ULTRASONIC INSPECTION OF TI-AL BASED ALLOYS

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Abstract

As a turbine manufacturer, Turbomeca needs to permanently develop and use new materials, such as Titanium Aluminide based alloys, for improving engine performance. Therefore, we must develop inspection solutions for new parts in order to achieve engine health monitoring. The first steps of our investigation consisted in manufacturing and controlling master parts including well known artificial defects, before testing inspectability methods on randomly polluted samples. Due to the limitation on the inclusion sizes we were able to detect and the low S/N ratio obtained on A-Scan representations, we decided to develop a signal processing method based on the wavelet transform. This method yielded encouraging results from two points of view:

1/ Signal denoising for improved echo detection in unfavourable conditions, i.e. when defect echoes have low magnitude (60 dB below the interface echo level) or when S/N ratio is very low (this ratio is thus increased from 10 to 60 dB),

2/ visualisation of frequency filtering due to propagation and/or reflection.

Introduction

The promising properties of gamma Titanium-Aluminide based alloys have led to a considerable amount of studies dedicated to these materials over the last decade. In France, the Snecma group industries, including Turbomeca, launched in 1997 an important research program on Ti-Al-based alloys, which aims at confirming the exceptional mechanical and thermal properties of such materials.

Ti-Al based alloys are intended to be used as engine component materials in rotating parts such as Low pressure Turbine blades or static ones such as casings. Because of the critical importance of such components, we initiated an inspectability study in order to evaluate the performance of non destructive techniques on such materials. Ultrasonic inspection seems to be the only non destructive technique able to detect the considered inclusions, due to their specific sizes: their equivalent reflective diameter ranges from 0.1 mm to 0.5 mm and their depth is at most 20 mm. Our objectives were at first, to perform and improve ultrasonic inspection with immersion techniques, and secondly to study our capability to detect different types of defects, in terms of nature, size and geometry.

Because flaw cannot be accepted in some engine rotating parts, we needed to improve detection in Ti-Al material. Therefore, we applied signal processing methods to temporal representations of ultrasonic propagation; our main objective was to improve the detectability of hypothetical inclusions to get better S/N ratio and/or resolution. For such a kind of application, we decided to implement the wavelet transform, this tool permitting signal decomposition in terms of time and frequency contents. By filtering the wavelet coefficients, we introduced a way to denoise signals and obtain a better S/N ratio.

This paper describes the experimental procedure we implemented, for performance evaluation of ultrasonic inspection dedicated to material obtained by powder metallurgy route (Argon Gas atomised prealloyed powder consolidated by hot isostatic pressing (H.I.P)).

Ti-Al part development

In order to evaluate the performance of ultrasonic inspection, we had to elaborate specific Ti-Al specimens.

On the one hand, we wanted to carry out measurements on reference blocks for calculating Ti-Al acoustic properties, such as the velocity of compression and shear waves, structural noise magnitude… On the other hand, we needed to have samples with equivalent reflectors as reference parts.

We realised nine cylindrical blocks having 50 mm diameter and different heights. Each block contained 0.5, 0.2 and 0.1 mm diameter flat bottom holes (F.B.H.). For each hole diameter we defined three different metal paths from 3 mm up to 20 mm. With those reference blocks we could evaluate the performance of immersion techniques for detecting voids in material using compression waves.

Secondly, in order to get closer to real conditions (inclusions of different natures, shapes and sizes), we inserted particles in the metal powder just before the compaction process. The chemical composition of particles was chosen on the basis of TI-Al elaboration methods; we selected different inclusion types such as steel, glass, zircon and ceramic with different size and shape parameters (from 0.2 mm to 0.8 mm equivalent diameters).

From each polluted slug, we made polluted cylindrical specimens with heights ranging from 3 mm to 20 mm.

Ultrasonic inspection

Ultrasonic inspection of Ti-A1 was performed by using an automatic scanning system. This system is able to display and store A-Scans, B-Scans and C-Scans in the case of immersion measurements. The scanning interface is controlled by a personal computer by means of a Krautkramer® software package called K-SCAN. The measurement system is a pulser/receiver USIP 20 HR (Krautkramer®). The best resolution for the scan is given by the minimum displacement step, i.e. 0.05 mm.
Because of the small inclusion sizes we wanted to detect, we performed measurements with focused transducers and probes having the highest possible center frequencies (5 MHz to 25 MHz depending on transducers). Those probes allowed us to scan samples with a focal zone between 0.3 mm and 1.1 mm and with a focal distance in water between 50 and 150 mm.

Our first experiments on Ti-Al consisted in measuring acoustic parameters. The velocities of compression and shear waves were respectively 7100 m/s and 4100 m/s for a density close to 3.9.

The inspection of F.B.H. in Ti-Al gave good results: we succeeded in detecting all the above-mentioned equivalent reflectors, by optimising the transducer choice. Even the F.B.H. with 0.1 mm diameter could be detected with a 25 MHz transducer which has a 0.3 mm focal zone. Nevertheless, the measurement gain required to the end was very high, i.e. we needed to have 100 dB amplification to correctly detect this F.B.H.. For reference parts like the 0.5 mm diameter one, the measurement gain was about 68 dB for the defect echoes to fill 80% of the display. The structural noise is not significant, i.e. lower than 10% of the display size for 90 dB amplification.

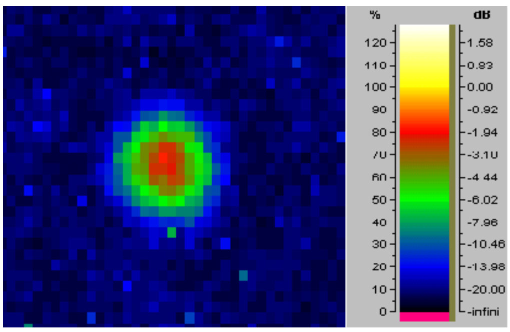

Figure 1. C-Scan of flat bottom hole (∅ 0.1 mm).

Ultrasonic inspection for different real inclusions yielded good results too. The magnitude of longitudinal waves reflected by inclusions depends at first on the acoustic impedance variation between inclusions and Ti-Al, and secondly on inclusion shape. In the case of steel or ceramic, we were able to detect accurately inclusions with diameters ranging from 0.8 mm down to 0.3 mm using probes with 10 to 20 MHz central frequencies.

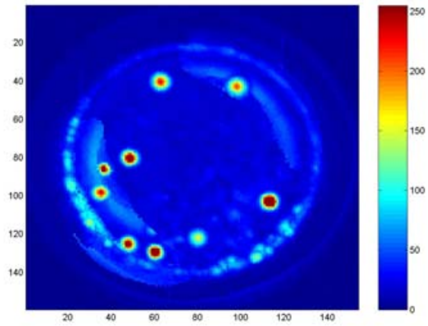

Figure 2. C-scan of Ti-Al part with steel inclusions (compression waves, normal incidence).

For 3 mm and 6 mm thick specimens, we could not carry out experiments in the normal incidence configuration, because of the width of echoes on A-Scans resulting from the sample thickness (detection cannot be made in the blind zone). So, we performed angle beam testing: by calculating the refraction angle of shear waves, we performed C-Scan inspection with a suitable incidence angle with regard to the sample upper surface. This method permitted us to detect each kind of inclusions in such specimens.

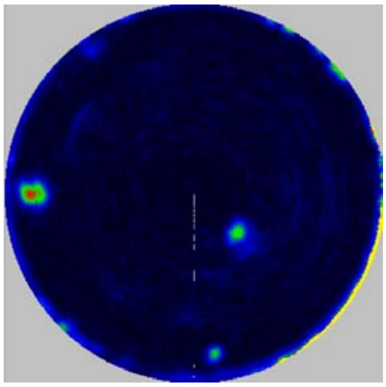

Figure 3. C-scan of Ti-Al part with steel inclusions (shear waves, oblique incidence).

As a conclusion, void detection in materials is limited to 0.1 mm equivalent reflective diameter. Moreover, in the case of real inclusions with different chemical compositions, the detection capability is decreased because of the low impedance shifts between matrix and defect. For this reason, we developed A-Scan processing techniques aiming at improving S/N ratios and echo detection.
Wavelet analysis seemed to be the most promising technique due to its ability to distinguish echoes from noise.

Wavelet techniques to improve inspectability

Wavelet analysis is a well-known tool in the signal processing community [1]. It provides a scale representation of a signal by decomposing it onto a set of basis functions that are obtained by scaling and time shifting a mother wavelet Ψ.

The Continuous Wavelet Transform (CWT) can be defined as:

$$CWT(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} s(t)\Psi^{*}_{a,b}\left(\frac{t-b}{a}\right)dt$$

This transform yields a two-dimensional set of coefficients, depending on the two parameters (a,b), where each coefficient measures the similarity between the signal and the scaled and shifted wavelet. The parameter a describes dilation or compression of the mother wavelet and gives the notion of scale. The parameter b represents the translation of the wavelet with respect to the signal, and corresponds to time location.

The 2D set of coefficients gives a time-scale representation of a signal, that may also be interpreted as a time-frequency representation.

In addition to the defect echoes of interest, ultrasonic signals include a lot of undesired acoustic phenomena such as grain noise or multi-path echoes. Fortunately, the latter components are localised in different frequency bands or different time ranges than the echoes we are interested in. As the CWT representation describes the signal into different frequency bands and time positions, it helps distinguishing those signal components.

The selection of the mother wavelet depends on the goal of the analysis. Due to Heisenberg's principle, the resolution depends on the frequency and time supports of the selected wavelet. Knowing that these supports are mutually dependant (their product is a constant, we have to choose between time and frequency accuracy).

In our case, the precision in the time domain is as important as the precision in the frequency domain; therefore we chose a gaussian-like wavelet such as the Morlet wavelet [1].

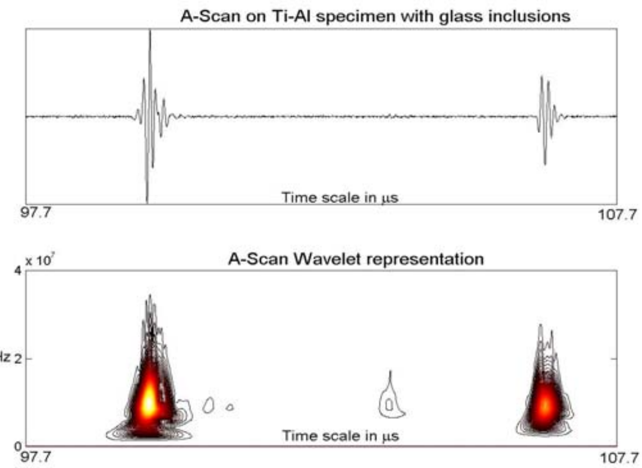

Figure 4. Steels inclusions: a) A-Scan; b) Wavelet representation.

For practical implementation, we used a discrete wavelet transform (DWT), i.e. we quantized the scaling and time-shift parameters. For the scaling parameter a, we chose a "dyadic" representation:

$$a = a_0 2^j \quad where\ j \in Z$$

We applied a non optimal algorithm, i.e. we computed the DWT directly by calculating the convolution between a wavelet and the signal. The coefficient representation thus obtained is highly redundant, but is more readable especially for low frequencies.

Figure 4 shows the A-scan in a specimen containing steel inclusions and its wavelet representation. We can appreciate that the defect echo is not immediately visible on the A-Scan, just because the magnitude difference between the interface echo and this echo is superior to 60 dB, due to the low impedance variation between steel and Ti-Al. On the other hand, the contour plot of DWT coefficients having the same value clearly shows that the signal contains a defect echo. Moreover, because grain noise and electronic noise are high frequency noises, they are not represented in the same range. This further increases detectability.

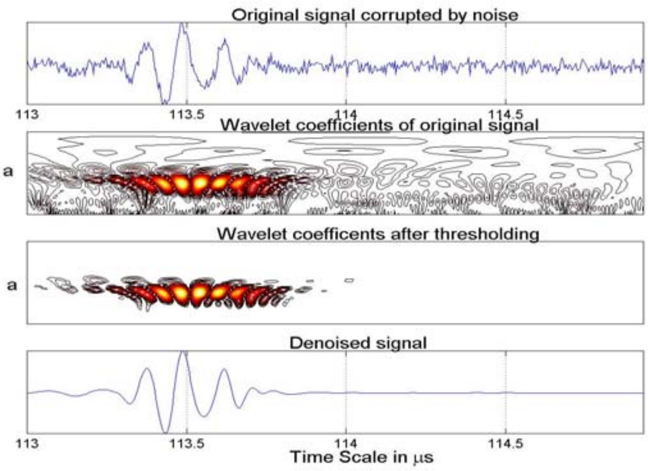

Figure 5. Wavelet denoising example (with hard thresholding).

The second advantage clearly appearing on this DWT representation, is the visualisation of frequency content modifications: we can see that propagation through Ti-Al affects frequency content since the coefficient "shape" in the time-scale representation is modified from one echo to the other.

Wavelet denoising techniques

Denoising applications of wavelets are based on the following very simple idea.

Consider the situation when a signal of interest *s(t)* is corrupted by noise *n(t)* and the following conditions are met:

1. *s(t)* is localised in the time and frequency domains, so that its DWT coefficients only take large values in these domains,

2. *n(t)* is stationary gaussian and white, so that it has a moderate DWT coefficients in all the time-scale plane.

The overall signal *s(t)+n(t)* then only has large DWT coefficient in the time-scale domain corresponding to its useful components. Therefore, by only keeping these large coefficients and resetting the other ones to zero, most of information related to the useful signal is kept, while most of the noise contributions are removed. Applying an inverse DWT to these thresholded coefficients then yields the time-representation of a denoised version of this signal (as shown in Figure 5).

Donoho and Johnstone developed thresholding methods for coefficient selection [2]. We chose this kind of methods because it is easy to implement. We considered two such denoising methods: for hard thresholding, each coefficient that falls under a selected threshold is cancelled out as stated above, and for soft thresholding, we applied a continuous non-linear function to the wavelet coefficients.

If *C(a,b)* corresponds to the DWT coefficients, hard thresholding is defined as follows:

$$C'(a,b) = \begin{cases} C(a,b) & if\ |C(a,b)| \geq \lambda \\ 0 & if\ |C(a,b)| < \lambda \end{cases}$$

and soft thresholding is defined as described hereafter:

$$C'(a,b) = \begin{cases} C(a,b) - sign(C(a,b))\lambda & if\ |C(a,b)| \geq \lambda \\ 0 & if\ |C(a,b)| < \lambda \end{cases}$$

λ defines the threshold and its optimum value depends on the noise level σ and on the number N of samples in the signal:

$$\lambda = \sigma\sqrt{2\log N}$$

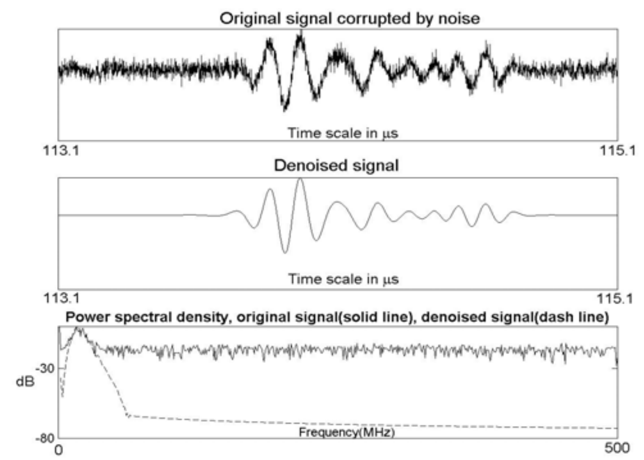

Figure 6. Wavelet denoising with soft thresholding.

As we can see in figure 6 and 7 we applied those shrinkage functions to A-Scans. The noise level was measured in a signal zone without any echoes. For different experiments with different parts and probes, we measured ratios between echoes and noise amplitudes between 60 dB and 5 dB.

For noisy signals with 10 dB S/N ratios between noise and interface echoes, we succeeded in improving this ratio up to 60 dB.

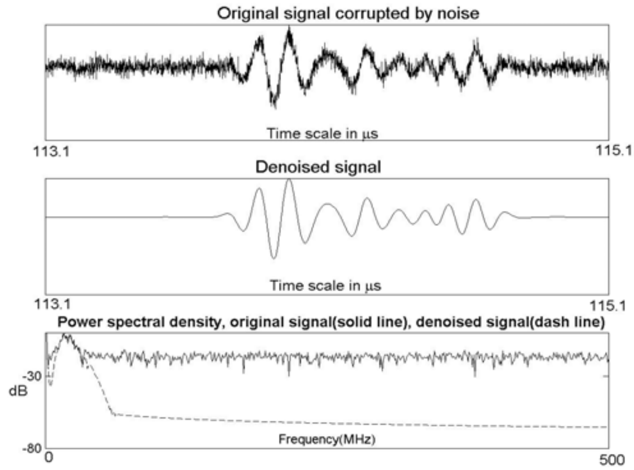

Figure 7. Wavelet denoising with hard thresholding.

For S/N ratios smaller than 10 dB, the algorithms do not succeed in separating coefficients corresponding to signal and noise.

Conclusion

In this work, we evaluated immersion ultrasonic inspection performance for gamma-Ti-Al based alloys. For this study, we realised reference blocks and polluted specimens with real inclusions. Ultrasonic testing is suitable for this kind of alloys: we can detect voids in materials down to 0.1 mm equivalent diameters in 20 mm of materials. For real inclusions, detection capability depends on the nature and shape of particles: we detected inclusions in the 0.2-0.5 mm diameter range within material depth ranging from 3 to 20 mm.

Wavelet techniques showed promising performance for detecting echoes in low S/N ratio conditions. Moreover, with wavelet coefficient thresholding, we could improve detectability and S/N ratios up to 60 dB. At this stage, we used shrinkage rules depending on global noise power, but we plan to apply other thresholding methods (statistical, adaptive…).

References

[1] O. Rioul and M. Vetterli, "Wavelets and signal processing", IEEE Signal Processing Magazine, Oct. 1991.

[2] D.L. Donoho and L.M. Johnstone, "Ideal spatial adaptation via wavelet shrinkage", Biometrika 81, pp. 425-455, 1994.