theta_0$ and a close alternative hypothesis $\theta = \theta_0 + \Delta/\sqrt{N}$, where Δ is an unknown but fixed change vector. A « residual » is generated under the form

$$\zeta_N = \frac{1}{\sqrt{N}} \sum_{n=0}^{N} H(\theta_0, Z_n) = \sqrt{N}\, U_N(\theta_0) \ .$$

The identifiability condition: $\mathbb{E}_\theta[U_N(\theta_0)] = 0$ if and only if $\theta = \theta_0$ (with θ_0 fixed), is enforced. If the matrix $M_N = -\mathbb{E}_{\theta_0}[U_N'(\theta_0)]$, which is also the derivative of the function $\theta \longmapsto \mathbb{E}_\theta[U_N(\theta_0)]$ computed at θ_0, converges towards a limit M, then the central limit theorem shows [79] that the residual is asymptotically Gaussian :

$$\zeta_N \Longrightarrow \begin{cases} \mathcal{N}(0, \Sigma) & \text{under } \mathbb{P}_{\theta_0} \ , \\[2mm] \mathcal{N}(M\,\Delta, \Sigma) & \text{under } \mathbb{P}_{\theta_0 + \Delta/\sqrt{N}} \ , \end{cases}$$

where the asymptotic covariance matrix Σ can be estimated [6]. Deciding between $\Delta = 0$ and $\Delta \neq 0$ in this « limit » model amounts to compute the following χ^2–test, provided that M is full rank and Σ is invertible :

$$t = \overline{\zeta}^T \mathcal{I}^{-1} \overline{\zeta} \gtrless \lambda \ .$$

where $\overline{\zeta} = M^T \Sigma^{-1} \zeta_N$ and $\mathcal{I} = M^T \Sigma^{-1} M$.

With this approach, it is possible to decide, with a quantifiable error level, if a residual value is significantly non zero for assessing whether a fault has occurred. It is important to note that the residual and the sensitivity and covariance matrices M and Σ can be evaluated (or estimated) for the nominal model, namely for the true value of the parameter. In particular, it is not necessary to re–identify the model, and the sensitivity and covariance matrices can be pre–computed off–line.

3.2.2. Diagnostics

Assuming that the question « which fault type occurred » boils down to the question « which component of vector θ has changed », the diagnosis problem can be solved using standard nuisance parameters elimination methods. The fault vector Δ is partitioned into an informative part and a nuisance part, and the sensitivity matrix M, the Fisher information matrix $\mathcal{I} = M^T \Sigma^{-1} M$ and the normaized residual $\overline{\zeta} = M^T \Sigma^{-1} \zeta_N$ are partitioned accordingly

$$\Delta = \begin{pmatrix} \Delta_a \\ \Delta_b \end{pmatrix} \ , \quad M = \begin{pmatrix} M_a & M_b \end{pmatrix} \ , \quad \mathcal{I} = \begin{pmatrix} \mathcal{I}_{aa} & \mathcal{I}_{ab} \\ \mathcal{I}_{ba} & \mathcal{I}_{bb} \end{pmatrix} \ , \quad \overline{\zeta} = \begin{pmatrix} \overline{\zeta}_a \\ \overline{\zeta}_b \end{pmatrix} \ .$$

For deciding between $\Delta_a = \Delta_b = 0$ and $\Delta_a \neq 0$, $\Delta_b = 0$ in the « limit » model, a « sensitivity » approach results in the following test statistics

$$t_a = \overline{\zeta}_a^T \mathcal{I}_{aa}^{-1} \overline{\zeta}_a \ ,$$

where $\overline{\zeta}_a$ is the « partial » residual (score). If $t_a \geq t_b$, the component responsible for the fault will be considered to be a rather than b. Alternatively, a « minimax » approach can be used for deciding between $\Delta_a = 0$ and $\Delta_a \neq 0$, in the « limit » model, with Δ_b unknown, which results in the following test statistics

$$t_a^* = \overline{\zeta}_a^{*T} \mathcal{I}_a^{*-1} \overline{\zeta}_a^* \ ,$$

where $\overline{\zeta}_a^* = \overline{\zeta}_a - \mathcal{I}_{ab}\,\mathcal{I}_{bb}^{-1}\,\overline{\zeta}_b$ 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 $\mathcal{I}_a^* = \mathcal{I}_{aa} - \mathcal{I}_{ab}\,\mathcal{I}_{bb}^{-1}\,\mathcal{I}_{ba}$ is the associated Fisher information matrix. If $t_a^* \geq t_b^*$, the component responsible for the fault will be considered to be a rather than b.

3.2.3. Physical diagnostics

This approach also allows us to perform a physical diagnostics, namely in terms of a parameter ϕ with a physical meaning rather than in terms of the parameter θ used for the identification and the monitoring. Our approach to this problem is basically a detection approach again, and not a (generally ill–posed) inverse problem estimation approach. The basic idea is to note that the physical sensitivity matrix writes $M\,\mathcal{J}$, where $\mathcal{J}$ is the Jacobian matrix at ϕ_0 of the application $\phi \mapsto \theta(\phi)$, and to use the above diagnostics procedure for the components of the parameter vector ϕ.

The above systematic approach to monitoring provides us with a general framework for monitoring and troubleshooting continuous industrial processes and machines. The key issue to be addressed within each parametric model class is the residual generation, or equivalently the choice of the estimating function. The present activities of the team address two main model classes :

- the nonlinear dynamical systems, see module 6.1,

- the linear dynamical systems, for mechanical structures subject to vibrations, see module 6.2.

3.3. Statistical inference in hidden Markov models, and particle filtering

Key words: *hidden Markov model (HMM)*, *asymptotic statistics*, *exponential stability*, *particle filtering*.

Glossary

> HMM Hidden Markov model : stochastic automaton (or Markov chain) whose internal state is not observed directly, and should be estimated from noisy observations. More generally, the model itself should be identified. These models are widely used in speech recognition, for the alignment of biological sequences, and more recently for the diagnosis of distributed discrete events dynamical systems, see module 3.4.

> **Particle filtering** Numerical method which allows to approximate the conditional probability distribution of an hidden state given observations, by means of the empirical distribution of a system of particles, which explore the state space following independent realizations of the state equation (or state transition), and which are redistributed according to their consistency (quantified by the likelihood function) with the observations.

Statistical inference of hidden Markov models relies on studying the asymptotic behavior of the prediction filter (i.e. the probability distribution of the hidden state given observations at all previous time instants) and of its derivative with respect to the parameter. Two different type of asymptotics have been studied : (i) large time asymptotics, where we have proposed a systematic approach, based on an exponential stability property of the filter, and (ii) small noise asymptotics, where it is easy to obtain interesting explicit results, in terms close to the language of nonlinear deterministic control theory.

We have also proposed numerical methods of Monte Carlo type, very easy to implement and known under the generic name of particle filters, for the approximate computation of the filter, of the linear tangent filter, and other filters associated with the recursive computation of additive functionals of the hidden state (as for instance in the EM algorithm).

Hidden Markov models (HMM), form a special case of partially observed stochastic dynamical systems, in which the state of a Markov process (in discrete or continuous time, with finite or continuous state space) should be estimated from noisy observations. These models are very flexible, because of the introduction of

latent variables (non observed) which allows to model complex time dependent structures, to take constraints into account, etc. In addition, the underlying Markovian structure makes it possible to use numerical algorithms (particle filtering, Markov chain Monte Carlo methods (MCMC), etc.) which are computationally intensive but whose complexity is rather small. Hidden Markov models are widely used in various applied areas, such as speech recognition, alignment of biological sequences, tracking in complex environment, modeling and control of networks, digital communications, etc.

Beyond the recursive estimation of an hidden state from noisy observations, the problem arises of statistical inference of HMM with general state space, including estimation of model parameters, early monitoring and diagnosis of small changes in model parameters, see module 3.2, etc.

3.3.1. Large time asymptotics

Our main contribution is the asymptotic study, when the observation time increases to infinity, of an extended Markov chain, whose state includes (i) the hidden state, (ii) the observation, (iii) the prediction filter (i.e. the conditional probability distribution of the hidden state given observations at all previous time instants), and possibly (iv) the derivative of the prediction filter with respect to the parameter. Indeed, it is easy to express the log–likelihood function, the conditional least–squares criterion, and many other clasical contrast processes, as well as their derivatives with respect to the parameter, as additive functionals of the extended Markov chain.

We have proposed the following general approach :

- first, we prove an exponential stability property (i.e. an exponential forgetting property of the initial condition) of the prediction filter and its derivative, for a misspecified model,
- from this, we deduce a geometric ergodicity property and the existence of a unique invariant probability distribution for the extended Markov chain, hence a law of large numbers and a central limit theorem for a large class of contrast processes and their derivatives, and a local asymptotic normality property,
- finally, we obtain the consistency (i.e. the convergence to the set of minima of the associated contrast function), and the asymptotic normality of a large class of minimum contrast estimators.

This programme has been completed in the case of a finite state space [7][8], and has been generalized in [81] under a uniform minoration assumption for the Markov transition kernel, which typically does only hold when the state space is compact.

Clearly, all the approach relies on the existence of exponential stability property of the prediction filter, and the main challenge currently is to get rid of this uniform minoration assumption for the Markov transition kernel [110][112], so as to be able to consider more interesting situations, where the state space is noncompact.

3.3.2. Small noise asymptotics

Another asymptotic approach can also be used, where it is rather easy to obtain interesting explicit results, in terms close to the language of nonlinear deterministic control theory [97].

Taking the simple example where the hidden state is the solution of an ordinary differential equation, or a nonlinear state model, and where the observations are subject to additive Gaussian white noise, this approach consists in assuming that covariances matrices of the state noise and of the observation noise go simultaneously to zero. If it is reasonable in many applications to consider that noise covariances are small, this asymptotic approach is less natural than the large time asymptotics, where it is enough (provided a suitable ergodicity assumption holds) to accumulate observations and to see the expected limit laws (law of large numbers, central limit theorem, etc.). In opposition, the expressions obtained in the limit (Kullback–Leibler divergence, Fisher information matrix, asymptotic covariance matrix, etc.) take here much more explicit form than in the large time asymptotics.

The following results have been obtained during the last few years using this approach :

- the consistency of the maximum likelihood estimator (i.e. the convergence to the set M of global minima of the Kullback–Leibler divergence), has been obtained using large deviations techniques, with an analytical approach [93],

- if the abovementioned set M does not reduce to the true parameter value, i.e. if the model is not identifiable, it is still possible to describe precisely the asymptotic behavior of the estimators : in the simple case where the state equation is a noise–free ordinary differential equation, we have shown in [94] in a Bayesian framework, that (i) if the rank r of the Fisher information matrix $\mathcal{J}$ is constant in a neighborhood of the set M, then this set is a differentiable submanifold of codimension r, (ii) the posterior probability distribution of the parameter converges to a random probability distribution in the limit, supported by the manifold M, absolutely continuous w.r.t. the Lebesgue measure on M, with an explicit expression for the density, and (iii) the posterior probability distribution of the suitably normalized difference between the parameter and its projection on the manifold M, converges to a mixture of Gaussian probability distributions on the normal spaces to the manifold M, which generalized the usual asymptotic normality property,

- more recently, we have shown that (i) the parameter dependent probability distributions of the observations are locally asymptotically normal (LAN) [113], from which we deduce the asymptotic normality of the maximum likelihood estimator, with an explicit expression for the asymptotic covariance matrix, i.e. for the Fisher information matrix $\mathcal{J}$, in terms of the Kalman filter associated with the linear tangent linear Gaussian model, and (ii) the score function (i.e. the derivative of the log–likelihood function w.r.t. the parameter), evaluated at the true value of the parameter and suitably normalized, converges to a Gaussian r.v. with zero mean and covariance matrix $\mathcal{J}$.

3.3.3. Particle filtering

Studying HMM with general state space immediately raises the question of computing, even approximately, the optimal filter and related quantities, such as the derivative of the optimal filter w.r.t. an unknown parameter of the model (more generally, the linear tangent optimal filter), or other filters [78] associated with the recursive computation of conditional expectations, given the observations, of additive functionals (FA) of the hidden state (an example of such a FA is the auxiliary function in the EM algorithm).

An attractive and promising answer has been proposed recently under the generic name of *particle filtering*, which is the subject of intense research activities, in the direction of practical implementation, and in the direction of extension to more general models and problems. Most of the currently available mathematical results are presented in the survey paper [111], many theoretical and practical aspects are presented in the contributed volume [82], applications of particle filtering to signal processing specifically are presented in the special issue [80].

In its simplest version [90], often called *bootstrap filter*, the algorithm consists in approximating the optimal filter by means of the empirical probability distribution of a particle system. Between two observations, particles explore the state space by mimicking independent trajectories / transitions of the hidden state sequence, and whenever a new observation becomes available, a resampling step (with replacement) is performed, by which particles are selected in terms of their consistency (quantified by the likelihood function). As a result of this resampling mechanism, which is the key step in the algorithm, particles automatically concentrate in regions of interest of the state space. The algorithm is extremely easy to implement, since it is enough to simulate independent trajectories / transitions of the hidden state sequence. Interacting particle methods can also be used to solve various statistical problems for HMM with general state space, including recursive estimation of model parameters, early monitoring and diagnosis of small changes in model parameters, etc. These two problems require to compute, even approximately, the linear tangent optimal filter, in addition to the optimal filter.

3.4. Stochastic models for the supervision of distributed systems

Key words: *distributed system*, *discrete event (dynamic) system (DES)*, *concurrency*, *Petri net*, *unfolding*, *automata network*, *partially stochastic model*, *hidden Markov model (HMM)*, *distributed algorithm*.

Glossary

Hybrid system Generically denotes systems that combine aspects which are usually treated separately. For example : discrete vs. continuous state space, discrete vs. continuous time, logical vs. real time, time driven vs. event driven, equations or constraints vs. random variables, etc.

HMM see module 3.3.

Concurrency In a DES, two events are called concurrent if they may occur in any order, or simultaneously, without changing the outcome

Great parts of the investigations in this subject are done jointly with the TRISKELL project–team (Claude Jard), the common target application being the supervision of telecommunication networks, in particular fault diagnosis. For this, we extended techniques known as HMM to distributed systems. Those systems are modelled by safe Petri nets, under a dynamics — or, following the use of language in computer science, a semantics — that is adequate for the distributed nature of those systems, namely : based on « partial orders ».

For this, we had to

1. develop a state observer technique based on the unfolding [84][83] of a Petri net or a product of automata,

2. introduce a new notion of « partially stochastic » system that fits into the partial order semantics, and

3. adapt the Viterbi algorithm for computing a max–likelihood trajectory for HMM's to the partial order setting.

An important result in this area is the fact that the diagnosis / observation algorithms can be « distributed ». That is, only local states of the supervised system — which is often of considerable size — need to be treated. This result is based on a close analogy between Markov fields (a.k.a. networks of random variables) and distributed systems viewed as networks of elementary dynamical systems. Therefore, the existing inference algorithms for Markov fields carry over naturally to distributed systems, thus offering a wealth of techniques.

Our current work aims at

1. the further development of the probabilistic framework, towards identification of local transition probabilities,

2. a greater robustness of the supervision algorithms, especially w.r.t. incomplete knowledge of the system,

3. a better understanding of relations between distributed algorithms and known models for concurrent processes (specifically the wide variety of formalisms for event structures),

4. being able to handle distributed systems with changing structure.

3.4.1. Distributed systems

We are dealing with distributed systems that are at the same time DES, or finite state machines : they are obtained as the combination of elementary subsystems, and therefore distributed. *Petri nets* constitute typical examples for this : one can easily connect two Petri nets via « shared » places. The tokens on those places can thus pass from one net to the other, and one can model in this way interactions such as resource transimission or mutual exclusion. More generally, a distributed system can be viewed as a network of elementary automata, each acting on some set of state variables. Interaction is then brought about by shared variables, which play the role of places in Petri nets. The graph of connections between the subsystems thus defines an interaction network.

Modeling a complex system becomes much easier under a modular approach. However, the real advantage of distributed systems is elsewhere : by identifying the interactions between subsystems, one also exhibits the domains of concurrent behaviour. In other words, as long as two subsystems do not interact via their shared variables, they evolve independently. If this is a tautology, it deserves to be noted : there exist « regions of concurrency » between subsystems, inside which the respective behaviour can be governed by independent

clocks, without impact on the global behaviour. This means that events in a distributed system are only partially ordered in time, that is, there is no adequate notion of global time. The trajectories of distributed systems are hence to be described by a « partial order », or « true concurrency », semantics, in which partial orders of events are given rather than sequences. The space of trajectories is given by the « unfolding », rather than the marking graph, of the system : this leads to a considerable reduction in the size of the trajectory space.

3.4.2. *Stochastic framework*

Several concepts of stochastic Petri nets have been proposed in the literature : exept the case of free choice nets, none of these models reflects correctly the « concurrency » of transitions by « stochastic independence ». In fact, two concurrent transitions that share no place should behave, under randomized firing, like independent random variables.

It can be shown that this requirement contradicts any Petri net dynamics given by Markov chains, such as in all usual models of stochastic Petri nets. Indeed, the concept of Markov chain requires a global time to synchronize events : it follows that the probability of two concurrent events will depend on their order of occurrence.

A better framework is given by the CSS model in [4], in the form of Markov fields subject to constraints. This leads to a partially stochastic model in which the constraint part is not randomized. Our current work deals with approaches in which the randomization is complete, that is, the net behavior is deterministic for each fixed random element $\omega \in \Omega$; the probability space can be identified with the space of partially ordered runs of the system. The construction of adequate probability measures on this space has been the subject of our research, and results have been published in [13] [92][91]. Currently, the thesis research of Samy Abbes, supervised by A. Benveniste and S. Haar, bears on the solidification of the mathematical framework and aims at the construction of inference algorithms for local probability germs from observed behaviour.

3.4.3. *Distributed algorithms for state reconstruction*

The diagnosis problem consists in identifying the most likely behaviour of the system, given the partial order of system events observed. We have established that it suffices to consider « tiles » formed by a transition and the set of variables (or places) on which the transition acts. A « likelihood » is associated to each individual tile, based on the probabilistic model and conditional on the observations. The system trajectories can thus be viewed as puzzles formed by those tiles, and their likelihood is obtained as the product of the tile likelihoods. Max–likelihood diagnosis therefore amounts to constructing inductively the optimal puzzles via dynamic programming [1].

This principle works if the observations from the entire system are collected in a single site, the « supervisor ». This assumption is not the most appropriate one in practice : rather, it seems natural to have a distributed structure of observers for a distributed system. We have shown that there is no need to centralize the observations, and that distributed HMM algorithms are much more efficient. Such algorithms rely on several agents, each of them handling observations emanating from the subsystem under its supervision, by means of tiles local for that subsystem. In this way, part of the global puzzle is constructed locally. Communication among agents concern only those tiles pertaining to shared resources. One thus obtains a truly parallel and asynchronous reconstruction of the global puzzles, while handling only local states and exploiting fully the interaction graph, as well as concurrency between subsystems. These distributed algorithms are being experimented in an industrial network management platform, for SDH or GMPLS/WDM network models, see the Magda2 project, module 7.8.

4. Application Domains

4.1. Introduction

Applications involving an industrial partnership, with access to real data, cover a wide range of domains : vibration mechanics, onboard electronics for the automotive industry, diagnosis of large telecommunication

networks. We have chosen to give a detailed presentation of our activity in vibration mechanics, which clearly represents our main cumulated investment, and we describe next our activity in telecommunications.

4.2. In–operation analysis and monitoring of vibrating structures

See modules 3.2, 6.2 and 7.1.

Key words: *vibration*, *mechanical structure*, *modal analysis*, *subspace–based method*.

Glossary

> **Modal analysis** Identification of the « modes of vibration », namely 1) the eigenfrequencies and associated damping coefficients, and 2) the observed components of the associated eigenvectors or « modeshapes ».
>
> **Subspace–based methods** Generic name for an identification algorithm for linear systems based on output covariance matrices, in which different subspaces of Gaussian random vectors play a key role [115].

In a long serie of investigations, the SIGMA2 project–team has developed an original set of techniques performing the following services, « for a structure under ambiant operating conditions » : 1) modal analysis, 2) correlation between measurements and model, 3) detection and diagnostics of fatigues. Performing in–operation data processing imposes the following constraints : 1) the excitation is natural, it results from the very functioning conditions of the structure, it is often nonstationary, 2) the excitation is not measured.

In–situ damage monitoring and predictive maintenance for complex mechanical structures and rotating machines is of key importance in many industrial areas : power engineering (rotating machines, core and pipes of nuclear power plants), civil engineering (large buildings subject to hurricanes or earthquakes, bridges, dams, offshore structures), aeronautics (wings and other structures subject to strength), automobile, rail transportation. These systems are subject to both fast and unmeasured variations in their environment and small slow variations in their vibrating characteristics. Of course, only the latter are to be detected, using the available data (accelerometers), and noting that the changes of interest (1% in eigenfrequencies) are not visible on spectra.

For example, offshore structures are subject to the turbulent action of the swell which cannot be considered as measurable. Moreover, the excitation is highly time–varying, according to wind and weather conditions. Therefore the challenge is as follows. The available measurements 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 FDImethod must rather rely on a model which will help in discriminating between the two mixed causes of the changes that are contained in the accelerometer measurements.

A different example concerns rotating machines such as huge alternators in electricity power plants. Most of the available vibration monitoring techniques require to stop the production, in order to vary the rotation speed and, by the way, get reliable spectra. When monitoring the machine without speeding it down, one is faced with the following challenge. The non–stationary and non–measured excitation is due to load unbalancing which creates forces with known frequency range (harmonics of the rotation speed) but unknown geometry, and to turbulence caused by steam flowing through the alternator and frictions at the bearings. The problem is again to discriminate between two mixed causes of changes in vibrating characteristics.

Classical modal analysis and vibration monitoring methods basically process data registered either on test beds or under specific excitation or rotation speed conditions. The object of Eureka project SINOPSYS « Model Based Structural Monitoring Using in–Operation System Identification » coordinated by LMS (Leuven Measurements Systems, Leuven, Belgium) has been to develop and integrate modal analysis and 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. The SIGMA2 project–team and the METALAU project–team of INRIA at Rocquencourt have been jointly involved within SINOPSYS.

The main contribution of INRIA to SINOPSYS is an original set of algorithms for multi–sensor signal processing (e.g. accelerometer measurements) that produces intelligent warnings, that is to say warnings that reveal the hidden causes of the defects or damage undergone by the machine or structure. This software can be embedded and work online. Among the actual data that Inria had to process with this software is the Ariane 5 test flight data.

During the first stage of the SINOPSYS project, focused on modal analysis, we have improved our interactive mode selection and validation procedures, and developed a module for « model validation », performing a crossed validation of an identification result on a validation data set. Within a second stage, we have developed a fatigue detection tool, which evaluates for each mode the extent of the modification in the modal behavior. This works on laboratory data sets involving a measured excitation, as well as on in–situ data without measuring the excitation. A third stage has been devoted to the develoment of a fatigue diagnostics tool, where the fatigues or damages are explained in terms of modifications in volumic mass or Young modulus, with a localization of the changes on the structure.

The entire set of tools has been integrated within the LMS CADA_X system on the one hand, and within the MODAL / COSMAD toolbox for the Scilab « freeware » on the other hand, see http://www.irisa.fr/sigma2/constructif/modal.

Another cooperation in the aeronautics domain, still within the Eureka framework, has been devoted to improving the exploitation of flight test data, under natural excitation conditions (e.g. turbulence), enabling more direct exploration of the flight domain, with improved confidence and at reduced cost, see module 7.1.

A new project, launched by the Computer Security program of the French Ministry of Research, is devoted to statistical rejection of environmental effects in structural health monitoring, and related issues, see module 8.1.

These monitoring and diagnosis algorithms were generalized to models that are more complex than vibration models and can be used for monitoring in industrial process control (gas turbine, electric plant) or for on board diagnosis (catalytic exhaust and particulate filter of automobiles, see module 7.4).

4.3. Telecommunications : fault diagnosis in network management, turbo–codes, joint processing in digital communications

See modules 3.4, 6.4, 6.5, 7.8 and 7.7.

Key words: *telecommunication network*, *network management*, *supervision*, *alarm correlation*, *diagnosis*, *turbo–code*, *joint source–channel decoding*.

Glossary

> **Network management** Denotes the top level of management of telecommunication, i.e. supervision, monitoring, maintenance, etc.
>
> **Alarm management** Comprises processing, filtering and interpretation of alarms sent across the network.
>
> **Diagnosis** Interpretation of alarms, based on which reconfiguration and maintenance operations can be triggered.
>
> **HMM** see module 3.3.
>
> **Turbo–code** Error correcting codes introduced by Berrou, Glavieux and Thitimajshima [75], joining two convolution codes by means of an interleaver. The name is due to the iterative decoding algorithm, which uses « soft » probabilistic information.

Currently, important efforts in network management concern « fault diagnosis ». Based on a suitably abstract network model, one strives to automatically generate algorithms for behavior monitoring, and diagnosis in particular. This technique allows to update more easily the diagnosis software, as the network evolves. The originality of this approach lies in the fact that we aim at a modular modeling from the start, so as to obtain distributed diagnosis algorithms. This work is carried out jointly with the TRISKELL project-team, and is at the heart of the exploratory RNRT project MAGDA2, see module 7.8.

Besides, we are also interested in turbo–codes and their extensions. Digital communications at the physical layer have evolved from a traditional approach where the different functions of modulation, coding, and equalization were considered separately, to an integrated systems approach. To achieve this goal, we propose joint design of different functions for receivers based on turbo–techniques.

5. Software

5.1. Nonlinear modelling Matlab toolbox

Key words: *system identification*, *nonlinear system*, *black–box modeling*, *non–parametric estimation*, *neural network*, *wavelet network*, *Matlab toolbox*.

In cooperation with Lennart Ljung of Linköping University and Anatoli Juditsky of université Joseph Fourier, we develop a Matlab toolbox for nonlinear system identification. This toolbox is designed as an extension to nonlinear systems of the existing System Identification Toolbox (SITB) authored by Lennart Ljung and distributed by The Mathworks. In addition to classical parametric estimation for grey–box models, algorithms based on non–parametric estimation with regression trees, wavelet networks and neural networks are also implemented. The dynamic model structures include nonlinear autoregression with exogenous inputs (NLARX) and some output error models.
Participant: Qinghua Zhang [corresponding person].

On the basis of a joint study with colleagues of Linköping University in Sweden [95][105], a Matlab toolbox for nonlinear dynamic system identification is under development. As an extension to nonlinear systems of the existing System Identification Toolbox (SITB), its command line syntax and graphical user interface are designed closely following those of the SITB. An experienced user of the SITB can thus easily learn to work with the new toolbox.

The considered model structures cover both parametric state space models for nonlinear system grey–box modeling and non–parametric models for black–box modeling. The black–box part includes nonlinear autoregressive with exogenous inputs (NLARX) models and block–oriented output error models (Wiener and Hammerstein models). For the estimation of nonlinearities, general estimators such as regression trees, wavelet networks and neural networks are proposed, in addition to some specific nonlinearity estimators (saturation and dead zone). The main algorithm originality consists of the use of non iterative algorithms for nonlinearity estimation with regression trees and wavelet networks. These algorithms are faster than the classical gradient–based iterative search and avoid the problem of bad local minima [95][105].

The implementation of the toolbox strongly relies on the object–oriented programing functionalities of Matlab. The algorithms have been implemented and tested. The current development efforts are mainly about the user interface improvement.

5.2. Modal analysis and health monitoring Scilab toolbox

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

In collaboration with Maurice Goursat (METALAU project-team at INRIA Rocquencourt), we have pursued the development of the Scilab toolbox devoted to modal analysis and vibration monitoring of structures or machines subject to known or ambiant (unknown) excitation.

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

In collaboration with Maurice Goursat (METALAU project-team at INRIA Rocquencourt), we have pursued the development of the Scilab toolbox [45][47] devoted to modal analysis and vibration monitoring of structures or machines subject to known or ambiant (unknown) excitation.

This toolbox performs the following tasks :

- Output–only subspace–based identification, see modules 6.2 and 7.1. The problem is to identify the eigenstructure (eigenvalues and observed components of the associated eigenvectors) of the state transition matrix of a linear dynamical system, using only the observation of some measured outputs summarized into a sequence of covariance matrices corresponding to successive time shifts. For this method, see [70].

- Input–output subspace–based identification, see modules 6.2 and 7.1. The problem is again to identify the eigenstructure, but now using the observation of some measured inputs and outputs summarized into a sequence of cross–covariance matrices. For this method, see [37].

- Subspace–based identification through moving sensors data fusion, see module 6.2 of our 2001 activity report. The problem is to identify the eigenstructure based on a joint processing of signals registered at different time periods, and under different excitations. For this method, see [99][100].

- Automated online identification package, see module 6.2. The problem is still to identify the modes of a mechanical structure. The main question is to react to non stationarities and fluctuations in the evolution of the modes, especially the damping. The developed package allows the extraction of such modes using a graphical interface allowing to follow the evolution of all frequencies and damping over time and to analyse their stabilization diagram (from which they were extracted). Automated modal extraction is performed based on the automated analysis and classification of the stabilization diagram. For this method, see [51][50].

- Damage detection, see modules 3.2, 4.2 and 6.2. Based on vibration measurements processing, the problem is to perform early detection of small deviations of the structure w.r.t. a reference behavior considered as normal. Such an early detection of small deviations is mandatory for fatigue prevention. The algorithm confronts a new data record, summarized into covariance matrices, to a reference modal signature. For this method, see the articles [68][101].

- Damage monitoring. This algorithm solves the damage detection problem above, based on on–line (and not block) processing. For this method, see [21].

- Modal diagnosis, see modules 3.2, and 4.2. This algorithm finds the modes the most affected by the detected deviation. For this method, see [71] and [11].

- Damage localization, see modules 3.2, 4.2 and 6.2. The problem is to find the part of the structure which have been affected by the damage and the associated structural parameters (masses, stiffness coefficients). For this method, see [69] and [43][21][11].

- Optimal sensor positioning for monitoring. A criterion is computed, which quantifies the relevance of given sensor number and positioning for the purpose of monitoring. For this criterion, see [72][69].

This software has been registered at the APP. Its modules have been tested by different partners, especially some industrial partners within the FLITE project, see module 7.1.

6. New Results

6.1. Adaptive observer and nonlinear system fault diagnosis

See module 3.2.

Key words: *nonlinear system*, *nonlinear observer*, *adaptive observer*, *state and parameter estimation*, *fault diagnosis*.

Participants: Qinghua Zhang, Olivier Perrin, Arnaud Guyader.

Our study on adaptive observers is mainly for the purpose of fault diagnosis by means of state and parameter estimation. When faults are modeled as parametric changes, adaptive observers provide direct and indirect methods for fault diagnosis.

Recently, a globally convergent adaptive observer has been developed for some nonlinear systems. It is based on a non trivial combination of a nonlinear high gain observer and a linear adaptive observer. The study of this year has been carried out on several aspects of both theoretic and practical interests.

The first one is for the generalization of the results to a larger class of nonlinear systems, while still preserving the global convergence of the algorithm. Through a joint work with Gildas Besançon (LAG, Laboratoire d'Automatique de Grenoble) and Hassan Hammouri (LAGEP, Laboratoire d'Automatique et de Génie des Procédés, Lyon), now the result is extended to the case of nonlinear systems with product between unknown parameters and nonlinear functions of states [30].

In order to deal with more general nonlinear systems, researches have been made on local convergence of adaptive observers. The resulting algorithm is applicable to a large class of nonlinear systems of quite general structure. It is tested in a preliminary study on particulate filter fault detection for cars equipped with diesel engines, in the framework of the thesis study of Olivier Perrin. The result will be presented at the 1st IFAC Symposium on Advances in Automotive Control [54].

The role of the persistent excitation condition is better understood, as explained in [59], and some improvement on the gain adaptation has also been made [54]. Finally, adaptive observer for discrete time linear systems has been studied [38], whereas most results on adaptive observers are for continuous time systems.

6.2. Identification and monitoring of linear dynamical systems. Application to structures subject to vibrations

See modules 3.2, 4.2 and 7.1.

Key words: *vibration*, *mechanical structure*, *modal analysis*, *subspace–based method*.

Participants: Michèle Basseville, Albert Benveniste, Laurent Mevel.

This research is conducted in cooperation with Maurice Goursat (METALAU project-team at INRIA Rocquencourt), in the framework of the Eureka project FLITE which has followed SINOPSYS, see modules 4.2 and 7.1.

The problem is the identification and the monitoring of the eigenstructure (eigenvalues and observed components of the associated eigenvectors) of the state transition matrix F of a linear dynamical system :

$$\begin{cases} X_{k+1} & = & FX_k + V_k \\ Y_k & = & HX_k + W_k \end{cases}$$

where the dimension of the observation Y_k is much smaller than the dimension of the state X_k. We exloit, in a different manner for identification and for monitoring, the following subspace property : the observability matrix $\mathcal{O}$ of the pair (H, F) and the Hankel matrix $\mathcal{H}$ filled with the empirical covariances of the observations have the same left kernel. Our vibration monitoring method is based on the application of the local approach, see module 3.2, to this subspace property [68].

The achievements of this year include conceptual investigations, experimental results and software developments.

On the conceptual side, our damage localization paper has been accepted for publication [11], and three investigations have been conducted, on recursive subspace, particle filtering and flutter monitoring algorithms, respectively. Recursive subspace algorithms have been investigated in the context of output–only data. Looking

back to the classical subspace algorithm, it appears that the most computationally expensive part is the computation of the singular value decomposition (SVD). During the visit of Ivan Goethals (KUL / SISTA), we have tried to speed up the algorithm by implementing recursive versions of the SVD. For the input–output case, recursive subspace method have been studied to extend the applicability of those algorithms from off–line to on–line frameworks. Especially the use of fast approximation subspace tracking algorithms like projection approximation subspace tracking (PAST) and its instrumental variable extenson IV–PAST have been studied. We have derived a recursive version of the classical subspace realization algorithm using IV–PAST. This algorithm has been shown to be a relatively good algorithm for tracking modes in the case of vibrational modes from in–flight test data sets [36].

Based on the work on interacting particle systems, see module 6.3, we have studied the performance of such algorithms for estimating and tracking the parameters of linear systems. The underlying application which motivated the study is the tracking of vibration modes for in–flight data sets. The classical subspace algorithm and its recursive implementation, requires the computation of a SVD for the extraction of the state matrix. These algorithms do not keep track of the previous state matrix when the number of observations grows to infinity. Everything is done without accumulating the information from previous data. The idea underlying the study is to apply together stochastic algorithms and particle filtering to perform such parameter estimation. For more information on the computation of the conditional probability distribution of hidden states given the observations, and on the computation of its derivative with respect to the parameter [77], see modules 3.3 and 6.3. Given those two statistical objects, we derive the efficient score and we use it for computing recursive algorithms. The performance evaluation of such algorithms and the comparison with the classical Kalman filter have been performed. The new algorithm has shown comparable results with much easier and faster implementation. These algorithms have also much more promising behaviour when the dimension increases. Simulation studies have been performed for both estimation and tracking. Data from real structures have yet to be tested. This work has been done by Johan Fichou, during his student internship under the supervision of Laurent Mevel and in collaboration with François Le Gland.

We have investigated a first theoretical solution to the problem of monitoring a damping coefficient, which results from the flutter monitoring problem, see module 7.1. The idea is to use the same subspace–based residual as we use for structural health monitoring, and to design a unilateral test statistics for detecting that a given damping coefficient decreases towards zero. Since this hypothesis problem is no longer a local hypotheses testing problem, we have used another asymptotic approximation for the residual, and a cumulative sum test [42][44][66].

From an experimental point of view, the Eureka FLITE project has provided lots of opportunities for testing and improving our identification and detection techniques, including the new flutter monitoring algorithm; see module 7.1. Another opportunity for improving, tuning and testing our techniques through our modal toolbox, has been provided by a contract with EADS Launch Vehicles, see module 7.3.

On the software side, the development of the MODAL / COSMAD toolbox to be used with Scilab has been pursued, the above recursive identification algorithms and the flutter monitoring algorithms incorporated, see module 5.2.

6.3. Applications of interacting particle systems to statistics

Key words: *HMM*, *particle filtering*, *rare event*.

See modules 3.3, 7.4, 7.5 et 8.4.
Participants: Fabien Campillo, Natacha Caylus, Frédéric Cérou, Arnaud Guyader, François Le Gland.

Particle methods are sequential methods of Monte Carlo type, in which particles explore the state space, by mimicking the dynamics of some underlying stochastic process, and interact under the effect of a selection mechanism which automatically concentrates particles, i.e. the available computing power, into regions of interest of the state space. This methodology is currently applied within the SIGMA2 project-team to several types of problems and applications : simulation of rare events and evaluation of collision

risk (IST project Hybridge, see module 7.5), tracking of mobiles in a cellular network (thesis study of Natacha Caylus), turbo–synchronization for satellite communications (research contract with Alcatel Space Industry, see module 7.7), identification and monitoring of particulate filters (PhD thesis of Olivier Perrin, see module 7.4), estimating and tracking vibration modes for in–flight data sets (internship of Johan Fichou, see module 6.2). Particle methods are also studied in the VISTA project-team, with applications in target tracking, and in tracking of points or extended objects in video sequences.

6.3.1. Simulation of rare events

The numerical evaluation of extremely small probabilities, such as the probability of occurrence of a rare event — typically the probability that a set is reached by a continuous–time Markov process before a fixed or a random time, is a challenging numerical problem whose applications are numerous : analysis and performance evaluation of a telecommunication network, evaluation of conflict or collision risk in air traffic management, see module 7.5, etc. To deal with this class of problems, there are on one hand probabilistic methods, which provide asymptotic results and are based on large deviations theory, and on the other hand simulation methods, the most widely used of which is « importance sampling », where independent sample paths (i) are generated under a proposal probability distribution for which the considered event is not so rare, and (ii) are weighted by the Radon–Nikodym derivative of the proposal probability distribution w.r.t. the true probability distribution.

An alternative method is « importance splitting », in which a sequence of increasingly rare events is defined, and a selection mechanism is introduced where sample paths for which an intermediate event holds true split / branch into several offsprings, while sample paths for which none of the intermediate events hold true are terminated [88][89]. This selection mechanism allows to generate many sample paths for which the rare event holds true, and to evaluate statistics of such sample paths. Another very similar method is the RESTART algorithm [107][108]. These methods have been studied in the ARMOR project-team, with applications in telecommunication networks.

In collaboration with Pierre Del Moral (LDP, laboratoire de Statistique et Probabilités, université Paul Sabatier in Toulouse) and with Pascal Lezaud (CENA, Centre d'Études de la Navigation Aérienne, in Toulouse), we have started [76] to study the « importance splitting » algorithm within the framework of flows of Feynman–Kac distributions for the discrete time Markov chain induced by the intermediate events.

Several extensions have been considered this year. We have studied a new algorithm which combines « importance splitting » and « importance sampling » : sample paths are generated under a proposal probability distribution for which the intermediate events are not so rare, and those sample paths for which an intermediate event holds true are given a number of offsprings related to their weight, i.e. to the Radon–Nikodym derivative of the proposal probability distribution w.r.t. the true probability distribution. In other words, among all the sample paths for which an intermediate event holds true, those which are closest to a typical sample path from the true probability distribution are given more offsprings than others.

6.3.2. Particle filters for joint Markov chains

We have studied particle filters for models where the hidden states and the observations form jointly a Markov chain, which means that the hidden states alone do not necessarily form a Markov chain. This model includes as a special case hidden Markov models, switching AR models, non–linear state–space models with correlated Gaussian noise, etc. The evolution of the optimal filter is defined in terms of an unnormalized kernel defined on the state space, which combines the prediction step and the correction step simultaneously, and we have studied particle filters associated with an arbitrary decomposition of this unnormalized kernel into a Markov mutation kernel and a selection weight function. There is no universally optimal decomposition that would minimize the approximation error for any test function, and we have characterized the optimal decomposition for the approximation of the likelihood function. We have studied the propagation of approximation errors, the stability properties of the filter, and we have obtained uniform error estimates [31], using the framework of LeGland and Oudjane [26].

6.3.3. Particle approximation of finite signed measures

We consider joint Markov chains depending on an unknown parameter. Under the assumption that a probabilistic representation exists for the derivative w.r.t. the parameter of the unnormalized kernel characterizing

the evolution of the optimal filter, the linear tangent filter, which is the derivative of the optimal filter w.r.t. the parameter, is absolutely continuous w.r.t. the optimal filter. Exploiting this fact, several joint particle approximation schemes have been proposed in the form of the empirical probability distribution and a weighted empirical signed measure associated with a unique particle systems.

The problem is very close to the problem of computing sensibilities of mathematical expectations, using Monte Carlo methods, which is a very active area of research in mathematical finance. This motivates our contacts with the MATHFI project-team at INRIA Rocquencourt, in particular within a project of the Lyapunov Institute.

Applications of particle methods to recursive MLE has been studied [39], for estimating and tracking vibration modes, see module 6.2, and for estimating a mean–reverting model for electricity spot price [67].

6.4. Supervision of distributed systems

See modules 3.4, 4.3 and 7.8.

Key words: *distributed system, discrete event (dynamic) systems (DES), Petri net, unfolding, automata network, Bayes network, hidden Markov model (HMM), multi–agent.*

Participants: Éric Fabre, Albert Benveniste, Stefan Haar, Samy Abbes, Bruno Marquié.

For the description of distributed systems, we dropped the Petri net framework and used instead the more general one of « Bayes networks of dynamic systems ». There, a system is considered as an automaton acting, via « tiles », on a set of state variables. The state variables play the role of places in Petri nets, the tiles correspond to transitions. Systems can be composed via shared variables, i.e. such that several components can act on those variables. We thus obtain a distributed dynamic system as the product of elementary components. This construction is akin, and close, to the techniques of specifying Markov fields (or Bayesian networks), using potentials whose action is restrained to a subset of the field variables; the main difference (besides the stochastic framework) lies therefore in the introduction of the dynamics.

This analogy between familiar models from signal and image processing on one hand and of distributed dynamic systems on the other turns out to be very fruitful, both for the formal study of large systems and for developing algorithms. For instance, Bayesian networks reflect the factorization properties of a joint probability distribution; for a distributed system, the interaction graph reflects the factorization properties of the set of global system trajectories in a true concurrency semantics. This interesting result allows to rewrite directly, for distributed systems, an entire class of efficient inference algorithms developed for Bayesian networks and graphical models.

A natural application of this consists in recovering all system trajectories that are compatible with a set of events that have been observed during its evolution, and that are themselves of a distributed nature since they have been sampled on different components. The main advantage of these methods is that they handle only the factorized form of the set of those compatible trajectories. We therefore never need to deal with global states of the system, which would be unfeasible : instead, we only handle local states of the components, ensuring their consistency with the state of the neighbouring components. More is true : these algorithms for reconstructing hidden trajectories can themselves be distributed : associate a « local supervisor » to each component, such that each such supervisor constructs the local trace of the global trajectories on its component, based on its local observations together with information received from the neighbouring component supervisors. One can therefore define a truly distributed supervision architecture [86][87][85].

Our current research on this subject focuses on three points.

- First, the extension of the algorithmic framework. A minimal axiomatics has been exhibited, allowing the implementation of distributed algorithms. The theoretical framework thus obtained allows to go beyond the case of tree–shaped interaction graphs : using turbo–code techniques, it can be shown that the inference algorithms proposed for the tree–shaped case behave relatively well in cyclic graphs. The axiomatic framework allows to understand how « turbo »–type algorithms can be transposed to distributed dynamic systems, and to study some of their convergence properties [62].

Current work concerns the robustness of the algorithms, in particular w.r.t. losses of alarms and incomplete knowledge / modelling of the supervised system.

- A second research direction aims at defining an adequate stochastic framework for distributed dynamic systems. The difficulty is here to randomize the set of all trajectories of a distributed system while respecting the concurrent nature of the interactions in it. More precisely, when two components have no interaction with one another, one should expect stochastically independent behaviour. This is not possible in usual Markovian dynamics since those require a global time, and hence interleaving of concurrent events. We have proposed several ways of constructing a stochastic framework for probabilizing partial orders of events. The first solution, partially stochastic models [1], uses a finite time horizon, thus excluding any limit theorems.

  A second approach, recursive and therefore with an infinite horizon, consists in probabilizing sets of increasingly long trajectories, represented directly in the form of partial orders. One then defines a filtration on the « unfolding » of the Petri net describing the system [73] : this approach, however, works only for a limited class of models, there being no adequate filtration in the general case. Recent results of S. Abbes thesis research allow, however, to lift restrictions in this approach, and the development of a rich theory is under way.

  Finally, a third possibility is based on a different semantics, « cluster unfolding » [91], that yields a different form of data structure, giving a Markovian model of concurrent runs of distributed systems in logical time : its extension to timed Petri nets [41] has possible applications to performance evaluation.

- Our third research direction concerns the use of the unfolding of a distributed system to solve the diagnosis problem. This work was carried out for centralized diagnosis, that is, recursive identification of global trajectories that explain a given partial order pattern of observed events [74]. In particular, diagnosability issues have been studied for these partially ordered runs [40].

  Solving the diagnosis problem with unfoldings has led to interesting results in the case of *distributed* systems. We have evidenced factorization properties on the unfolding of a distributed system : specifically, the unfolding of the global system decomposes as the product of local unfoldings, one for each component [63]. The advantage of this representation is that each factor has a reasonable size, which reduces the combinatorial explosion due to large systems. We have proved that the centralized diagnosis problem could be also solved on a factorized representation of the unfolding. And to do so, we again make use of our distributed « turbo–like » algorithms. Distributed diagnosis using unfoldings has been studied and presented in [29][28].

6.5. Joint processing in digital communications

See module 4.3.

Key words: *turbo–code*, *graphical model*, *Bayesian network*.

Participants: Aline Roumy, Éric Fabre, Mutlu Koca.

Glossary

> **Turbo–code** Error correcting codes introduced by Berrou, Glavieux and Thitimajshima [75], joining two convolution codes by means of an interleaver. The name is due to the iterative decoding algorithm, which uses « soft » probabilistic information.

The algorithms we propose for joint processing, arise from the turbo (or iterative) algorithm in digital communications. The applications however concern not only the communication community (coding, multiple access) but also signal processing (equalization). Our current research on this subject focuses on the analysis of such algorithms in order to propose new designs.

Our work stems from [109][98], where the connection between the turbo algorithm of Berrou et al. (1993) and Pearl (1982) belief propagation algorithm, well known in the artificial intelligence community was shown.

This allowed [96] to cast all the turbo–iterative schemes in a unified scheme, in which the transmitter is naturally described by graphs (factor graph, or bipartite graph) and the data are estimated at the receiver by the message passing algorithm (the sum–product or the max–product algorithm). Then, one of the most promising approaches for analyzing iterative decoding schemes was proposed. It employs the notion of density evolution [103][102], where the density of the soft messages exchanged is tracked. Instead of the whole density, tenBrink proposed to visualize the mutual information [114]. In the following, we describe the main focuses of our research.

6.5.1. Coding

In [56][23], we have shown that mutual information can also be used to design the transmitter. We therefore optimized the random–like ensemble of irregular repeat accumulate (IRA) codes for binary–input symmetric channels in the large blocklength limit. Our optimization technique is based on approximating the evolution of the densities of the messages exchanged by the belief–propagation message–passing decoder by a one–dimensional dynamical system. In this way, the code ensemble optimization can be solved by linear programming. We propose four such density evolution approximation methods, and compare the performance of the obtained code ensembles over the binary symmetric channel and the binary–antipodal input additive white Gaussian channel. Our results clearly identify the best among the proposed methods and show that the IRA codes obtained by these methods are competitive with respect to the best–known irregular low–density parity–check (LDPC) codes. In view of this and the very simple encoding structure of IRA codes, they emerge as attractive design choices.

6.5.2. Multiple access

A very efficient multiplexing method is the code division multiple access (CDMA). This technique has raised a lot of interest in mobile communications due to its large spectral efficiency [106] and is already standardized (IS-95, IMT-2000, UMTS). We propose here two approaches : an LDPC–encoded CDMA system and then a competitor to the CDMA.

For the first one, we investigated in [16] the spectral efficiency achievable by random synchronous CDMA with QPSK modulation and binary error–control codes, in the large system limit where the number of users, the spreading factor and the code block length go to infinity. For given codes, we maximize spectral efficiency assuming an MMSE successive stripping decoder for the cases of equal rate and equal power users. In both cases, the maximization of spectral efficiency can be formulated as a linear program and admits a simple closed–form solution that can be readily interpreted in terms of power and rate control. We provide examples of the proposed optimization methods based on off–the–shelf LDPC codes and we investigate by simulation the performance of practical systems with finite code block length.

Regarding the second approach, we started a new study on codes (and their related iterative decoding algorithms) that are able to get close to the boundary of the capacity region of the Gaussian multiple access channel, without the use of time sharing or rate splitting. The approach will be based on density evolution and/or its variant (mean, mutual information).

6.5.3. Source–channel coding

Here we propose to adapt standard design tools (e.g. density evolution) to capture *heterogeneous* graphical structures, where correlations between bits are introduced both at the bit level (error correcting code), and at the symbol level (multiple description coding of a source). The target application is related to image coding for transmission over wireless IP, where both packet losses and bit errors may occur, see the VIP RNRT project 7.9.

6.6. Cognitive radio and equalization

Participant: Jacques Palicot.

6.6.1. Cognitive radio

This study, performed in a collaboration with Christian Roland from LESTER in Lorient, is twofold. First, we have studied the blind recognition of the standard in use [22], and secondly we have started a new study on the interest of the cognitive radio concept to decrease the electromagnetic pollution. This will take the form of

a forthcoming paper in the IEEE Communications Magazine. We are also studying the possible sensors which could be used in the cognitive radio context.

6.6.2. Parameterization techniques

Under these terms we understand two different approaches. The first one, considers the common functions of many standards. The second one, tries to identify a common operator which could be used by the greatest number of functions of many standards. This last approach was the one we considered, and we found that the FFT operator could be used as a common basic operator [52]. This study is still in progress by inspecting the posibility to perform in the frequency domain functions such as channel decoding.

6.6.3. Equalization

We have proposed a variation of the Euclid algorithm [19], which is important in equalization to obtain the channel coefficients for the ZF criteria in a **simo** context. We also proposed a geometrical derivation of the EMSE for the Bussgang algorithm [18]. Finally, we have proposed a ML–like improvement of the ouput sequence of the SIMO DFE.

Concerning the block equalization and frequency domain equalization techniques, we continue our collaboration with the University of Patras. This includes a work on the QN DFE [15], and another on a semi–blind channel parameter estimation [55]. We are also working on a new DFE scheme which we first presented in Globecom 2001. This collaboration will continue through a project that was approved within the PLATON bilateral program between France and Greece, see module 8.6.

6.7. Optimization methods in statistical signal processing

Participants: Jean–Jacques Fuchs, Sébastien Maria.

6.7.1. Sparse representations in redundant dictionaries

This is merely an application of previous work, that we started in 1997, to a quite simple problem proposed recently in the litterature and that now attracts a lot of attention. The question that is considered is the following : given a matrix A of dimension (n, m) with $m > n$ and a vector $b = A x$, find a sufficient condition for b to have a unique sparsest representation as a linear combination of columns of A. Answers to this question were known in case A is the concatenation of two unitary matrices and either an extensive combinatorial search is performed or a linear program is solved. It was shown that if a solution x_o of $A x = b$ satisfies

$$|x_o|_0 < \frac{1}{2}(1 + \frac{1}{M}) \qquad \text{with} \qquad M = \sup_{1 \leq i \neq j \leq m} |a_i^T a_j| \ ,$$

where $|x|_0$ denotes the number of non–zero components in x, then it is the unique sparsest solution of $A x = b$ and it is also the unique minimum point of the following linear program

$$\min_x |x|_1 \qquad \text{subject to} \qquad A x = b$$

where $|x|_1 = \sum |x_i|$ denotes the ℓ_1 norm of x.

We consider the extension to arbitrary A matrices, i.e. matrices with an arbitrary number of unit euclidean norm column vectors and we have shown that the same condition remains sufficient. Furthermore this result holds not only for the linear program (LP) but also for the following criterion

$$\min_x \frac{1}{2}|A x - b|_2^2 + h |x|_1 \qquad \text{with} \qquad h > 0$$

which is a quadratic (convex) program. In this case provided the parameter h is taken small enough, the same condition guarantees that the optimum point of this criterion is unique and allows to recover x_o. The optimum,

say x^* of (QP) is indeed different from x_o since $A\,x^* - b \neq 0$ but their non–zero components are at the same locations and have the same signs and it is therefore possible to deduce x_o from x^*.

The advantage of (QP) over (LP) lies precisely in the possibility of having $A\,x^* - b \neq 0$ since this allows for the presence of noise or modeling errors. We are presently investigating these aspects of the same question : what can one say if $b = A\,x_o + e$?

6.7.2. *Robust detection and estimation*

This corresponds to the prospective subject of the thesis that Sebastien Maria starts this fall. In a linear regression context, the aim of robust estimation schemes is to downweight the influence of potential outliers that are present on some components of the observation vector. Our objective is to analyse several extensions to this scheme.

If outliers, i.e. abnormal noise components, are also present on the regression matrix and not just in the observation vector, then one should take this into account and for instance replace in the total least squares approach the squares by a different convex function that penalizes less heavily large errors. One possibility is to replace the ℓ_2 norm (Frobenius norm) by the ℓ_1 norm and some preliminary results in this direction have been obtained. It appears that one can actually define in this context a new decomposition of a matrix into the sum of rank one matrices. More generally this amounts to approximate a matrix by a matrix of lower rank.

If each outlier affects not just one component but all the observations they are called interferences and one generally assumes to know the interfering subspace and performs the parameter estimation on its orthogonal complement. This is a quite restrictive model. We plan to investigate scenarios where the interferences belong to a known parametrized family that spans the whole space. The number and the range space of the interferences that are indeed present are unknown and the robust estimation scheme has to select the interferences that are present and downweight their influence.

An application on real data is sought. Preliminary contacts have been taken in the area of synthetic aperture radars.

7. Contracts and Grants with Industry

7.1. Exploitation of flight test data — Projet Eurêka flite

See modules 4.2, 5.2 and 6.2.

Contract INRIA *2 02 C 0040 — May 2001/October 2003.*

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

This activity is conducted in collaboration with Maurice Goursat (METALAU project-team at INRIA Rocquencourt).

The Eureka project FLITE (« Flight Test Easy ») falls within the aeronautical domain. It is coordinated by the industrial test laboratory Sopemea. The partners are Dassault–Aviation and EADS (AeroMatra Airbus) (France), LMS and KUL (Belgium), Cracow University and the company PZL–Swidnik (Poland), and INRIA (SIGMA2 and METALAU project–teams).

The development of new aircrafts requires a careful exploration of the dynamical behaviour of the structure subject to vibration and aero–servo–elastic forces. This is achieved via a combination of ground vibration tests and in–flight tests. For both types of tests, various sensors data are recorded, and modal analyses are performed. Important challenges of the in–flight modal analyses are the limited choices for measured excitation inputs, and the presence of unmeasured natural excitation input (turbulence). The FLITE project aims at a better exploitation of flight test data, exploiting data recorded under natural excitation conditions (e.g., turbulent), without resorting to artificial control surface excitation and other types of excitation inputs. A second objective of FLITE is an improvement of the flight test procedures themselves. One of the intended application examples is the A3XX.

Our expertise in output–only system identification methods, for modal analysis of vibrating structures under ambiant and nonstationary excitation, and thus under unknown inputs, is central in the project [70][99][100].

The involved INRIA project–teams are responsible for the task « development of algorithms and associated methods », and for the corresponding task reports. Moreover, Albert Benveniste helps Sopemea in the scientific coordination of the project.

The achievements of this year include conceptual investigations, experimental results and software developments.

On the conceptual side, three investigations have been conducted, on recursive subspace, particle filtering and flutter monitoring algorithms, respectively, see module 6.2. The work on recursive subspace algorithms has been the topic of the visit of Ivan Goethals (KUL / SISTA), see module 9.4.

The flutter monitoring problem has been addressed as the problem of monitoring a damping coefficient, and a first theoretical solution has been investigated. The idea is to use the same subspace–based residual as we use for structural health monitoring, and to design a unilateral test statistics for detecting that a given damping coefficient decreases towards zero. Since this problem is no longer a local hypotheses testing problem, we have used another asymptotic approximation for the residual (different from the local approximation in module 3.2), and a cumulative sum test built on the residual. This algorithm works on–line [42][44][66].

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

On the software side, the development of the MODAL / COSMAD toolbox to be used with Scilab has been pursued, the above recursive identification algorithms and the flutter monitoring algorithms incorporated, see module 5.2.

7.2. Structural assessment monitoring and control — Growth thematic network samco

See modules 4.2, 5.2, and 6.2. Contract CNRS 500232 — February 2002/September 2005.
Participant: Michèle Basseville.

This thematic network has been launched in October 2001 within the framework of the Growth program. It aims at becoming a focal point of reference in the field of assessment, monitoring and control of civil and industrial structures, in particular the transportation infrastructure (bridges, etc.).

Several partners of the network have proposed our participation, and we became a participating member, involved especially in the thematic group « Monitoring and Assessment ». This turns out to be a useful complement to the diffusion of our knowledge and expertise in vibration monitoring.

Within this framework, we have been involved in the FP6 IP E–MOI proposal submitted in March 2003 within the NMP framework. We have offered Scilab as an open platform for the integration of the modules for algorithms and methods covering the objectives of automatic modal analysis, automatic modal and statistical damage detection methods. We have also offered the Scilab modal analysis modules, see module 5.2.

7.3. Modal analysis of a launch vehicle — Contract with eads Launch Vehicles

See modules 4.2, 5.2 and 6.2.
Contrat INRIA 1 03 D 1046 — December 2002/June 2003.
Participants: Laurent Mevel, Auguste Sam.

This activity is also conducted in collaboration with Maurice Goursat (METALAU project–team at INRIA Rocquencourt).

The objective was to provide a methodology for off–line/on–line monitoring of vibration modes of a launcher in launch situation. The project is a follow–up of a previous contract, where rough evaluations of the launcher data sets were conducted. In this year project, we went deeply into analysing those datasets using input and feedback from the industrial partner (they provided datasets, end results requirements and comments). The intended result was to obtain both a fully automated identification procedure and to evaluate the influence of the tuning parameters on the identification results. The objective was then to hide as much as possible unnecessary parameters and to explain as much as possible the important and required tuning buttons.

This contract has thus provided us with another opportunity for improving, tuning and testing our techniques through our modal toolbox. A massive rewriting of our online monitoring toolbox has been performed, both for the features and in the graphical user interface [49][46][51][50], see module 5.2.

7.4. Modeling and fault diagnosis for components of low consuming automobile vehicles — Contract with Renault

Contract INRIA *1 01 C 0104 — January 2001/December 2003.*
Participants: Olivier Perrin, Qinghua Zhang, Michèle Basseville, Frédéric Cérou.

This activity is jointly performed with Michel Sorine (projet SOSSO of INRIA Rocquencourt).

For the purpose of reducing fuel consumption and thus also exhaust emission, Renault is developing new car components based on the most advanced technologies in the fields of car engine and post–combustion processing of exhaust pollutants. Because of the high technological complexity of the new components, it is necessary to develop monitoring devices for the detection and the diagnosis of their possible failures, in order to increase their maintenance facilities and to fulfill the requirement of the legislation on automobile pollution.

In the framework of a contract Renault–INRIA on the PhD thesis of Olivier Perrin (CIFRE grant, Convention Industrielle de Formation par la Recherche), studies have been focused on exhaust–pipe particle filters for vehicles equipped with diesel engines. Special attention is paid to catalytic particle filters which eliminate continuously the filtered particles through chemical reactions with the aid of catalyst. This new technology is in opposite to the conventional one which needs regeneration phases to burn the filtered particles at a high temperature.

After the work of the previous years on exhaust–pipe particle filter modeling and on model simplification, several approaches to fault diagnosis have been tested this year with the simplified models. A new nonlinear adaptive observer is applied to the detection of cracks in a filter, see module 6.1. Experiments with real data have shown satisfactory results of the method. This work [54] will be presented at the 1st IFAC Symposium on Advances in Automotive Control, to be held in Salerno, in April 2004.

For the detection of failures affecting the catalytic reaction, a method based on the particle filtering algorithm, see module 6.3, is first applied. A simple method based on the specific model structure is also designed. No real data is available for the moment. Numerical simulations have been satisfactory with both methods, but the second one needs much less numerical computation, and is thus more suitable for on–board diagnosis.

7.5. Stochastic analysis and distributed control of hybrid systems — ist project hybridge

See module 6.3.
    Contract INRIA *1 02 C 0037 — January 2002/December 2004*
Participants: Fabien Campillo, Frédéric Cérou, François Le Gland.

The IST project HYBRIDGE deals with stochastic analysis and distributed control of hybrid systems, with conflict management in air trafic, as its target application area. It is coordinated by National Aerospace Laboratory (NLR, Netherlands) and its partners are Cambridge University (United Kingdom), Universita di Brescia and Universita dell'Aquila (Italy), Twente University (Netherlands), National Technical University of

Athens (NTUA, Greece), Centre d'Études de la Navigation Aérienne (CENA), Eurocontrol Experimental Center (EEC), AEA Technology and BAE Systems (United Kingdom), and INRIA (SIGMA2 project–team).

Our contribution to this project concerns the work package on modeling accident risks with hybrid stochastic systems, and the workpackage on risk decomposition and risk assessment methods, and their implementation using conditional Monte Carlo methods. This problem has motivated our work on the « importance splitting » algorithm for the simulation of rare events, see module 6.3.

7.6. Training in particle filtering — Contract with sagem

See module 3.3.

Contract INRIA *4 03 C 1409 — June 2003/October 2003*
Participants: Fabien Campillo, François Le Gland.

F. Le Gland and F. Campillo have given a four–days training course on particle filtering at SAGEM, Argenteuil. Further cooperation should take the form of a PhD thesis with a CIFRE grant (Convention Industrielle de Formation par la Recherche) support.

7.7. (Turbo) synchronization for satellite communications — Research contract with Alcatel Space Industry

Contrat INRIA *1 03 C 1356 — November 2002/April 2003*
Key words: *turbo–synchronization*, *stochastic filtering*.

Participants: Frédéric Cérou, Aline Roumy, Jean–Jacques Fuchs.

The purpose of this work was to evaluate the particle filtering approach for the synchronization of digital signals, and to see whether stochastic filtering algorithms may improve the new turbo–synchronization techniques.

The problem under investigation is the following : we want to transmit a binary sequence, which is coded and modulated into symbols $\{d_k, k \in \mathbb{N}\}$. The symbols d_k take their values in a finite set, typically of cardinality 4 (QPSK). It is assumed that the measurements take the form

$$Y_k = A\, e^{j\theta_k}\, d_k + W_k \quad,$$

where A is the amplitude, θ_k the unknown phase, and W_k an i.i.d. sequence of complex Gaussian noises. The SNR is assumed less than 3 dB. We consider that the signal coding and modulation follow the DVB (Digital Video Broadcasting) norm. The phase dynamics is modelled as

$$\theta_k = \theta_{k-1} + \delta + \sigma_\theta\, V_k \quad,$$

where δ is a drift (unknown but constant all along the message) due frequency errors, and V_k an i.i.d. sequence of real Gaussian noise. Note that there is no interference in the model because in the direct link to the satellite there is no multipath problem.

We tried to apply particle filtering techniques to the recovery of the hidden state θ. Unfortunatly we could not exhibit a reasonable case for which the particle approach did substantially better than other classical approaches based on SSL and/or partial decoding. Particle methods give about the same precision but at a much higher computational cost.

Considering then other non linear stochastic filtering tools, we developed a new and promising turbo–synchronization algorithm, where a extended Kalman filter is embedded in the decoder. This method is still under evaluation, but it already proved suitable when the δ parameter is larger than what can be tackled with standard methods.

7.8. Fault diagnosis in telecommunication networks — Exploratory rnrt project magda2

See modules 3.4, 4.3 and 6.4.

  Contract INRIA *2 01 C 0694 MPR 01 1 — November 2001/January 2004*

Participants: Éric Fabre, Albert Benveniste, Stefan Haar, Bruno Marquié.

Glossary

> **Network management** Denotes the top layer of management for a telecommunication network, i.e. the supervision operations : monitoring, maintenance, etc.
>
> **Alarm management** Processing, filtering and interpretation of alarms sent across the network.
>
> **Diagnosis** Interpretation of alarms, for possible reconfiguration and maintenace operations.
>
> **HMM** see module 3.3.

This is joint work with Claude Jard from the TRISKELL project–team. It started within CTI–CNET 95 1B 151, and continued in the exploratory RNRT projects « Modélisation et Apprentissage pour une Gestion Distribuée des Alarmes », or MAGDA, until November 2001, then MAGDA2 until January 2004. Besides TRISKELL and SIGMA2, as well as the AÏDA project–team of IRISA, the participants of this project are France Télécom R&D (leader of MAGDA), Alcatel (leader of MAGDA2), ILOG, and université de Paris–Nord.

  The goal is to develop a systematic approach to fault diagnosis in telecommunication networks, under the following principles :

- account explicitly for the distributed nature of the networks,
- follow a « model–based » approach, such that the diagnosis algorithms can be derived automatically from the model,
- take hazards such as loss of alarms, confusions, etc. into account,
- allow the diagnosis software to be distributed over the network.

An original technology of designing distributed algorithms has been developed. It is based on modelling distributed systems as networks of automata. Such structures can be viewed as generalizations, to dynamical systems, of Bayesian networks, or Markov fields. This analogy allows to import an entire set of well–founded inference algorithms, easily distributable by nature. More details are given in module 3.4 and in module 6.4.

  In the MAGDA2 project, joint work with TRISKELL aims at constructing automatically the model of the supervised network, based on its UML description. The internal model thus obtained is used directly as the inference base for distributed supervision algorithms. This technology was originally developed for SDH networks, and has been extended to heterogeneous networks, using a GMPLS communication model allowing for circuit based, routed (e.g. IP), or packet switch based networks of SDH or WDM type.

  A prototype gathering the two aspects above is being developed in close collaboration with TRISKELL. This prototype is integrated into a commercialized management platform by Alcatel, and experiments are carried out on small models of SDH and GMPLS/WDM networks. In 2003, efforts on the prototype were oriented towards two objectives :

- the automatic discovery of the underlying network, and deployment of the *ad hoc* distributed monitoring architecture (the so–called local supervisors),
- the reformulation of the algorithm run by each supervisor above a commercialized rule engine (JRules, provided by Ilog), in order to minimize the proprietary part of the prototype.

7.9. Video transmission over ip channels — rnrt project vip

Contract INRIA *2 01 A 0650 MC 01 1 — October 2001/June 2004*
Participants: Éric Fabre, Aline Roumy, Mutlu Koca.

The overall goal of the VIP project is to design and develop new techniques for multimedia transmission over Internet protocol (IP) wireline and wireless networks. It implies digital video transmission and real-time services. The total duration of the project is 33 months and started October 2001. Our role in IP is limited, the main team involved at IRISA is TEMICS, headed by Christine Guillemot.

The contribution of our group is to design an encoder / decoder pair that deals with both packet losses and bit errors. We propose to adapt standard design tools (e.g. density evolution) to capture *heterogeneous* graphical structures, where correlations between bits are introduced both at the bit level (error correcting code), and at the symbol level (multiple description coding of a source).

8. Other Grants and Activities

8.1. Monitoring of mechanical structures — aci Sécurité Informatique constructif

Contrat INRIA *1 03 C 1559 — July 2003/June 2006*
Participants: Michèle Basseville, Laurent Mevel, Houssein Nasser.

The strong emerging of safety and environmental norms, and the massive and widespread diffusion of various kinds of sensors, result in a thorough renewal of sensor information processing problems. Fatigue and aging prevention, and integrity monitoring for mechanical and civil structures (airplanes, bridges, dams) are the subject of intensive research efforts abroad, especially in the US, Japan, Great Britain, Italy, including within connected fields (such as automatic control). The French research effort on these issues has not yet been sufficiently developed. In particular, research on advanced information processing methods for structural analysis, non destructive evaluation, monitoring for aging prevention, damage diagnostic and localization, are mandatory. Because the associated scientific and economic challenges are of crucial importance, the synergy between information science, engineering science and scientific computing should be increasingly favored and stimulated.

The objectives of the present project supported by the French Ministry of Research within the ACI Sécurité Informatique programme, are on one hand the intrinsic coupling of statistical models of sensor data with fine models of the physical phenomena governing the instrumented structures, and, on the other hand, the mixing of statistical inference, data assimilation, finite element model updating and optimization methods for structural dynamics. The investigation of potential mutual benefits of criteria used for different purposes by various methods designed in different scientific communities, is the central axis of the project. The main object of the study is the intrinsic involvement of the temperature effect, which is a generic issue for vibration monitoring of civil engineering structures, and a major scientific challenge.

8.2. System identification — tmr network si

Contract université de Rennes 1 MW 33 — March 1998/February 2003.
Participants: Jean–Jacques Fuchs, Michèle Basseville, Albert Benveniste, Éric Fabre, Fabien Campillo, Frédéric Cérou, François Le Gland, Laurent Mevel, Qinghua Zhang.

The SIGMA2 project–team participates in the european network SI « System Identification » which gathers nine european research groups : CWI (coordinator, Netherlands), Technische Universität Wien (Austria), université catholique de Louvain (Belgium), INRIA Sophia–Antipolis and IRISA/université de Rennes 1 (France), University of Cambridge (United Kingdom), LADSEB/CNR et Università degli Studi di Padova (Italy), KTH et Linköpings Universitet (Sweden), within the TMR program. The annual workshop has been held in Noordwijkerhout (Netherlands), in October 2003. The proposal of a follow–up Marie Curie research training

network ERNSI+, coordinated by Bo Wahlberg (KTH, Stockholm), has been submitted to the April 2003 call of the FP6, with an additional research group from SZTAKI (Hungary) : it has received a very positive evaluation, but has finally not been selected in the last stage. It has been updated and submitted again to the subsequent November 2003 call. Our contribution in the current network is focused on identification of hybrid systems, particle filtering and hidden Markov models (HMM), system monitoring, and nonlinear observers.

8.3. Statistical methods for dynamical stochastic systems — ihp network dynstoch

Affiliation to the French partner of the network — September 2000/August 2004.
Participants: Fabien Campillo, Natacha Caylus, Frédéric Cérou, Arnaud Guyader, François Le Gland, Laurent Mevel.

The SIGMA2 project–team participates in the european network DYNSTOCH « Statistical Methods for Dynamical Stochastic Models », which gathers nine european research groups : Københavns Universitet (coordinator, Denmark), Universiteit van Amsterdam (Netherlands), Humboldt Universität zu Berlin and Albert Ludwigs Universität Freiburg (Germany), Universidad Politécnica de Cartagena (Spain), Helsingin Yliopisto (Finland), University College London (United Kingdom), LADSEB/CNR (Italy), université de Paris 6 (France), within the IHP program. The annual workshop has been held in Helsinki in May 2003. Our contribution within the French team of the network (PMA, laboratoire de Probabilités et Modèles Aléatoires, université de Paris 6/7), is focused on asymptotic statistics of HMM with finite or continuous state space, and their particle implementation. The proposal of a follow–up Marie Curie research training network DYNSTOCH, coordinated by Peter Spreij (UvA, Amsterdam), has been submitted to the November 2003 call of the FP6, with INRIA Rennes as a research group on its own, and with additional research groups from SZTAKI (Hungary), Universiteit Gent (Belgium), Ruprecht Karls Universität Heidelberg (Germany), and Linköpings Universitet (Sweden).

8.4. Particle methods — cnrs dstic action spécifique as67

Participants: Fabien Campillo, Natacha Caylus, Frédéric Cérou, Arnaud Guyader, François Le Gland.

Since September 2002, F. Le Gland is coordinating with Olivier Cappé (ENST Paris) a project (action spécifique) « Méthodes particulaires » supported by the STIC department of CNRS, and promoted by the RTP « Mathématiques de l'Information et des Systèmes ». This project follows another project « Chaînes de Markov cachées et filtrage particulaire », which started in December 2001 within the inter–departmental CNRS programme Math–STIC, and was coordinated by F. Le Gland and Éric Moulines (ENST Paris).

A one–day workshop has been organized in December 2003 on applications of particle filtering, with the joint support of the AS67 and of the GdR-PRC ISIS.

8.5. Network of excellence in wireless communication newcom

Participant: Aline Roumy.

The NEWCOM project (Network of excellence in wireless communication) addresses the design of systems « beyond 3G ». This requires to successfully solve problems such as : the inter–technology mobility management between 3G and ad–hoc wireless LANs, the coexistence of a variety of traffic/services with different and sometimes conflicting Quality of Service (QoS) requirements, new multiple–access techniques in a hostile environment like a channel severely affected by frequency selective fading, the quest for higher data rates also in the overlay cellular system, scaling with those feasible in a wireless LAN environment, permitting seamless handover with the same degree of service to the user, the cross–layer optimisation of physical coding/modulation schemes with the medium access control (MAC) protocols to conform with fully packetised transmission as well as the TCP/IP rules of the core network, and the like. The duration of the NEWCOM project is 18 months and our contibution is 6 manmonths. It has started in fall 2003.

8.6. Iterative turbo–like channel equalization techniques in the frequency domain for dfe performance improvement — pai–Platon

Participants: Jacques Palicot, Aline Roumy.

This is a collaboration between IRISA and the Signal Processing and Communications Lab headed by Kostas Berberidis, University of Patras in Greece. The goal of the proposed project is the development of an efficient equalization scheme, suitable for wireless burst communication systems. The basic characteristic of the proposed scheme will be the iterative operation of a channel estimator and a decision feedback equalizer on a data burst, in a way similar to turbo techniques. This project has a duration of one year and can be extended to one more year. The grant supports travel and living expenses of investigators for short visits to partner institutions abroad. It has started in summer 2003.

9. Dissemination

9.1. Scientific animation

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

She is co–chair of the IFAC technical committee IFAC IAF–TC « Fault Detection, Supervision and Safety of Technical Processes », within the coordinating comittee IA–CC « Industrial Applications », and member of the technical committee SSM–TC « Modelling, Identification and Signal Processing », within the coordinating comittee SSM–CC « Systems and Signals ».

She is associate editor for the IFAC journal « Automatica », and for the journal « Mechanical Systems and Signal Processing ». She has been member of the international program committees of Safeprocess'03, Sysid'03 and ECC'03. She has been sollicited for the evaluation of two « Research Grant Projects » submitted to the Swedish Research Council, in the « Signals and Systems » area.

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

J.–J. Fuchs is a member of the program committee of the French 19th symposium on Signal and Image processing (GRETSI) which was held in Paris in September 2003, and of the international program commitee of the 13th IFAC–IFORS symposium on Identification and System Parameter Estimation (SYSID) which was held in Rotterdam in August 2003. He is a member of the IEEE SAM « Sensor Array and Multichannel » technical committee and a co–chair of the technical program committee of the 3rd IEEE Sensor Array and Multichannel Signal Processing workshop (SAM'04) to be held in July 2004 in Barcelona.

Since September 2002, F. Le Gland is coordinating a project (action spécifique, AS67) « Méthodes particulaires » supported by the STIC department of CNRS, and promoted by the RTP 24 « Mathématiques de l'Information et des Systèmes », see module 8.4. He has coorganized with Olivier Cappé (ENST Paris) a one–day workshop in December 2003 on applications of particle filtering, with the joint support of AS67 and of the GdR-PRC ISIS.

L. Mevel is coordinating a project (action concertée incitative CONSTRUCTIF) on monitoring of mechanical structures, supported within the national « ACI Sécurité Informatique » programme, see module 8.1.

Q. Zhang is co–organizer of « Sûreté, Supervision, Surveillance » (S3), a national research group on safety, supervision and monitoring. He participates in the activities of the RTP 20 « Fiabilité, Diagnostic et Tolérance aux Fautes des Systèmes Complexes ». He is member of IFAC technical committee on Fault Detection, Supervision and Safety of Technical Processes.

9.2. Teaching

In the DEA–STIR (Signal, Télécommunications, Images, Radar) (école doctorale MATISSE, université de Rennes 1) : J.–J. Fuchs gives a course on optimization, and a course on spectral estimation. F. Le Gland gives a course on Kalman filtering and hidden Markov models.

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

É. Fabre and Q. Zhang teach numerical optimization techniques at DIIC, IFSIC, université de Rennes 1.

É. Fabre and A. Roumy teach information theory and coding theory at Ecole Normale Supérieure de Cachan, Ker Lann campus, in the computer science and telecommunications magistère program.

S. Haar teaches problem sessions for the applied probability course of DIIC, IFSIC, université de Rennes 1, and for the course on mathematics in computer science and telecommunications of the magistère program at Ecole Normale Supérieure de Cachan, Ker Lann campus.

A. Roumy teaches « Modern coding theory » and « Multiuser detection » in the DEA TIS (Traitement des Images et du Signal) at ENSEA, université de Cergy Pontoise.

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

M. Basseville has been invited to deliver the opening plenary talk at the IFAC triennal symposium Safeprocess'03 in Washington DC, in June 2003, on the subject « Model–based statistical signal processing and decision theoretic approaches to monitoring ».

F. Le Gland has been invited to give a plenary talk on particle filtering [60] at the « 19ème GRETSI Colloque sur le Traitement du Signal et des Images » in September 2003 in Paris.

F. Le Gland and F. Campillo have been invited to give a four–days training course on particle filtering at SAGEM, Argenteuil, and to give a one–day seminar on particle filtering at CNES, Toulouse.

J. Palicot has organized two training courses on software radio, in May 2003 at ENST Brest and in June 2003 at ENST Paris.

In addition to presentations with a publication in the proceedings, and which are listed at the end of the document, members of the SIGMA2 project–team have also given the following presentations.

At the annual workshop of the TMR SI network, see module 8.2, which has been held in Noordwijkerhout in October 2003, F. Le Gland has given a tutorial presentation on particle methods for stochastic systems, and Q. Zhang has given a talk on nonlinear systems fault diagnosis based on adaptive estimation.

F. Le Gland has been invited in November 2003 by Hans–Rüdi Künsch in the Seminar für Statistik of ETH Zürich, and has given there a seminar on recursive identification of state–space models, and its implementation with particle techniques.

É. Fabre has given a seminar on turbo–codes at Ecole Normale Supérieure de Cachan, Ker Lann campus.

S. Haar has presented probabilistic net unfoldings at the meeting of GdR STQRDS in Paris in March 2003. He has also given a tutorial on distributed diagnosis for asynchronous systems at the FORTE Conference in Berlin in September 2003.

A. Roumy has presented her work on the design of IRA codes at the IEEE international symposium on Information Theory (ISIT) in Yokohama in June 2003.

9.4. Visits and invitations

Ivan Goethals, a PhD student of Bart De Moor at KUL / SISTA has visited us during two weeks in February 2003, in the framework and with the support of the FLITE project. We have jointly tried to speed up the output–only subspace–based identification algorithm by implementing recursive versions of the SVD [36].

The French embassy in Antananarivo in Madagascar has provided Rivo Rakotozafy, assistant professor at the university of Fianaranstoa, with a grant to support three visits (one per year, each stay of three months duration) to prepare a Madagascar habilitation thesis (HDR) under the supervision of Fabien Campillo. A related objective is to set up a collaboration between the university of Fianaranstoa, IRD Montpellier and INRIA. This collaboration is focussed on Bayesian inference applied to engineering for renewable resources.

Our first subject is the use of Monte Carlo Markov chain (MCMC) algorithms for fisheries stock assessment. The biomass of the stock of a fishery at a given year could be modelled as a nonlinear function first of the biomass and catch for the two previous years, then of different parameters (recruitment, growth rate, natural mortality rate). Given a time series of annual catch (considered as given parameters) and effort data (considered as observation process), we would like to achieve the best fitting between the data and the model.

10. Bibliography

Major publications by the team in recent years

[1] A. AGHASARYAN, É. FABRE, A. BENVENISTE, R. BOUBOUR, C. JARD. *Fault detection and diagnosis in distributed systems : an approach by partially stochastic Petri nets.* in « Journal of Discrete Events Dynamical Systems », number 2 (Special issue on Hybrid Systems), volume 8, June, 1998, pages 203–231.

[2] M. BASSEVILLE. *On–board component fault detection and isolation using the statistical local approach.* in « Automatica », number 11, volume 34, November, 1998, pages 1391–1416.

[3] M. BASSEVILLE, I. V. NIKIFOROV. *Detection of Abrupt Changes — Theory and Applications.* series Information and System Sciences Series, Prentice Hall, Englewood Cliffs, 1993, http://www.irisa.fr/sigma2/kniga/.

[4] A. BENVENISTE, B. C. LÉVY, É. FABRE, P. LE GUERNIC. *A calculus of stochastic systems : specification, simulation, and hidden state estimation.* in « Theoretical Computer Science », number 2, volume 152, 1995, pages 171–217.

[5] A. BENVENISTE, M. MÉTIVIER, P. PRIOURET. *Adaptive Algorithms and Stochastic Approximations.* series Applications of Mathematics, volume 22, Springer Verlag, New York, 1990.

[6] Q. ZHANG, M. BASSEVILLE, A. BENVENISTE. *Early warning of slight changes in systems.* in « Automatica », number 1 (Special issue on Statistical Methods in Signal Processing and Control), volume 30, January, 1994, pages 95–113.

[7] F. LE GLAND, L. MEVEL. *Basic properties of the projective product, with application to products of column–allowable nonnegative matrices.* in « Mathematics of Control, Signals, and Systems », number 1, volume 13, 2000, pages 41–62.

[8] F. LE GLAND, L. MEVEL. *Exponential forgetting and geometric ergodicity in hidden Markov models.* in « Mathematics of Control, Signals, and Systems », number 1, volume 13, 2000, pages 63–93.

Doctoral dissertations and "Habilitation" theses

[9] J. PALICOT. *Traitement du signal pour augmenter l'efficacité spectrale des réseaux de télécommunications.* Habilitation à diriger des recherches, université de Rennes 1, July, 2003.

[10] O. PERRIN. *Modélisation et diagnostic de pannes dans des organes de véhicules automobiles à basse consommation.* Thèse de doctorat, université de Rennes 1, December, 2003.

Articles in referred journals and book chapters

[11] M. BASSEVILLE, L. MEVEL, M. GOURSAT. *Statistical model–based damage detection and localization : subspace–based residuals and damage–to–noise sensitivity ratios.* in « Journal of Sound and Vibration », to appear.

[12] M. BASSEVILLE, L. MEVEL, A. VECCHIO, B. PEETERS, H. VAN DER AUWERAER. *Output–only subspace-based damage detection — Application to a reticular structure.* in « Structural Health Monitoring », number 2, volume 2, June, 2003, pages 161–168.

[13] A. BENVENISTE, É. FABRE, S. HAAR. *Markov nets : Probabilistic models for distributed and concurrent systems.* in « IEEE Transactions on Automatic Control », number 11, volume AC–48, November, 2003, pages 1936–1950.

[14] A. BENVENISTE, É. FABRE, S. HAAR, C. JARD. *Diagnosis of asynchronous discrete event systems, a net unfolding approach.* in « IEEE Transactions on Automatic Control », number 5, volume AC–48, May, 2003, pages 714–727.

[15] K. BERBERIDIS, S. RANTOS, J. PALICOT. *A step by step quasi–Newton algorithm in the frequency domain and its application to channel equalization.* in « IEEE Transactions on Signal Processing », to appear.

[16] G. CAIRE, S. GUEMGHAR, A. ROUMY, S. VERDÚ. *Maximizing the spectral efficiency of coded CDMA under successive decoding.* in « IEEE Transactions on Information Theory », to appear.

[17] B. GAUJAL, S. HAAR, J. MAIRESSE. *Blocking a transition in a free choice net, and what it tells about its throughput.* in « Journal of Computer and System Sciences », number 3, volume 66, May, 2003, pages 515–548.

[18] A. GOUPIL, J. PALICOT. *A geometrical derivation of the excess mean square error for Bussgang algorithms in a noiseless environment.* in « Signal Processing », to appear.

[19] A. GOUPIL, J. PALICOT. *Variation on the Euclid algorithm.* in « IEEE Signal Processing Letters », to appear.

[20] L. MEVEL, M. GOURSAT, M. BASSEVILLE. *Stochastic subspace–based structural identification and damage detection — Application to the steel–quake benchmark.* in « Mechanical Systems and Signal Processing », number 1 (Special issue on COST F3 Benchmarks), volume 17, January, 2003, pages 91–101.

[21] L. MEVEL, M. GOURSAT, M. BASSEVILLE. *Stochastic subspace–based structural identification and damage detection and localization — Application to the Z24 bridge benchmark.* in « Mechanical Systems and Signal Processing », number 1 (Special issue on COST F3 Benchmarks), volume 17, January, 2003, pages 143–151.

[22] J. PALICOT, C. ROLAND. *A new concept for wireless reconfigurable receivers.* in « IEEE Communications Magazine », number 7, volume 41, July, 2003, pages 124–132.

[23] A. ROUMY, S. GUEMGHAR, G. CAIRE, S. VERDÚ. *Design methods for irregular repeat accumulate codes.* in « IEEE Transactions on Information Theory », to appear.

[24] A. Xu, Q. Zhang. *Residual generation for fault diagnosis in linear time varying systems.* in « IEEE Transactions on Automatic Control », 2004, to appear.

[25] F. Le Gland, N. Oudjane. *A robustification approach to stability and to uniform particle approximation of nonlinear filters : the example of pseudo-mixing signals.* in « Stochastic Processes and their Applications », number 2, volume 106, August, 2003, pages 279-316.

[26] F. Le Gland, N. Oudjane. *Stability and uniform approximation of nonlinear filters using the Hilbert metric, and application to particle filters.* in « The Annals of Applied Probability », number 1, volume 14, February, 2004, to appear.

Publications in Conferences and Workshops

[27] M. Basseville. *Model–based statistical signal processing and decision theoretic approaches to monitoring.* in « 5th Symposium on Fault Detection, Supervision and Safety for Technical Processes (SAFEPROCESS), Washington », IFAC / IMACS, pages 1–12, June, 2003, Plenary talk.

[28] A. Benveniste, É. Fabre, S. Haar, C. Jard. *Distributed and asynchronous discrete event systems diagnosis.* in « 42nd IEEE Conference on Decision and Control (CDC), Maui », IEEE Control Systems Society, December, 2003.

[29] A. Benveniste, S. Haar, É. Fabre, C. Jard. *Distributed monitoring of concurrent and asynchronous systems.* in « CONCUR'03 », August, 2003, Plenary talk.

[30] G. Besanon, Q. Zhang, H. Hammouri. *Adaptive high–gain observer for a class of nonlinear systems affine in unknown parameters.* in « Multiconference on Computational Engineering in Systems Applications (CESA), Lille 2003 », July, 2003, Paper S1–TA1–A2.

[31] N. Caylus, A. Guyader, F. Le Gland. *Particle filters for partially observed Markov chains.* in « IEEE Workshop on Statistical Signal Processing (SSP), Saint–Louis », IEEE–SPS, September, 2003.

[32] J.–J. Fuchs. *Estimation in the presence of interferences.* in « 13th Symposium on System Identification (SYSID), Rotterdam 2003 », IFAC / IFORS, pages 1160–1164, August, 2003.

[33] J.–J. Fuchs. *More on sparse representations in arbitrary bases.* in « 13th Symposium on System Identification (SYSID), Rotterdam 2003 », IFAC / IFORS, pages 1357–1362, August, 2003.

[34] J.–J. Fuchs. *Selecting the best among several estimates in DOA estimation.* in « 28th IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP), Hong–Kong », volume Volume V, IEEE Signal Processing Society, pages 201–204, April, 2003.

[35] J.–J. Fuchs. *Solution parcimonieuse pour des systèmes linéaires sous déterminés.* in « 19ème Colloque sur le Traitement du Signal et des Images, Paris », volume I, GRETSI, pages 189–192, September, 2003.

[36] I. Goethals, L. Mevel, A. Benveniste, B. de Moor. *Recursive output–only subspace identification for in–flight flutter monitoring.* in « 22nd International Modal Analysis Conference (IMAC–XXII), Dearborn », SEM, Inc., January, 2004.

[37] A. GUYADER, L. MEVEL. *Covariance–driven subspace methods : input/output vs. output–only.* in « 21st International Modal Analysis Conference (IMAC–XXI), Kissimmee », SEM, Inc., February, 2003.

[38] A. GUYADER, Q. ZHANG. *Adaptive observer for discrete time linear time varying systems.* in « 13th Symposium on System Identification (SYSID), Rotterdam 2003 », IFAC / IFORS, pages 1743–1748, August, 2003.

[39] A. GUYADER, F. LE GLAND, N. OUDJANE. *A particle implementation of the recursive MLE for partially observed diffusions.* in « 13th Symposium on System Identification (SYSID), Rotterdam », IFAC / IFORS, pages 1305–1310, August, 2003.

[40] S. HAAR, A. BENVENISTE, É. FABRE, C. JARD. *Partial order diagnosability of discrete event systems using Petri net unfoldings.* in « 42nd IEEE Conference on Decision and Control (CDC), Maui », IEEE Control Systems Society, December, 2003.

[41] S. HAAR. *Distributed semi–Markov processes in stochastic T–timed Petri nets.* in « 10th Workshop on Petri Nets and Performance Models (PNPM), Urbana–Champaign », September, 2003.

[42] L. MEVEL, M. BASSEVILLE, A. BENVENISTE. *Statistical approach to flutter monitoring.* in « 13th Symposium on System Identification (SYSID), Rotterdam 2003 », IFAC / IFORS, pages 713–718, August, 2003.

[43] L. MEVEL, M. BASSEVILLE, M. GOURSAT, A. HASSIM. *A subspace detection approach to damage localization.* in « 21st International Modal Analysis Conference (IMAC–XXI), Kissimmee », SEM, Inc., February, 2003.

[44] L. MEVEL, A. BENVENISTE, M. BASSEVILLE. *Quick detection of flutter onset, a statistical approach.* in « 22nd International Modal Analysis Conference (IMAC–XXII), Dearborn », SEM, Inc., January, 2004.

[45] L. MEVEL, M. GOURSAT, M. BASSEVILLE, A. BENVENISTE. *Subspace–based modal identification and monitoring of large structures, a Scilab toolbox.* in « 13th Symposium on System Identification (SYSID), Rotterdam 2003 », IFAC / IFORS, pages 1405–1410, August, 2003.

[46] L. MEVEL, M. GOURSAT, M. BASSEVILLE. *Detection for in–operation structures : a Scilab toolbox use of the GUI for the localization.* in « 22nd International Modal Analysis Conference (IMAC–XXII), Dearborn », SEM, Inc., January, 2004.

[47] L. MEVEL, M. GOURSAT, A. BENVENISTE. *Using subspace on flight data, a practical example.* in « 21st International Modal Analysis Conference (IMAC–XXI), Kissimmee », SEM, Inc., February, 2003.

[48] L. MEVEL, M. GOURSAT. *Une boîte à outils Scilab pour l'analyse et la surveillance vibratoires.* in « 19ème Colloque sur le Traitement du Signal et des Images, Paris », volume III, GRETSI, pages 383–386, September, 2003.

[49] L. MEVEL, M. GOURSAT. *A complete Scilab toolbox for output–only identification.* in « 22nd International Modal Analysis Conference (IMAC–XXII), Dearborn », SEM, Inc., January, 2004.

[50] L. MEVEL, M. GOURSAT, A. SAM. *Automated on–line monitoring during a flight.* in « 22nd International Modal Analysis Conference (IMAC–XXII), Dearborn », SEM, Inc., January, 2004.

[51] L. MEVEL, A. SAM, M. GOURSAT. *Blind modal identification for large aircrafts — The case of a high number of close poles.* in « 22nd International Modal Analysis Conference (IMAC–XXII), Dearborn », SEM, Inc., January, 2004.

[52] J. PALICOT, C. ROLAND. *FFT : A basic function for a reconfigurable receiver.* in « 10th International Conference on Telecommunications (ICT), Papeete », February, 2003.

[53] B. PEETERS, L. MEVEL, S. VANDANLUIT, P. GUILLAUME, M. GOURSAT, A. VECCHIO, H. VAN DER AUWERAER. *Online vibration based crack detection during fatigue testing.* in « 5th International Conference on Damage Assessment of Structures (DAMAS), Southampton », July, 2003.

[54] O. PERRIN, M. BASSEVILLE, M. SORINE, Q. ZHANG. *On-board diesel particulate filter fault detection using an adaptive observer.* in « 1st IFAC Symposium on Advances in Automotive Control, Salerno », IFAC, April, 2004.

[55] A. A. RONTOGIANNIS, K. BERBERIDIS, A. MARAVA, J. PALICOT. *Efficient estimation of multipath channel parameters via a separable least–squares approach.* in « 28th IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP), Hong–Kong », April, 2003.

[56] A. ROUMY, S. GUEMGHAR, G. CAIRE, S. VERDÚ. *Design methods for irregular repeat accumulate codes.* in « IEEE International Symposium on Information Theory (ISIT), Yokohama », IEEE Information Theory Society, 2003, Abstract.

[57] Q. ZHANG, M. BASSEVILLE. *Advanced numerical computation of χ^2–tests for fault detection and isolation.* in « 5th Symposium on Fault Detection, Supervision and Safety for Technical Processes (SAFEPROCESS), Washington », IFAC / IMACS, pages 211–216, June, 2003.

[58] Q. ZHANG, M. BASSEVILLE. *Robustness of generalized likelihood ratio test for linear regression.* in « 5th Symposium on Fault Detection, Supervision and Safety for Technical Processes (SAFEPROCESS), Washington », IFAC / IMACS, pages 223–228, June, 2003.

[59] Q. ZHANG, A. XU, G. BESANON. *An efficient nonlinear adaptive observer with global convergence.* in « 13th Symposium on System Identification (SYSID), Rotterdam 2003 », IFAC / IFORS, pages 1737–1742, August, 2003.

[60] F. LE GLAND. *Filtrage particulaire.* in « 19ème Colloque sur le Traitement du Signal et des Images, Paris », volume II, GRETSI, pages 1–8, September, 2003, Plenary talk.

Internal Reports

[61] A. BENVENISTE, É. FABRE, S. HAAR. *Markov nets : Probabilistic models for distributed and concurrent systems.* Publication Interne, number 1538 (extended version, update of 1415), IRISA, May, 2003, ftp://ftp.irisa.fr/techreports/2003/PI-1538.ps.gz.

[62] É. FABRE. *Convergence of turbo algorithms for systems defined by local constraints.* Publication Interne, number 1510, IRISA, June, 2003, ftp://ftp.irisa.fr/techreports/2003/PI-1510.ps.gz.

[63] É. FABRE. *Factorization of unfoldings for distributed tile systems. Part 1 : Reduced interaction case.* Publication Interne, number 1529, IRISA, April, 2003, ftp://ftp.irisa.fr/techreports/2003/PI-1529.ps.gz.

[64] S. HAAR. *Distributed semi–Markov processes in stochastic T–timed Petri nets.* Publication Interne, number 1518, IRISA, March, 2003, ftp://ftp.irisa.fr/techreports/2003/PI-1518.ps.gz.

[65] S. HAAR. *Probabilistic cluster unfoldings for Petri nets.* Publication Interne, number 1517 (update of 1428), IRISA, March, 2003, ftp://ftp.irisa.fr/techreports/2003/PI-1517.ps.gz.

[66] L. MEVEL, M. BASSEVILLE, A. BENVENISTE. *Fast in–flight detection of flutter onset — A statistical approach.* Publication Interne, number 1541, IRISA, November, 2003, ftp://ftp.irisa.fr/techreports/2003/PI-1541.ps.gz.

Bibliography in notes

[67] M. T. BARLOW, Y. GUSEV, M. LAI. *Parameter estimation of multifactor models in power markets.* (preprint).

[68] M. BASSEVILLE, M. ABDELGHANI, A. BENVENISTE. *Subspace–based fault detection algorithms for vibration monitoring.* in « Automatica », number 1, volume 36, January, 2000, pages 101–109.

[69] M. BASSEVILLE, A. BENVENISTE, B. GACH–DEVAUCHELLE, M. GOURSAT, D. BONNECASE, P. DOREY, M. PREVOSTO, M. OLAGNON. *Damage monitoring in vibration mechanics : issues in diagnostics and predictive maintenance.* in « Mechanical Systems and Signal Processing », number 5, volume 7, 1993, pages 401–423.

[70] M. BASSEVILLE, A. BENVENISTE, M. GOURSAT, L. HERMANS, L. MEVEL, H. VAN DER AUWERAER. *Output–only subspace–based structural identification : from theory to industrial testing practice.* in « Journal of Dynamic Systems, Measurement, and Control », number 4 (Special issue on Identification of Mechanical Systems), volume 123, December, 2001, pages 668–676.

[71] M. BASSEVILLE, A. BENVENISTE, G. V. MOUSTAKIDES, A. ROUGÉE. *Detection and diagnosis of changes in the eigenstructure of nonstationary multivariable systems.* in « Automatica », number 4, volume 23, July, 1987, pages 479–489.

[72] M. BASSEVILLE, A. BENVENISTE, G. V. MOUSTAKIDES, A. ROUGÉE. *Optimal sensor location for detecting changes in dynamical behavior.* in « IEEE Transactions on Automatic Control », number 12, volume AC–32, December, 1987, pages 1067–1075.

[73] A. BENVENISTE, É. FABRE, S. HAAR. *Markov nets : Probabilistic models for distributed and concurrent systems.* Publication Interne, number 1415, IRISA, September, 2001, ftp://ftp.irisa.fr/techreports/2001/PI-1415.ps.gz.

[74] A. BENVENISTE, É. FABRE, C. JARD, S. HAAR. *Diagnosis of asynchronous discrete event systems, a net unfolding approach.* Publication Interne, number 1456 (update of 1399), IRISA, May, 2002,

ftp://ftp.irisa.fr/techreports/2002/PI-1456.ps.gz.

[75] C. BERROU, A. GLAVIEUX, P. THITIMAJSHIMA. *Near Shannon limit error–correcting coding and decoding : turbo codes.* in « Proceedings of the IEEE International Conference on Communications, Geneva 1993 », volume 2, IEEE–CS, pages 1064–1070, May, 1993.

[76] F. CÉROU, P. DEL MORAL, F. LE GLAND, P. LÉZAUD. *Genetic genealogical models in rare event analysis.* Publication du Laboratoire de Statistique et Probabilités, Université Paul Sabatier, Toulouse, 2002.

[77] F. CÉROU, F. LE GLAND, N. J. NEWTON. *Stochastic particle methods for linear tangent filtering equations.* J.–L. MENALDI, E. ROFMAN, A. SULEM, editors, in « Optimal Control and PDE's — Innovations and Applications. In honor of Alain Bensoussan on the occasion of his 60th birthday », IOS Press, Amsterdam, 2001, pages 231–240.

[78] F. CAMPILLO, F. LE GLAND. *MLE for partially observed diffusions : direct maximization vs. the EM algorithm.* in « Stochastic Processes and their Applications », number 2, volume 33, 1989, pages 245–274.

[79] B. DELYON, A. JUDITSKY, A. BENVENISTE. *On the relationship between identification and local tests.* Publication Interne, number 1104, IRISA, May, 1997, ftp://ftp.irisa.fr/techreports/1997/PI-1104.ps.gz.

[80] *Special issue on Monte Carlo Methods for Statistical Signal Processing (P. M. Djurić and S. J. Godsill, guest editors).* in « IEEE Transactions on Signal Processing », number 2, volume SP–50, February, 2002.

[81] R. DOUC, C. MATIAS. *Asymptotics of the maximum likelihood estimator for general hidden Markov models.* in « Bernoulli », number 3, volume 7, June, 2001, pages 381–420.

[82] A. DOUCET, N. DE FREITAS, N. GORDON, editors, *Sequential Monte Carlo Methods in Practice.* series Statistics for Engineering and Information Science, Springer–Verlag, New York, 2001.

[83] J. ESPARZA, S. RÖMER. *An unfolding algorithm for synchronous products of transition systems.* J. C. M. BAETEN, S. MAUW, editors, in « CONCUR'99 : Concurrency Theory », series Lecture Notes in Computer Science, volume 1664, Springer–Verlag, Berlin, 1999, pages 2–20.

[84] J. ESPARZA, S. RÖMER, W. VOGLER. *An improvement of McMillan's unfolding algorithm.* T. MARGARIA, B. STEFFEN, editors, in « TACAS'96 : Tools and Algorithms for the Construction and Analysis of Systems », series Lecture Notes in Computer Science, volume 1055, Springer–Verlag, Berlin, 1996, pages 87–106.

[85] É. FABRE, A. BENVENISTE, C. JARD. *Distributed diagnosis for large discrete event dynamic systems.* in « 15th IFAC World Congress, Barcelona », IFAC, July, 2002.

[86] É. FABRE. *Compositional models of distributed and asynchronous dynamical systems.* in « 41st IEEE Conference on Decision and Control (CDC), Las Vegas », IEEE Control Systems Society, December, 2002.

[87] É. FABRE, V. PIGOURIER. *Monitoring distributed systems with distributed algorithms.* in « 41st IEEE Conference on Decision and Control (CDC), Las Vegas », IEEE Control Systems Society, December, 2002.

[88] P. GLASSERMAN, P. HEIDELBERGER, P. SHAHABUDDIN, T. ZAJIC. *A large deviations perspective on the efficiency of multilevel splitting.* in « IEEE Transactions on Automatic Control », number 12, volume AC–43, December, 1998, pages 1666–1679.

[89] P. GLASSERMAN, P. HEIDELBERGER, P. SHAHABUDDIN, T. ZAJIC. *Multilevel splitting for estimating rare event probabilities.* in « Operations Research », number 4, volume 47, July–August, 1999, pages 585–600.

[90] N. J. GORDON, D. J. SALMOND, A. F. M. SMITH. *Novel approach to nonlinear / non–Gaussian Bayesian state estimation.* in « IEE Proceedings, Part F », number 2, volume 140, April, 1993, pages 107–113.

[91] S. HAAR. *Probabilistic cluster unfoldings.* in « Fundamenta Informaticæ », number 3–4, volume 53, December, 2002, pages 281-314.

[92] S. HAAR. *Probabilistic unfoldings and partial order fairness in Petri nets.* H. HERMANNS, R. SEGALA, editors, in « Process Algebra and Probabilistic Methods. Performance Modeling and Verification (PAPM–PROBMIV), Copenhagen », series Lecture Notes in Computer Science, volume 2399, Springer–Verlag, Berlin, 2002, pages 95–114.

[93] M. R. JAMES, F. LE GLAND. *Consistent parameter estimation for partially observed diffusions with small noise.* in « Applied Mathematics & Optimization », number 1, volume 32, July/August, 1995, pages 47–72.

[94] M. JOANNIDES, F. LE GLAND. *Small noise asymptotics of the Bayesian estimator in nonidentifiable models.* in « Statistical Inference for Stochastic Processes », number 1, volume 5, 2002, pages 95–130.

[95] A. JUDITSKY, H. HJALMÄRSSON, A. BENVENISTE, B. DELYON, L. LJUNG, J. SJÖBERG, Q. ZHANG. *Non–linear black–box modelling in system identification : mathematical foundations.* in « Automatica », number 12, volume 31, December, 1995, pages 1725–1750.

[96] F. R. KSCHISCHANG, B. J. FREY, H.–A. LOELIGER. *Factor graphs and the sum–product algorithm.* in « IEEE Transactions on Information Theory », number 2 (Special issue on Codes and Graphs and Iterative Algorithms), volume IT–47, February, 2001, pages 498–519.

[97] Y. A. KUTOYANTS. *Identification of Dynamical Systems with Small Noise.* series Mathematics and its Applications, volume 300, Kluwer Academic Publisher, Dordrecht, 1994.

[98] R. J. MCELIECE, D. J. C. MACKAY, J.–F. CHENG. *Turbo decoding as an instance of Pearl's belief propagation algorithm.* in « IEEE Journal on Selected Areas in Communications », number 2, volume SAC–16, February, 1998, pages 140–152.

[99] L. MEVEL, M. BASSEVILLE, A. BENVENISTE, M. GOURSAT. *Merging sensor data from multiple measurement setups for nonstationary subspace–based modal analysis.* in « Journal of Sound and Vibration », number 4, volume 249, January, 2002, pages 719–741.

[100] L. MEVEL, A. BENVENISTE, M. BASSEVILLE, M. GOURSAT. *Blind subspace–based eigenstructure identification under nonstationary excitation using moving sensors.* in « IEEE Transactions on Signal Processing », number 1, volume SP–50, January, 2002, pages 41–48.

[101] L. MEVEL, L. HERMANS, H. VAN DER AUWERAER. *On the application of subspace–based fault detection methods to industrial structures.* in « Mechanical Systems and Signal Processing », number 6 (Special section on Model–Based Structural Identification and Monitoring Using in–Operation Data), volume 13, November, 1999, pages 823–838.

[102] T. J. RICHARDSON, M. A. SHOKROLLAHI, R. L. URBANKE. *Design of capacity–approaching irregular low–density parity–check codes.* in « IEEE Transactions on Information Theory », number 2 (Special issue on Codes and Graphs and Iterative Algorithms), volume IT–47, February, 2001, pages 619–637.

[103] T. J. RICHARDSON, R. L. URBANKE. *The capacity of low–density parity–check codes under message–passing decoding.* in « IEEE Transactions on Information Theory », number 2 (Special issue on Codes and Graphs and Iterative Algorithms), volume IT–47, February, 2001, pages 599–618.

[104] G. G. ROUSSAS. *Contiguity of Probability Measures : Some Applications in Statistics.* series Cambridge Tracts in Mathematics, volume 63, Cambridge University Press, Cambridge, 1972.

[105] J. SJÖBERG, Q. ZHANG, L. LJUNG, A. BENVENISTE, B. DELYON, P.–Y. GLORENNEC, H. HJALMÄRSSON, A. JUDITSKY. *Non–linear black–box modelling in system identification : a unified overview.* in « Automatica », number 12, volume 31, December, 1995, pages 1691–1724.

[106] S. VERDÚ, S. SHAMAI. *Spectral efficiency of CDMA with random spreading.* in « IEEE Transactions on Information Theory », number 2, volume IT–45, March, 1999, pages 622–640.

[107] M. VILLÉN–ALTAMIRANO, J. VILLÉN–ALTAMIRANO. *RESTART : a method for accelerating rare event simulation.* J. W. COHEN, C. D. PACK, editors, in « Queueing, Performance and Control in ATM : Proceedings of the 13rd International Teletraffic Congress, Copenhagen 1991 », series North–Holland Studies in Telecommunications, number 15, North–Holland, Amsterdam, June, 1991, pages 71–76.

[108] M. VILLÉN–ALTAMIRANO, J. VILLÉN–ALTAMIRANO. *RESTART : a straightforward method for fast simulation of rare events.* in « Proceedings of the 1994 Winter Simulation Conference, Orlando 1994 », J. D. TEW, M. S. MANIVANNAN, D. A. SADOWSKI, A. F. SEILA, editors, pages 282–289, December, 1994.

[109] N. WIBERG. *Codes and Decoding on General Graphs.* Linköping Studies in Science and Technology, Dissertation No. 440, Department of Electrical Engineering, University of Linköping, Linköping, April, 1996.

[110] P. DEL MORAL, A. GUIONNET. *On the stability of interacting processes with applications to filtering and genetic algorithms.* in « Annales de l'Institut Henri Poincaré, Probabilités et Statistiques », number 2, volume 37, 2001, pages 155–194.

[111] P. DEL MORAL, L. MICLO. *Branching and interacting particle systems approximations of Feynman–Kac formulae with applications to nonlinear filtering.* J. AZÉMA, M. ÉMERY, M. LEDOUX, M. YOR, editors, in « Séminaire de Probabilités XXXIV », series Lecture Notes in Mathematics, volume 1729, Springer–Verlag, Berlin, 2000, pages 1–145.

[112] F. LE GLAND, N. OUDJANE. *Stability and uniform approximation of nonlinear filters using the Hilbert metric, and application to particle filters.* Publication Interne, number 1404, IRISA, June, 2001, ftp://ftp.irisa.fr/techreports/2001/PI-1404.ps.gz.

[113] L. LE CAM. *Asymptotic Methods in Statistical Decision Theory.* series Springer Series in Statistics, Springer–Verlag, New York, 1986.

[114] S. TEN BRINK. *Convergence behavior of iteratively decoded parallel concatenated codes.* in « IEEE Transactions on Communications », number 10, volume COM–49, October, 2001, pages 1727–1737.

[115] P. VAN OVERSCHEE, B. DE MOOR. *Subspace Identification for Linear Systems.* Kluwer Academic Publishers, Boston, 1996.