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NDE applications of compressed sensing, signal decomposition and echo estimation

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Abstract— **In this investigation, a compressed sensing (CS) sampling scheme is closely incorporated into ultrasound signal decomposition. The CS is used to exploit the sparsity of ultrasound echo signals and thereby significantly reduce the sampling rate with 20-30 times lower than the Nyquist rate. Furthermore, the time-of-arrivals (TOAs) of dominant echoes are estimated with the sparse sampling. The estimated TOAs along with a priori information of the transducers are used for model-based signal decomposition on the incomplete ultrasonic data, where Gaussian Chirplet (GC), a commonly used echo model, is adopted. Parameters of GC echoes are estimated for pattern recognition and defect characterization in the presence of noise with SNR as low as -5 dB. Through an experimental study, the decomposition results and estimated parameters confirm the robustness and effectiveness of the proposed technique. The study has a broad range of application in signal analysis including sparse representation, parameter estimation, and defect detection.**

Keywords– Ultrasonic NDE, compressed sensing, echo parameter estimation, signal decomposition

I. INTRODUCTION

In ultrasonic NDE applications, the pattern of ultrasound echo signal reveals important physical information such as the location, size and orientation of defects, as well as attenuation and dispersion characteristics of the propagation path. Numerous signal processing techniques including parametric and nonparametric methods have been utilized to examine ultrasound echoes [1-6]. It has been shown that model-based signal analysis is robust in echo evaluation and parameter estimation, especially when the adopted model has parameters strongly pertinent to the physical information of reflectors in material and structures. Estimated parameters of echoes can be used to quantitatively evaluate structures and characterize material. Nevertheless, signal processing and analysis is still challenging due to the non-stationary nature of ultrasound NDE signals.

It becomes more problematic when there is a large volume of data to be collected and processed for in-situ assessment of outsized structures. In the conventional sampling scheme, Nyquist sampling rate dictates the lower bound of data acquisition. Recently, an emerging low-rate sampling scheme, compressed sensing (CS), has been utilized in data intensive imaging applications. The CS exploits the sparseness of signal in a certain domain, where a fractional number of coefficients are used to represent signals with minimum loss in the quality of imaging [7-10]. The prominent examples are magnetic resonance imaging and tomography. Moreover, Vetterli *et al* showed sparse sampling of signal innovation [11-13]. Y. C. Eldar et. al. have introduced the sparse sampling of innovation to medical ultrasound and proposed a sub-Nyquist sampling scheme [14]. The received ultrasound echo signal is modeled as a finite Gaussian pulse stream. Parameters of those pulses such as time-of-arrival (TOA) and amplitude are estimated and utilized for signal restoration. It has been also shown that the TOAs of echoes are estimated accurately, whereas there is a large error in the amplitude estimation of echoes.

In ultrasonic NDE applications, accurate estimation of both TOA and amplitude is significant for material characterization and structure evaluation. Our previous work explores the feasibility of echo estimation based on the new CS sampling scheme [15]. This study aims to connect the existing model-based signal decomposition algorithm with the CS sampling scheme. The interest is particularly in ultrasonic echo parameter estimation and signal decomposition algorithms using the CS framework, where a commonly used echo model, Gaussian Chirplet (GC), is adopted. An experimental study is presented to demonstrate the effectiveness of the CS based decomposition algorithm.

This paper is organized as follows: Section II describes the CS-based signal decomposition algorithm for ultrasonic NDE. Section III presents experimental results. Section IV concludes the paper.

II. CS-BASED SIGNAL DECOMPOSITION AND PARAMETER ESTIMATION

In the context of ultrasonic NDE signal in noise, an ultrasound echo signal, $x(t)$, can be represented as

$$\begin{aligned} x(t) &= s(t) + n(t) \\ &= \sum_{k=1}^{K} h_{\Theta_k}(t) + n(t) \end{aligned} \tag{1}$$

where $s(t)$ denotes the noise-free reflected ultrasound signal,

$n(t)$ denotes a white Gaussian noise.

$h_{\Theta_k}(t)$ denotes the Gaussian Chirplet (GCs), which is

$$h_{\Theta_k}(t) = a_k\, e^{-\alpha_{1k}(t-\tau_k)^2} \cos\left(2\pi f_{ck}(t-\tau_k) + \alpha_{2k}(t-\tau_k)^2\right) \tag{2}$$

Here Θ_k denotes the parameter vector of the $k\,th$ GC, which includes the time-of-arrival τ_k, the center frequency f_{ck}, the amplitude a_k, the bandwidth factor α_{1k}, and the chirp-rate, α_{2k}.

The proposed CS-based signal decomposition is summarized as follows[15].

1. Obtain signal envelope using Hilbert Transform (HT),

$$e(t) = \left|HT\left(x(t)\right)\right| \tag{3}$$

When a severe noise is present, preprocessing with a low pass filter or simple thresholding can be applied to the signal before the envelope detection .

2. A sampling kernel, $g(t)$, is used to condition the envelope signal $e(t)$ for sparse sampling.

$$y(t) = e(t) * g(t) \tag{4}$$

where $*$ denotes the convolution operation

$$g(t) = \sum_{m=-K}^{K} b_m e^{j2\pi mt} \tag{5}$$

The M-length Hamming window coefficients, b_m, are given by[14]

$$b_m = 0.54 - 0.46\cos\left(2\pi \frac{m + \left\lfloor \frac{M}{2} \right\rfloor}{M}\right),$$

$M = 2K + 1$ and K is the number of GC echoes. It is shown that the Hamming window, b_m, generates a smooth and compactly-supported sampling kernel .

3. Perform the sparse sampling on measured signal $y(t)$ and find sparse samples,

$$c(n) = y(t)\Big|_{t=\frac{n}{M}} \tag{6}$$

where $n = 0 \cdots M-1$.

4. Calibrate the sparse samples by

$$X(m) = S_{M\times M}{}^{-1} C_f(m) \tag{7}$$

where $C_f(m)$ denotes M-point discrete Fourier transform (DFT) of the sparse samples sequence $c(n)$.

$$S_{M\times M} = diag\left(b_m e^{-\frac{\omega_m{}^2\sigma^2}{2}}\right),$$

$$\omega_m = 2\pi m, \quad m = -K, \cdots, K$$

The simulation study in [15] shows that the variance, σ^2, can be estimated using the prior information from the transducer (i.e., the bandwidth factor).

5. Solve the Yule-Walker equation below to find the coefficients, $A(k)$, $k = 1 \cdots K$. [13] :

$$\begin{bmatrix} X[0] & X[-1] & \cdots & X[-K+1] \\ X[1] & X[1] & \cdots & X[-K] \\ \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots \\ X[K-1] & X[K-2] & \cdots & X[0] \end{bmatrix} \begin{bmatrix} A[1] \\ A[2] \\ \cdots \\ \cdots \\ A[K] \end{bmatrix} = - \begin{bmatrix} X[1] \\ X[2] \\ \cdots \\ \cdots \\ X[K] \end{bmatrix} \tag{8}$$

6. Estimate TOAs (τ_k) by setting the z-transform polynomial,

$$\mathrm{A}(z) = 0 \tag{9}$$

where $\mathrm{A}(z) = \prod_{k=1}^{K}\left(1 - u_k z^{-1}\right) = 1 + \sum_{k=1}^{K} A(k) z^{-k}$

here $u_k = e^{-j2\pi\tau_k}$ and $A(k)$ are from Step 5.

It can be seen that u_k happens to be the roots on unit cycle. The annihilating-filter approach can be used to solve Equation (9) for estimated TOAs, τ_k .

7. Estimate the amplitudes of GCs , a_k, by solving the equation of Fourier series coefficients[11].

$$\begin{bmatrix} a_1 \\ a_2 \\ \cdots \\ \cdots \\ a_K \end{bmatrix} = \begin{bmatrix} 1 & 1 & \cdots & 1 \\ u_1 & u_2 & \cdots & u_K \\ u_1{}^2 & u_2{}^2 & \cdots & u_K{}^2 \\ \cdots & \cdots & \cdots & \cdots \\ u_1{}^{K-1} & u_2{}^{K-1} & \cdots & u_K{}^{K-1} \end{bmatrix} \begin{bmatrix} X[0] \\ X[1] \\ \cdots \\ \cdots \\ X[K] \end{bmatrix}$$

where $u_i = e^{-j2\pi\tau_{est\,i}}$ (10)

Although the estimated amplitudes, a_k, are not accurate enough for signal restoration[14], it could be used as an initial value to assist the searching of dominant echoes and parameter estimation.

8. With the estimated TOAs, τ_{est_i}, and a priori knowledge of the transducer bandwidth, a second data acquisition with windowing is used to isolate and acquire incomplete data for dominant GCs. Chirplet transform is applied to estimate the parameters of each GC [3]. The reconstructed ultrasound echo signal, $s_{est}(t)$, is then obtained by plugging the estimated parameters in the model given in Equation 2, i.e.,

$$s_{est}(t) = \sum_{k=1}^{K} h_{\Theta_{k\_est}}(t) \tag{11}$$

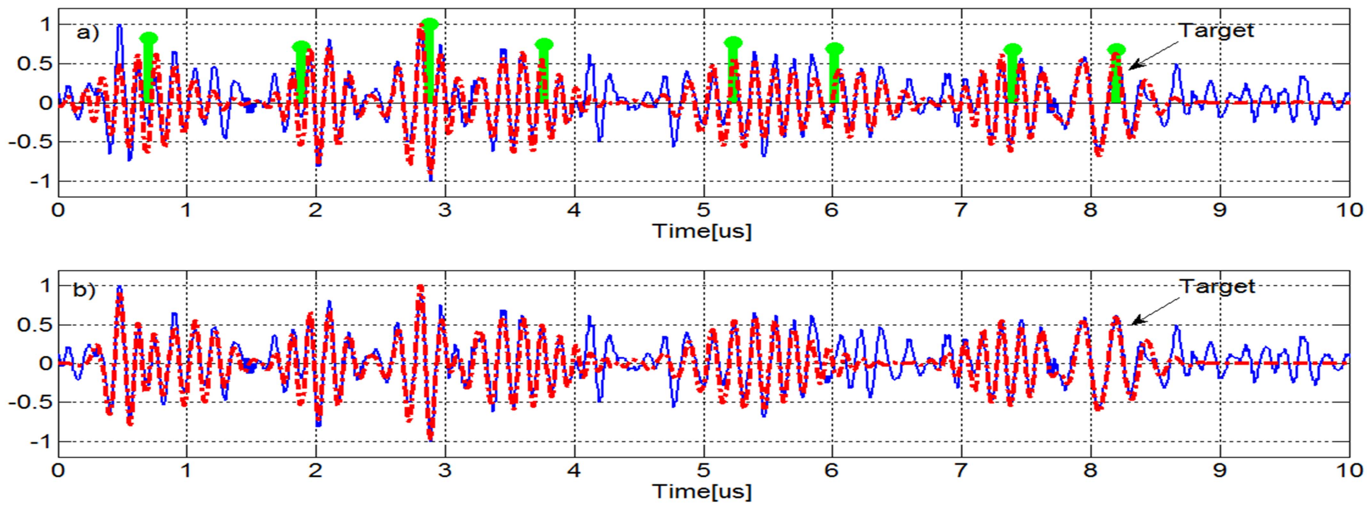

Figure 1. a) Experimental results using CS-based signal decomposition: Original experimental ultrasound echo signal (in Blue), the reconstructed signal with the first 8 dominant GCs (in Red), and the estimated TOAs and amplitudes using CS (in Green)
b) Experimental results directly using chirplet signal decomposition: Original experimental ultrasound echo signal (in Blue) and the reconstructed signal with the first 8 dominant GCs (in Red)

III. EXPERIMENTAL STUDY

An experimental study has been conducted to evaluate the performance of the proposed CS-based signal decomposition in ultrasonic signal processing. Ultrasound microstructure scattering signals are acquired from a steel block with embedded defects using a 5 MHz broadband transducer. The CS sampling scheme is used to estimate the TOAs and amplitudes of the first 8 dominant echoes, then the second data acquisition is used to acquire the dominant echoes for iterative parameters estimation. An ultrasound signal with 8 echoes is reconstructed based on the estimated parameters. Figure 1a shows the original experimental ultrasonic signal (in Blue) superimposed with the reconstructed signal (in Red). In addition, the estimated TOAs and amplitudes in the sparse sampling are highlighted (in Green). It can be seen that the estimated parameters from the CS stage provide a good reference for the follow-up signal decomposition.

Table 1. Parameter estimation results via CS-based signal decomposition for the signal in Figure 1

Echo Number	TOAs τ_k [us]	Center Frequency f_c [MHz]	Amplitude a
1	2.83	6.08	0.90
2	2.03	6.80	0.68
3	**8.09**	**3.87**	**0.61**
4	3.59	6.62	0.58
5	0.69	7.04	0.56
6	7.34	6.64	0.55
7	5.27	6.14	0.52
8	6.10	5.90	0.39

Table 2. Parameter estimation results via chirplet signal decomposition for the signal in Figure 1

Echo#	TOAs τ_k [us]	Center Frequency f_c [MHz]	Amplitude a
1	2.82	5.91	0.91
2	0.50	6.26	0.89
3	2.03	6.80	0.67
4	**8.10**	**3.85**	**0.58**
5	5.39	6.35	0.55
6	3.55	6.27	0.55
7	1.03	6.28	0.51
8	7.33	6.74	0.5

As a comparison, the same experimental data is processed by Chirplet signal decomposition [3] and the results are shown in Figure 1b. The estimated TOAs, center frequency and amplitude of GCs from these two different algorithms are listed in Table1 and Table 2, respectively. From the results in Figure 1, Table 1 and Table 2, one can conclude that the CS-based signal decomposition not only provides a sparse representation of experimental data, but successfully tracks the embedded target (i.e., the echo number 3 highlighted in Table 1).
Additionally, the proposed algorithm has high computation efficiency of parameter estimation due to the nature of low sampling rate and the initialization stage through the CS sampling scheme.

Another experiment is conducted to test the 2005 benchmark data from World Federation of NDE centers. The experiment setup (see Figure 2) is to evaluate disk-shaped cracks in a diffusion-bonded titanium alloy sample.

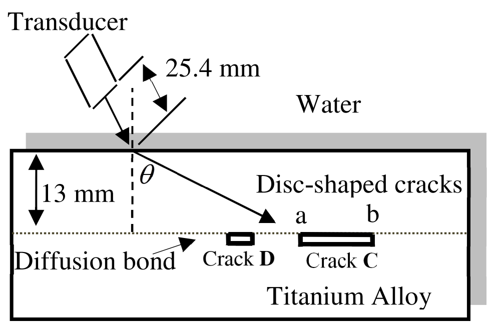

Figure 2. Experiment setup for disc-shaped cracks in a diffusion-bonded titanium alloy.

A 10 MHz planar transducer is used to obtain ultrasound data of these synthetic cracks at normal or oblique refracted angles, θ . The diameter of the transducer is 6.35 mm. The water depth is 25.4 mm. The surface of diffusion bond is 13 mm below the front surface of water/titanium alloy interface. The diameter of crack D is 0.762 mm. The ultrasound signal acquired from crack D at a refracted angle of 30 degree is used to evaluate the proposed CS-based signal decomposition. Figure 3 shows that the proposed algorithm can successfully reconstruct the experimental signal with high accuracy. It is also noticed that chirplet signal decomposition shows a slightly better performance than the CS-based signal decomposition, in terms of signal reconstruction, which might be the performance tradeoff between accurate parameter estimation using oversampled data and significant sampling rate deduction in the sparse sampling.

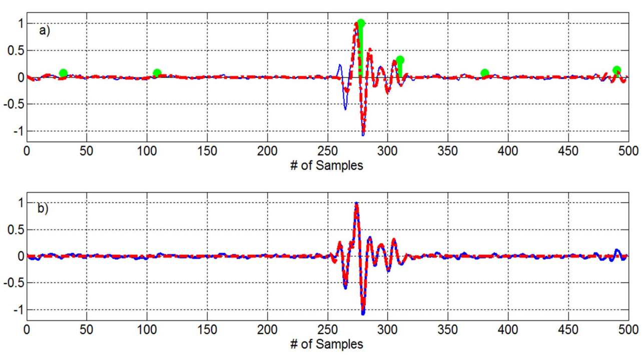

Figure 3. Experimental data of Crack D (with normalized amplitudes) superimposed with the estimated GSs (depicted in dashed red line). a) Experimental data (refracted angle 30) superimposed with the reconstructed signal using the CS and the initial estimation from the sparse sampling b) Experimental data (refracted angle 30) superimposed with the reconstructed signal using the chirplet signal decomposition.

IV. CONCLUSION

In this study, a CS-based signal decomposition and parameter estimation algorithm is investigated for ultrasound NDE applications. The new technique not only successfully characterizes defects in complex materials but also shows high computation efficiency in parameter estimation. The decomposition results and estimated parameters confirm the robustness and effectiveness of the proposed technique. The study has a broad range of applications in signal analysis including sparse representation, parameter estimation, and defect detection.

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