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Virtual sensing in the reverberant field based on the harmonic signal from the emitting source.

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ABSTRACT

To perform active noise control it is necessary to establish sensors locations, knowing that the error sensors should be placed near to areas that we want to reduce the noise. It´s quite inconvenient the need of positioning the error sensor in the center of a room, or in walking areas, or near of the observer's ears, so, It has been investigated a new method, that does a virtual detection from the physical sensors. In this paper we investigate the remote responses obtained in a reverberant room, from a generated harmonic signal. The acoustic emission is characterized from one vibrational sensor and it is used artificial neural networks to estimate a virtual detection response. Was compared and investigated: the neural network architecture, the usage of reference signals, influences due to environment changes, operating condition changes and noises from other sources. Frequency responses in magnitude and phase were also evaluated and compared. It has been investigated ways to accomplish the system identification, and the evaluation of the answers accuracy when there are changes in the dynamics of propagation.

Keywords: Virtual response, Neural Network, Reverberation Room I-INCE Classification Number: 25.4

1. INTRODUCTION

The active noise control (ANC) is an attractive approach to get noise reduction at low frequencies, creating a quiet zone at a determined location or even to get global noise reduction. However it is difficult to find the best location for the system due to a large amount of possible combinations, environmental variations, tridimensional propagation, alterations on the operational conditions and influence from other sources.

Another inconvenient is that the error sensors must be placed near the areas where noise should be reduced. It can be quite difficult the need to put sensors at the center of a room or next to observer's ears. Thus, the challenge turns in create a quiet zone surrounding the destination points, without putting any physical sensor in these locations. One method that has been investigated is the virtual detection from the physical sensors, placed near the objective of control.

The technique of virtual detection consists in putting the physical sensors in possible place. From those physic sensors, the signals are acquired, processed and must be equivalent to the signal in those desired location. Such technique provides improvements over traditional ANC, bypassing the physical constraints encountered in the field.

To establish the virtual microphone, are necessary the systems models or transfers functions to process the data sets from the real sensors. This way, the precision of the model is crucial. Wilson (1997) had proposed the use of artificial neural network (ANN) to model a system.

Many algorithms for virtual detection have been searched on the last years. The method of the virtual microphone proposed by Elliott and David (1992), used a primary sound field to predict the sound pressure in a short distance from a real microphone. It was supposed that the sound pressure

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would be the same for physic and virtual microphones.

Roure and Albarrazin (1999) had used the concept of remote microphone technique to get a set of transfer functions without the need to assume the sound field for physical and virtual microphones.

The technique for future estimation, based on polynomial extrapolation of acoustics signals was applied and afterwards it was extended using the LMS (Least Mean Square) in one type of adaptive algorithm, to get the ideal weights for the extrapolation (MUNN et. al.; 2002), (CAZZOLATO; 2002).

Petersen et al. (2006, 2007) investigated the movement of virtual sensor using active control system to get local attenuation. They were able to generate a silent zone that could move, following the observer's ear.

Moreau et al. (2008) studied the performance of a virtual microphone system that accompany the head spin movement in a tridimensional field. As a result, there was attenuation improvement compared with the static or fixed position of the virtual microphone. Based on the estimation of the ideal state, Petersen et al. (2008) used the Kalman filter to design the virtual sensor applied to active noise control. Also, there was the study of virtual sensing in the diffuse field. (MOREAU et al., 2009).

Das et al. (2010, 2013) presented applications of the FSLMS nonlinear algorithm, for virtual microphone. Some of the nonlinear algorithms commonly used in active control are FXLMS (Filtered-x Least Mean Square), FSLMS (Filtered-s Least Mean Square) and NARX (Nonlinear autoregressive exogenous model).

As advantages, the development of virtual detection techniques: A better efficiency in the noise attenuation when compared with the positioning of a real microphone, and also, the possibility to promote the microphone displacement from its virtual location, in order to follow small movements of the receiver such as the head spin, maintaining the efficiency on the sound attenuation. (PETERSEN et al.; 2006, 2007), (MUREAU et al.; 2008).

2. METHODOLOGY AND MODELING

2.1 Experimental Setup

Aiming to investigate virtual sensing applications in active noise control, it was generated an harmonic signal at frequency of 160 Hz in a woofer that is a kind of speaker, placed at the bottom corner of an empty room with dimensions: 4841 x 4023 mm^2 and 2465 mm tall. The acquisition of responses was taken in 4 physical positions in rate of 0 a 719 Hz, using 16384 points and cut frequency at 700 Hz. The figure 1 illustrates the block diagram from generation set until signals acquisition.

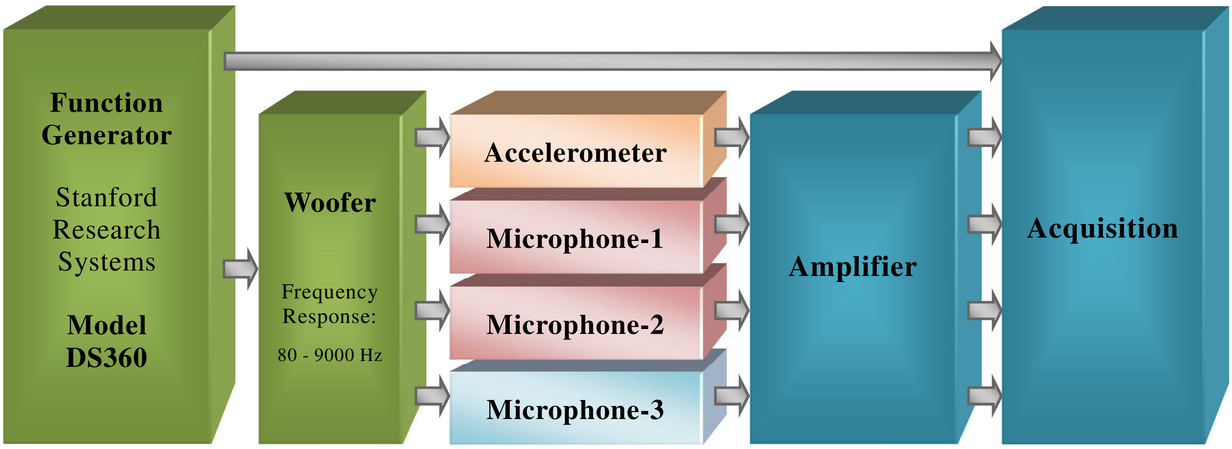


Figure 1 – Block diagram from the generation set until the signals acquisition.

An accelerometer was attached on the speaker membrane to characterize acoustic field of vibrational signal. The microphone 1 measures acoustic signal next the speaker while the microphones 2 and 3 measure the signal from reverberant field. The microphone 3 was used to compare and to estimate the virtual response. The microphone 2 was positioned between microphones 1 and 3 at distance of 450 mm from microphone 3.

2.2 Network Architectures

To define the network architecture, were designed static neural networks, time delay and recurrent neural networks. At first step, were defined neural networks with 2 and 3 hidden layers, 10 and 20 neurons on the input layer, 4 position delay, activation functions “tansig” and “purelin”, 01 or 02 signals as input and 500 interactions as maximum epoch. Each set used on training was composed by 53000 data points.

For static neural networks, we have been defined: Feedforward (FF) and Cascade Feedforward (CFF). The main characteristics for these neural networks are their capability to adapt to any function with a finite number of discontinuities, since that there be an enough number of neurons in the hidden layers, so, these networks are quite used as an universal approximator of functions. (FONSECA, 2013).

For dynamics neural networks, with time delay and feedback characteristics, it was defined: Focused Time Delay (FTD), Distributed Time Delay (DTD), Layer Recurrent (LR) and Nonlinear Autoregressive Network with Exogenous Inputs (NARX).

The NARX neural networks have feedback connections between layers in architectures based on autoregressive models. A regression model as ARMAX type, can be defined as an extension of a linear model. Equations (1) and (2) represent a model with one input and one output.

$$\begin{aligned} a_0.y(k) + a_1.y(k-1) + \cdots + a_q.y(k-Q) \\ = w_0.x(k) + w_1.x(k-1) + \cdots + w_R.x(k-R) \end{aligned} \tag{1}$$

$$y(k) = \frac{1}{a_0}\left(\sum_{i=0}^{R} w_i\, x(k-i) - \sum_{j=1}^{Q} a_j\, y(k-j)\right) \tag{2}$$

This kind of model implies that actual output $y(k)$ is given as a weighted sum of past values of output and exogenous values from the input $x(k)$. In Eq. (1), the terms $x(k), \ldots, x(k-R), y(k-1), \ldots, y(k-Q)$ are the input variables and the lagged outputs, called regressors. In this way, the actual output $y(k)$ on ARX model is the weighted sum of its regressors. This linear structure can be extended to create the nonlinear form called (NARX):

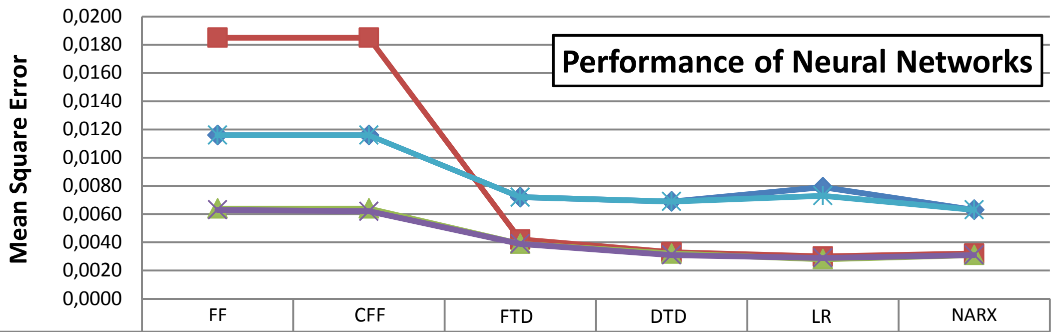
$$y(k) = f\big(x(k), x(k-1), \ldots, x(k-R), y(k-1), y(k-2), \ldots, y(k-Q)\big) \tag{3}$$

Where the function f is a nonlinear function in which the inputs are regressors of the model. It is also possible that there be delayed inputs and outputs.

2.3 Selection of the Neural Network

To select the best neural network based on performance and low computational cost, were considered changes in the number of neurons, number of hidden layers and input signals, where could be observed:

- The Feedforward (FF) and Cascade Feedforward (CFF) neural networks present the worst performance, compared with the other architectures, when using the same settings for training.
- There was no significative improvement at performance when increasing the number of neurons. Curves (1) and (5) in graph of figure 2.
- There was no significative improvement at performance when increasing the number of hidden layers. Curves (3) and (4) in graph of figure 2.
- The use of microphone (Mic1) as input signal provides a better estimate than using accelerometer as input signal. See curve (2) compared with curves (1) and (5) in the graph of figure 2. This is due to higher microphone sensibility to background noise and due to the reverberant field in the room. The accelerometer is more sensitive to vibrational field of source.
- The better results were obtained when using the accelerometer and microphone (Mic1) as input signals. Curve (3) in the graph of figure 2.
- In all configurations, the Layer Recurrent (LR) neural network, present good results on performance. However these networks present high computational cost.



	FF	CFF	FTD	DTD	LR	NARX
Ax10x1	0,0116	0,0116	0,0072	0,0069	0,0079	0,0063
M1x10x1	0,0185	0,0185	0,0042	0,0033	0,0030	0,0032
(A+M1)x10x1	0,0064	0,0064	0,0039	0,0032	0,0028	0,0031
(A+M1)x10x5x1	0,0063	0,0062	0,0039	0,0031	0,0029	0,0031
Ax20x1	0,0116	0,0116	0,0072	0,0069	0,0073	0,0063

Figure 2 – Comparative graph between performances by the neural networks.

Thus, neural networks with Focused Time Delay (FTD) and Nonlinear Autoregressive Network with Exogenous Inputs (NARX) provided the best results. When performing a more refined study among these networks, can be noticed that the NARK neural network has the best performance and the configuration with 03 neurons, has shown to be a good choice for this architecture.

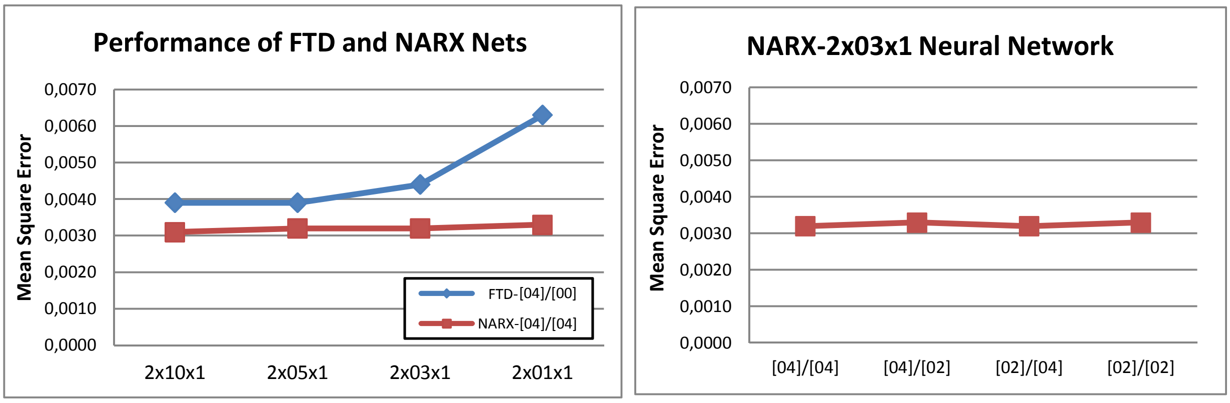


Figure 3 – (a) Performance when changing the number of neurons
(b) Performance when changing time delay for NARX neural network.

3. RESULTS

3.1 Virtual response in a closed room

Were considered signal generation and signal acquisition at 06 levels of amplitude (24, 26, 28, 30, 32, 34V) adjusted on the DS360 Generator, in an empty room with closed doors, in the frequency of 160 Hz. For the neural network training, were provided 196608 sets and configured 06 NARX neural networks: (A)x03x1, (M1)x03x1, (M2)x03x1, (A+M1)x03x1, (A+M2)x03x1, (A+M1+M2)x03x1

For evaluate the estimative of response were used three sets of data:

a) Case 1 - Amplitude of 25 V obtained in an empty room with closed doors.
b) Case 2 - Amplitude of 28 and 32 V obtained in an empty room with opened doors.
c) Case 3 - Amplitude of 26 and 30 V performing movements into the room, opening and closing door and curtains.

These sets weren´t presented previously for neural network training. The figures 4 and 5 illustrate the estimated responses by the (A+M2)x03x1 neural network. OBS: The labels RNA in the following figures illustrate the estimated signals by NARX Neural Networks.

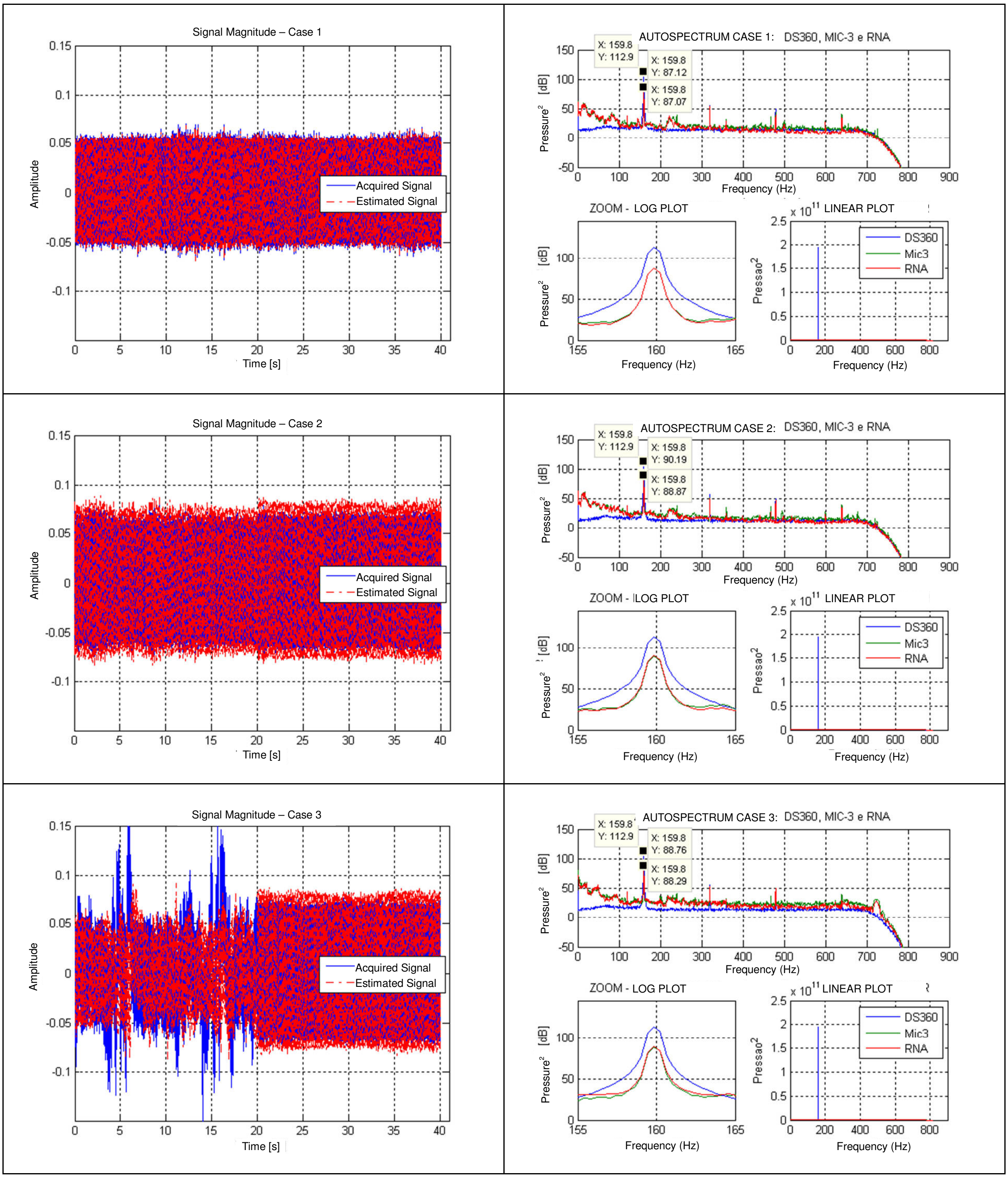


Figure 4 – Comparation among the real and estimated response:
(a) Time signals. (b) Auto spectrum: Generated signal, real signal and estimated signal.

Although there are differences in the time and the frequency spectrum of magnitude signals, it can be notice in figure 4 that the error of cases 1, 2 and 3 were in 0.06%, 1.48% and 0.53% respectively.

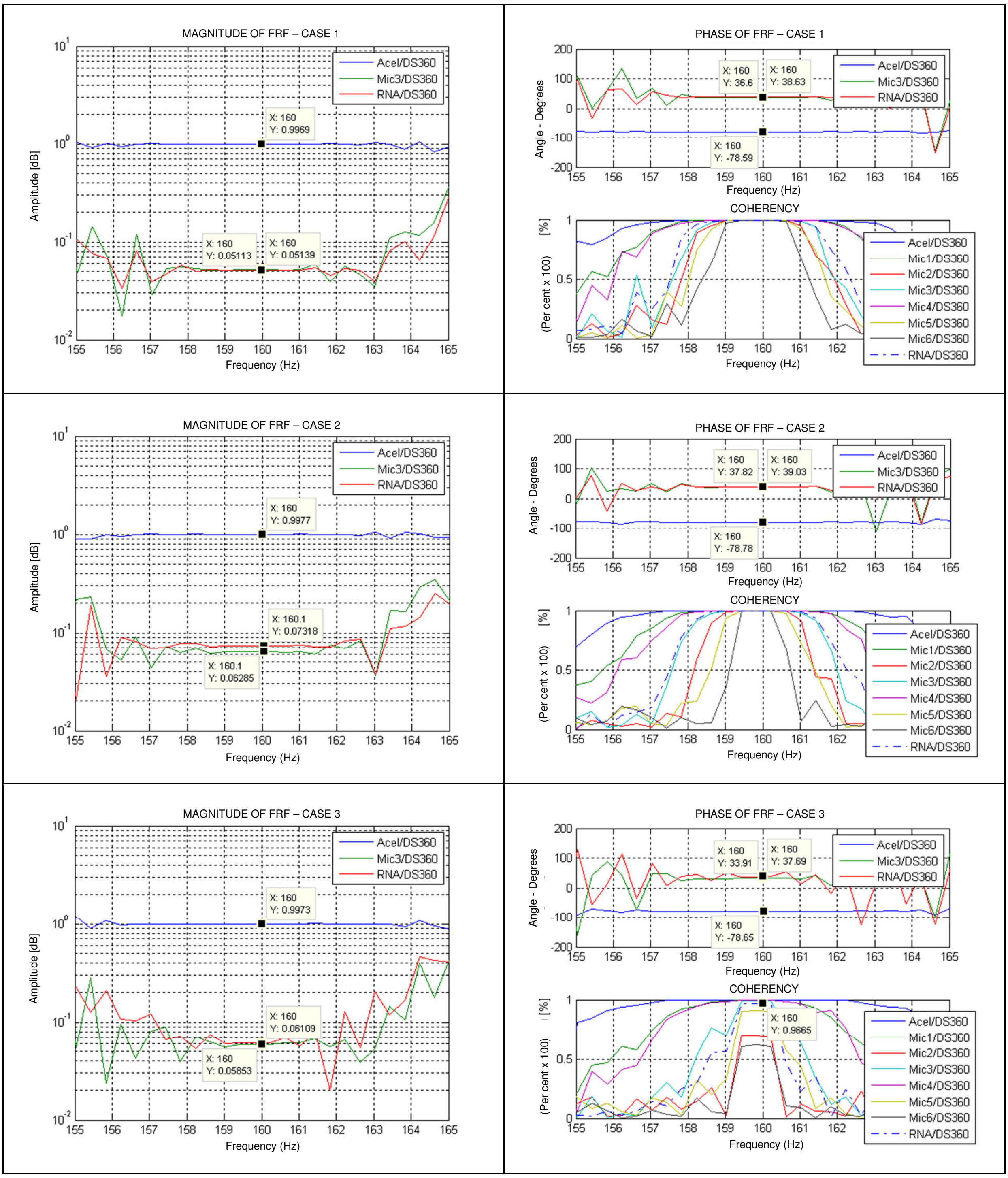


Figure 5 – Comparation among the real and estimated response:
(a) Magnitude of FRF (b) Phase and coherence among signals.

In the figure 5, can be observed that the magnitude of the FRFs, the error stays in 0.51%, 16.44% and 4.37% for the cases 1, 2 and 3. In the phase, the estimated error was in 5.55%, 3.19% and 11.15% for the three cases respectively. Also, it can be noticed that the coherence remains in 96.65%.

3.2 Virtual response in a opened room

At this step, was remained the signal generation and signal acquisition at the 06 levels of amplitude (24, 26, 28, 30, 32, 34V) and in the frequency of 160 Hz used before, nevertheless, the doors were open to change the reverberation level of the room. The strategies of retraining, reset and reinforcement were defined for a new training of the neural networks. For the retrain, was maintained the training done in the previous step and it was brought the new data set obtained in this step. For reset, we presented the data sets from both steps to start a new training. For reinforcement, was kept the training of the first step and was presented, all the entire data set obtained in steps 1 and 2.

Obviously, the better results, occurs to the cases 1 and 2 due to the data from both set, presented for training. However, to evaluate the strategy used to training (retraining, reset and reinforcement), observed that the strategy of reset showed the smaller errors (mean square) and the smaller computational costs.

The figures 6 and 7 illustrated the estimated responses by (A+M2)x03x1 neural network, using the strategy of reset for the training.

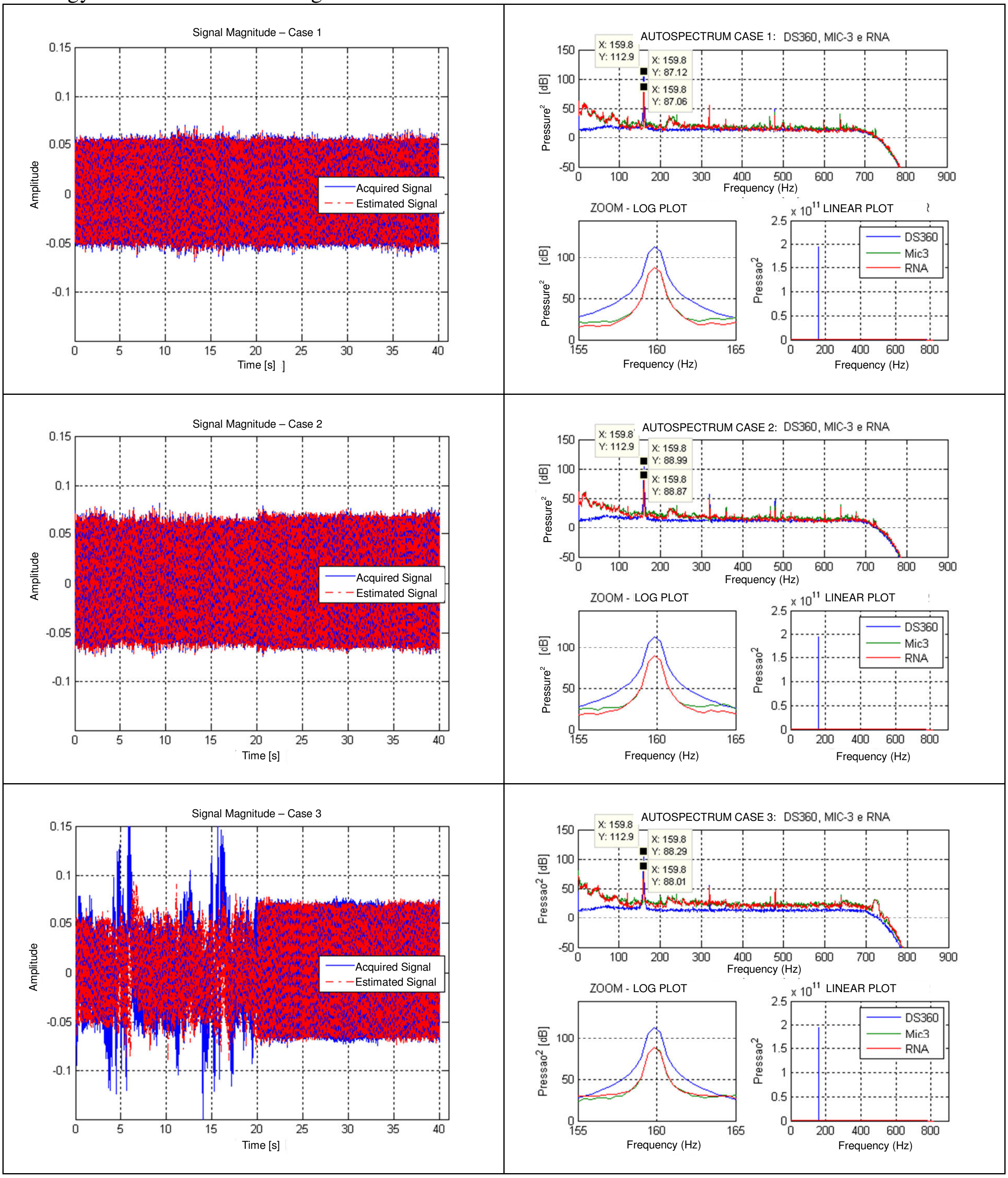


Figure 6 – Comparation among the real and estimated response:
(a) Time signals. (b) Auto spectrum: Generated signal, real signal and estimated signal.

It can be noticed in figure 6, that the error in the auto spectrum of cases 1, 2 and 3 were in 0.07%, 0.14% and 0.32% respectively. There was a global improvement compared to figure 4.

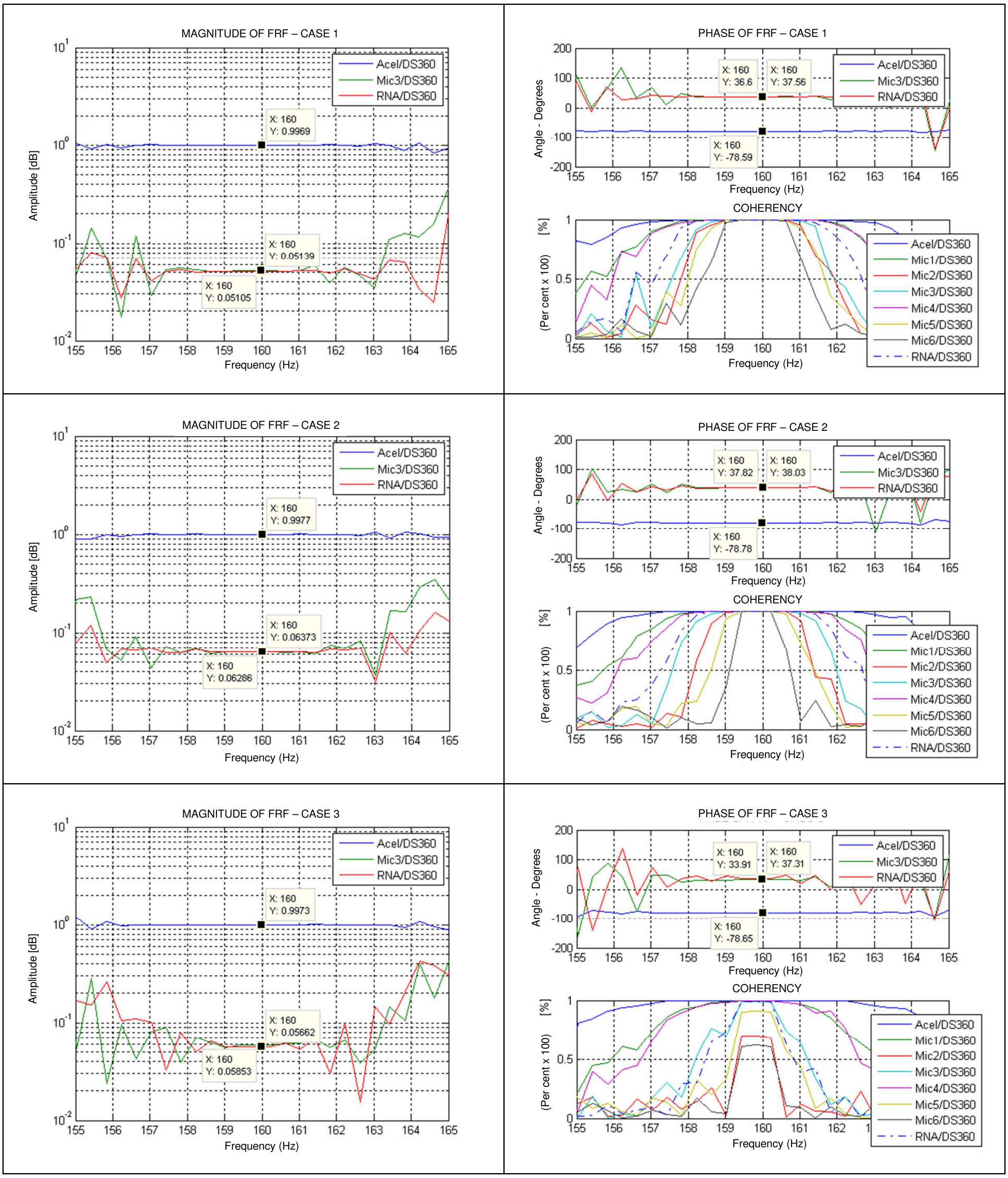


Figure 7 – Comparation among the real and estimated response:
(a) Magnitude of FRF (b) Phase and coherence among signals.

In the figure 7, can be observed that the magnitude of the FRFs, the error stays in 0.74%, 1.34% and 3.28% for the cases 1, 2 and 3. In the phase, the estimated error was reduced to 2.62%, 0.56% and 10.03% for the three cases respectively. At general, there was improvement compared with figure 5, including coherence elevation for case 3.

4. CONCLUSIONS

The accelerometer sensor attached at the source is able to estimate the sound pressure produced in terms of magnitude and phase, with the advantage of measuring directly the source. It also has the advantage of being robust of interference at the reverberant field in the acquisition.

It is also observed that the accelerometer characterizes very well the signal from neural network, doing the filtering of the disturbances due to noise and from the reverberant field. Nevertheless, putting one microphone next the virtual location, it is possible to characterize those disturbances. Thus, the fidelity of signals will be directly affected by the amount of data sets presented for neural network on training, by the quantity of sensors and its locations.

The virtual response was quite representative, showing low error in magnitude, phase and high coherence of FRFs. Also, can be noticed that the estimate gets improvements when increases the number of data sets incorporating characteristics of environment changes, using the reset strategy to training.

Finally, can be concluded that the technique of virtual response is quite promising, to get estimative of acoustic signal. Although it was used a harmonic signal to perform this study, was possible to reach the proposed goals.

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