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## Invited Keynote Address: Advanced Signal Processing and Condition Monitoring Session

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# **Advanced Signal Processing and Condition Monitoring Session**

## **Keynote address**

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## **ABSTRACT**

When physical models are of a high complexity, a signal processing approach is helpful for providing accurate information about a system and its failures. The session entitled “Advanced Signal Processing and Condition Monitoring” contains papers who propose new advanced signal processing methods in the context of condition monitoring, diagnostic and fault detection. The methods proposed tackle with the analysis, modelling and/or detection of nonstationary and/or nonlinear signals in time, frequency, time-frequency and/or time-scale domains using parametric, non-parametric and/or statistical approaches. Tools as optimization techniques can cope with the high non-linearity of the system to solve. The methods proposed are successful in decision making and bring on a step up in real-life signal processing applications. Signals or considered models come from domains such as acoustics, vibroacoustics, mechanics and electrical engineering. This keynote address introduces the session papers and gives some insight in spectral and time-frequency analysis.

## **KEYWORDS**

Signal processing, time-frequency, detection, segmentation, condition monitoring,

## **II. OVERVIEW OF THE SESSION**

In the session entitled *Advanced Signal Processing and Condition Monitoring*, each paper proposes a new signal processing method adapted to a particular physical problem. This section outlines the methods proposed and states their ability to be applied in a wider context.

Motivated by a reduction of cost but due often to technical constraints, it can be interesting to estimate a physical quantity of a system without a dedicated sensor. This type of monitoring brings into view the requirement of accurate analysis of current or voltage signals, quantities easily available. In [1], for modelling the thermal behaviour of an induction motor without considering an exhaustive identification and without a thermal sensor, the authors propose an equivalence between an electrical model, which inputs are motor current and voltage, and a thermal model, which outputs are the stator and rotor temperatures. The parameter estimation of the electrical model is operating via a harmonic detection in the spectra.

In [3], the authors settle the matter of classifying mechanical failures from a monitoring of the stator current only. As in [1], the interest is a sensorless estimation. The strategy consists in benefiting from properties of a given time-frequency transform. Results are illustrated thanks to an experimental setup. Regard as a signal-processing problem, the algorithm is able to make a distinction between amplitude and phase modulation. Consequently the method can be applied in all domains where this problem arises.

In [2], the authors propose a new time-frequency transform able to handle signals more complex than the well-known spectrogram does it, while preserving robustness. Moreover, the application domain is as wide as that of the spectrogram. Results are given for acoustic echoes of a moving object but the method can be applied on any signal having a variable instantaneous frequency.

In [4], the author investigates the problem of estimating the motion of an object in video sequences. By making an analogy between each straight line in an image and a planar propagating wave front impinging on an array of sensors, a mathematical model classically used in spectral analysis is derived. The motion is then estimated by means of an estimation of the instantaneous frequency of this model.

In [5], the authors are interested by a time-phase representation to be able to estimate a phase delay. Going further than [3] which aims at a classification only, the method proposed consists of filtering each time-frequency patterns by a non-unitary time-warping filter. Finally a continuity constraint is applied on the phase of the signal reconstructed to separate components in the patterns previously extracted. The authors present results on modulated signals as phase or frequency shift keying and on bioacoustic signals. The method can be applied on any modulated signals even if there are multicomponent and embedded in a noisy environment.

### **III. TREND ....**

A maintenance operation needs a very complex approach, which consists first to have a great knowledge of the integral organs of all of the system, then to have a full control of the running mechanism, finally to be able to identify the possible defaults, their natures and sources.

Nowadays industrial systems are complex in the sense that several machines interact between them at dissimilar power levels. Excitations can derive from different origins. A default can stem from a small part of the system and at a small power level related to the other parts of the system. In this case, classical maintenance is unsuccessful. Moreover, forward-looking maintenance requires the processing of different types of measures, vibratory and acoustic signals but also currents, tensions, velocities, torques, temperatures and so on. A correct approach of the maintenance of such systems has to integrate advanced post-processing.

However, signal processing methods become more and more sophisticated to be effective in increasingly broad contexts.

Consequently, in order to facilitate more general use of sophisticated methods requiring high signal processing skills and to keep the ability of increasing reliability of the maintenance, the methods proposed have to be automatic. This point of view gives then evidence of the trend in signal processing. Ongoing methods must integrate more than the analysis of the signals acquired. Steps of classification, detection, interpretation or decision have to be incorporated. A decision in signal processing will be an input for a physical decision. Thereby, signal-processing approaches can be developed in more general contexts.

This task is the job of specialists in signal processing. This signal part of the maintenance has not to be merged with the physical part. Signal processing yields an additional help.

Signal processing methods will act from observations of the system. System outputs are more often compound of complicated or hybrid structures: they can be nonstationary, a mixture of different spectral structures, narrow spectral bands and/or wide spectral bands, multicomponents, nonlinearly modulated in frequency and/or in amplitude, embedded in different types of noise, white, colored, Gaussian or impulsive noise. Whatever the physical meaning of these structures a signal processing approach is of utmost importance and has to be taken into consideration. The strength of a signal approach has to be exploited in the same way than the physics of the phenomenon observed.

In the session presented, the whole of the approaches suggested are based on spectral analysis or time-frequency analysis, which are leading methods in the domain of surveillance. Papers [1] and [3] are good examples of the trend described above.

#### **IV. ADVANCED SPECTRAL ANALYSIS**

To illustrate this section another example based on spectral analysis is shortly described. Spectral analysis is well known since a very long time. Several methods have been published since the Forties. We can cite the paper of Bartlett in 1948 [6] and the well-known book of Jenkins and Watts in 1968 [7]. Since the Eighties, parametric methods, which include model of the signal, have emerged. Synthesis chapters and references can be found in [8]. Parametric methods have the advantage to provide direct estimation of signal parameters, such as frequency, amplitude or phase. When using a nonparametric approach, perhaps easier to implement and set the parameters, the problem of interpretation the results, that is to say the spectrum, is not trivial. This is why further investigation has been done in that way to satisfy the trend mentioned above.

The project called TetrAS has been partly published in [9-12]. TetrAS is a new concept for Analysis. Interpretation is a part of its job and experience is inside. The « super spectrum analyzer » TetrAS is a self-governing analyzer designed to help. The system applies spectral analysis methods with adapted parameters, compares different estimations and calls most of statistical properties of the estimators. TetrAS decides how to do it and extracts the characteristics of each spectral pattern of the signal.

In a first step, basic properties of the signal analysed are controlled [12] by means of several tests such as a Shannon test, periodicity tests, a global signal to noise estimation, a correlation support estimation, stationarity tests in time and in time-frequency [11].

Afterwards, a full classification strategy described in [9] and [10] is applied in order to conclude on a description as an Identity Card about each spectral pattern of the spectrum. To do this, several methods based on the Fourier transform are matching up in order to benefit of the best properties of each of them. A non-linear n-pass filter combining a median filter and a detection test provides an estimation of the noise spectrum. A hypothesis testing based on Neyman-Pearson criterion taking into account the estimated-noise statistic is applied at each peak of each estimated spectrum. Finally,

an iterative adjustment between each peak detected and the spectral window related to the spectral estimator yields a classification of all of the peaks.

The system needs only one click to be run. The user has no choice to carry out. All is automatic and the system has been designed such that no random choice or no *a priori* choice is carried out by the system. Figure 1 highlights some results when applying TetrAS on two real acoustic signals, the first being acquired in the passenger cell of a vehicle in slow motion and referred to *Acoustic signal 1* and the second one in the same vehicle with a mechanical structure modified and referred to *Acoustic signal 2*.

Table 1: Results of TetrAS - Number of peaks detected by class for the 2 acoustic signals of 4.88 s sampled at 20 491 Hz. PF is for Pure Frequency and NB for Narrow Band

		<i>Acoustic signal 1</i>		<i>Acoustic signal 2</i>	
<i>Class</i> <i>PF / Noise</i>	Class PF	23	<b>107</b>	16	<b>65</b>
	Class PF/ doubt Noise	14		8	
	Class N / doubt PF	70		41	
<i>Class NB / NB</i>	Class PF / doubt NB	55	<b>120</b>	51	<b>85</b>
	Class NB / PF	21		11	
	Class NB	44		23	

Table 1 sums up the number of peaks detected by class. In a first glance and before looking at the details of the results, this table shows clearly that the number of peaks has strongly decreased in the *Acoustic signal 2*. A more detailed observation in the band 600-800 Hz corroborates locally this different spectral behaviour. In the *Acoustic signal 1*, 18 peaks were detected in this band with a mean time-amplitude of 42.3 whereas, in the *Acoustic signal 2*, only 5 peaks were detected with a mean time-amplitude of 10.5 only.

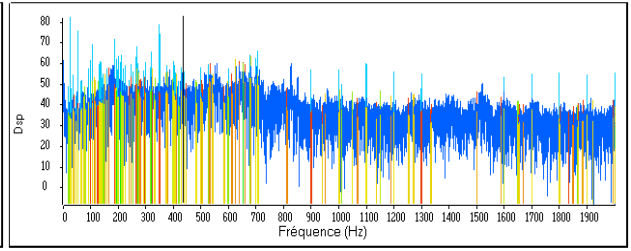
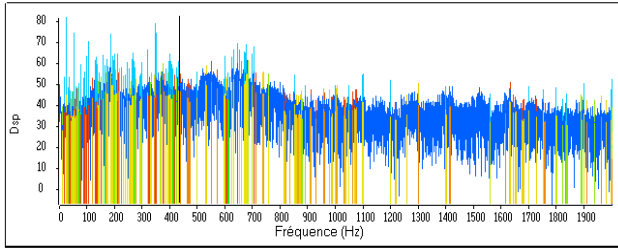
A zoom of each spectrum (first line of figure 1) shows the richness of the signals. A reading of all the peaks should need a lot of time and know-how. On the contrary, with one click, TetrAS yields the characteristics of all the peaks. For instance, once the peaks are detected, it is easy to group them in harmonic families. Two main families were observed, one at fundamental 26.64 Hz and the other at 99.99 Hz. The tracking of the amplitude shows that the modification of the mechanical structure has no effect on the first family (second line of figure 1) but an important effect on all harmonics of the second family (third line of figure 1).

The tables at bottom of figure 1 show the details of the Identity Cards of the 12 first peaks of this family for both signals.

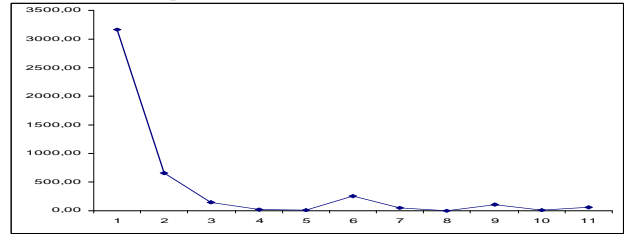
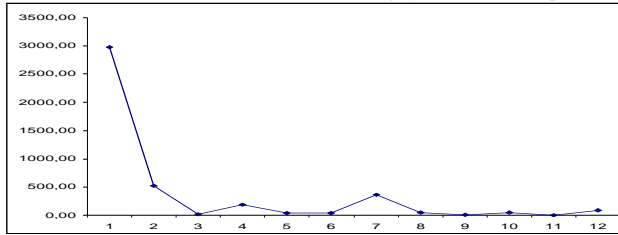
Acoustic signal 1

Acoustic signal 2

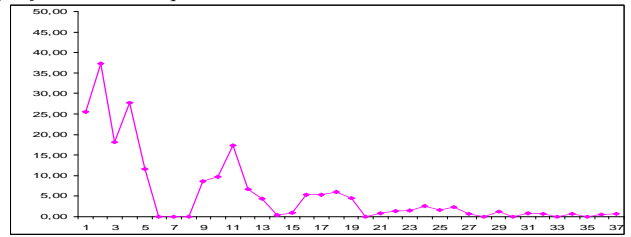
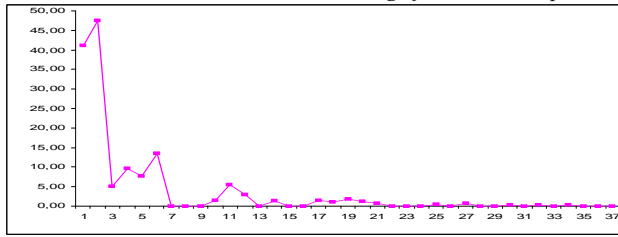
Spectrum zoom at TetrAS output



Tracking of harmonic amplitude for fundamental equal to 26.64 Hz



Tracking of harmonic amplitude for fundamental equal to 99.99 Hz



The 12 first Identity Cards computed by TetrAS for the harmonic family with fundamental 99.99 Hz

Stability	Frequency	Amplitude	Class	PFA	Local RSB
100	99,991	41,20	PF	$10^{-6}$	24,7
100	199,873	47,45	NB	$10^{-6}$	19,3
59	299,974	5,00	NB	$10^{-6}$	12
100	399,98	9,64	PF / doubt NB	$10^{-6}$	12
80	499,94	7,71	PF / doubt NB	$10^{-6}$	12,5
75	599,244	13,47	PF / doubt NB	$10^{-6}$	22
	Not detected	0,00			
	Not detected	0,00			
	Not detected	0,00			
76	999,959	1,52	PF / doubt NB	$10^{-6}$	15
100	1099,919	5,49	PF / doubt NB	$10^{-6}$	13,6
78	1199,91	2,93	PF / doubt NB	$10^{-6}$	16,9

Stability	Frequency	Amplitude	Class	PFA	Local RSB
HH0	100	99,99	PF	$10^{-6}$	24,3
HH1	80	199,97	NB	$10^{-6}$	19,5
HH2	58	299,94	NB / doubt PF	$10^{-6}$	16,6
HH3	100	399,98	PF / doubt NB	$10^{-6}$	20,6
HH4	78	499,94	PF / doubt NB	$10^{-6}$	12,5
HH5		Not detected	0,00		
HH6		Not detected	0,00		
HH7		Not detected	0,00		
HH8	75	899,86	PF / doubt NB	$10^{-6}$	22
HH9	78	999,85	PF / doubt NB	$10^{-6}$	19,7
HH10	100	1099,84	PF / doubt NB	$10^{-6}$	21,6
HH11	80	1199,80	PF / doubt NB	$10^{-6}$	22,3

Figure 1. TetrAS applied on the 2 acoustic signals of 4.88 s sampled at 20 491 Hz, each column is for one signal. First line is a zoom of each spectrum on the range 0-2000 Hz (Welch method with Blackman window and no average). The peaks colored correspond to the peaks detected and classified by TetrAS. Second line is the tracking of harmonic amplitude for fundamental equal to 26.64 Hz. Third line is the same but for a fundamental equal to 99.99 Hz. The two tables are the identity cards of the 12 first peaks of the family at 99.99Hz. PF is for Pure Frequency and NB for Narrow Band.

## V. A FEW FACETS OF TIME-FREQUENCY

The theoretical foundations of spectral analysis are unambiguous. Beginning with deterministic signals and the harmonic analysis by Fourier series, it was extended to continuous signals with the Fourier integral and to random signals with the Fourier-Stieltjes integral. A stationary hypothesis makes easier the definition of the correlation function, function of the delay only, and of a power spectral density if the spectrum is continuous. Without the stationary hypothesis, the estimation of the energy repartition of such a nonstationary signal is not so well defined. Two main problems occur. First is the definition of the concept of frequency, which implicitly induces an infinite temporal wave. Second is the reconsideration of the base functions used in the stationary case, the exponential functions, which are not adapted to show up an evolution in the signal, whatever this evolution is. This explains the numerous methods proposed in the literature.

A part of them introduce variable terms in the exponential function or replace them by more adaptable functions. Others assume a local stationary hypothesis or apply a nonlinear transform in order to make the signal stationary. My purpose in this paper is not to present an overview of that subject but only to point out some of them given that time-frequency analysis is used in almost all the papers of the session presented.

The most older, the spectrogram or sonogram,  $SPECT[n, k]$  at time index  $n$  and frequency index  $k$ , of a discrete signal  $s[n]$  of length  $N$  assumes a local stationarity over length  $N$  and writes

$$SPECT[n, k] = \left| \sum_{m=1}^N w[m-n] s[m] e^{-2j\pi \frac{mk}{N_w}} \right|^2, \quad (1)$$

with  $w[n]$  a time window of length  $N_w$ .  $SPECT[n, k]$  is an energy distribution and can be improved by a Short Time Fourier Transform,  $STFT[n, k]$ , a complex transform, which also gives information about the phase of the signal and writes

$$STFT[n, k] = \sum_{m=1}^N w[m-n] s[m] e^{-2j\pi \frac{mk}{N_w}}. \quad (2)$$

The reading of the phase needs an unwrapping, that is somewhat difficult to handle.

The Wigner-Ville distribution  $WV[n, k]$  is a bilinear transform of the signal defined for discrete time as

$$WV[n, k] = 2 \sum_{m=1}^N s[n+m] s^*[n-m] e^{-4j\pi \frac{mk}{N}}, \quad (3)$$

with  $*$  stands for the conjugate.  $WV[n, k]$  is the Fourier transform of a quadratic form of the signal, which has the property of transforming each linear modulation in a constant frequency. Consequently, the Wigner-Ville distribution has a perfect localization on linear chirp signal. On the contrary, multicomponent signal generates interferences. Both time and frequency smoothing were introduced to reduce interferences, what results in a reduction of the resolution [13].

For that matter, interferences are not always embarrassing given that they display information of the signal. In [3] of the session presented, the authors use the interference of the Wigner-Ville distribution to distinguish an amplitude modulation from a frequency modulation.

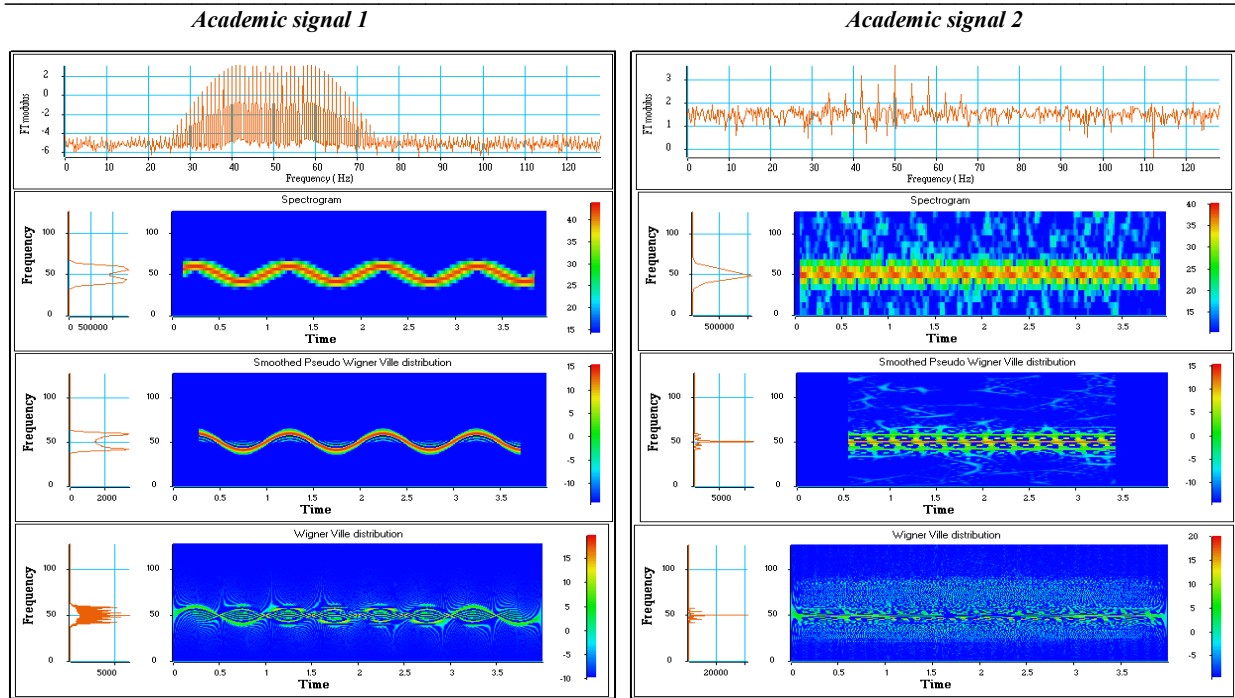


Figure 2. Spectral and time-frequency analysis of the 2 academic signals of 4 s sampled at 256 Hz, each column is for one signal. Academic signal 1 is noise-free, signal to noise ratio of Academic signal 2 is equal to 15 dB. First line is the modulus of the Fourier Transform. Second line is the Spectrogram (Hanning window of 64 points for Academic signal 1 and 32 points for Academic signal 2) Third line is the Smoothed (Hanning window with 64 points for Academic signal 1 and 32 points for Academic signal 2) and Pseudo (Hanning window with 128 points for Academic signal 1 and 256 points for Academic signal 2) Wigner-Ville distribution. Fourth line is Wigner-Ville distribution.

Figure 2 shows the analysis of two academic signals

$$s_i[n] = (a_i + b_i \sin(2\pi f_i n / F_s)) \sin(2\pi(v_i + \mu_i \sin(2\pi\lambda_i n / F_s))), \quad (4)$$

where

$$s_1[n] \quad a_1 = 10 \quad b_1 = 0 \quad f_1 = 0 \text{ Hz} \quad v_1 = 50 \text{ Hz} \quad \mu_1 = 10 \text{ Hz} \quad \lambda_1 = 1 \text{ Hz}$$

$$s_2[n] \quad a_2 = 10 \quad b_2 = 3 \quad f_2 = 4 \text{ Hz} \quad v_2 = 50 \text{ Hz} \quad \mu_2 = 5 \text{ Hz} \quad \lambda_2 = 8 \text{ Hz}$$

**Academic signal 1** referred to  $s_1[n]$  is a noise-free signal with sinusoidal-frequency modulation and constant amplitude. **Academic signal 2** referred to  $s_2[n]$  is also a sinusoidal-frequency modulated but with a sinusoidal-amplitude modulation. Furthermore, this second signal is embedded in a white noise of 15 dB and the modulation parameters are such that the analysis by the methods mentioned is not acceptable. We shall see in the following section that others methods have to be considered for this signal.

Beyond the diverse time-frequency representations, these results highlight a different aspect between a global analysis, showed by the modulus of the Fourier Transform in the first line of figure 2, and a time-frequency one, all the other lines of figure 2. Both are of interest but the interpretation has to be done carefully.



The S-transform introduced in [14] and used in [4] in the session presented was established from the observation of the following relation

$$WV[n, k] = 2 \sum_{m=1}^N STFT[n, k+m] STFT^*[n, k-m], \quad (5)$$

obtained by combining a pseudo transform of (2), i.e. with a frequency smoothing or a time weighting, and (3). By this consideration, the S-method  $SM[n, k]$  was proposed in its discrete form as

$$SM[n, k] = \sum_{m=1}^{N_p} P[m] STFT[n, k+m] STFT^*[n, k-m], \quad (6)$$

where  $P[m]$  is a window of length  $N_p$ . The introduction of this window is a way to reduce interferences mostly if the window width is adapted to the signal content in order to consider only one component at a time in the summation in (6). Two crossing components cannot be considered by this method, which has the advantage of a low computing time.

## VI. A HIGH RESOLUTION METHOD IN A NUTSHELL

In all the methods mentioned above and belonging in fact to the Cohen class, the resolution is limited by the Heisenberg uncertainty. To get away from this constraint and to be able to estimate nonlinear modulated signals with a better resolution need to add some hypothesis mostly if the signal analysis is of short duration.

A classical and general model  $x[n]$  of a complex signal writes

$$x[n] = a[n] e^{j\varphi[n]} \quad n = -N/2, N/2 \quad (7)$$

where the amplitude  $a[n]$  is strictly positive, the phase  $\varphi[n]$  is differentiable and shows no discontinuity. The constraint on the amplitude and the phase guarantees the unicity of the model. A way of modelling the signal with a better accuracy is to increase the number of parameters to describe it without be over the point number of the signal. [15-16] propose a polynomial modelling of the amplitude  $a[n]$  and of the frequency  $f[n]$ , which yields then the phase  $\varphi[n]$  by an integration up to  $2\pi$ . This approximation writes

$$\begin{aligned} a[n] &= \sum_{m=0}^{M_a} a_m p_m[n], \\ f[n] &= \sum_{m=0}^{M_f} f_m p_m[n], \\ \varphi[n] &= \varphi_0 + 2\pi \left( \sum_{k=-N/2}^n f[k] - \sum_{k=-N/2}^0 f[k] \right), \end{aligned} \quad (8)$$

where  $M_a$  and  $M_f$  are the approximation orders and  $\varphi_0$  stands for the initial phase of the signal in (7). The set  $\{p_m[n]\}_{m=0, \max(M_a, M_f)}$  stands for a polynomial base, which can be computed from a discretization of continuous-time base such as the canonical polynomial base or the orthogonal

polynomial bases such as Legendre, Tchebychev or Hermite. However the orthogonal property is lost when discretizing these functions. The orthogonal property is fundamental to guarantee the independence between the parameters estimated. Therefore, a discrete base derived in [18] corresponding to the application of the Gram Schmidt procedure in discrete-time directly is used. Expressions of this base are given in [16].

Finally the parameters to estimate can be gathered in a vector  $\mathbf{V}$  of dimension  $M$  equal to  $(M_a+M_f+3)$ , which writes

$$\mathbf{V} = [a_0 \dots a_{M_a} f_0 \dots f_{M_f} \dots \varphi_0]^T. \quad (9)$$

Dimension  $M$  of  $V$  has to be lower than  $N$ , the length of the signal. In addition to the choice of the base, the choice of modelling the frequency instead of the phase and the centring of the polynomial at the signal middle to ensure a minimum variance, the idea of the method proposed in [15-16] was to also consider only small approximation orders.  $M_a$  and  $M_f$  are less than or equal to 3. This rule does not induce a constraint since the signal analysed is by assumption short enough to be adapted to this approximation. We would say that the signal duration should at least contain one or two periods. In [18-19], the method was extended to a signal whatever its length and modulation by considering a local approximation on nonsequential parts of the signal.

Let us come back to the approximation of a short signal. One possible method is to consider the maximisation of the likelihood function which is equivalent to a minimization of the least square function  $l_{LS}(\mathbf{V})$  when the error can be assumed to be a Gaussian noise. This minimization writes

$$\hat{\mathbf{V}} = \arg \min_{V \in R^M} l_{LS}(\mathbf{V}), \quad (10)$$

with

$$l_{LS}(\mathbf{V}) = \sum_{n=-N/2}^{N/2} |s[n] - x[n]|^2, \quad (11)$$

where  $s[n]$  is the observation and  $x[n]$  the model defined in (7). The error between the observation and the model, namely the difference  $(s[n] - x[n])$ , represents both the noise, in which the deterministic signal we want to estimate is embedded, and the model error. We verify *a posteriori* that this error is distributed as a Gaussian law.

Direct minimization of (11) is extremely difficult due to the high non-linearity of the function and the parameter number. Classical optimization techniques such as gradient descent, Gauss-Newton and EM algorithm do not ensure convergence to the global minimum when local minima are numerous. This problem can be overcome by meta-heuristic approaches, and in particular, by simulating annealing. Simulating annealing has an analogy with thermodynamics where metal cools and anneals. In the same way, after an initialization of the parameter vector to estimate, an iterative loop controlled by a scalar referred to as a temperature generates a new candidate of the vector that minimize the cost function, namely the least square function  $l_{LS}(\mathbf{V})$ . A statistical significance test relied on the assumption that the error is normally distributed stops the algorithm.

In lieu of a likelihood maximum approach, estimation of (9) can be investigated upon Bayesian point of view. In that case, parameter  $V$  and variance of the error  $(s[n] - x[n])$ , namely  $\sigma^2$ , are viewed as random variables. After having assigned a prior distribution to each of this random

variable referred to as  $p(\mathbf{V}, \sigma^2 | I_p)$ ,  $I_p$  being the prior information, a joint posterior distribution conditionally to the observation vector  $\mathbf{S}$  and the prior information  $I_p$ , namely  $p(\mathbf{V}, \sigma^2 | \mathbf{S}, I_p)$  writes as

$$p(\mathbf{V}, \sigma^2 | \mathbf{S}, I_p) = \frac{p(\mathbf{S} | \mathbf{V}, \sigma^2, I_p) p(\mathbf{V}, \sigma^2 | I_p)}{p(\mathbf{S} | I_p)} \quad (12)$$

where  $p(\mathbf{S} | \mathbf{V}, \sigma^2, I_p)$  is the likelihood function and  $p(\mathbf{S} | I_p)$  is the probability of the observation  $\mathbf{S}$  conditionally to the prior information  $I_p$ . This last probability would be consider as a constant.

The likelihood function is get from the fact that the error is assumed to be Gaussian.

Given that we assume independence between all the parameters to estimate, the prior distribution  $p(\mathbf{V}, \sigma^2 | I_p)$  is a product of the prior of each parameter. This prior is set to the uniform distribution for the elements of vector  $\mathbf{V}$  and is set to the Jeffrey distribution for  $\sigma^2$ .

Taking account of all of these hypotheses and, after having integrated over  $\sigma^2$ , the joint posterior distribution writes, up to normalisation constant,

$$p(\mathbf{V}, \sigma^2 | \mathbf{S}, I_p) \propto \left[ \sum_{n=-N/2}^{N/2} |s[n] - x[n]|^2 \right]^{-(N+1)}. \quad (13)$$

This posterior distribution is highly nonlinear. We propose to use a Metropolis-Hasting MCMC algorithm to sample from this distribution. Once this distribution estimated, the parameters are estimated by a Minimum Mean Square Error method.

In [15-16] are given all the details of the algorithms. Figure 3 shows the results given by Simulating Annealing when applied on the *Academic Signal 2* defined in the previous section. The method proposed is of course more complex and needs more computer time than the classical methods presented in the previous section. Nevertheless, in the case of more complex signals such as *Academic Signal 2*, the results obtained defend this complexity.

The method has been extended to multicomponent signals [20], [21].

## VII. CONCLUSIONS

Beginning with a brief presentation of the papers of the structured session entitled ‘‘Advanced Signal Processing and Condition Monitoring Session’’, this keynote address gives some insights in the ongoing trend of spectral and time-frequency analysis.

## Acknowledgment

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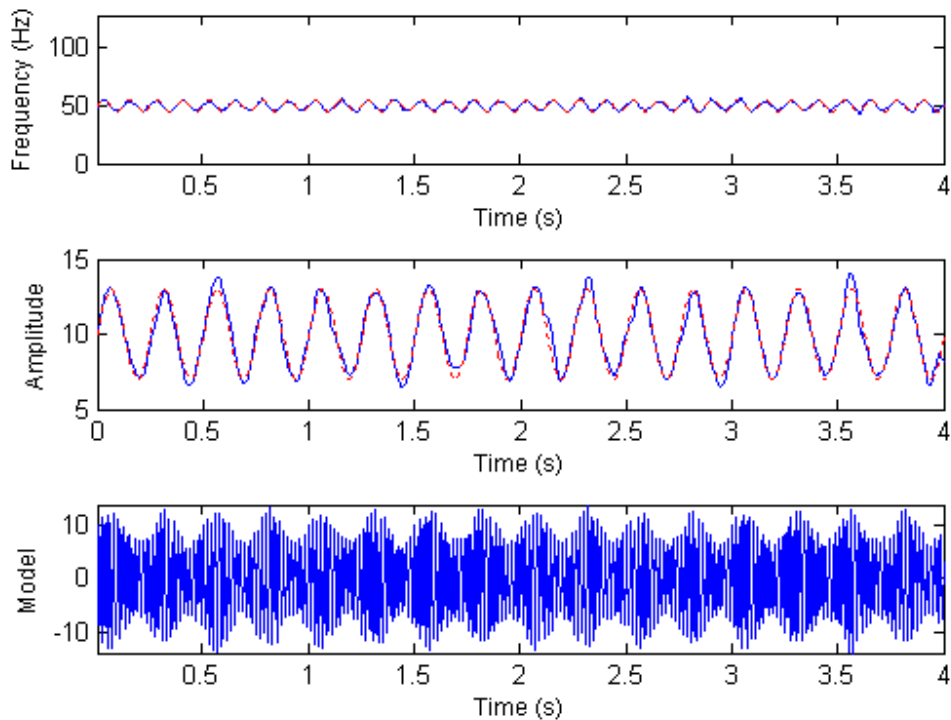


Figure 3. Academic signal 2 processed by a high-resolution method. First curve is the instantaneous frequency in red for the theoretical one, in blue for the estimated one. Second curve is the instantaneous amplitude in red for the theoretical one, in blue for the estimated one. Third curve is a reconstruction of the model from the amplitude and frequency estimations.

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