VIII SEPOPE
19 a 23 de maio de 2002
May, 19th to 23rd – 2002
Brasília (DF) – Brasil

VIII SIMPÓSIO DE ESPECIALISTAS EM PLANEJAMENTO DA OPERAÇÃO E EXPANSÃO ELÉTRICA

VIII SYMPOSIUM OF SPECIALISTS IN ELECTRIC OPERATIONAL AND EXPANSION PLANNING

IP–067

Power System Phenomena Analysis using Time-Frequency Decompositions

Marco Antonio M. Rodrigues[*♦]
Eduardo A. B. da Silva[#♣]
Lisandro Lovisolo[#♣]
Paulo S. R. Diniz[#♣]

♦ CEPEL
♣ COPPE/UFRJ

BRAZIL

Summary – A precise understanding of power system behavior is an increasing need in different areas of the power industry. Instruments for monitoring a number of different phenomena are capable of storing and transmitting a large amount of data. A problem that naturally arises is how to deal with such information overload. This article presents a new approach to the problem of working on the large amount of data resulting from oscillographic measurements in power systems using an algorithm referred as Matching Pursuits.

Keywords: Oscillography, automatic data interpretation, data compression, Matching Pursuits, Gabor dictionary, signal processing.

1 INTRODUCTION

New digital instruments are capable of storing and transmitting a large amount of data resulting from measurements of voltage and current quantities. Particularly, the oscillographic recordings store time variation of electrical quantities, mainly voltage and currents. The most common classification for oscillography is as follows:

- **Short time or transient oscillography**: employed for monitoring of transient phenomena, to study and fix protection systems, to observe equipment malfunctions and to perform fault location. It can be used also for harmonic analysis and other signal processing tasks necessary for system analysis and power quality assessment;
- **Long time oscillography**: responsible for monitoring low-frequency oscillations and slow transients and used to assess the dynamic behavior of large interconnected electrical systems.

To better understand the problem, consider, for example, the case of short-time oscillography. The measuring device is called Digital Fault Recorder (DFR). In many situations, protection experts want to register fault occurrences as well as switch re-closings without loosing high-frequency data. Usually, a value variation or an external sensor is used to trigger the DFR exactly at the fault moment. However, there are a number of phenomena, like switching noise, line energizing, systemic faults (especially faults affecting voltage and current values in various transmission lines, but not observable from these lines) and defective sensors, which may increase the number of registered events. Also, consider that the Brazilian ISO (Independent System Operator), requests transmission and generation agents to monitor a large number of points [1]. The result is a large amount of DFR files, many of which with a lot of redundant information.
A problem that naturally arises is how to deal with such information overload. Although fault analysis requires an expertise difficult to automate using a computer, it is possible to alleviate this task. A usual approach is to employ an expert system to enter the logics of fault analysis [2][3]. For analog channels, the expert system does not work directly on the raw time-domain data, but on the results of a pre-analysis, using signal-processing techniques. Usually, the signal waveforms are transformed in RMS values, phasor values or

[*]Centro de Pesquisas de Energia Elétrica (CEPEL), Caixa Postal 68007, CEP 21944-970, Rio de Janeiro-RJ, Brazil, mamr@cepel.br
[#] Signal Processing Lab - COPPE/UFRJ, Cx. P. 68504, Rio de Janeiro-RJ, 21945-970, Brazil

Fourier transform values. These values are used to characterize the phenomena.

The objective of the paper is to present a signal processing technique, called *Matching Pursuits* (**MP**), capable of performing a richer analysis of a signal, as well as providing for what is called coherent (see section 3) analysis and compression (file transmission is still an issue in remote substations with slow connections).

Section **2** presents the concept of time-frequency distributions, which is a key point to understand the **MP** algorithm. Section **3** introduces the concepts of signal representations and presents the **MP** algorithm. Section **4** presents a specific model for power system signals and the modifications needed on the original algorithm. Section **5** shows how **MP** behaves when applied to synthetic and real life oscillographic data.

2 TIME-FREQUENCY REPRESENTATIONS

Time-frequency representations (**TFR**) or time-frequency distributions are "distributions that represents the energy or intensity of a signal simultaneously on time and frequency" [4]. An example can be seen on Figure 1, were the **TFR** of a voltage sag in a line fault is shown. In the left and bottom it can be seen respectively the time and frequency-domain representations. It is easy to see that the **TFR** gives a more complete signal characterization than solely time or frequency domain analysis.

TFRs, however, cannot accurately measure, at a given time/frequency point, both instantaneous frequency and instantaneous amplitude, because of the uncertainty principle [5][6]. For this reason, a number of different kernels are used to calculate **TFRs**, like the *Wigner-Ville Distribution* and the *Short-Time Fourier Transform* (spectrogram). Each kernel partitions (or analyses) the time-frequency domain in a distinct way. In [5][6] the advantages and drawbacks of each kernel are shown. Reference [6] defines a kernel using the **MP** algorithm and shows its advantages when compared to usual kernels.

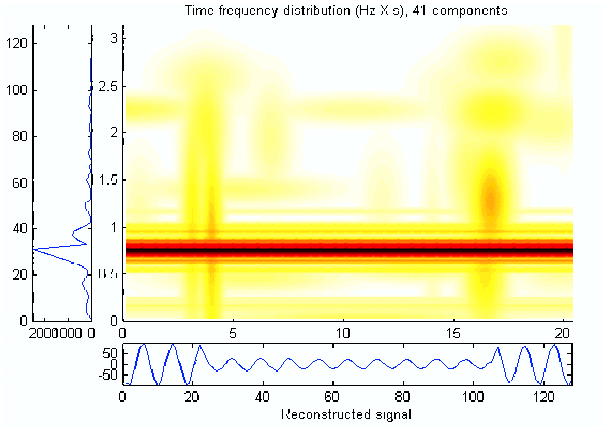

Figure 1: TFR of a signal using MP kernel.

Although **TFRs** graphics are appealing, they fail to distinguish a number of phenomena usual in power system signals. For example, just observing a **TFR** it is not possible to distinguish a damped sinusoid from an abrupt change of amplitude, resulting from a fault or line switching. Experiments using **TFRs** for signal analysis showed a poor performance [7].

3 ADAPTIVE SIGNAL DECOMPOSITIONS

A signal $x(t)$ can be represented as a sum of other pre-defined signals $f_k(t)$, $k \in \{0, 1, \ldots, K\}$ as [6]:

$$x(t) = \sum_{n=0}^{M-1} \alpha_n f_{k(n)}(t) \quad (1)$$

We refer to $f_k(t)$ as atoms or structures. The value α_n is an energy factor for the atom $f_{k(n)}(t)$. The set of all possible atoms $f_k(t)$ is the so called dictionary ***D***. In general, dictionary ***D*** is overcomplete (i.e., it has much more than M atoms). In eq. (1), M atoms, given by $f_{k(n)}(t)$, are used to represent $x(t)$. The key point is how to chose atoms $f_{k(n)}(t)$ and how to calculate the coefficients α_n. We accomplish this using the *Matching Pursuits* (**MP**) algorithm.

3.1 Matching Pursuits

The **MP** algorithm is a greed algorithm used to choose the M atoms to be used in the decomposition. It produces a decomposition that is coherent with the dictionary. If the atoms in the dictionary are outputs of a system, corresponding to phenomena to be detected or studied, the **MP** algorithm has the potential of identifying these typical output waveforms even if the desired signal component is weak. This technique is

being used in different areas such as radar signal analysis, spectral analysis and music and video compression, just to mention a few. In addition, it has been also used for system identification, feature extraction, denoising etc.

As the decompositions using the *Matching Pursuits* algorithm tend to have a greater degree of freedom than orthogonal ones, they have the potential of being more powerful than wavelet analysis. While wavelet analysis spans the time-frequency domain with limited time or limited frequency resolution, the **MP** algorithm can freely adapt atom properties to yield better resolutions both in time and frequency. Wavelet analysis decomposes the signal into a fixed frame of components whereas the Matching Pursuits algorithm allows for choosing the most suitable components. When finding the components $f_{k(n)}(t)$ that best match the signal, the **MP** algorithm forces a coherent decomposition, i.e., the signal representation is based on the atoms of the dictionary. Due to this coherency, elimination of non-coherent as well as noisy features (denoising) is easily accomplished. Also, high compression ratios can be achieved because only the components of interest need to be stored.

The **MP** algorithm was first introduced by *Mallat* and *Zhang* [9]. At each step, the **MP** algorithm chooses the function from the dictionary that has the higher inner product with the signal. The signal is therefore represented by successive approximations. Suppose we want to decompose the signal $x(t)$. Define a dictionary $\boldsymbol{D} = g_\gamma$, $\gamma \in \Gamma$ (γ is a set of parameters and Γ is the set of all possible γ), such that $\|g_\gamma\| = 1$. If $\boldsymbol{D}$ is complete [6][9], we can represent x as a sum of elements of the dictionary $g_{\gamma(n)}$, that we call atoms or structures:

$$x = \sum_n \alpha_n g_{\gamma(n)} \tag{2}$$

In order to compute the coefficients α_n we begin by choosing $g_{\gamma(0)}$ such that $\alpha_0 = \langle x, g_{\gamma(0)} \rangle = \mathrm{Max}_{\gamma\in\Gamma} \langle x, g_\gamma \rangle$, and then split x in two parts defining $R_x^0 = x - \alpha_0 g_{\gamma(0)}$. Carrying out this process iteratively, we can compute the $n+1$ order residue, R_x^{n+1}, as:

$$R_x^{n+1} = R_x^n - \alpha_{n+1} g_{\gamma(n+1)} \tag{3}$$

where $\alpha_{n+1} = \langle R_x^n, g_{\gamma(n+1)} \rangle$ which is obtained with the γ, that gives its maximum value. It is computed at step $n+1$ from the residue of step n. Observe that R_x^n and $g_{\gamma(n)}$ are orthogonal and therefore the signal energy is conserved [9]. We can also see that the energy of the residual decreases with each approximation step.

4 MATCHING PURSUITS OF SIGNALS USING DAMPED SINUSOIDS

4.1 Electric signal Model

A model for power system signals based on damped sinusoids was proposed in [7]. In this model the signals are represented by a sum of damped sinusoids (in fact damped harmonics of a fundamental frequency F):

$$x(t) = \sum_{q=0}^{Q-1} A_q \cos(2\pi k_q F + \theta_q) e^{\lambda_q (t - t_{0_q})} [u(t - t_{o_q}) - u(t - t_{f_q})] \tag{4}$$

Each component is represented by a 6-tuple (A_q, k_qF, λ_q, θ_q, t_{o_q}, t_{f_q}), where A_q represents the amplitude, k_qF the frequency, λ_q the damping factor, θ_q is the phase, and t_{o_q} and t_{f_q} represent the starting and ending times of a component (being $u(t)$ the unit step function). Note that the frequencies of the sinusoids are integer multiples of the fundamental frequency F. By representing the signal by a set of these 6-tuples, one would obtain a very compact and accurate representation of signals from power systems. In fact, the formula of eq. (4) is equivalent to that of eq. (1) where the form of the atoms is explicitly shown as a function of the set of six parameters (A_q, k_qF, λ_q, θ_q, t_{o_q}, t_{f_q}).

The problem is how to obtain the set of 6-tuples that characterize well a given signal. In the next section the **MP** is improved to solve this problem.

4.2 The Gabor Atom

The **MP** was proposed in [9] using a set of time-frequency atoms called the *Gabor* dictionary. These atoms are defined by:

$$g_\gamma(t) = \frac{1}{\sqrt{s}} 2^{\frac{1}{4}} e^{-\pi\left(\frac{t-u}{s}\right)^2} \cos(\xi t + \phi) \tag{5}$$

where $\gamma = [s, u, \xi, \phi]$, s is the scale, u is the center of the atom, ξ is the atom frequency and ϕ its phase. The aspects of the implementation of the **MP** with the *Gabor* dictionary are discussed in [9][10]. The main feature of this dictionary is that the parameter space of the atoms can be sampled while still obtaining a complete dictionary whose atoms are well localized in time and frequency [9][10]. This feature of localization in the time-frequency plane provides a good tool to characterize different phenomena conjugating time and frequency components of the signal. For instance, the time-frequency distribution of Figure 1 was obtained with these atoms. However, the *Gabor* atoms, or, generally speaking, the *Gabor* dictionary, are not well

suited to represent power system phenomena. In other applications, a number of different approaches for choosing the dictionary atoms have been proposed, namely: training, stochastic generation or even a collection of dictionaries (library). Here, we want to use a dictionary based on the power signals model of eq. (4), yielding atoms defined by:

$$f_\gamma(t) = \cos(\xi t + \phi) e^{\lambda(t-t_0)} [u(t-t_0) - u(t-t_f)] \quad \textbf{(6)}$$

One problem is that the sampling of the parameter set $\gamma = [\lambda,\xi,\phi,t_0,t_f]$ for the atom of eq. (6) is not trivial. To solve this problem we obtain the decomposition into a dictionary of functions f_γ (see eq. (6)) indirectly from the decomposition into the dictionary composed by g_γ (see eq. (5)). In the following subsection we describe the general guidelines of the algorithm. Note that for both the *Gabor* atoms and the damped sinusoids atoms, we do not need to sample the atom's phase to reconstruct the dictionary. It can be computed using a complex representation of the atom. Details can be found in [8][10].

4.3 General Outline

The *Gabor* atom that best matches the signal is obtained with the **MP** algorithm. Once this atom is chosen, we use it as a guess for the exponential atom that best matches the signal. This is done as follows:

1) Find the set $\gamma = [s,u,\xi,\phi]$ that maximizes the inner product of the *Gabor* atom with the signal at the given step.

2) With the parameters $\gamma = [s,u,\xi]$, find the exponential atom that best matches half of $g_\gamma(t)$ in the vicinity of its inflection point, as follows (we define the left half of the *Gabor* atom as the points to the left of the symmetry point of its *Gaussian* envelope, and the right half of the *Gabor* atom as the points to the right of the symmetry point of its *Gaussian* envelope):

a) Verify which half of the *Gabor* atom has a higher inner product with the signal, the left or the right one. From that we can consider that the exponential we are looking for is increasing for the first case or decreasing for the second case. Now compute λ in order to fit the exponential at the inflection point of the half-Gaussian by choosing:

i) $\lambda = -1/s \times \sqrt{\pi/2}$ if its an increasing exponential;

ii) $\lambda = 1/s \times \sqrt{\pi/2}$ if it is decreasing;

iii) If $s<1$ a slightly different guess is done choosing $\lambda = 1/\sqrt{2}$ for an increasing exponential and $\lambda = -1/\sqrt{2}$ for a decreasing one.

In the case of a decreasing exponential we assume for the search $t_0 = u$ and t_f equal to the signal length; in the case of an increasing one, $t_0 = 0$ and t_f equal to the signal length.

b) Using the parameters obtained above as an initial solution, optimize them using a pseudo-Newton method, in order to obtain the damped sinusoid, that is find the 3-tuple $\gamma = [\lambda,\xi,t_0]$, with larger inner product with the signal.

3) After finding the 3-tuple $\gamma = [\lambda,\xi,t_0]$, compute the optimum phase [8][10] for the corresponding atom, and search for the best time support. The search for the best time support is done considering the inner product between the atom and the signal, and also the error in the support region. The resulting time support leads to the largest inner product and smallest error in the support region. From these values we re-optimize the parameters $\gamma = [\lambda,\xi,t_0]$, obtaining the 5-tuple that characterizes the atom given by $\gamma = [\lambda,\xi,\phi,t_0,t_f]$ and also the norm of the atom given by $A = \langle R_x^n, g_{\gamma(n+1)} \rangle$.

This solves the problem of finding the damped sinusoid to match the signal, thus obtaining a decomposition using the **MP** with a dictionary of damped sinusoids. However for power systems signals this is not enough because some errors may occur:

I. Signals formed by two or more sinusoids of same frequency but different amplitudes may be confused as a damped sinusoid. To avoid this problem, we search for a pure sinusoid instead of a damped one. The procedure is described in [12].

II. When there are sinusoids of same frequency and amplitude but different phase, the sinusoids tend to be grouped as one damped sinusoid atom with phase that maximizes the inner product with the signal. This does not represent the structures present in the signal, which comprise phase shifts of the same harmonic. Thus, after the identification of a damped sinusoid we must verify if this type of error happened. The procedure is also described in [12].

With these procedures we cope with the limitations stated at the introduction of the paper for the traditional **MP**. The performance and effectiveness of the procedures presented are accessed in next section.

5 RESULTS

The synthetic signals of Figure 2 and Figure 3 were generated with the proposed model. Table 1 shows the

parameters used in the generation of the synthetic signals as well as the parameters obtained by the decomposition. The decomposition of these signals with the same number of structures used to generate them gives reconstructed signals with SNR of 213.82 dB for *S1* and 148.30 dB for *S2*.

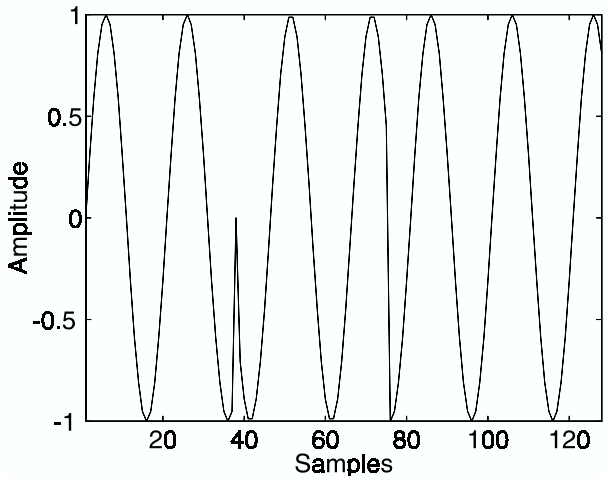

Figure 2: Synthetic Signal S1

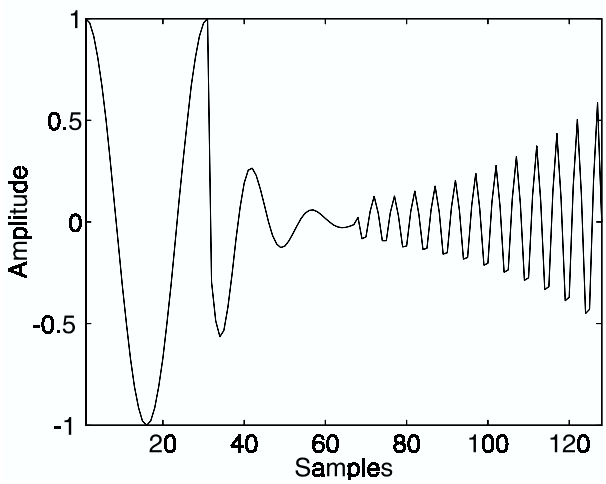

Figure 3: Synthetic Signal S2

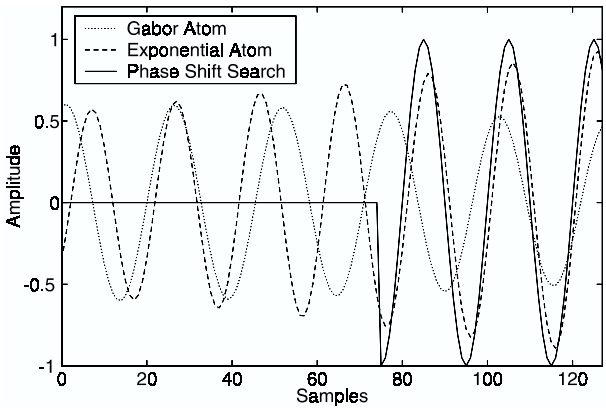

Figure 4: First step in the decomposition of S1.

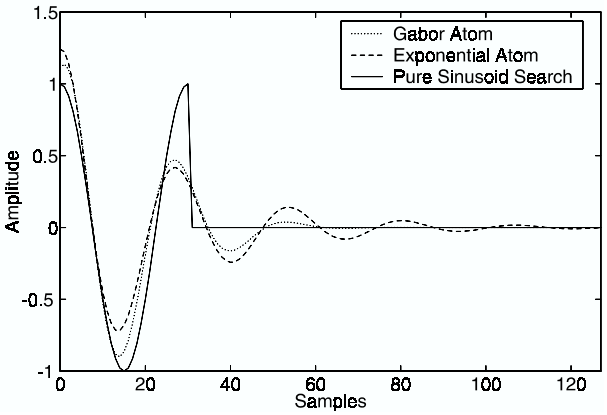

Figure 5: First step in the decomposition of S2.

The first step of the decomposition for the synthetic signals **S1** and **S2** are depicted in Figure 4 and Figure 5. In these examples we see the effectiveness of the Gaussian to exponential envelope matching at the first step of the decomposition at both cases, as well as the pure sinusoid detection procedure for the case of signal **S2** and the phase shift detection algorithm for the case of signal **S1**. This effectiveness can also be confirmed through the parameters estimated by the decomposition process, as shown in Table 1. Also, using a linear quantizer for each of the parameters we can compress the signals obtaining a compression ratio of 8.46 with a SNR of 49.52 dB for **S1** and 8.16 with 45.01 dB of SNR for **S2.** This decomposition can be stopped automatically either after a given error criterion is met or based on the approximation ratio presented at [9][11].

6 CONCLUSIONS

The results shown here are strikingly good, because they enable the decomposition of the signal in "expected" (or coherent) components, rejecting noisy artifacts. At the same time, lossy compression can be performed using components that really matter to the system expert, minimizing any undesired effects introduced by the compression algorithm. This is not the case when using other approaches, like vector quantization or subband coding.

Although the examples used at the paper focus on short time oscillography, the authors understand that oscillography of slow power variations phenomena and power quality can also benefit from this technique, because it is capable of analyzing frequency and modal-domain dynamics of the phenomena.

Table 1: - Parameters used in the generation of synthetic signals *S1* and *S2* according to the model of eq. (4), and the parameters obtained by the decomposition.

Signal	α_q	F_q(Hz)	ϕ_q	λ_q	To_q	Tf_q
S1 Generated	5.2497	60.00	180.00	0.000	0.0625	0.1059
	4.3479	60.00	-90.00	0.000	0.0000	0.0308
	4.4435	60.00	135.00	0.000	0.0317	0.0625
S2 Generated	4.0000	50.00	0.00	0.000	0.0000	0.0200
	1.7226	300.00	75.00	-0.030	0.0447	0.0847
	1.2302	100.00	90.00	0.100	0.0200	0.0533
S1 Decomposed	5.2497	60.00	180.00	0.000	0.0625	0.1059
	4.3480	60.00	-90.00	0.000	0.0000	0.0300
	4.4437	60.00	144.00	0.000	0.0317	0.0617
S2 Decomposed	4.0000	50.00	0.00	0.000	0.0000	0.0200
	1.7230	299.97	68.32	0.029947	0.0447	0.0840
	1.2303	100.01	89.94	0.099994	0.0207	0.0527

7 BIBLIOGRAPHY

[1] ONS, *Procedimentos de Rede, Módulo - 11 Proteção e Controle*, Revisão 0, 07/07/2000, In Portuguese.

[2] Marco A. M. Rodrigues, Mônica V. F. Figueiredo, André L. L. Miranda, Suealine S. Diniz, "Oscillography for Power System Operational Planning", *VII Symposium of Specialists in Electric Operational and Expansion Planning – SEPOPE*, Curitiba, Brazil, May 2000.

[3] M. Kezunovic, A. Hertz, M. V. Gonzales Sabato e Y. Tsujikura, "Practical Intelligent System Applications to Protection and Substation Monitoring and Control", *Proceedings of the 1998 Cigré Session* (1998 - France), Paper 34-104.

[4] Leon Cohen, "Time-Frequency Distributions - A Review", *Proceeding of the IEEE*, vol. 77, no. 7, July 1989, pp. 941-981.

[5] F. Hlawatsch and G. F. Boudreaux-Bartels, "Linear and Quadratic Time-Frequency Signal Representations", *IEEE Signal Processing Magazine*, April 1992.

[6] Stéphane Mallat, "*A Wavelet Tour of Signal Processing*", Academic Press, 1998.

[7] Marco A. M. Rodrigues, "*Efficient Decompositions for Signal Coding*", D.Sc. Thesis, COPPE/UFRJ 1999, Rio de Janeiro, RJ Brazil.

[8] M. E. Goodwin and M. Vetterli, "Matching Pursuits and Atomic Signal Models Based on Recursive Filters Banks", *IEEE Transactions on Signal Processing*, vol. 47, no. 7, July 1999, pp. 1890—1902.

[9] Stéphane Mallat and Zhifeng Zang, "Matching Pursuits With Time-Frequency Dictionaries", IEEE Transactions on Signal Processing, vol. 41 no. 12, Dec. 1993, pp. 3397—3415.

[10] S. E. Ferrando and L. A. Kolasa and N. Kovačević, "A Flexible Implementation of Matching Pursuit for Gabor Dictionaries", the report can be found at **http://www.scs.ryerson.ca/~ferrando/Research/-mpGaborInterval.ps**, 2000.

[11] G. Davis, "*Adaptive Nonlinear Approximations*", Ph.D. Thesis, Courant Institute of Mathematical Sciences, Computer Science Department, New York University, USA, Sept. 1994.

[12] Lisandro Lovisolo, Eduardo A. B. da Silva, Marco A. M. Rodrigues and Paulo S. R. Diniz, "Coherent Decompositions of Power Systems Signals using Damped Sinusoids with Applications to Denoising", to be published in the IEEE International Symposium on Circuits and Systems – ISCAS, May 2002, Arizona, USA.