New insights on SINTRACK, a real-time algorithm for aircraft structural-modes identification.

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ABSTRACT

SINTRACK is a real-time signal-processing algorithm providing estimates of low damped sinusoids. Its good balance between accuracy and low CPU cost makes it an attractive tool for on-board applications. Some first theoretical analysis on its performances were performed and presented in EUSIPCO 98, along with heuristics for an optimal tuning of some algorithm parameters. Further studies were lately performed in order to fulfil industrial requirements. Domain of use with regard to signal-to-noise ratio and number of modes in the signal was evaluated. Normalization of the dependencies to the last two tuning-parameters was performed. Then optimisation of their tuning using neural networks was conducted. The result consists in an optimal universal solution valid for any single-mode signal. Many aeronautical applications requiring real-time estimates deal with such signals. Coding of the algorithm was performed in a very basic aeronautical language, used for embedded code production, authorizing only elementary functions.

KEYWORDS

Real-time estimation, structural modes identification, neural network.

1. INTRODUCTION

This article depicts new insights on SINTRACK, a real-time modes estimation method. This algorithm proposed by Patrice Duvaut [2] is very attractive for industrial applications. It offers a good trade-off between accuracy, detection and estimation delays, and CPU. It appears as one of the simplest real-time algorithms available. It is of particular interest in the identification of flexible structures' modes, which is a major concern in aeronautics and astronautics. Sintrack's main properties were deeply analysed in [4;5], and some first aeronautical applications studied in [3,4]. The complete set of equations of SINTRACK can easily be found in [2-5]. In parallel some research was conducted that estimated and applied neural networks to aeronautics [7]. They rapidly become of interest for the tuning of SINTRACK. The works presented hereafter consist in new developments that achieve the long-term process engaged to transform SINTRACK from a research signal-processing tool into an industrial tool. A short memorandum about previous works is given in §2. A description of SINTRACK is then given in §3. New insights consist first in a complete study of SINTRACK domain-of-use given in §4. Then a theoretical work was performed to reformulate and normalize the equations, so as to obtain universal tunings independent of signal characteristics – see §5. Use of neural networks to optimise the tuning of parameters is described in §6. It has been developed after neither analytical nor experimental optimal tunings were identified. Then §7 explains how SINTRACK was coded using only very basic functions. §8 finally gives a glance at foreseen applications that potentially would benefit from SINTRACK.

2. BACKGROUND

Authors began studying SINTRACK in 1996, at a time when a lot of concern was put to control flexible structures. Severe robustness constraints on these structures limit the achievable performances with time-invariant laws. To overtake these limits, engineers began thinking of automatically adapting their laws to the structural variations, thus avoiding robustness requirements. An adequate real-time signal-processing algorithm was then searched. Among the few available in the scientific community, authors focused on SINTRACK, an algorithm proposed by P. Duvaut [2]: This algorithm offers a good compromise between accuracy and CPU.

Performances of this algorithm were deeply studied, as well as the optimal way to tune its parameters: T, N, L, μ, ε_1, ε_2 [4;5]. Aeronautical applications were performed based on these first results [3;5], while in parallel a more complex and accurate real-time algorithm was developed in collaboration with ENSEEIHT [6]. Nevertheless SINTRACK remains attractive, mainly because of its relative simplicity, and further works have been performed [1], presented hereafter.

3. ALGORITHM DESCRIPTION

SINTRACK is mainly composed of three parts: detection, tracking and survey as described Fig. 1. The detection part is based on a Matrix-Pencil algorithm. By using a truncated SVD , it separates signal from noise, thus detecting the number of modes inside the signal,

and giving a first estimate of the modes characteristics: frequency, damping and amplitude. The tracking part is an LMS algorithm based on a Prony modelling of the signal, initialised by the detection part. It requires very few CPU and is able to track slowly varying characteristics of the modes. The survey computes an estimate of the error. If this error remains low enough it means the Prony modelling is sufficient to track model-variations, otherwise a new detection step is required (for instance in case of appearance of a new mode, or sudden shift in a mode characteristics).

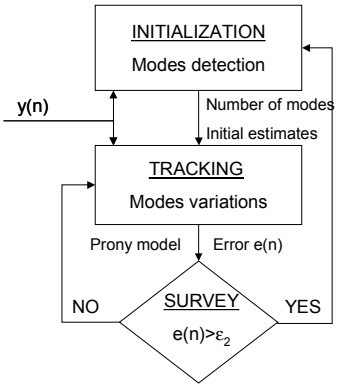

Fig. 1: Sintrack algorithm.

Some parameters directly influence SINTRACK performances. Most of these parameters have been exhaustively studied through theoretical and statistical analyses [4,5] that describe their influence on the accuracy and complexity of the algorithms. For instance it is well-known that the more close to Shannon-frequency the sampling rate T is, the more accurate the estimates are. Other parameters such as number of samples N, size of the Prony model L, LMS constant μ were also studied and results for their optimal tuning are now well-known. Still it remained two parameters which influence was found difficult to evaluate, so that final tuning of the algorithm was in some cases difficult to perform, and anyway highly dependent on the characteristics of the signal to analyse. These two parameters are ε_1, the threshold to separate singular-values associated to signal from the ones associated to noise, and ε_2, the threshold to switch from tracking to survey. The objective of this article is to present the works performed, firstly in order to give the limits of the algorithm in term of SNR (Signal-to-Noise Ratio), and secondly to normalize the equations with respect to the parameters magnitude. Objective of this normalization is to avoid any correlation between the signal characteristics (amplitude of modes, SNR…) and the choice of an optimal tuning. Thirdly a neural-network based approach was developed to optimise the tuning independently from the signal characteristics. These three new steps are very important in an industrial approach. Thanks to these new insights, the algorithm is now emancipated from expert-knowledge regarding its tuning and its validity domain.

4. LIMITS

Numerical tests have been performed to identify which SNR level the algorithm was able to sustain. This level is highly dependent on the number of modes to be detected in the signal, and in the frequency-gap between modes. This information provides the limits of the algorithm, a very important point to decide whether SINTRACK is worthy or not for a dedicated application. Fig. 2 shows time-histories of two signals (upper plots). Left plot is a two-modes signal at 2.0 and 2.2 Hz, with amplitudes 1.0 and 0.8 and a white noise σ=0.02. Right plot is the same with a 2.1 Hz second mode instead of 2.2. Middle plots give the frequency estimates. Lower plots give the amplitude estimates.

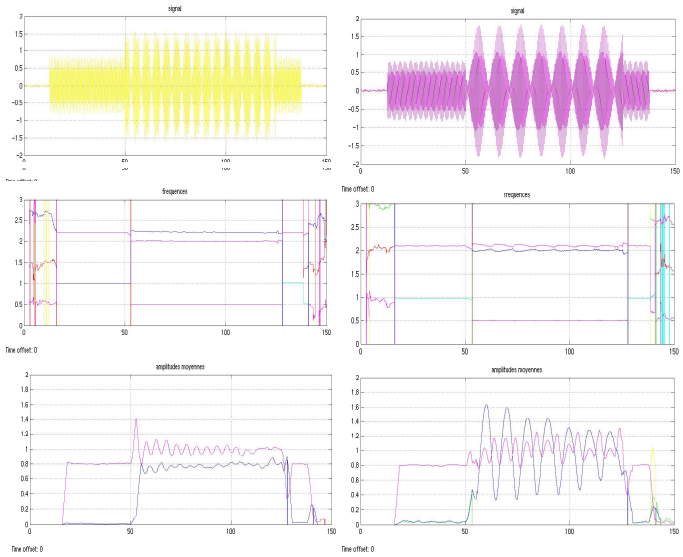

Fig. 2: Estimation of modes: frequency and amplitude in a two-modes signal with noise.

Estimation of frequencies and amplitudes is reliable in the first case, although one notices a short coupling between the frequencies of the two modes. In the second case the frequencies of the two modes are too close for this SNR, and SINTRACK do not succeed in estimating both modes separately.

Similar investigations have been performed for signals with different numbers of modes, different frequency-gaps between modes and different SNR levels. Tab. 1 resumes the limits observed in the frame of these investigations.

Number of modes Δf	1	2	3	4
0.1 Hz	< 15%	< 2 %	< 2 %	
0.2 Hz		< 5 %	< 2 %	< 2 %
0.5 Hz		< 15 %	< 10 %	< 2 %

Tab. 1: SNR limitations (max. $\sigma_{white\text{-}nois}$/mode amplitude) depending on the signal characteristics.

5. NORMALIZATION

The optimal choice of ε_1 and ε_2 for optimal tuning is, in P. Duvaut's version of SINTRACK, highly dependent on the signal to analyse. Amplitudes of the modes directly affect the singular values of the Prediction Matrix. Comparing these singular values to ε_1 in order

to separate noise from signal was not providing universal tuning. By normalizing the singular values

$$\sigma_i = \frac{\sigma_i}{\bar{\sigma}} \quad \text{with} \quad \bar{\sigma} = \sqrt{\sum_i \sigma_i^2}$$

and separating noise from signal on these normalized values, one obtains tunings independent from the signal amplitudes.

In the survey phase, same problem occurred on the estimation error, that is, in P. Duvaut's version, dependent on signal amplitudes. Here again by normalizing the error one is able to tune ε_2 independently from signal amplitudes.

$$e(n) = \frac{y(n) - y_{estime}(n)}{\sqrt{E}} \quad \text{with} \quad E = \frac{\sum_k |y(k)|^2}{L-1}$$

These normalisations guarantee that performances of SINTRACK for a given set of parameters are independent from signal amplitudes.

6. PARAMETERS TUNING USING A NEURAL NETWORK

Obtaining the optimal set of parameters (ε_1,ε_2) for sophisticated signal with varying characteristics, such as the one encountered on board an aircraft in gust-turbulence for instance, remained sophisticated even with the normalization of equations. No simple dependencies were identified between parameters' values and performances. Finding an optimal tuning was for some signals very long and empiric to obtain, even for some signals as simple as mono-mode signals. Thus we investigated neural networks to identify SINTRACK dependencies to parameters. Once such a neural network obtained, the objective was to provide optimal set of parameters for wide class of signals such as mono-mode signals, two-modes signals, etc. independently from SNR levels and gaps between frequencies.

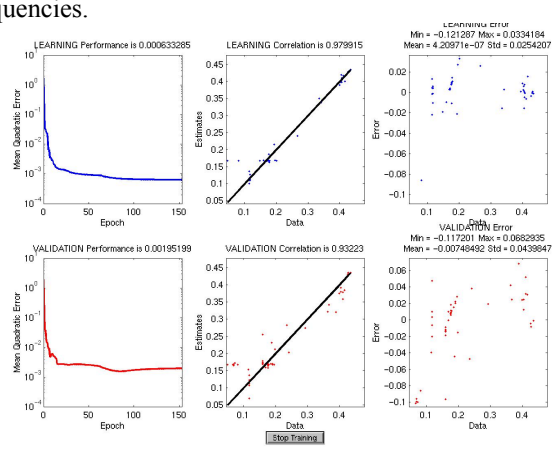

Fig. 3: Neural network learning phase for mono-mode signals.

The learning is based on a 1 hidden-layer neural-network of 5 neurons. 100 sets of (ε_1,ε_2) are randomly chosen and evaluated on a common reference signal. This signal is supposed to be representative of one class of signals. The mean error $\underline{e}$ is computed for each set of parameters. 50 sets of (ε_1,ε_2,$\underline{e}$) are used to identify the neural network dependency $\underline{e}=g(\varepsilon_1,\varepsilon_2)$.

The performances of this learning are given for the mono-mode class of signals in the first line of Fig. 3. The remaining 50 sets of (ε_1,ε_2,e) are used to validate the learning on sets different from those used for learning. This validation is given for mono-mode signals on the second line of Fig. 3.For those familiar with neural networks Fig. 3 shows the good learning of the chosen neural network for mono-mode signals. Then inversion and optimisation of the g(.) function gives the best set of parameters, which is for mono-mode signals ε_1=0.50 and ε_2=0.57.

Fig. 4 shows the estimates computed by SINTRACK on two different aircraft signals with this tuning. First column corresponds to the reference signal used for learning with a mode at 0.86 Hz. Second column is another signal that corresponds to another flight-point and payload aircraft model, for which the mode's frequency is 1.18 Hz. As observed on the middle plots, frequencies are accurately estimated. Lower plots shows the good estimation of amplitudes as well, compared to the signal envelope of the upper plots. Many other evaluations were successfully performed on mono-mode signals of very different nature: various amplitudes, variations and SNR levels, showing the robustness of the tuning provided by the neural network.

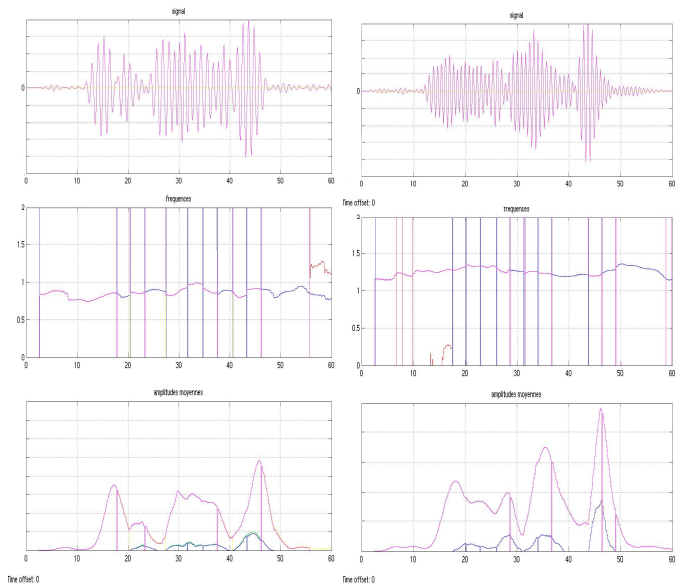

Fig. 4:Evaluation of SINTRACK on two different mono-mode aircraft signals.

Same kind of learning and tuning was tried for two-modes class of signals, using the same neural network architecture. 200 sets of parameters were used for learning, and 200 for validation. Fig. 5 shows the learning is very far from being representative of the real dependencies. The optimal tuning then furnished is ε_1=0.51 and ε_2=0.99.

Unfortunately, neither this one, nor the previous one was acceptable when tested on some aircraft two-modes signals. Either the neural network architecture is not appropriate to deal with these signals, or SINTRACK is

intrinsically not able to provide a universal tuning for two-modes signals. Investigations have to be pursued on such signals.

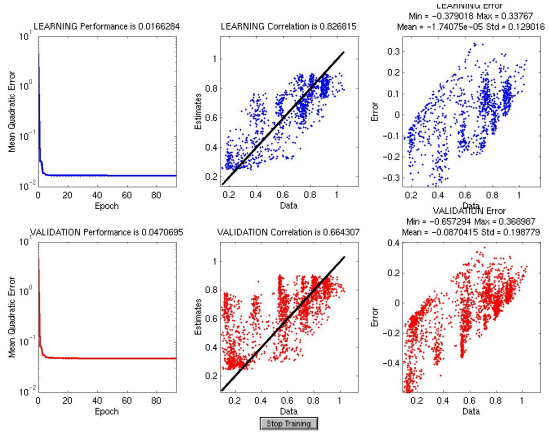

Fig. 5: Neural network learning phase for two-modes signals.

Nevertheless, results obtained on mono-mode signals are still of great interest. Many aeronautical applications deal with such signals, in particular in the field of control where it is often of interest to detect one main flexible mode inducing structural oscillations. In such cases, SINTRACK offers very attractive low complexity, for accuracy comparable to some more complex algorithms.

7. SAO CODING USING ONLY ELEMENTARY FUNCTIONS

SAO is the language used internally for real-time applications. This language has been developed for aeronautical purposes: it generates automatically C-code and is compatible with all Airbus validation tools. It is very similar to Simulink^{TM}, but with a very limited library of elementary functions, such as multiplier, divider, sum, logical operators, delays, 1st and 2nd order filters and limiters. It does not permit to handle vectors or matrixes, only scalars. Fig. 6 produces an example of such an SAO sheet.

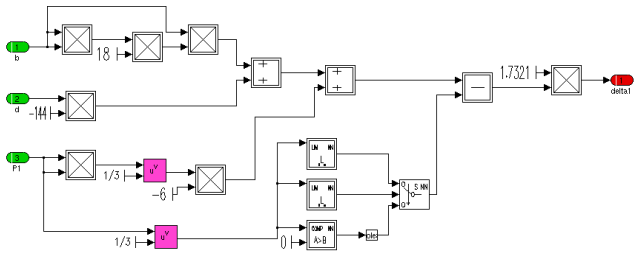

Fig. 6: Example of SAO sheet used to code SINTRACK.

Anyway if one restricts potential SINTRACK-applications to mono-mode signals, size of data and equations become a lot simpler. Prony model can be restricted to L=4 (size 2 for the mono-mode signal, and size 2 for the noise space). Then optimal number of samples for the initialisation phase becomes N=10 (N/3<L<2N/3 as demonstrated in [4;5]). However, SINTRACK still requires among other functions to compute the SVD of a (N-L)*L matrix and the roots of a Lth order polynomial, using only SAO elementary functions and scalars. A huge work of decomposition into elementary operations was done. Finally the entire algorithm was coded using about 60 SAO sheets. This amount is relatively small compared to the potential amount of sheets that can be implemented on-board an aircraft computer. As a comparison, the algorithm proposed in [6] requires a full computer, and its coding had to be done directly in C because no decomposition into SAO elementary functions could be performed. Of course the potential of both algorithms are very different: [6] is able to deal with 15-modes signal, to sustain high SNR levels and does not require any particular tuning (all tunings are managed automatically). But this comparison still gives an idea of the low complexity of SINTRACK, which is always a plus when dealing with aeronautical real-time applications.

8. PROSPECTS

SINTRACK coded in SAO has passed all the pre-validation process. No regression due to the SAO language has been detected, and its performances are compatible with the Airbus foreseen applications. More validations will be conducted in 2004 on a dedicated real-time test-bed prior to going in flight for real testing.

Among the foreseen applications, one consists in detecting the first wing-bending mode characteristics of an aircraft. These characteristics highly vary depending on wing tanks filling. Studies are presently conducted to use estimates of this mode in an adaptive control law dedicated at alleviating wing oscillations.

9. REFERENCES

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