

# Automatic Classification of Impact–Echo Spectra I

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## INTRODUCTION

We investigate the application of artificial neural networks (ANNs) to the classification of spectra from impact-echo signals. In this paper we provide analyses from simulated signals and the second part paper details results of lab experiments.

The data set for this research consists of sonic and ultrasonic impact-echo signal spectra obtained from 100 3D-finite element models. These spectra, along with a categorization of the materials among homogeneous and defective classes depending on the kind of material defects, were used to develop supervised neural network classifiers. Four levels of complexity were proposed for classification of materials as: material condition, kind of defect, defect orientation and defect dimension. Results from Multilayer Perceptron (MLP) and Radial Basis Function (RBF) neural networks with Linear Discriminant Analysis (LDA), and k-Nearest Neighbours (kNN) algorithms (Duda, Hart, & Stork, 2000), (Bishop C.M., 2004) are compared. Suitable results for LDA and RBF were obtained.

The impact-echo is a technique for non-destructive evaluation based on monitoring the surface motion resulting from a short-duration mechanical impact. It has been widely used in applications of concrete structures in civil engineering. Cross-sectional resonant modes in impact-echo signals have been analyzed in elements of different shapes, such as, circular and square beams, beams with empty ducts or cement fillings, etc. In addition, frequency analyses of the displacement of the fundamental frequency to lower values for detection of cracks have been studied (Sansalone & Street, 1997), (Carino, 2001).

The impact-echo wave propagation can be analyzed from transient and stationary behaviour. The excitation signal (the impact) produces a short transient stage where the first P (normal stress), S (shear stress) and

Rayleigh (superficial) waves arrive to the sensors; afterward the wave propagation phenomenon becomes stationary and a manifold of different mixtures of waves including various changes of S-wave to P-wave propagation mode and viceversa arrive to the sensors. Patterns of waveform displacements in this latter stage are known as the resonant modes of the material. The spectra of impact-echo signals provide of information for classification based on resonant modes the inspected materials. The classification tree approached in this paper has four levels from global to detailed classes with up to 12 classes in the lowest level. The levels are: (i) Material condition: homogeneous, one defect, multiple defects, (ii) Kind of defect: homogeneous, hole, crack, multiple defects, (iii) Defect orientation: homogeneous, hole in axis X or axis Y, crack in planes XY, ZY, or XZ, multiple defects, and (iv) Defect dimension: homogeneous, passing through and half passing through types of holes and cracks of level iii, multiple defects. Some examples of defective models are in Figure 1.

## BACKGROUND

Neural networks applications in impact-echo testing include: detect flaws on concrete slabs, combining spectra of numerical simulations and real signals for network training (Pratt & Sansalone, 1992), identification of unilaterally working sublayer cracks using numerically generated waveforms as network inputs (Stavroulakis, 1999), classification of concrete slabs in solid and defective (containing void or delamination), use of training features extracted from many repetitions of impact-echo experiments on three specimens to be classified in three classes (Xiang & Tso, 2002), and to predict shallow crack depths in asphalt pavements using features from an extensive real signal

dataset (Mei, 2004). All these studies used multilayer perceptron neural network and monosensor impact-echo systems.

In a recent work, we classified impact-echo data by neural networks using temporal and frequency features extracted from the signals, finding that the better features were frequency features (Salazar, Uni6, Serrano, & Gosalbez, 2007). Thus the present work is focused in exploiting only spectra information of the impact-echo signals. These spectra contain a large amount of redundant information. We applied Principal Component Analysis (PCA) to spectra for compressing and removing noise. The proposed classification problem and the use of spectra PCA components as classification features are a new proposal in application of neural networks to impact-echo testing.

There is evidence that the first components of PCA retain essentially all of the useful information and this compression optimally removes noise and can be used to identify unusual spectra (Bailer-Jones, 1996), (Bailer-Jones, Irwin, & Hippel, 1998), (Xu et al., 2004). The principal components represent sources of variance in the data. The projection of the  $p^{th}$  spectrum onto the  $k^{th}$  principal component is known as the admixture coefficient  $a_{k,p}$ . The most significant principal components contain those features which are most strongly correlated in many of the spectra. It follows that noise (which is uncorrelated with any other features by definition) will be represented in the less significant components. Thus by retaining only the more significant components to represent the spectra we achieve a data compression that preferentially remove noise. The reduced reconstruction,  $\mathbf{y}_p$  of the  $p^{th}$  spectrum  $\mathbf{x}_p$ , is obtained by using only the first  $r$  principal components to reconstruct the spectrum, i.e.

$$\mathbf{y}_p = \bar{\mathbf{x}} + \sum_{k=1}^{k=r} a_{k,p} \mathbf{u}_k, \quad r < N, \quad (1)$$

where  $\bar{\mathbf{x}}$  is the mean spectrum which is subtracted from the spectra before the eigenvectors are calculated, and  $\mathbf{u}_k$  is the  $k^{th}$  principal component.  $\bar{\mathbf{x}}$  can be considered as the zeroth eigenvector, although the degree of variance it explains depends on the specific data set and may be much less than that explained by the first eigenvectors.

Let  $\varepsilon_p$  be the error incurred in using this reduced reconstruction. By definition  $\mathbf{x}_p = \mathbf{y}_p + \varepsilon_p$ , so

$$\varepsilon_p = \sum_{k=r+1}^{k=N} a_{k,p} \mathbf{u}_k. \quad (2)$$

## RECOGNITION OF DEFECT PATTERNS IN IMPACT-ECHO SPECTRA -SIMULATIONS

### Impact-Echo Signals

Simulated signals came from full transient dynamic analysis of 100 3D finite element models of simulated parallelepiped-shape material of 0.07x0.05x0.22m. (width, height and length) supported to one third and two thirds of the block length (direction  $z$ ). Figure 1 shows different examples of the models of defective pieces. From the transient analysis the dynamic response of the material structure (time-varying displacements in the structure) under the action of a transient load is estimated. The transient load, i.e. the hammer impact, was simulated by applying a force-time history of a half sine wave with a period of 64 $\mu$ s as a uniform pressure load on two elements at the centre of the model front face. The elastic material constants for the simulated material were: density 2700 kg/m<sup>3</sup>, elasticity modulus 69500 Mpa. and Poisson's ratio 0.22.

Elements having dimensions of about 0.01 m. were used in the models. These elements can accurately capture the frequency response up to 40 kHz. Surface displacement waveforms were taken from the simulation results at 7 nodes in different locations on the material surface, see Figure 1a. Signals consisted of 5000 samples recorded at a sampling frequency of 100 kHz. To make possible to compare simulations with experiments, the second derivative of the displacement was calculated to work with accelerations, since the sensors available for experiments were mono-axial accelerometers. These accelerations were measured in the normal direction to the plane of the material surface accordingly to the configuration of the sensors in Figure 1a.

### Feature Extraction and Selection

We investigate if the changes in the spectra, particularly in the zones of the fundamental frequencies, are related

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