Ultrasonic signature: a signal processing concept for material characterization

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Abstract

Ultrasonic inspection of materials can be substantially improved by using advanced algorithms of signal processing. Material properties or flaw presence affect the time-frequency transforms of the A-scans. A key concept for unifying the different signal processing schemes is presented. The ultrasonic signature allows us to deal with different ultrasonic inspection problems with a unique formulation. Two applications of this concept are presented: archaeological ceramic classification and foreign bodies detection in the alimentary industry.

Keywords: Signal processing, Time-frequency representation, Ultrasonic characterization of materials, archaeological ceramics, foreign bodies detection, quality control, alimentary industry.

1. Introduction

This paper is based on the work done by the Signal Processing Group of the Polytechnic University of Valencia (SPAIN) during the last years in the area of ultrasonic non-destructive evaluation of materials. A key element of the work has been the incorporation of advanced signal processing algorithms into the analysis of the recorded signals, thus allowing increased capabilities in so diverse applications like: estimation of porosity in cement derived materials, classification of dimensional blocks of marble, restoration of heritage historical buildings and characterization of archaeology pieces and characterization of products derived from the alimentary industry.

An ultrasonic inspection system consists in “interrogating” the material, by means of an ultrasonic pulse emitted by an adequate sensor, and receiving the ultrasound “response” in the same sensor (pulse-echo mode) or in other(s) receiver sensor(s) (transmission mode). Many different interrogation-response pairs may be combined to enhance the required information. This later can be very different depending on the application. For example we can be trying to obtain a statistical parameter of the recorded ultrasonic signal, which is to be correlated with some physical property of the material (like resistance or porosity), or we may be interested in detecting the echoes of significant inner reflectors (like flaws or layers). In the context of this variability of goals, we show in this paper that a common framework is possible, both from the signal modelling and signal processing perspectives. In particular we enhance a fundamental concept unifying the different signal processing schemes: the ultrasonic signature, to be explained in the next sections.

2. Signal model

In essence, all the different applications share a common model: the recorded signal is the convolution of the material reflectivity with a linear time varying system (LTV) (see figure 1). The variant impulse response of the LTV is the own ultrasonic pulse travelling along the material, thus suffering from attenuation and dispersion effects which affect both its amplitude and frequency content. Actually, some non-linearity may be incorporated into the model in some specific cases but, in general, the linear assumption is adequate for a large number of situations, or at least is enough to arrive to practical solutions yielding reasonable performance. Thus the received signal usually has the general aspect of figure 1, where three main components are to be considered. Firstly, we have a grain noise component due to the scattering from the material microstructure; the superposition of many small echoes produces a noise-like signal which can be modelled as a non-stationary coloured (Gaussian or non-Gaussian) noise. The significance of this component depends on the ratio of the ultrasonic operating wavelength to the mean grain diameter value: the higher the frequency the higher the possibility of obtaining grain noise. The second component is due to the possible presence of echoes from significant reflectors; the waveform of these echoes depend on the interrogating pulse, on the path between the emitter/receiver and on the own response of the reflector (even some non-linearity could appear in the reflector response, thus originating new frequency components). The final component is the observation stationary white Gaussian noise.

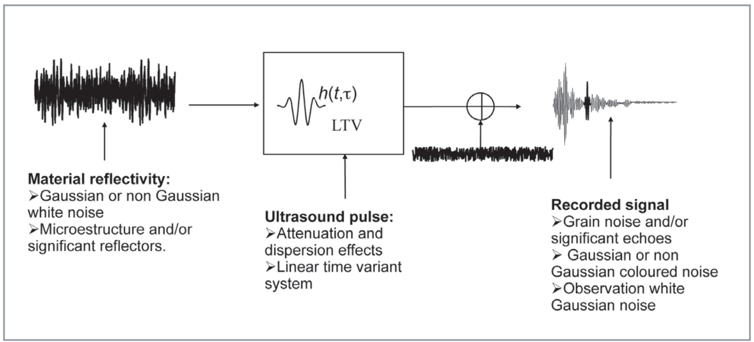

Figure 1. *The linear time variant model*

3. Type of problems

Many different kind of problems can be unified under the ultrasonic signature concept.

The different problems of material characterization can be divided in two categories:

- To pursue for an approximate knowledge of some properties of the material. Some examples are:

  - Determination of the porosity of cement derived materials (cement paste, mortar, and concrete). Porosity is strongly correlated with the strength of cement materials, so it can be used to predict the durability of building components both in the fabrication and in the maintenance steps [1], [2], [3].

  - Classification of the overall quality of dimensional marble blocks. Early stage classification can prevent many problems in the block cutting stage and allows establishing the marble quality of a given quarry [5].

- Determination of the consolidation quality or other properties of archaeological pieces (ceramic, waterlogged wood), which is very relevant for an adequate conservation [6]. To pursue for the detection of inner significant reflectors. Some example are:

  - Detection of cracks in unfired ceramic tiles. It is a critical factor to avoid lost of material, and recycling before firing [7] [8].

  - Location of cracks in dimensional marble rock blocks. It is very useful to optimize the restoration of the blocks, if required, allowing to focus in the deteriorated volume [5].

  - Tracing of the inner layers of walls or vaults in historical heritage monuments as helping information both before and after restoration [9].
  - Detection of foreign bodies in an alimentary product already bottled.

In the first category of problems we require significant levels of grain noise, as this is the source of information about the material that we have in hand after the ultrasonic inspection. Grain noise depends both on the reflectivity (LTV input) and on the way that the material affects the pulse propagation (LTV impulse response). In the second category we would like to have the minimum possible amount of grain noise, as it may hide the echoes from significant reflectors. Unfortunately, reducing grain noise implies reducing the operating frequency and then increasing the wavelength, and this defines a lower bound in the minimum size for a reflector to be detected. Thus in many applications there is not possible to avoid the presence of grain noise, and we have to face a difficult detection problem, as, in general, both the signal to be detected and the grain noise share most of their respective frequency bands. Both categories may be unified under the ultrasonic signature concept, as we do in the next section.

4. Signal processing: ultrasonic signature

As already mentioned, information about the material is included in the reflectivity and in the variant impulse response of the LTV. Obtaining the reflectivity implies some kind of deconvolution. Other possibility is to directly relate the statistics of the recorded signal (LTV output) to the statistics of the LTV input [10]. However deconvolution is an ill-conditioned problem when signals are essentially band-pass, and extracting statistics of the reflectivity is only relevant in the non-Gaussian case. Then we move to analyze the variant impulse response (or equivalently the variant frequency response) of the LTV.

The time variant characteristic of the model leads naturally to a non-stationary analysis of the recorded signal. Figure 2 shows a general processing scheme which is valid for the two categories of problems outlined in the previous section. First of all a short-term frequency analysis of the signal is done to isolate the evolution of the different frequency components. This can be done by means of explicit implementation of a bank of filters or, more usually, by means of some type of linear or non-linear time-frequency transformation, including non-constant bandwidth analysis like wavelet transform. From the time-frequency signal we obtain the ultrasonic signature which is a one-dimensional signal hopefully encompassing the relevant information needed for every particular purpose. The ultrasonic signature $us(t)$ is obtained by computing for every time instant, along a finite discrete time interval, a spectral parameter; some possible alternatives are:

• Centroid frequency (normalized first moment)

$$us(t) = f_c(t) = \frac{\int_{f_1}^{f_2} f \cdot |TF(f,t)| df}{\int_{f_1}^{f_2} |TF(f,t)| df},$$

where $|TF(f,t)|$ is the magnitude of the time-frequency transformation, and f_1 - f_2 defines the integration band.

$$us(t) = BW(t) = \frac{\int_{f_1}^{f_2} (f - f_c(t))^2 \cdot |TF(f,t)| df}{\int_{f_1}^{f_2} |TF(f,t)| df}.$$

• Higher moments of $|TF(f,t)|$.

• The maximum frequency

$$us(t) = f_{\max}(t) = \underbrace{\max}_{f} |TF(f,t)|$$

• The maximum, the minimum, the median or any other order statistics (OS) of $|TF(f,t)|$, $us(t) = \underbrace{OS}_{f} |TF(f,t)|$.

• Number of values of $|TF(f,t)|$ in a given band which are greater than a given threshold,…

All these possibilities are summarized in Table 1. Once we have the ultrasonic signature we may continue in different ways depending on the final goal:

• We may directly use it as a feature vector input to an automatic classifier to classify the material in a given number of classes.

• We can compute a specific value of the signature, for example the transition instant of the centroid frequency from the interval where grain noise is predominant to the interval where there is only observation noise. This transition depends on the penetrability of the ultrasonic energy into the material and may be related to some material properties.

• We can track the signature variations with time, to detect the influence of possible significant reflectors on it.

The feature vector may be directly used as an input to an automatic classifier.

5. Open questions for optimum design

Let us consider the three alternatives indicated in figure 2, with the aim of briefly establishing the open problems from and optimum statistical design perspective.

Classifier

We need the class-conditioned multivariate probability density function (pdf) of $us(t_i)$ $i = 1,\ldots N$ to make and optimum design of the classifier. Assuming linear time-frequency transform, the difficulty of the problem is mainly dependent on the combiner.

A simplified approach is to estimate the mean and the covariance matrix of $us(t_i)$ $i = 1,\ldots N$, and to assume Gaussianity. Mean and variance analyses of the centroid frequency and the maximum frequency signatures have been done respectively in [3] and [11]. Other non-parametric approaches are also possible. Supervised, non-supervised and hybrid training frameworks are usual in material characterization.

Detection of echoes

For every t_i we have to decide the possible presence of a pulse echo in a background of grain plus observation noise. To achieve optimum detection, we need the marginal pdf of $us(t_i)$ under both hypotheses. This is again a problem much dependent on the type of combiner. It is proposed in [10] an optimum detector by using an algebraic approach, where every frequency channel implies a projection into an adequately defined subspace, and exploiting the well established distributed detection theory for the combiner implementation.

Centroid frequency	$us(t) = f_c(t) = \frac{\int_{f_1}^{f_2} f \cdot \lvert TF(f,t)\rvert df}{\int_{f_1}^{f_2} \lvert TF(f,t)\rvert df}$	The maximum frequency	$us(t) = f_{\max}(t) = \underbrace{\max}_{f} \lvert TF(f,t)\rvert$
The bandwidth	$us(t) = BW(t) = \frac{\int_{f_1}^{f_2} (f - f_c(t))^2 \cdot \lvert TF(f,t)\rvert df}{\int_{f_1}^{f_2} \lvert TF(f,t)\rvert df}$	Order statistics (OS)	$us(t) = \underbrace{OS}_{f} \lvert TF(f,t)\rvert$
Third order statistics	$us(t) = E[\lvert TF(f,t)\rvert, \lvert TF(f-1,t)\rvert, \lvert TF(f-2,t)\rvert]$		

Table 1. *Ultrasound signal features*

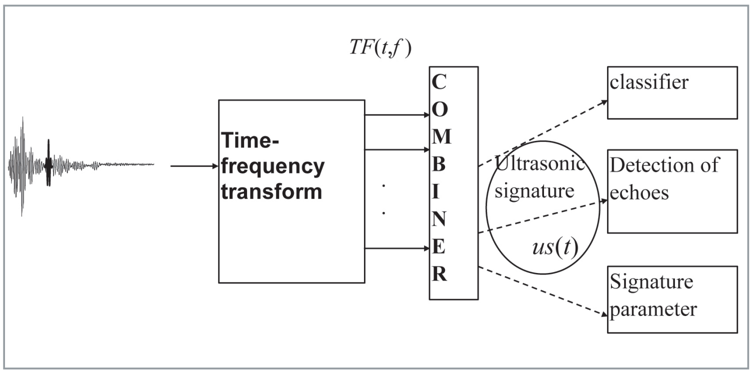

Figure 2. *Signal processing: ultrasonic signature*

Signature parameter

The goal now is to estimate some material property (mp) like resistance or porosity from the ultrasonic signature. Ideally, we should know the mp mean conditioned to the "observed" signature, to obtain minimum mean-square error estimators. In practice this is approached by first extracting a signature parameter (sp) which compresses the signature information in just one number. Then empirical mean-conditioned curves $E[mp/sp]$ are built by interpolating in the two-dimensional space mp-sp after exhaustive measurements. An example of this type of procedure can be seen in [2], [3] and [4] for the estimation of cement paste porosity.

6. An archaeology application

Here we consider an application in the archaeology area [12], [13]. The problem is to determine by non-destructive methods the origin of a given archaeology ceramic piece among four possibilities: Roman, Iberian, Middle Age and Bronze Age. A set of 64 pieces of known origin (16 from every class) were available from the Archaeological Museum of Requena (Valencia, Spain).

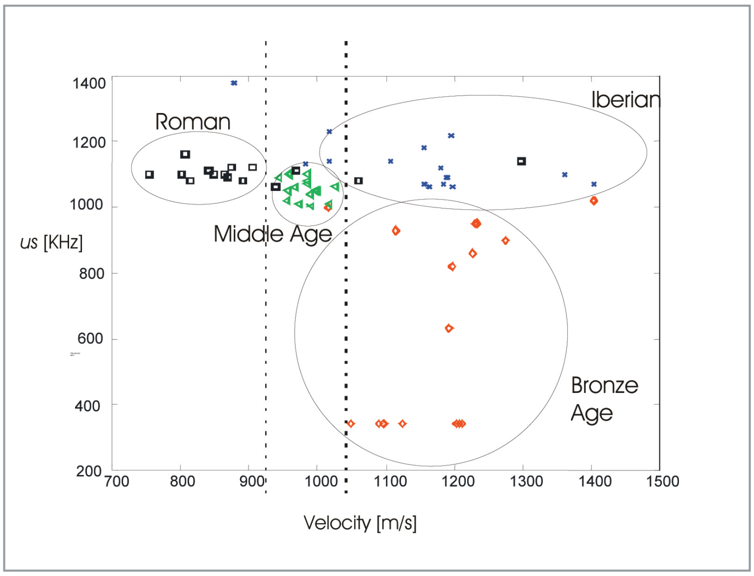

Figure 3. *Clusters of features corresponding to archaeological pieces of four different epochs*

Ultrasonic testing was made in transmission mode by using two sensors having nominal frequency of 2.5 MHz. A pulse was emitted in one side of every piece and a delayed, distorted and noise corrupted version of it was received in the other side. In figure 3 we show the clusters obtained by using two features. The first feature (x-axis) corresponds to the ultrasound velocity of propagation in every piece obtained from the delay of the received pulse. Propagation velocity is a classical ultrasound measurement in non-destructive testing of materials. As we can see in figure 3, Iberian and Bronze Age pieces can not be discriminated by just using velocity information. However, when an additional feature, derived from the ultrasonic signature of the received signal, is incorporated into the classifier, all the four classes are reasonably well separated. In this case we have used $us(t) = f_{\max}(t) = \underbrace{\max}_{f}|TF(f,t)|$.

The y-axes of figure 3 actually corresponds to the average value

$$us = \sum_{i=1}^{N} us(t_i)$$

thus allowing an easy visualization of the clusters.

More complete results in a variety of applications may be found in the included references.

7. Foreign bodies detection in an alimentary product already bottled.

The detection of foreign bodies in the alimentary industry is an important topic in alimentary security. However, the detection systems usually found are quite rudimentary. Sieves of different diameters or metal detectors are in a great number of applications the only employed systems [14]. Although this simple techniques are very effective for some products there are some others where they are useless. For instance foreign bodies detection in marmalades or jams that contain fruit pieces is impossible because fruit pieces are normally larger than the desired foreign body size. However the presented grain noise concept and the ultrasonic signature can be used to design effective detection systems [15]. The following result illustrates how ultrasonic signature helps to resolve the foreign bodies detection problem.

Twelve glass jars were filled with peach jam. In six of them foreign bodies of different natures were artificially introduced (see figure 4). The bottled samples with foreign bodies were labelled as, "wo" for the stick of wood foreign body, "st" for the stone foreign body and "ch" for the wooden panel foreign body. The bottled jam was inspected with an ultrasonic IPR100 board from Euro Physical Acoustics S.A. and a 5 MHz ultrasonic transducer from Krautkramer&Branson (Ref. MSWQC5). The ultrasonic signature of the recorded A-scans was calculated. In this case, energy at the central frequency

$$us_x = \left(\underbrace{\max}_{t} \left(\underbrace{\max}_{f} \left| TF(f,t) \right| \right) \right)^2$$

was selected as the ultrasonic signature in the x-axis. For the y-axis minimum bandwidth was used $us_y = \underbrace{\min}_{t}(BW(t))$.

The figure 5 shows the clusters for the glass jars with foreign bodies and without them.

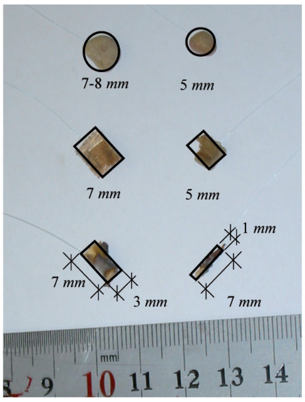

Figure 4. *Artificially introduced foreign bodies*

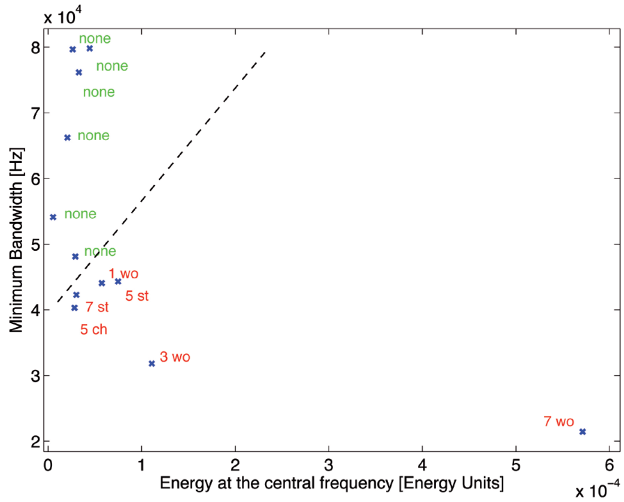

Figure 5. *Classification of the 12 peach jam glass jar with and without foreign bodies. The glass jars with foreign bodies were labeled as "st", "wo" and "ch" for the stone, stick and wooden panel respectively (numbers are related to the size in millimeters). Label "none" refers to glass jars without foreign bodies.*

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Biographies

Prof. Luis Vergara was born in Madrid (Spain) in 1956. He received the Ingeniero de Telecomunicación and the Doctor Ingeniero de Telecomunicación degrees from the Universidad Politécnica de Madrid (UPM) in 1980 and 1983 respectively. Until 1992 he worked at the Departamento de Señales, Sistemas y Radiocomunicaciones (UPM) as an Associate Professor. In 1992 he joined the Departamento de Comunicaciones (Universidad Politécnica de Valencia UPV, Spain), where he became Professor and where it was Department Head until April 2004. From April 2004 to April 2005 he was Vice-rector of New Technologies at the UPV. He is now responsible of the Signal Processing Group of the UPV, a member group of the Institute of Telecommunication and Multimedia Applications (I-TEAM) of UPV.

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Dr. Ramón Miralles was born in Valencia (Spain) in 1971. He received the Ingeniero de Telecomunicación and the Doctor Ingeniero de Telecomunicación degrees from the Universidad Politécnica de Valencia (UPV) in 1995 and 2000 respectively. In 1996 he became a lecturer in the Departamento de Comunicaciones at the Escuela Politécnica Superior de Gandia. From 2000 until now he has been working as an Assistant Professor in the Escuela Tecnica Superior de Ingenieros de Telecomunicación (Valencia). He is member of the management team of the Institute of Telecommunication and Multimedia Applications (I-TEAM).

His research interests include statistical signal processing, nonlinear signal processing and higher order statistics. He is responsible of developing algorithms and systems for ultrasound quality control in the industry, especially in the alimentary industry. His research has been funded by the national R+D programme, the local administrations and the industry. He has published more than 60 papers including journals and conference communications.

Dr. Ignacio Bosch was born in Valencia (Spain) in 1975. He received the Ingeniero de Telecomunicación and the Doctor Ingeniero de Telecomunicación degrees from the Universidad Politécnica de Valencia (UPV) in 2001 and 2005 respectively. He is Assistant Professor at Departamento de Comunicaciones (UPV) and member of the Signal Processing Group of the Institute of Telecommunication and Multimedia Applications (I-TEAM) of UPV.

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MSc. Addisson Salazar is working towards the Doctorate degree in Telecommunications at Universidad Politécnica de Valencia (UPV). He has received the B.Sc. and M.Sc. in Informatics degrees from Universidad Industrial de Santander and the D.E.A. degree in Telecommunications from UPV in 2003. He is a researcher of the Signal Processing Group of the Institute of Telecommunication and Multimedia Applications at UPV. His research interest is focused on statistical signal processing, pattern recognition and in data mining and knowledge discovery where he has worked in different theoretical an applied problems, many of them under contract with the industry. His theoretical aspects of interest are signal classification, time-frequency analysis, independent component analysis and algorithms for data mining. He has published more than 70 papers including journals and conference contributions.