ULTRASONIC MICROSCOPY USING LOW FREQUENCY TRANSDUCERS

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ABSTRACT - Ultrasonic microscopy that mainly concerns itself with depth profiling and characterizing thin layers relies on not only the resolution of the transducer impulse response but also the frequency characterization of propagation paths. The frequency dependent absorption and scattering limits the use of high frequency transducers for improved resolution, detection, and characterization. The information obtained from low frequency transducers is significantly concealed, and not readily resolvable but can be improved by deconvolving the transducer impulse echo from the backscattered echoes. In this study, we adaptively estimate the echo wavelets and their arrival times directly from the experimental measurement using echo models. The estimation of model parameters is addressed using the SAGE algorithm. The model order selection is carried out using the Minimum Description Length (MDL) principle. We have observed that the model-based estimation significantly improves the accuracy and resolution of echo location and amplitude when compared to conventional techniques such as the Wiener Filter and Pseudoinverse solution.

I. INTRODUCTION

Ultrasonic backscattered echoes present valuable information pertaining to the characteristics of materials but this information is highly integrated, significantly mired and is not readily resolvable due to the bandlimited characteristic of the transducer pulse-echo wavelet. On the other hand, frequency dependent absorption and scattering limits the use of high frequency transducers for improved resolution, detection, and characterization. Nevertheless, the resolution of information obtained by the bandlimited transducer can be improved by decoupling the effects of the measuring system (i.e., deconvolution). In this study, we present a solution to the deconvolution problem using a model-based estimation algorithm.

The model for M superimposed echoes can be defined as:

$$r(t) = \sum_{m=1}^{M} f(\theta_m;t) + \nu(t) \qquad (1)$$

where $\nu(t)$ is a WGN process and $f(\theta;t)$ represents the model echo wavelet. Our objective is to estimate vector parameters $\theta_1, \theta_2, \ldots, \theta_M$ and the model order M.

The parameter estimation of M-Superimposed Gaussian echoes in WGN has been addressed in our previous work [1] using the SAGE algorithm assuming the model order is known. In this paper we present the estimation of the model order by incorporating the minimum description length (MDL) principal [2] into the SAGE algorithm:

$$MDL(M) = (\mu M + 1)\log N + N \log \frac{E}{N} \qquad (2)$$

where μ denotes the number of free parameters in the model, M denotes the model order, N denotes the record length and E denotes the mean-square error between the data and the model. The minimum value of MDL provides the optimal model order.

The procedure for implementing the SAGE algorithm coupled with the MDL principle is as follows:

1. Set M=1 (Model order).

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2. Use initial guesses for parameter vectors, $\theta_1^{(0)}, \theta_2^{(0)}, \ldots, \theta_M^{(0)}$ and set k=0 (iteration number) and m=1 (echo number).

3. **Expectation Step:** Compute
$$\hat{x}_m^{(k)} = f(\theta_m^{(k)}) + \frac{1}{M}\{r - \sum_{i=1}^{M} f(\theta_m^{(k)})\}$$

4. **Maximization Step:** Iterate the m-th parameter vector by minimizing:
$$\hat{\theta}_m^{(k+1)} = \arg\min \left\| \hat{x}_m^{(k)} - f(\theta_m^{(k)}) \right\|^2$$
and set $\hat{\theta}_m^{(k)} = \hat{\theta}_m^{(k+1)}$

5. Set m=m+1 and go to Step 2 unless m >M
6. Check convergence, if converged, go to 9.
7. Set m=1, k=k+1 and go to Step 3.
8. Compute MDL(M) and compare it to the MDL(M-1).
9. If MDL decreases, set M=M+1 and go to 2.
10. If not, model order is M. The estimated parameters are $\theta_1, \theta_2, \ldots, \theta_M$.

The steps 2-7 correspond to the SAGE algorithm for M-Superimposed echo estimation. Steps 8-10 carry out the model order selection. The MDL is computed for each model order and compared to that of the previous order. If the MDL metric decreases, the model order is updated. If it stays the same or higher, the current model order is said to be optimum. However, for each model order, a new set of parameter vectors needs to be estimated. This brings about an extra computational load. To ease the computational burden, the estimated parameters from the previous model order can be used for an initial guess in the current model.

II. DECONVOLUTION

In general, the backscattered signal can be modeled by M echoes:
$$y(t) = \sum_{m=1}^{M} \beta_m h(t - \tau_m) + v(t) \qquad (3)$$
where $h(t)$ is the transducer impulse response (Pulse-echo wavelet). The reflection parameters $\psi_m = [\tau_m \ \beta_m]$ represent the time-of-arrival and amplitude of the received echoes. The term $v(t)$ accounts for the measurement noise (WGN). This model may represent the backscattered echoes from thin layers. In this study, we address the deconvolution problem given by Equation 3 in the context of model based estimation.

The SAGE algorithm translates the estimation of the M-echo problem into the estimation of one echo at a time, hence providing computational versatility. The detection problem, i.e., estimation of the number of echoes, is incorporated in the algorithm using the MDL metric. Starting from one, the model order is increased as long as the MDL metric decreases. If there is no further decrease in the MDL, that model order is then said to be optimum.

To demonstrate the performance of the algorithm, three overlapping echoes are generated according to $y(t) = \sum_{m=1}^{3} \beta_m h(t - \tau_m) + v(t)$, where $h(t)$ is the transducer pulse-echo wavelet. The amplitudes are, $\beta = [1 \ -0.75 \ -0.5]$, and the locations are, $\tau = [0.52 \ 0.62 \ 0.72]\ \mu s$. The echoes are closely spaced in time. The WGN is added to the echoes to generate a signal with SNR=5.2 dB. These three echoes may model the reverberation echoes from a layered media. Then, the SAGE algorithm is applied to estimate the position and the amplitude of the echoes (Figure 1b). For comparison, the Pseudoinverse and the Wiener Filter [3] solutions are also shown in the same figure (Figure 1c and 1d). It can be observed that the SAGE algorithm can recover the spikes corresponding to the echoes with high accuracy where the Wiener Filter and Pseudoinverse restoration blur the spike locations and amplitudes. We also note that the model order selection has been carried out successfully using the MDL principle in the algorithm.

III. LAYER THICKNESS MEASUREMENT

The thickness and ultrasound velocity estimation of thin layers is common in NDE testing. The backscattered echoes from a thin layer can be represented by the model [4]:
$$r(t) = \rho h(t) + \varsigma_{12}\varsigma_{21} \sum_{m=1}^{\infty} \rho^{2m-1} h(t - 2mT) \qquad (4)$$

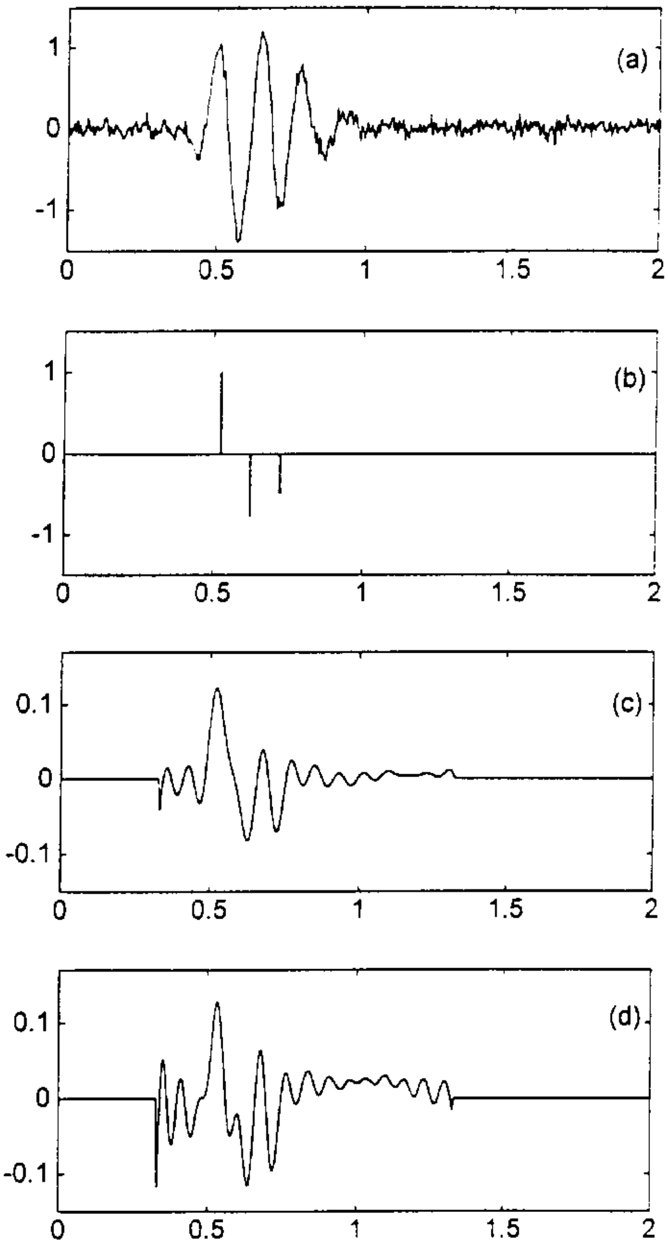

Fig. 1. a) Three overlapping pulse-echo wavelets corrupted by WGN.

b) Estimation of the echo locations and amplitudes using the SAGE algorithm.

c) Pseudoinverse deconvolution of the signal shown in (a).

d) Wiener Filter deconvolution of the signal shown in (a).

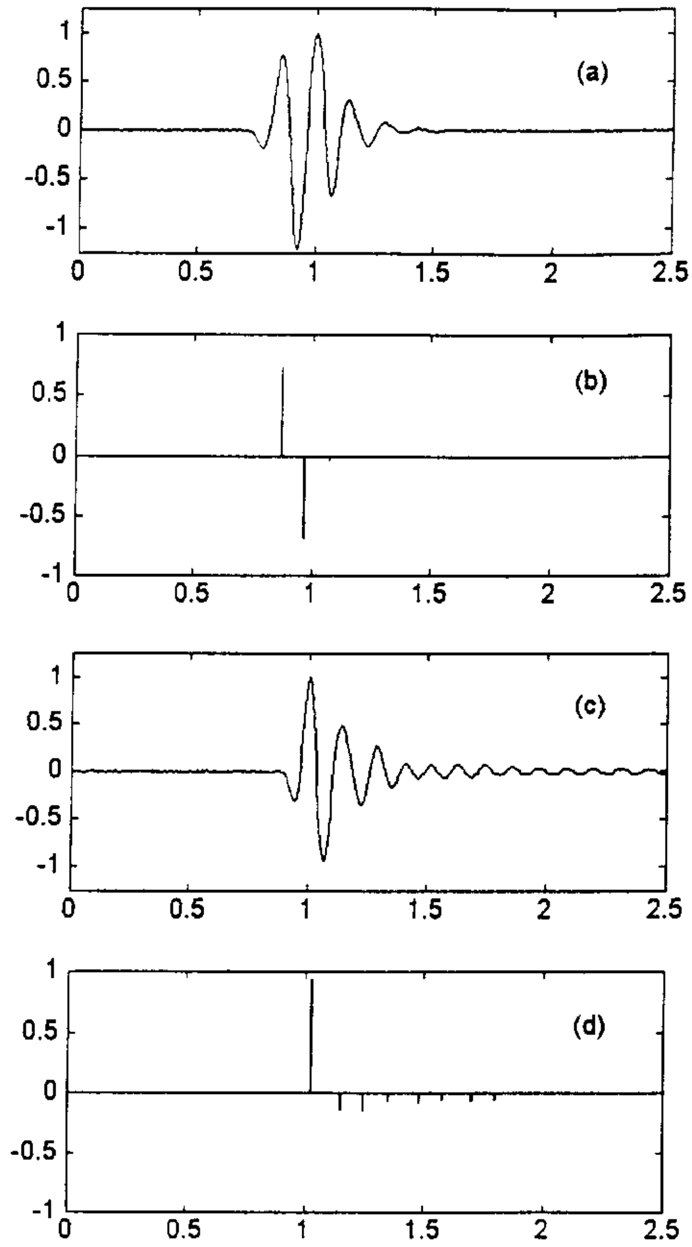

Fig. 2. a) The measured echoes backscattered from the transparency film.

b) The estimated echo locations and amplitudes for the signal shown in (a).

c) The measured echoes backscattered from the thin steel layer.

d) The estimated echo locations and amplitudes for the signal shown in (c).

where $h(t)$ denotes the transducer impulse response, ρ and ς denote the reflection and transmission coefficients of the medium respectively, and T denotes the time difference of arrivals of the successive reverberation echoes. It is possible to determine various properties (acoustic impedance, density) of the layer if the parameters of the model can be estimated accurately from the measured echoes. The model given by Equation 4 can be approximated by a model consisting of M echoes as described in Equation 3.

In this study, the SAGE algorithm is performed on the experimental data acquired from a thin transparency film (0.1 mm) using a 10 MHz transducer. The measured echoes are shown in Figure 2a (see the previous page). The estimated spike locations and amplitudes are shown in Figure 2b. The estimation results suggest that in addition to two reflections from the front and back surface of the film, there also is present a reverberation echo with small amplitude. The difference in time-of-flights can be related to the thickness of the material and the amplitudes can be related to the reflection and transmission coefficients.

Using the same experimental setup, a thin steel sample (0.3-mm) is placed in the water tank. The measured echoes are shown in Figure 2c. The estimated spike locations and amplitudes corresponding to the reverberant echoes are shown in Figure 2d. Contrary to the transparency film, a steel sample causes many reflections due to the greater impedance mismatch with respect to water.

REFERENCES

[1] R. Demirli and J. Saniie, "Parameter Estimation of Multiple Interfering Echoes Using the SAGE Algorithm", IEEE Ultrasonics Symposium, October 1998.

[2] M. Wax and I. Ziskind, "Detection of the Number of Coherent Signals by the MDL Principle", IEEE Trans. on ASSP, Vol. 37, No. 8, August 1989.

[3] S. M. Kay, *Fundamentals of Statistical Signal Processing*, Prentice Hall, 1993.

[4] J. Saniie and D.T. Nagle, "Pattern Recognition in the Ultrasonic Imaging of Reverberant Multilayered Structures", IEEE Trans. on UFFC, Vol. 36, No. 1, January 1989.