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AN EXPERIMENTAL ASSESSMENT OF FIR FILTERS APPLIED ON MECHANICAL SYSTEM IDENTIFICATION

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Abstract. *The present work is aimed at assessing the performance of adaptive Finite Impulse Response (FIR) filters on the identification of vibrating structures. Four adaptive algorithms were used: Least Mean Squares (LMS), Normalized Least Mean Squares ($NLMS$), Transform-Domain Least Mean Squares ($TD-LMS$) and Set-Membership Binormalized Data-Reusing LMS Algorithm ($SM-BNDRLMS$). The capability of these filters to perform the identification of vibrating structures is shown on real experiments. The first experiment consists of an aluminum cantilever beam containing piezoelectric sensors and actuators and the second one is a steel pinned-pinned beam instrumented with accelerometers and an electromechanical shaker.*

Keywords: *FIR filter, Adaptive filter and LMS algorithms*

1. Introduction

In the last years, System Identification (Juang, 1994) has emerged as an important discipline providing valuable tools within the Structural Dynamics Field. The applications are very diverse, ranging from active control of vibrations (Clark et. al, 1998) to model updating (Friswell and Mottershead1995), passing through damage detection (Castello et al., 2002) and (Natke and Cempel, 1997). Identification is intended to improve the robustness and performance of the involved systems by helping on building reliable models which provide the ground of modern engineering. Those models are used to understand, to control involved phenomena and, probably their key feature, to predict future behavior.

Broadly speaking, identification consists on the process of developing a mathematical model for a real system by combining physical principles with experimental or field data. Therefore, identification uses a priori information, characterized by the model structure and characteristics, and a posteriori data, such as input-output observations. The main idea is to identify a set of parameters such that, over a desired range of operating conditions, the model outputs are close, in some well-defined sense, to the system outputs when both are submitted to the same inputs. Due to the incompleteness of available information and unavoidable measurement errors, system identification only achieves an approximation of the actual system. Usually this mismatch is treated in a task-oriented perspective, meaning that the assessment of an identification performance approach is carried out directly involving the aimed applications (Morris, 1999). That strongly motivates the development of the present article. It deals with using adaptive Finite Impulse Response (FIR) filter theory (Glentis et. al, 1999), (Diniz, 1997) and (Kuo and Morgan, 1996) to identify second order structural vibrating systems (Castello and Rochinha, 2001) and (Clark et al., 1998). Structural dynamics deals, essentially, with three categories of identification, namely: modal parameter identification, model-based parameter identification and control-oriented identification. The first one, often referred to as modal testing, consists on obtaining modal parameters (e.g. damping, mode shapes, frequencies and modal participation factors) that, commonly, are taken as a basis to update analytical models or detect flaws in structures. The second category normally relies on a set of partial differential equations that expresses the physical principles that support the system's response. The sought parameters are physically meaningful and their identification leads to both a reliable modelling and to a deeper understanding of the physics behind the processes. The last approach, which is tailored to control and fault diagnosis applications, often uses the so called black-box models, whose parameters are, normally, physically meaningless. The structure of the model is chosen from established families of finitely parameterised time-domain representations, like, for instance, difference equations. A remarkable feature of those methods is their ability of handling stochastic environments. Indeed, a fourth category, sometimes referred to as grey or semi-physical modelling, must be mentioned. It combines physical insights with parametric representations, like those mentioned above in the last category. It might be interpreted as an intensive use of a priori information in a black-box approach. The capabilities and limitations of a myriad of identification methods included in each one of the aforementioned categories are investigated and reported in a vast literature (Juang, 1994), (Castello and Rochinha, 2001), (Alvin et. al, 1995), (Ljung, 1987), (Woodbury, 2003), (Fassois et al, 2001), (Fassois et al, 2001), (Ma and Meltcher, 2003), (Fassois, 2001) and (Hemez and Doebling, 2001) to cite a few. In the authors opinion, none of them alone can achieve all the goals defined in different applications. Therefore, there is a need of clearly understanding the performance of a determined method when applied to a specific class of problems. That gives rise to the present work, in which the use of FIR filters for modelling structural dynamic systems is assessed by means of a number of experiments.

The remainder of the paper is organized as follows. Section 2 contains general aspects of applying FIR filters to vibrating structures. Section 3 presents the numerical algorithms applied to the parameters identification. Section 4 deals with some illustrative examples to assess the main characteristics of FIR filters modelling in real structures. Finally, section 5 presents final remarks, comments and future perspectives.

2. FIR FILTER MODELLING OF VIBRATING STRUCTURES

The autoregressive with exogenous excitation (ARX) (Ljung,1987) is a parametric black-box time domain model that describes the system response at a time step n as a function of its response history, system output $\{y(0), y(1), \ldots, y(n-1)\}$, and of the excitation contents, system input $\{u(0), u(1), ..., u(n)\}$, viz.

$$y(n) = \sum_{j=0}^{I} a_j u(n-j) + \sum_{k=1}^{K} b_k y(n-k) \tag{1}$$

where $\{b_1, b_2, \ldots, b_K\}$ are the constants known as the autoregressive (AR) parameters and $\{a_0, a_1, ..., a_I\}$ are constants constituting the exogenous part of the model. Here, all parameters are supposed to be obtained by means of identification techniques. Once specified the model structure, its order (parsimony), the number of parameters $(I + K + 1)$ which, in the context of vibrating structures is connected to the number of degrees of freedom, still remains to be determined.

FIR filters are widely used in signal processing for modelling dynamical systems. They can be interpreted as a particular ARX model in which linear system output at a time step n only depends on the input sequence excitation $\{u(0), u(1), ..., u(n)\}$. Thus, they are obtained setting $b_k = 0$ in Eq. (1), viz.

$$y(n) = \sum_{j=0}^{I} a_j u(n-j) \tag{2}$$

and in the Z-domain Eq.(2) casts as

$$\frac{\hat{y}(z)}{\hat{u}(z)} = H(z) = \sum_{j=0}^{I} a_j z^{-j} \tag{3}$$

where $\hat{r}$ denotes the z-transform of a signal r and $H(z)$ is the z-transfer function of the system.

According to Eq. (3), FIR filters do not possess poles. One should notice that despite the fact that FIR filters, at least in principle, are not capable of reproducing resonance behavior so easily (Kuo and Morgan, 1996), they will be used to describe mechanical systems, which possess resonances as an inherent feature. This is partially motivated by the successful use of FIR filters in mechanical applications like active noise control. In that case, the filters are used to provide models to be used in an adaptive control scheme (Kuo and Morgan, 1996). Here it is important to emphasize that, generally, more parsimonious identified models are obtained using different ARX filters such as the IIR filter. Such a filter possess not only zeros, but also, poles, what easily enables the reproduction of the actual system dynamics, which leads to lower-order identified filters when compared to using FIR. Nevertheless, the ARX filters are not unconditionally stable, i.e., it is necessary to monitor its stability at every step of the updating process (Diniz, 1997), (Kuo and Morgan, 1996) . Moreover, IIR adaptive algorithms are more complex and computationally intensive presenting slow convergence rates when compared with that of FIR filters.

2.1. Algorithms

As the following algorithms can be easily found in literature, this section is devoted to present their basic steps and characteristics .

2.2. LMS algorithm

Basically, the LMS algorithms casts as

$$\mathbf{a}(n+1) = \mathbf{a}(n) + \mu\, e(n)\mathbf{u}(n) \tag{4}$$

where μ is the convergence factor of the algorithm and $\mathbf{a}(n)$ is the filter coefficient vector at step n . In order to assure convergence of the coefficients in the mean to optimal solution $\mathbf{a}_0$, the convergence factor μ must be chosen in the range (Diniz, 1997)

$$0 < \mu < \frac{2}{\lambda_{max}} \tag{5}$$

where λ_{max} corresponds to the maximum eigenvalue of the matrix $\mathbf{R}$ (Diniz, 1997). In practice, one may use the following relation (Diniz, 1997)

$$0 < \mu < \frac{2}{\mathrm{Tr}(\mathbf{R})} \tag{6}$$

where $\mathrm{Tr}(\mathbf{R})$ denotes the trace of the matrix $\mathbf{R}$. It is significative to obtain an upper bound to the convergence factor μ, nevertheless, it should be remarked that inequality (6) was derived assuming several hypotheses, which are not easily reproduced in engineering applications. Therefore, in most of the cases, the value of μ should not be chosen close to its upper bound (Diniz, 1997).

2.3. NLMS algorithm

In order to increase the convergence speed of the LMS algorithm without using estimates of the input signal correlation matrix, a variable convergence factor is a natural solution (Diniz, 1997). Usually, convergence using the Normalized Least-Mean Squares (NLMS) algorithm is easily attained when compared to the LMS case as the choice of the involved parameters is simpler, what might lead to improved convergence rates. For the sake of simplicity, the summary of the adaptation process of the filter coefficients reads as

$$\mathbf{a}(n+1) = \mathbf{a}(n) + \frac{\mu_n}{\gamma + \mathbf{u}^T(n)\mathbf{u}(n)}\, e(n)\mathbf{u}(n) \tag{7}$$

where μ_n is the constant convergence factor and γ is a small constant introduced in the updating formula aiming at avoiding large step sizes when $\mathbf{u}^T(n)\mathbf{u}(n)$ gets very small. The constant convergence factor μ_n must reside in the interval $(0, 2)$. For further details about $NLMS$ algorithm see (Diniz, 1997) and (Glentis et al, 2001).

2.4. Transform-Domain LMS algorithm

In general it can be shown (Widrow at al., 1976) that for stationary input and sufficiently small convergence factor μ, the speed of convergence of the algorithm is dependent on the eigenvalue spread of the matrix $\mathbf{R}$, i.e., depends on the ratio

$$\frac{\lambda_{max}}{\lambda_{min}} \tag{8}$$

where λ_{max} and λ_{min} are the maximum and the minimum eigenvalues of $\mathbf{R}$. Slow convergence rate is expected when ratio (8) is large. When the input signal is highly correlated, one may use the transform-domain algorithm to increase the convergence speed of the LMS algorithm (Diniz, 1997), (Narayan and Peterson, 1983) and (Marshall et al., 1989). The basic idea is to somehow transform the input signal $\mathbf{u}(n)$ into another signal with the corresponding autocorrelation matrix having smaller eigenvalue spread. Aiming at this purpose, one may transform the input vector $\mathbf{u}(n)$ in a more convenient vector $\mathbf{s}(n)$, through the application of an orthonormal (or unitary) transform $\mathbf{T}$ (Diniz, 1997), viz.

$$\mathbf{s}(n) = \mathbf{T}\mathbf{u}(n) \quad \text{where} \qquad \mathbf{T}\mathbf{T}^T = \mathbf{I}_d \tag{9}$$

where $\mathbf{I}_d$ stands for the identity operator.

Hence the filter output is obtained by multiplying the input $\mathbf{s}$ by the transform-domain filter coefficient vector $\hat{\mathbf{a}}$

$$y(n) = \hat{\mathbf{a}}^T(n)\mathbf{s}(n) \tag{10}$$

The transform-domain filter coefficient update is given as follows

$$\hat{a}_i(n+1) = \hat{a}_i(n) + \frac{2\mu}{\gamma + \sigma_i^2(n)}\, e(n)s_i(n) \tag{11}$$

In (11) the signals $s_i(n)$ are normalized by their power denoted by $\sigma_i^2(n)$ only when applied in the updating formula such that

$$\sigma_i^2(n) = \alpha\, s_i^2(n) + (1-\alpha)\,\sigma_i^2(n-1) \tag{12}$$

where α is a small factor within the interval $0 < \alpha \leq 0.1$ and γ is also a small constant to avoid that the second term of the update equation becomes too large when $\sigma_i^2(n)$ is small.

In matrix form the updating equation casts as follows

$$\hat{\mathbf{a}}(n+1) = \hat{\mathbf{a}}(n) + 2\mu\, e(n)\boldsymbol{\sigma}^{-2}(n)\mathbf{s}(n) \tag{13}$$

where $\boldsymbol{\sigma}^{-2}(n)$ is a diagonal matrix which contains the inverse of the power estimates of the elements $\mathbf{s}(n)$ added to γ (Diniz, 1997). The convergence of the coefficient vector is determined by the eigenvalue spread of $\boldsymbol{\sigma}^{-2}(n)\,\mathbf{R}_s$, where $\mathbf{R_s} = \mathbf{T}\,\mathbf{R}\,\mathbf{T^T}$ (Diniz, 1997).

It can be shown that the effect of applying the transformation matrix $\mathbf{T}$ is to rotate the axis such that they become aligned with the principal axis of the hyperellipsoidal equal-error-contours. It should be emphasized that the eccentricity of the error surface remains unchanged by the application of the transformation and so does the eigenvalue spread. Therefore, aiming at reducing the eigenvalue spread, each element of the transform output $\mathbf{s}$ is power normalized, in the updating process, as we can be noticed in equation (11)(Diniz, 1997) and (Marshall et al, 1989). An important topic here is which orthogonal transformation should be used, and this issue is stressed elsewhere in (Diniz, 1997),(Narayan and Peterson, 1983) and (Marshall et al., 1989). For the present work, as the signals processed are real, the authors have chosen to use the discrete cosine transform DCT motivated by the experiences reported in (Diniz, 1997). Another approach that can be used to improve the performance of the LMS algorithm is based on the concept of structural subband decomposition (Mahalanobis et al., 1993), what is a generalization of the transform domain adaptive filtering. Doğançay (D OĞançay, 2003) analyses the computational complexity and convergence performance of transform-domain adaptive filtering algorithms including the so-called selective-partial-update strategy for transform-domain algorithms, where the adaptive filter coefficients are segmented into blocks and only a number of these blocks are selected to be updated at every iteration.

2.5. Set-Membership Binormalized Data-Reusing LMS Algorithm-II

Aiming at speeding up the convergence of the algorithm at the expense of low additional complexity, Diniz and Werner presented the Set-Membership Binormalized Data-Reusing LMS Algorithms (Diniz and Werner, 2003). The algorithm requires the introduction of a constraint set H_n which contains all filter coefficient vectors $\mathbf{a}$ that generate an output error $e(n)$ bounded in magnitude by an a priori defined quantity β, viz.

$$H_n = \{\mathbf{a} \in \mathbf{R}^{1+I} /\ |d(n) - \mathbf{a}^T\,\mathbf{u}(n)| \leq \beta\} \tag{14}$$

The basic idea consists on designing a filter whose solution belongs not only to H_n, but also to H_{n-1}, i.e.,

$$\mathbf{a}(n+1) \in H_n \cap H_{n-1} \tag{15}$$

Details about the algorithms are presented in (Diniz and Werner, 2003). For the present work the authors adopted the Set-Membership Binormalized Data-Reusing LMS Algorithm - II, which will be referred to as $SM - BNDRLMS$ throughout the text. For the sake of simplicity, the summary of the adaptation process of the filter coefficient vector reads as

$$\mathbf{a}(n+1) = \mathbf{a}(n) + \frac{\lambda_1^{'}}{2}\,\mathbf{u}(n) + \frac{\lambda_2^{'}}{2}\,\mathbf{u}(n-1) \tag{16}$$

Table 1: Natural frequencies (Hz) for the pinned-pinned beam.

Mode no.	Experimental	*FEM*
1	8.6	8.6
2	33.6	34.4
3	75.8	77.3

Table 2: Experiment setup.

Experiment no.	Excitation type	sampling frequency (Hz)	cut-off frequency (Hz)
1	white-noise	400	100
2	sine-chirp (0-100) Hz	800	100
3	$\sin(150\pi)$	800	100

where

$$\frac{\lambda_1^{'}}{2} = \frac{\eta(n)\, e(n)\, ||\mathbf{u}(n-1)||^2}{||\mathbf{u}(n)||^2\, ||\mathbf{u}(n-1)||^2 - [\mathbf{u}^T(n-1)\, \mathbf{u}(n)]^2} \tag{17}$$

$$\frac{\lambda_2^{'}}{2} = \frac{\eta(n)\, e(n)\, \mathbf{u}^T(n-1)\, \mathbf{u}(n)}{||\mathbf{u}(n)||^2\, ||\mathbf{u}(n-1)||^2 - [\mathbf{u}^T(n-1)\, \mathbf{u}(n)]^2} \tag{18}$$

$$\eta(n) = \{1 - \beta/|e(n)| \quad \text{if} \quad |e(n)| > \beta; \quad 0 \quad \text{otherwise.}\} \tag{19}$$

Two points should be remarked here, the first one is concerned with the fact that the updating step occurs only if the evaluation of $\eta(n)$ is positive, fact that corresponds to an innovation check as defined by Diniz and Werner (Diniz and Werner, 2003). Moreover, in a computational environment where different tasks must be accomplished at the same time, this innovation check reduces the computational burden. The second one is concerned with the denominator of the parameters $\lambda_j^{'}$. Whenever it is zero, the updating of the Set-Membership Normalized LMS ($SM-NLMS$) (Diniz and Werner, 2003) must be used, which casts as

$$\mathbf{a}(n+1) = \mathbf{a}(n) + \eta(n)\; e(n)\; \frac{\mathbf{u}(n)}{||\mathbf{u}(n)||^2} \tag{20}$$

The computational complexity associated to each one of the aforementioned algorithms is addressed in (Glentis et al. 1999), (Diniz, 1997) and (Diniz and Werner, 2003)

2.6. Illustrative examples

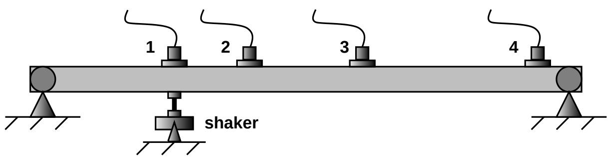

Figure 1: Testbed sketch of the second experiment.

The testbed for the second experiment is depicted in Figure (1). The beam is made of steel and its dimensions are: 1467x76.2x7.9 *mm*. Four piezoelectric accelerometers: 33B52-PCB-PIEZOTRONICS were used. Starting from the left end of the beam, the accelerometers are located at 1/4, 1/3, 1/2 and 5/6 of the beam length. Although there were four available accelerometers, only the number 1, placed in a collocated disposition, was used for the adaptation processes. Tables 1 and 2 present the first three natural frequencies obtained both experimentally and by a Finite Element Analysis (FEM) acquisition parameters utilized for all experiments respectively.

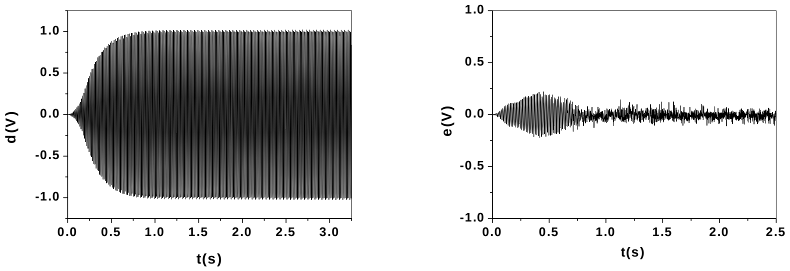

Figure 2: Desired response for experiment 3 and the error function based on the LMS algorithm.

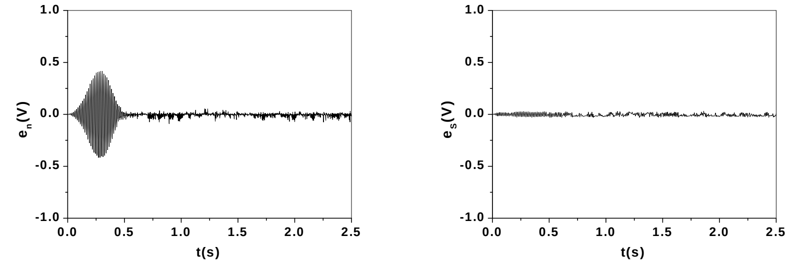

Figure 3: Error function based on $TD-LMS$ and on the $SM-BNDRLMS$ algorithm.

Figure (2) shows the experimental desired response of the system on the left and the error based on the identification performed by means of the LMS algorithm. Figure (3) depicts the errors obtained by the identification based on the $TD-LMS$ (on the left) and on the $SM-BNDRLMS$ algorithm (on the right). Analyzing the error functions e, e_n and e_s of the three algorithms, one may conclude all of them achieved to identified models that reproduce the actual response of the system. However, aiming at obtaining a closer look at the parameter convergence issue, one may define a normalized filter coefficient ω_j defined as follows

$$\omega_j(n) = \frac{a_j(n)}{a_{o,j}} \tag{21}$$

where $a_j(n)$ and $a_{o,j}$ correspond to the $j-th$ filter coefficient at the $n-th$ iteration and to the $j-th$ component of the optimum solution $\mathbf{a}_o$. Figure (4) show the evolution of the normalized parameters along the iterations for the LMS (on the left) and $TD-LMS$ (on the right) algorithms. Figure (5) show the evolution of the normalized parameters along the iterations for the $SM-BNDRLMS$ algorithm.

From figures (4) and (5) it is clear that the transform-domain accelerated the convergence of the filter coefficients. The LMS algorithm required more than 1500 iterations to achieve convergence while for the transform-domain LMS it was accomplished with at most 1100 iterations. From figure (5) it is clear that the second component of the filter coefficient based on the $SM-BNDRLMS$ achieved convergence at iteration number 1000 approximately while the first component of the filter starts oscillating around the optimum value at iteration number 1000. Nevertheless, the mean value of each filter coefficient is close to its respective optimum value and moreover, the $SM-BNDRLMS$ had only 1093 updates while LMS and $TD-LMS$ had 2500 ones.

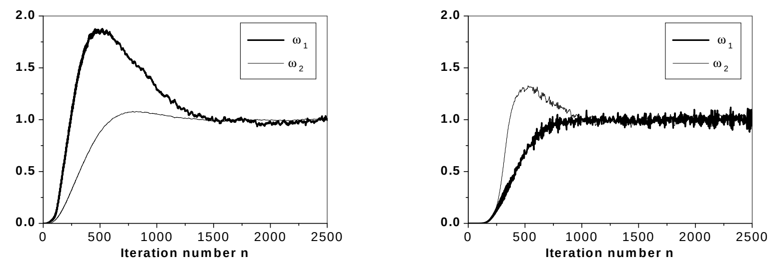

Figure 4: Evolution of the normalized filter coefficients of the LMS and $TD-LMS$ algorithms.

Aiming at investigating an identification process through which a broad-band input signal is used to excite the beam, and in which, mismodelling will probably play a role, the next case deals with experiment number 1

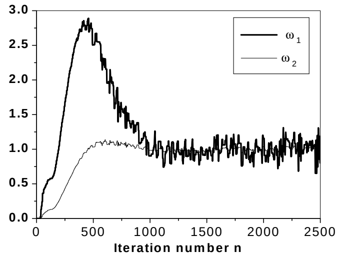

Figure 5: Evolution of the normalized filter coefficients ($SM-BNDRLMS$).

data. As the input is a white-noise excitation, it is expected that minimizing the error function will force the filter coefficients to approach the impulse response of the system.

The comparison of the performance of the different algorithms mentioned before is now carried out. A comparison in the frequency domain will be done considering the identified systems by LMS, $NLMS$, $TD-LMS$ and $SM-BNDRLMS$ algorithms and, for each one of them, an average of its respective filter coefficient vector. For this, the following parameters have been chosen: $I+1 = 200$, $\mu = \frac{1}{7}$, $\mu_{TD} = 1/200$ (convergence factor for the $TD-LMS$ algorithm), $\mu_n = 1.0$, $\gamma = 0.001$, $\alpha = 0.025$ and $\beta = 0.087$.

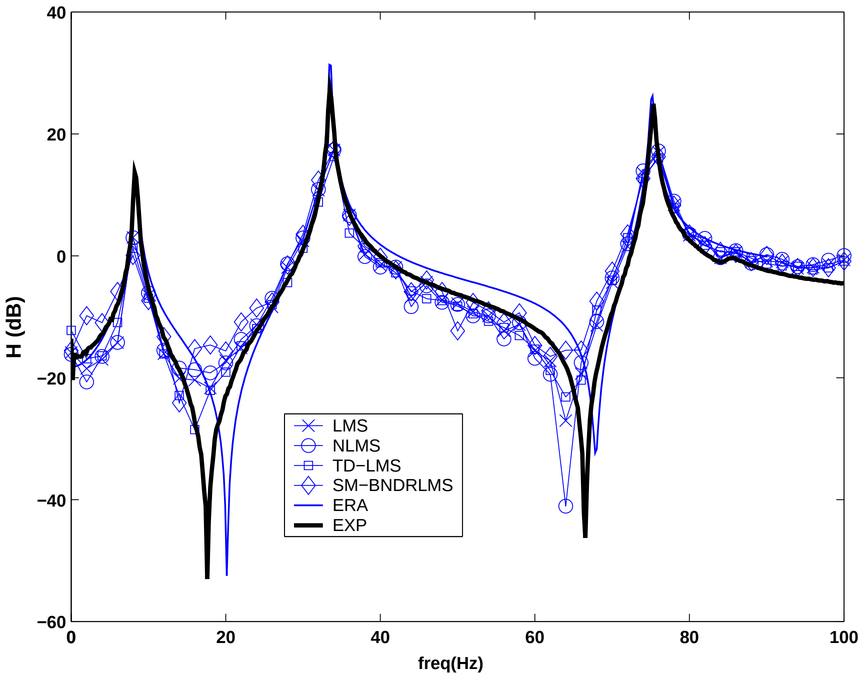

Figure 6: Identified systems.

Figure (6) depicts the representation of systems identified by means of the LMS, $NLMS$, $TD-LMS$ and $SM-BNDRLMS$ algorithms, one identified by means of the Eigensystem Realization Algorithm with Data Correlations (ERA/DC) (Juang, 1994) and the direct frequency response function H of the system, which is denoted by EXP. The identification by means of the ERA used the response coming from all the available accelerometers shown in figure (1) and took into account the experimental information within the band (0,100) Hz and it was added to the comparisons due to the fact that it is a well know identification technique in the vibration and modal analysis community. The data used for the direct frequency response function and for the ERA/DC had a sampling frequency of 400 Hz and cut-off frequency of 100 Hz.

It is clear from figure (6) that, despite the specific differences, all the LMS-based algorithms were able to capture the essence of the system dynamics, although the anti-resonances were not fully captured. The ERA was also able to capture the essence of the system, although it did not capture the anti-resonances either. A closer look at the system provided by the $SM-BNDRLMS$ reveals some small oscillations, but it has to be highlighted that only 1746 updates were necessary which represents, from the computational standpoint, a gain as all the other algorithms required at least 5000 iterations.

The running time of the algorithms, for an off-line identification, is shown in table 3. Two points should be remarked here. The first one is associated to the fact that, the final instant of time of the experimental signals is

Table 3: Running time for the algorithms.

LMS	$NLMS$	$SM-BNDRLMS$	$TD-LMS$	t_f (s)
2.03 s	2.15 s	2.75 s	376.02 s	12.50 s

$t_f = 12.5\,s$ and that the LMS, $NLMS$ and $SM-BNDRLMS$ performed all the required numerical operations in a period less than 3 s, i.e., they would probably accomplish their task in an on-line environment system identification process. Nevertheless, although the $TD-LMS$ algorithm provided an effective identification the period of time required to perform all the numerical operations was 376.02 s, due to the fact that the discrete cosine transformation had to be applied at every iteration of the algorithm.

Some points need to be highlighted now. The first one is that although $TD-LMS$ algorithm is aimed at accelerating the convergence rate of the LMS, the length of the adaptive filter is a more critical issue than it is for LMS, $NLMS$ and $SM-BNDRLMS$ algorithms. Such thing happens due to the required operations involved in the calculation of the unitary transformation of the vectors $\mathbf{u}(n)$. In a situation in which a large number of filter coefficients is required the complexity of the orthogonal transform and power normalization can be reduced by using a selective-partial-update strategy as reported in (DOǦançay, 2003). The second concerns the input signal and the transformation that was used here, i.e., the DCT was only one possibility among a myriad. Unfortunately, due to the mismodelling problem combined with measurement noise, and to the large number of coefficients, it is difficult to analyze the evolution of each filter coefficient as it was accomplished before.

3. Concluding Remarks

In the present work, vibrating systems were successfully identified by FIR filters combined with adaptive algorithms. The effectiveness of the method was assessed on experimental data and the provided results may be considered compelling and effective for the examples that were considered. Such examples have considered different types of excitation such as harmonic, sine-chirp and white-noise. The filter adaptation was performed using four LMS-based algorithms, LMS, $NLMS$, $TD-LMS$ and $SM-BNDRLMS$. A comparison of the models identified by means of FIR filters and ERA with the experimental FRF was carried out. This comparison showed a good agreement between the model identified by means of FIR filters with the direct frequency response function of the system. It should be remarked that the $SM-BNDRLMS$ algorithm seems to be prone to be used in control applications of linear systems inasmuch as it is able to obtain low-excess mean-squared error and to the fact that it does not need to update its filter coefficients at every iteration, what is very attractive for real time implementation. A point to be emphasized is that this type of identification, at least in principle, does not furnish any relation between the filter coefficients and the physical parameters of the system. Nevertheless, one should remark that this method possesses a relatively simple and stable implementation what enables its use in on-line identification involving situations where fast analysis is required to indicate any system's change that can be considered a signal of damage or faults.

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