A METHOD FOR MATERIAL'S CLASSIFICATION BASED ON IMPACTS AND NEURAL NETWORKS

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1. Introduction

On this work we present a procedure to classify materials using impacts between rigid bodies as the source of information. This procedure is based on the coin-tap test [1], which is mainly used to detect cracks on structures or composite materials [2-3] by hearing the sound of an impact and detecting differences between defective zones to normal ones [4]. Material's classification is performed by comparing responses of diverse materials in the frequency domain; this is founded on the concept that under similar impact conditions each material has its own vibrating response [5]. Difficulties arise when two bodies with similar properties are tested; in these cases, further analysis is required to detect differences. To achieve this, we apply the coin-tap test method in a systematic procedure using repeatable mechanical impacts, measuring the acceleration of the impact instead of the sound, performing a data compression on the frequency domain, and using an Artificial Neural Network (ANN) for classification.

2. Results and Discussion

To test the method, we compare responses from four cylinders, on two sizes made from steel and aluminum, impacted by four small bearing-balls of different diameter. The purpose of this is to investigate which bearing-ball diameter produces "the best" impact for classification.

Cylinders 1 (steel) and 2 (aluminum) are considered the small ones, with dimensions of Ø=30mm (diameter) and L=30mm (length); and cylinders 3 (steel) and 4 (aluminum) are the larger ones: Ø=30mm and L=50mm. The four impacting balls are made from steel with diameters of: b1=6mm, b2=3.2mm, b3=2mm, and b4=0.7mm.

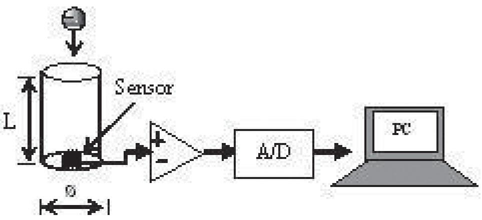

Figure 1. Experimental system.

Each cylinder has been sesorized with one piezoelectric accelerometer, at one of the flats
sections in-line with the impacts axis, as shown in Figure 1. Signals are conditioned with a differential charge amplifier, and digitized at a sampling rate of 2.5MHz and 12 bits of resolution.

A total of 80 impacts are recorded; 20 per cylinder –five impacts per ball per cylinder. All signals are windowed with a Nuttall window, to smooth the end of the time record and reduce leakage at the spectrum. Then, a Discrete Fourier Transform (DFT) is applied. To compress data the DFT is evaluated over 2048 points on the frequency domain and the first 64 coefficients are selected to be processed by the ANN. On them is concentrated the maximum energy of the signal, and the significant vibrating information used to classify the materials. Figure 2, shows the average spectrum of all impacts for each cylinder. The top graphic shows short cylinder's responses; differences between them are appreciated. The bottom graphic shows large cylinder's responses, which exhibit more similarities between them than responses of the other cylinders.

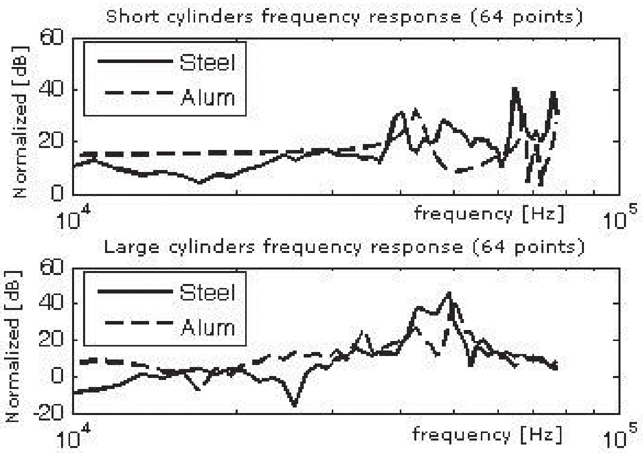

Figure 2. Impacts mean-values. Showing 64 points of the frequency response. Top, short cylinders. Bottom, large cylinders.

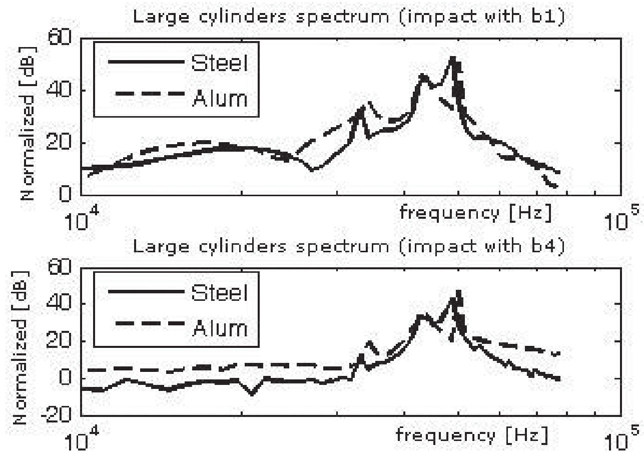

Figure 3 Spectrum response of the large cylinders when impacted by the largest (b1=6mm) and the smallest (b4=0.7mm) bearing balls.

Figure 3, shows the case of two very similar signals from the large cylinders when impacted by the largest and the smallest bearing-balls. To analyze and classify these responses a backpropagation ANN has been used. The proposed network has an input-layer with 64 inputs, one hidden-layer with three neurons, and two neurons at the output-layer. The learning is based on the Levenberg-Marquardt algorithm, and two set of signals are selected; one for training, with 48 signals composed by 3 signals per type of ball per cylinder. The second set has the remaining 32 signals, which are used for validation.

The output of the ANN has been setup to show results in a binary code, as shown on Table I. On the first colon appears the random input validation sequence introduced to test the ANN. The output appears on the next two colons, where "Size" and "Type" are the ANN output code. S=0 means small, and S=1 means large cylinder. T=0 means aluminum, and T=1 means steel. Last colon shows the translated code meaning.

Results show that the method can be used to classify two materials with similar responses, as is the case with steel and aluminum. In the case of the small bearing-balls, it has been found that for the large cylinders there is no significant difference among diameters, due all responses present similar characteristics. In the case of the small cylinders, it has been found that the large ball (b1) impacts are better, in order to observe difference among materials.

Table I. Validation test and ANN output. Size=0, 1 means short, and long. Type=0, 1 means aluminum, and steel.

Input Sequence (Validation)	ANN Output Output code		
	Size	Type	Detected Material
A1-S	0	0	Aluminum –Short
A1-S	0	0	Aluminum –Short
St-L	1	1	Steel –Large
A1-L	1	0	Aluminum –Large
St-S	0	1	Steel –Short
St-L	1	1	Steel –Large
A1-L	1	0	Aluminum –Large
St-S	0	1	Steel –Short

Table I. Validation test and ANN output. Size=0, 1 means short, and long. Type=0, 1 means aluminum, and steel.

3. Conclusions

We have presented a method which allows classifying materials using impacts and neural networks. The main problem on material's classification arises when responses are similar, in this case the method has been tested with steel and aluminum, and the ANN has proven to be a robust solution to detect differences. Further analysis will involve other materials as well.

4. Acknowledgement

Authors would like to thank financial support from Ministerio de Educación y Ciencia de España, under grant DIP-2003-08637-C03-03.
E. M. M. R. thanks to the financial support of the Mexican National Council for Science and Technology (CONACyT).

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APPLICATION OF A KALMAN FILTER ON MECHANICAL SYSTEMS TO ANALYZE IMPACTS

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1. Introduction

The purpose of this paper is to test the feasibility of using a Kalman filter and a simple mechanical model to analyze the velocity and the acceleration of an impact generated from the collision between two rigid bodies. To achieve this, the Kalman filter and a mechanical model are compared with experimental signals that have been obtained from real impacts, between a sensorized hammer and a steel cylinder.

The cylinder has been modeled as a first order dynamic system, as shown in Figure 1, with the impact signal, f(t), applied on its surface. The mechanical model is shown on equation (1).

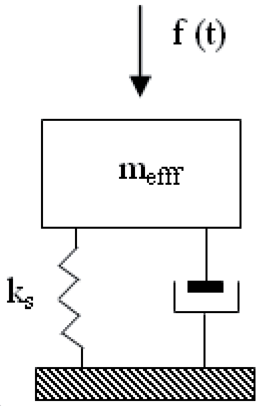

Figure 1. Metallic cylinder model.

$$\frac{d}{d}\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -\frac{k_s}{m_{eff}} & -\frac{k_d}{m_{eff}} \end{bmatrix}\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix}u(t) \qquad (1)$$

Where meff : effective mass [kg]
kd : damping constant [N•s/m]
ks : spring constant [N/m]
f(t)=u(t) : input force [N]
x1 , x2 : displacement and speed.

According to [1], the effective mass is the joint masses of the hammer and the cylinder, and this is given by equation (2).

where mh : hammer mass
mc : cylinder mass
And constants kd and ks are for steel.

1.1 Kalman Algorithm

Figure 2, shows the block diagram of the Kalman estimator.