Available online at www.sciencedirect.com
SCIENCE DIRECT®
NDT&E International 39 (2006) 487–492
NDT&E international
www.elsevier.com/locate/ndteint

High-resolution pursuit for detecting flaw echoes close to the material surface in ultrasonic NDT

N. Ruiz-Reyes*, P. Vera-Candeas, J. Curpián-Alonso, J.C. Cuevas-Martínez, J.L. Blanco-Claraco

Electronics and Telecommunication Engineering Department, University of Jaén, Polytechnic School, C/ Alfonso X El Sabio, 28, 23700—Linares, Jaén, Spain

Received 16 March 2005; accepted 13 February 2006
Available online 11 April 2006

Abstract

A new NDT method to detect ultrasonic flaw echoes close to the surface in strongly scattering materials is proposed. The method is based on high-resolution pursuit (HRP), which is a version of matching pursuit (MP) that emphasizes local fit over global fit. Since HRP produces representations which resolve closely spaced features, it is a very valuable signal processing tool for achieving the goal claimed in this work. Furthermore, HRP has the same order of complexity of MP. The good performance of the method is experimentally verified using ultrasonic traces acquired from a carbon fibre reinforced plastic (CFRP) material.

Keywords: Flaw echo; Ultrasonic; High-resolution pursuit; NDT; Scattering material; Object recognition

1. Introduction

Flaw detection by ultrasonic non-destructive evaluation or testing (NDE or NDT) has been proven to be an effective means to assure the quality of materials. In the analysis of back-scattered ultrasonic signals, the micro-structure of the tested materials can be considered as an unresolved and randomly distributed set of reflection centers. The back-scattered ultrasonic signal is the result of convoluting the transmitted acoustic pulse with these reflection centers. This noise-like signal of structural origin (ultrasonic grain noise) is time-invariant and, unfortunately, presents in some cases a frequency band very similar to that of the echoes issuing from the flaws to be detected. Furthermore, this situation become worse when flaw echoes are close to the material surface, because ultrasonic grain noise is higher than flaw echoes in the part of the back-scattered ultrasonic signal corresponding to the neighborhood of the material surface. Therefore, these flaw echoes cannot be canceled by classical time averaging or matched band-pass filtering techniques.

Many signal processing techniques have been utilized for detecting flaw echoes in ultrasonic NDE of highly scattering materials. The most popular one is the split spectrum processing (SSP) [1,2], because it makes possible real time ultrasonic test for industrial applications, providing quite good results. Adaptive time–frequency analysis by basis pursuit [3,4] is a quite recent technique for decomposing a signal into an optimal superposition of elements in an over-complete waveform dictionary. This technique has been successfully applied to denoising ultrasonic signals contaminated with grain noise in highly scattering materials [5], its main drawback being the computational cost of the BP algorithm.

In this paper, a new high resolution pursuit (HRP) -based signal processing method is proposed for detecting flaws close to the surface of strongly scattering materials, such as steel and composites, in NDT applications. The proposed method uses HRP [6], instead of basis pursuit (BP), looking for reducing the complexity. HRP is an enhanced version of the matching pursuit (MP) algorithm [7], which overcomes the shortcomings of the traditional MP algorithm by emphasizing local fit over global fit at each stage. In such sense, HRP provides high time-resolution time–frequency representations and enables to

*Corresponding author. Tel.: +34 953648554; fax: +34 953648508.
E-mail address: nicolas@ujaen.es (N. Ruiz-Reyes).

0963-8695/$ - see front matter © 2006 Elsevier Ltd. All rights reserved.
doi:10.1016/j.ndteint.2006.02.002

resolve closely time-spaced features, as happens in ultrasonic signals when detecting flaw echoes close to the material surface is intended. Furthermore, the HRP algorithm has the same order of complexity as MP, being fast enough to be real time implemented [8].

Experimental results with a carbon fibre reinforced plastic (CFRP) block have been carried out in order to assess the good performance of the proposed approach. Flaw echoes are detected even when they correspond to small defects close to the surface.

2. Matching pursuit

MP algorithm was introduced by Mallat and Zhang [7]. Let us suppose an approximation of the ultrasonic backscattered signal $x[n]$ as a linear expansion in terms of functions (or atoms) $g_i[n]$ chosen from an over-complete dictionary. Let $\mathbf{H}$ be a Hilbert space. We define the overcomplete dictionary as a family $D=\{g_i[n];\ i=0,\ 1,\ \ldots,\ L\}$ of functions in $\mathbf{H}$, such as $||g_i[n]||=1$.

The problem of choosing functions $g_i[n]\in D$ that best approximate the analyzed signal $x[n]$ is computationally very complex. MP is an iterative algorithm that offers sub-optimal solutions for decomposing signals in terms of expansion functions chosen from a dictionary, where l^2 norm is used as the approximation metric because of its mathematical convenience. When a well-designed dictionary is used in matching pursuit, the non-linear nature of the algorithm leads to compact adaptive signal models.

At each step of the iterative procedure, the function in the overcomplete dictionary which gives the highest correlation with the analyzed signal is chosen. The contribution of this function is then subtracted from the signal and the process is repeated on the residual. At the m-th iteration the residue is

$$r^m[n]=r^{m+1}[n]+\alpha_{i(m)}\ g_{i(m)}[n],\quad m\geqslant 1,\tag{1}$$

where $\alpha_{i(m)}$ is the weight associated to optimum atom $g_{i(m)}[n]$ at the m-th iteration and $r^1[n]$ is initialized to $x[n]$.

The weight α_i^m associated to each atom $g_i[n]\in D$ at the m-th iteration provides the inner product between each atom $g_i[n]$ and the residual $r^m[n]$, since MP defines the correlation function as the inner product [9]:

$$\alpha_i^m=C(r^m[n],g_i[n])=\langle r^m[n],g_i[n]\rangle.\tag{2}$$

Therefore, the optimum atom $g_{i(m)}[n]$ at the m-th iteration is given by Eq. (3):

$$\begin{aligned} g_{i(m)}[n] &= \arg\min_{g_i\in D}|r^{m+1}[n]|^2\\ &= \arg\max_{g_i\in D}|\alpha_i^m|\\ &= \arg\max_{g_i\in D}|\langle r^m[n],g_i[n]\rangle|.\end{aligned}\tag{3}$$

The computation of correlations $\langle r^m[n],g_i[n]\rangle$ for all vectors $g_i[n]\in D$ at each iteration implies a high computational effort, which can be substantially reduced using an updating procedure derived from Eq. (1).

The correlations at the $m+1$-th iteration can be obtained as follows:

$$\langle r^{m+1}[n],g_i[n]\rangle=\langle r^m[n],g_i[n]\rangle-\alpha_{i(m)}\ \langle g_{i(m)}[n],g_i[n]\rangle.\tag{4}$$

Correlations $\langle g_{i(m)}[n],g_i[n]\rangle$ can be pre-calculated and stored, once set D has been defined. Therefore, according to Eq. (4), computing correlations $\langle x[n],g_i[n]\rangle$ at the first iteration is only required.

3. High-resolution pursuit

MP is a greedy algorithm in that it optimizes at each iteration the amount of the signal energy it grasps. This often leads to a choice of features which globally fits the signal, but is not well adapted to its local structures. Aiming at avoiding this problem, Chen and Donoho introduced the basis pursuit, which makes a full optimization by minimizing $\sum_{i\in D}\alpha_i$over all possible decompositions $x[n]=\sum_{i\in D}\alpha_i\ g_i[n]$. However, this approach leads to large-scale linear-programming problems, being very expensive in terms of calculation time.

HRP is an enhanced version of MP, which, on the basis of a different correlation function, allows the pursuit to emphasize local fit over global fit at each iteration, being able to achieve a similar super-resolution to that exhibited by basis pursuit. HRP is similar in structure to the MP algorithm. In fact, it has the same computational complexity. The definitions below, taken from Ref. [10], have been included to make the paper easier to understand.

For each time–frequency atom $g_i[n]\in D$, a set of subatomic indexes I_i is introduced. The set I_i is associated to high-resolution atoms $g_{\lambda_i}[n]$, $\lambda_i\in I_i$, with a time support included in the support of $g_i[n]$ and modulated at the same frequency. If the atom $g_{i(m)}[n]$ is chosen by HRP at the m-th iteration, then

$$\begin{aligned} r^{m+1}[n] &= r^m[n]-C(r^m[n],g_{i(m)}[n])\ g_{i(m)}[n]\\ &= r^m[n]-\alpha_{i(m)}\ g_{i(m)}[n]\end{aligned}\tag{5}$$

becomes the residue produced by the pursuit at the m-th iteration. For all $\lambda_i\in I_i$, $\langle r^m[n],g_{\lambda_i}[n]\rangle$ represents the amount of "energy" of $r^m[n]$ located on the time–frequency support of $g_{\lambda_i}[n]$. This amount must be smaller than the signal "energy" $\langle x[n],g_{\lambda_i}[n]\rangle$ at the same location:

$$|\langle r^m[n],g_{\lambda_i}[n]\rangle|\leqslant|\langle x[n],g_{\lambda_i}[n]\rangle|.\tag{6}$$

Moreover, the following relation must also be fulfilled:

$$|\langle C(r^m[n],g_i[n])\ g_i[n],g_{\lambda_i}[n]\rangle|\leqslant|\langle r^m[n],g_{\lambda_i}[n]\rangle|.\tag{7}$$

From Eqs. (6) and (7), we derive the new correlation function $C(r^m[n],g_i[n])$ for the HRP algorithm, which maximizes the amount of signal energy that the pursuit can grasp when choosing the atom $g_i[n]$ at the m-th iteration:

$$\alpha_i^m = C(r^m[n], g_i[n]) = \varepsilon \min_{\lambda_i \in I_i} \frac{|\langle r^m[n], g_{\lambda_i}[n]\rangle|}{|\langle g_i[n], g_{\lambda_i}[n]\rangle|}, \tag{8}$$

where ε is evaluated as follows:

- If $\langle r^m[n], g_{\lambda_i}[n]\rangle$ has the same sign for all $\lambda_i \in I_i$, then ε is this common sign.
- Else $\varepsilon = 0$.

In MP, the inner product, used as a correlation function between a time–frequency atom $g_i[n]$ and the analyzed signal $x[n]$, disregards whether the signal contains energy on the whole time–frequency support of the chosen atom. On the contrary, the new correlation function in Eq. (8) avoids creating energy at time locations where there was none. It can thus distinguish close time features, as shown in the results.

4. Proposed method for flaw detection

According to the HRP algorithm, our method has to define the dictionary elements and the way to detect the flaw echoes. Since a real time implementation is claimed for usefulness, the complexity of the proposed method must be reduced as much as possible. Because HRP is an iterative algorithm, the goal can be achieved if both the amount of operations at each iteration and the number of iterations to detect a flaw echo are reduced.

The overcomplete dictionary D will be composed of pulsed functions $g_{\{i,k\}}[n]$ that mimic the echoes coming from the flaws to be detected, which in turn depend on the impulsive response of the transducer used in the experiments. Fig. 1 compares the Morlet pulse with a typical flaw signal.

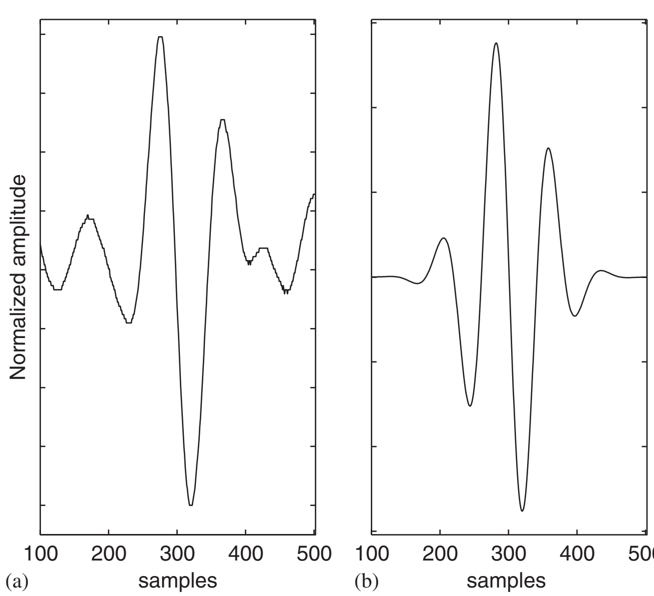

Fig. 1. Comparison: (a) flaw signal and (b) Morlet pulse.

Since the signal produced by the grain echoes is sparse in time, due to the convolution of the ultrasonic pulse with the reflection centers of the material, and flaw echoes have short time support, HRP can efficiently extract flaw echoes in only a few iterations by defining two types of functions:

- High time resolution functions, which fit well to the features to be extracted from the ultrasonic signal.
- Low time resolution functions, which represent the noise due to grain echoes.

According to the stated above, HRP requires functions $g_{\{i,k\}}[n]$, $i = 1, \ldots, L = N + M$, $k = 1, 2$, are defined, where L is the number of time shifts to take into account all possible flaw echo positions, N the ultrasonic data length and M the length of the pulsed functions $g_{\{i,k\}}[n]$. Therefore, the overcomplete dictionary size is $2L$. Functions $g_{\{i,1\}}[n]$ mimic the echoes coming from the flaws, while functions $g_{\{i,2\}}[n]$ represent the signal coming from the grain echoes, having low time resolution.

The functions required by our HRP-based method are defined as time-shifted Morlet pulses, and can be expressed as

$$g_{\{i,k\}}[n] = S_{\{i,k\}}\, e^{-\left((n-i)/T_k f_s\right)} \cos\left(2\pi \frac{f_m}{f_s}(n-i) + \phi_m\right)$$
$$i = 1, \ldots, L, \quad k = 1, 2, \;\; n = i - \frac{M}{2} + 1, \ldots, i + \frac{M}{2}, \tag{9}$$

where T_k, f_m and ϕ_m are the Morlet pulse parameters. In particular, f_m is related to the frequency of the transducer response. $S_{\{i,k\}}$ is a constant to achieve $||g_{\{i,k\}}[n]|| = 1$ and f_s is the sampling frequency of the ultrasonic signal. Parameter T_k resolves on the time support of functions $g_{\{i,k\}}[n]$. In such sense, T_1 is adapted to the bandwidth of the transducer response, giving rise to functions well correlated

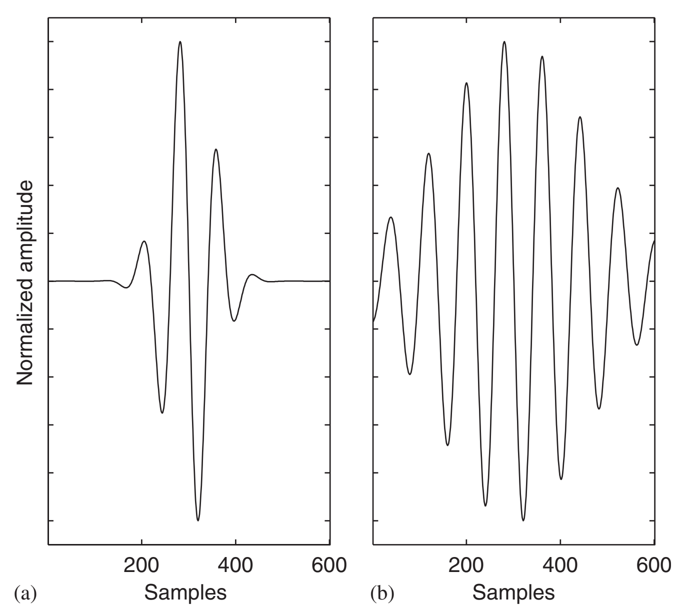

Fig. 2. (a) High time-resolution function and (b) low time-resolution function, both modulated at the same frequency.

to flaw echoes. Nevertheless, T_2 gives rise to long time support functions, which fit well to the signal coming from the grain echoes.

Fig. 2 shows an example of functions $g_{\{i,k\}}[n]$ for $k = 1, 2$. Both functions are modulated at the same frequency, but exhibit different time support due to parameter T_k. Fig. 2a shows the high time-resolution function, while the low time-resolution function is shown in Fig. 2b.

Once the functions required by our HRP-based method for detecting flaws close to the material surface by ultrasonic NDT have been defined, we focus on describing the method as such. For high time resolution atoms $g_{\{i,1\}}[n]$, which fit well to the flaw signal, the correlations between such atoms and the residue $r^m[n]$ at the m-th iteration are computed as in the MP algorithm:

$$\alpha^m_{\{i,1\}} = C(r^m[n], g_{\{i,1\}}[n]) = \langle r^m[n], g_{\{i,1\}}[n]\rangle. \quad (10)$$

From the HRP point of view, the previous expression is derived by defining the set of subatomic indexes $I_{\{i,1\}} = \{i,1\}$ corresponding to atoms $g_{\{i,1\}}[n]$ having high time resolution. However, for low time resolution atoms$g_{\{i,2\}}[n]$, which fit well to the grain noise signal, the correlations are computed according to expression (8), that is rewritten here for that particular case:

$$\begin{aligned}\alpha^m_{\{i,2\}} &= C(r^m[n], g_{\{i,2\}}[n]) \\ &= \varepsilon \min_{\{\lambda_i,1\}\in I_{\{i,2\}}} \frac{|\langle r^m[n], g_{\{\lambda_i,1\}}[n]\rangle|}{|\langle g_{\{i,2\}}[n], g_{\{\lambda_i,1\}}[n]\rangle|}. \quad (11)\end{aligned}$$

The definition of the set of subatomic indexes $\{\lambda_i, 1\} \in I_{\{i,2\}}$ has to be discussed. As first approximation, all atoms $g_{\{\lambda_i,1\}}[n]$ with non-zero cross-correlation with atom $g_{\{i,2\}}[n]$ could be included. However, this definition involves expression (11) is high time consuming, because there are $2M$–1 correlated atoms and a division is computed for each one. For the sake of decreasing the complexity, the set of subatomic indexes $I_{\{i,2\}}$ is reduced to the following one:

$$I_{\{i,2\}} = \{\{i-2P,1\}, \{i-P,1\}, \{i,1\}, \{i+P,1\}, \{i+2P,1\}\}, \quad (12)$$

where $P = \lfloor f_s/f_m \rfloor$ approximates the discrete period of the frequency f_m. The set $I_{\{i,2\}}$ is now composed of five components, which have been selected from the local maximum values of function $g_{\{i,2\}}[n]$. Fig. 3 depicts an example of function $g_{\{i,2\}}[n]$ and its constituent components. As can be seen, the set of indexes $I_{\{i,2\}}$ has been organized in the intention of extracting a function $\alpha^m_{\{i,2\}}\, g_{\{i,2\}}[n]$ without modifying a possible flaw echo in the ultrasonic signal.

We have designed our HRP-based method in order to detect a flaw echo when an atom $g_{\{i,1\}}[n]$ is selected. When an atom $g_{\{i,2\}}[n]$ is chosen by the HRP algorithm, it is eliminated from the signal because we have supposed this atom represents grain noise. The HRP algorithm is halted when the detected flaw is below a threshold, which is chosen in terms of the minimum flaw echo to detect. The experimental results assess that this simple method is suitable for achieving a meaningful reduction of the grain noise.

5. Experimental results

A carbon fibre reinforced parallelepiped plastic (CFRP) block of 50 mm thickness was machined on one of its plain surfaces to perform one flat-bottom hole (FBH) at a high-enough depth so as to consider the FBH a surface flaw. Experimental ultrasonic signals were recorded scanning with a contact transducer the FBH drilled close to the material surface in order to obtain a flaw echo, which

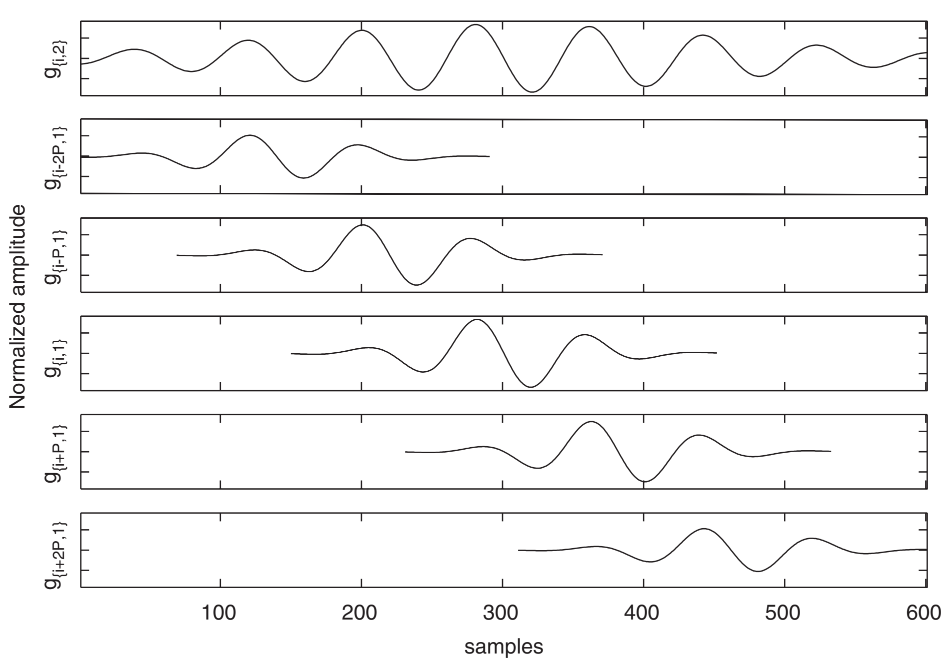

Fig. 3. Obtaining $g_{\{i,2\}}[n]$ from its constituent components.

initially appears, then grows, decreases and finally disappears.

A circular ultrasonic transducer for longitudinal waves, 6.35 mm in diameter, 5 MHz of nominal frequency and 50% bandwidth was used to obtain experimental echo traces. The probe was placed in contact and driven in pulse-echo operation with a Panametrics Ultrasonic Analyser 5052UA. The selected pulser/receiver parameters were: damping resistance = 200 Ω, energy position = 2 (810 pF for the HV discharge capacitor), receiver gain = 26 dB, cut-off frequency of the receiver high-pass filter = 300 kHz. The ultrasonic traces were acquired with a sampling frequency of 100 MHz by means of a digital oscilloscope (Tektronix TDS 744) of 2 GS/s and data length of 4000 samples, which were transferred via GPIB to a computer for further processing. The experimental set-up is shown in Fig. 4.

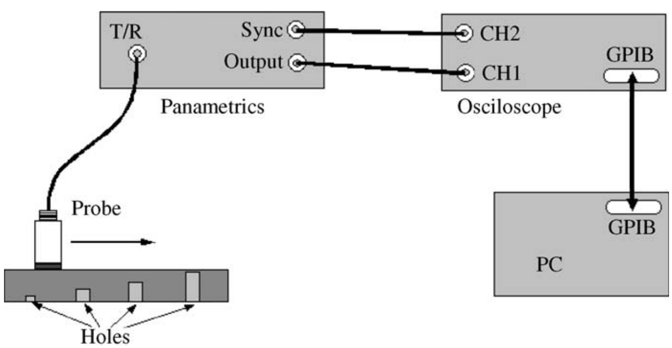

Fig. 4. Figure presenting the experimental set-up.

Fig. 5 shows the performance of the proposed method for two experimental signals. The first signal corresponds to a signal with a flaw echo close to the surface and the second signal has not any flaw echo. At each iteration the atom selected by the HRP algorithm is presented. As can be seen in Fig. 5, the flaw echo is chosen at the fourth iteration for the example.

Experimental signals were recorded scanning with the contact transducer the composite block over the plane opposite to the one where the FBH was drilled, in order to obtain input signals with and without hole indications. Fig. 6 shows four original ultrasonic signals together with the corresponding processed ones, which correspond to (a) initially appearing flaw echo, (b) slightly growing flaw echo, (c) decreasing flaw echo, and (d) no flaw. Pre- and post-processed signals are displayed in the same figure. Fig. 6 exhibits the good performance of the proposed method for detecting flaws close to the material surface.

6. Conclusions

A novel HRP-based method has been presented to detect flaws close to the material surface in ultrasonic NDT of highly scattering materials. Based on the use of a new correlation function, the method allows the pursuit to emphasize local fit over global fit at each iteration, being able to achieve a similar super-resolution to that exhibited by BP. Furthermore, taking into account that HRP and MP exhibit similar structure, the proposed method has the same order of complexity as MP. In addition, the number

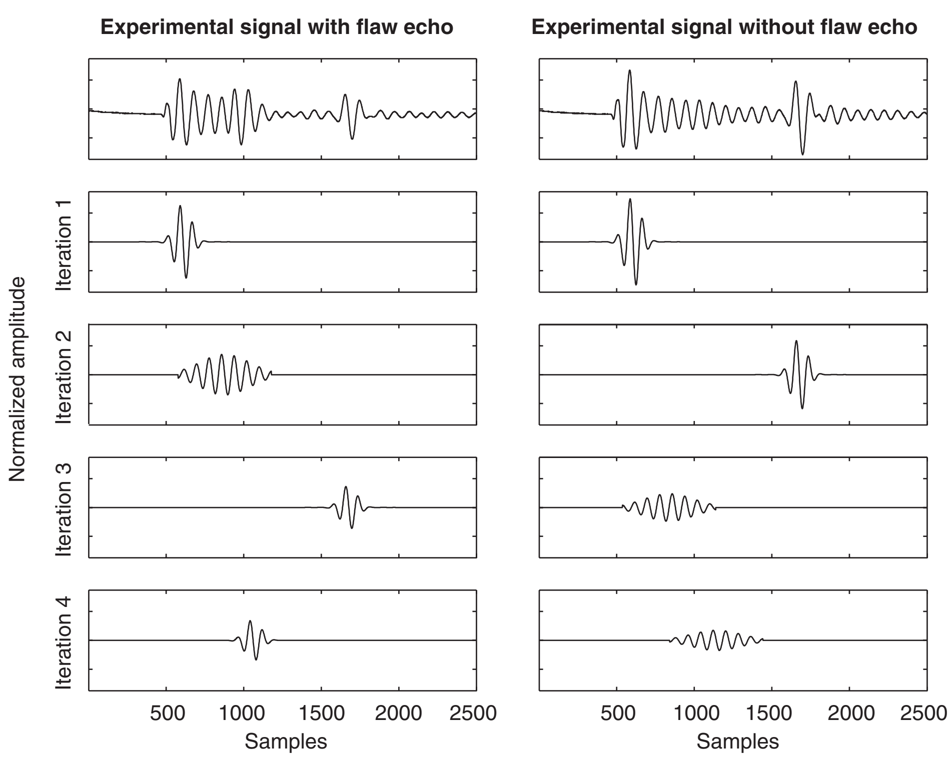

Fig. 5. Example of performance for the proposed method: (a) experimental signal with flaw echo and (b) experimental signal without flaw echo.

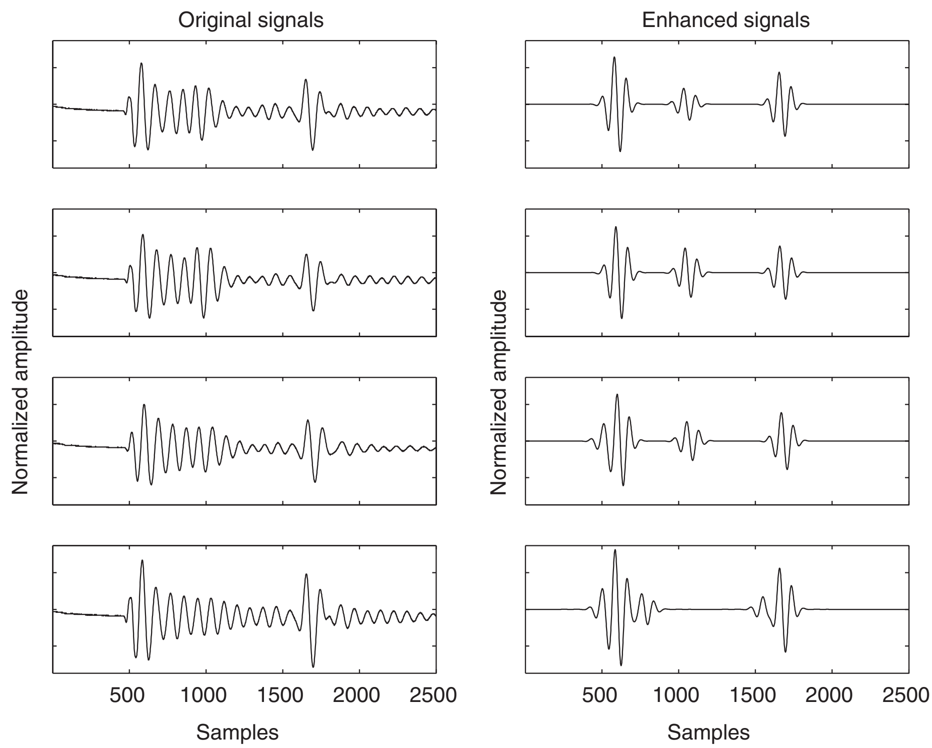

Fig. 6. Processed results using experimental signals.

of iterations needed to attain the detection of small surface flaws is low (5.75 on average in our experiments), which permits its use in practical real-time ultrasonic NDT systems for industrial applications.

The method is very efficient eliminating grain noise and increasing the visibility of ultrasonic flaw signals. Experimental results make evidence the good performance of the proposed approach, because flaw echoes are detected even when they correspond to small defects close to the surface.

References

[1] Newhouse VL, Bilgutay NM, Saniie J, Furgason ES. Flaw-to-gain echo enhancement by split spectrum processing. Ultrasonics 1982;20: 59–68.

[2] Sun HC, Saniie J. Ultrasonic flaw detection using split spectrum processing combined with adaptive-network-based fuzzy inference systems. Proc IEEE Ultrason Sympos 1999.

[3] Chen S, Donoho D. Basis pursuit. Proceedings of the 28th Asilomar conference on signals, systems and computers, vol. 1. 1994. p. 1–44.

[4] Chen S, Donoho D. Basis pursuit. Technical report. Stanford University: Statistics Department; 1995.

[5] Zhang G, Zhang S, Wang Y. Application of adaptive time-frequency decomposition in ultrasonic NDE of highly scattering materials. Ultrasonics 2000;38:961–4.

[6] Jaggi S, Karl WC, Mallat S, Willsky AS. High resolution pursuit for feature extraction, Technical report. Cambridge, MA: MIT; 1995.

[7] Mallat S, Zhang Z. Matching pursuits with time-frequency dictionaries. IEEE Trans Signal Process 1993;41:3397–415.

[8] Ruiz N, Vera P, Curpian J, Martinez D, Mata R. Matching pursuit-based signal processing method to improve ultrasonic flaw detection in NDT applications. IEE Electron Lett 2003:413–4.

[9] Goodwin MM. Adaptive signal models: theory, algorithms and audio applications. Dordrecht: Kluwer Academic Publishers; 1998.

[10] Gribonval R, Bacry E, Mallat S, Depalle Ph, Rodet X. Analysis of sound signals with high resolution matching pursuit. In: Proceedings of the IEEE-SP international symposium on time-frequency and time-scale analysis. 1996. p. 125–8.