

Automatic Classification of Impact–Echo Spectra II

Addisson Salazar

iTEAM, Polytechnic University of Valencia, Spain

Arturo Serrano

iTEAM, Polytechnic University of Valencia, Spain

INTRODUCTION

We study the application of artificial neural networks (ANNs) to the classification of spectra from impact-echo signals. In this paper we focus on analyses from experiments. Simulation results are covered in paper I.

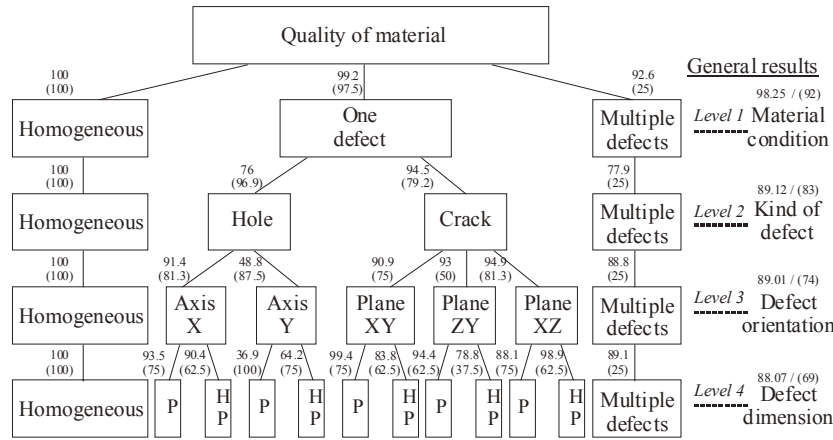
Impact-echo is a procedure from Non-Destructive Evaluation where a material is excited by a hammer impact which produces a response from the material microstructure. This response is sensed by a set of transducers located on material surface. Measured signals contain backscattering from grain microstructure and information of flaws in the material inspected (Sansalone & Street, 1997). The physical phenomenon of impact-echo corresponds to wave propagation in solids. When a disturbance (stress or displacement) is applied suddenly at a point on the surface of a solid, such as by impact, the disturbance propagates through the solid as three different types of stress waves: a P-wave, an S-wave, and an R-wave. The P-wave is associated with the propagation of normal stress and the S-wave is associated with shear stress, both of them propagate into the solid along spherical wave fronts. In addition, a surface wave, or Rayleigh wave (R-wave) travels throughout a circular wave front along the material surface (Carino, 2001).

After a transient period where the first waves arrive, wave propagation becomes stationary in resonant modes of the material that vary depending on the defects inside the material. In defective materials propagated waves have to surround the defects and their energy decreases, and multiple reflections and diffraction with the defect borders become reflected waves (Sansalone, Carino, & Hsu, 1998). Depending on the observation time and the sampling frequency used in the experiments we may be interested in analyzing the transient or the stationary stage of the wave propagation in im-

pact-echo tests. Usually with high resolution in time, analyzes of wave propagation velocity can give useful information, for instance, to build a tomography of a material inspected from different locations. Considering the sampling frequency that we used in the experiments (100 kHz), a feature extracted from the signal as the wave propagation velocity is not accurate enough to discern between homogeneous and different kind of defective materials.

The data set for this research consists of sonic and ultrasonic impact-echo signal (1-27 kHz) spectra obtained from 84 parallelepiped-shape (7x5x22cm. width, height and length) lab specimens of aluminium alloy series 2000. These spectra, along with a categorization of the quality of materials among homogeneous, one-defect and multiple-defect classes were used to develop supervised neural network classifiers. We show that neural networks yield good classifications (<15% error) of the materials in four levels of classification detail as material condition, kind of defect, defect orientation and defect dimension. Results for Multilayer Perceptron (MLP) and Radial Basis Function (RBF) neural networks, Linear Discriminant Analysis (LDA), and k-Nearest Neighbours (kNN) algorithms (Duda, Hart, & Stork, 2000), (Bishop C.M., 2004) are presented. Figure 1 shows the scheme of categories proposed as a hierarchical layout with different levels of knowledge on the material defects (the percentage of success in classification is explained in Experimental Result section).

Figure 1. Classification tree with percentages of success in classification by RBF network. Numbers in brackets are results for simulations (paper I). General results are weighted by class probability since classes are not equally-probable.



BACKGROUND

The phenomenon of volumetric wave propagation in impact-echo can be modelled by means of the following two equations (Cheeke J.D., 2002),

$$\frac{\partial T_{ij}}{\partial x_j} = \rho_0 \frac{\partial^2 u_i}{\partial t^2} \quad (1)$$

$$T_{ij} = c_{ijkl} S_{kl} \quad (2)$$

where

- ρ_0 : Material density.
- u_i : Length elongation with respect to starting point in force direction.
- $\frac{\partial T_{ij}}{\partial x_j}$: Force variation in i direction due to deformations in j directions.
- c_{ijkl} : Elastic constant tensor (Hooke's law).
- S_{kl} : Strain or relative volume change under deformation in face l in direction k in unitary cube that represents a material element.

Thus force variation in the direction i due to face stresses in j directions of the material elementary cube, is equal to the mass per volume (density) times the strain acceleration (Newton's third law in tensorial form). To

derive an analytical solution to problems that involve stress wave propagation in delimited solids is very complicated, so bibliography on this subject is not very extensive. Numeric models such as the Finite Element Method (FEM) can be used to obtain an approximation to the material theoretical response (Abraham O, Leonard C., Cote P., & Piwakowski B., 2000).

There are several studies that used the impact-echo signals in frequency domain to detect the existence of defects in materials (Sansalone et al., 1997), (Hill, McHung, & Turner, 2000), (Sansalone, Lin, & Street, 1998). It has been demonstrated that a sequence of tones and harmonics appears in the spectra, they are fundamental modes of propagation that travel inside the material (block-shape material) and its frequencies depend on the shape and size of the material inspected by impact-echo. According to the block face where a sensor is located, some or others fundamental modes are captured. However, other tones are formed by the reflections of the waves with the defects in the material, and their frequencies are related with the deepness of the flaws. In addition, the presence of defects causes shifting of the fundamental mode frequencies due to diffractions.

MLP neural network has been applied to impact-echo in mono-sensor configurations (using only one accelerometer) to detect flaws on concrete slabs (Pratt & Sansalone, 1992), identification of unilaterally working sublayer cracks (Stavroulakis, 1999), classification of concrete slabs in solid and defective (Xiang & Tso, 2002). Those applications used a few number of ex-

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