Model-Based Estimation of Ultrasonic Echoes Part II: Nondestructive Evaluation Applications

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***Abstract*—Accurate estimation of the ultrasonic echo pattern leading to the physical property of the object is desirable for ultrasonic NDE (nondestructive evaluation) applications. In Part I of this study, we have presented a generalized parametric ultrasonic echo model, composed of a number of Gaussian echoes corrupted by noise, and algorithms for accurately estimating the parameters. In Part II of this study, we explore the merits of this model-based estimation method in ultrasonic applications. This method produces high resolution and accurate estimates for ultrasonic echo parameters, i.e., time of flight (TOF) amplitude, center frequency, bandwidth, and phase. Furthermore, it offers a solution to the deconvolution problem for restoration of the target response, i.e., ultrasonic reflection and transmission properties of materials, from the backscattered echoes. The model-based estimation method makes deconvolution possible in the presence of significant noise. It can also restore closely spaced overlapping echoes beyond the resolution of the measuring system. These properties of the estimation method are investigated in various ultrasonic applications such as transducer pulse-echo wavelet estimation, subsample time delay estimation, and thickness sizing of thin layers.**

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 because of 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., deconvolving the pulse-echo wavelet from the backscattered echoes.

Most ultrasonic applications, i.e., subsample time delay estimation, depth profiling, and thickness measurement of thin layers, rely on the high resolution deconvolution of backscattered echoes. The aim of deconvolution is to restore the actual backscattering characteristics of the materials, i.e., impulse response of the system, without being mired by the transducer pulse-echo wavelet. In the most general case, when no a priori information is known, the desired system response can be restored by inverting the degradation operator, i.e., the convolution matrix that contains the circularly shifted samples of the pulse-echo wavelet. The solution based on the inversion of degradation is called the pseudoinverse solution [1]. When certain statistics are known about the desired system response, i.e., power spectral density, it can be incorporated into the estimation through the Wiener filter [2]. However, the solutions obtained by these methods are highly sensitive to noise level. Moreover, their resolution is limited by the resolution of the measuring system, which limits their use in ultrasonic applications for which high resolution is essential.

In this study, we approach the deconvolution problem from the model-based estimation perspective. A similar approach has been suggested for deconvolution of seismic signals [3]. Applying a parametric form to the desired system response significantly simplifies the problem. However, this applied parametric form should be consistent with the physical characteristics of the system. For example, if the impulse response of the system is expected to be a spike train, the solution to be sought should be spikes with unknown locations and amplitudes. Then, the deconvolution problem can be treated as a parameter estimation problem, which offers a more specific and a high resolution solution.

Several issues arise with a model-based approach to deconvolution. First, the observed data should be defined explicitly in terms of the parameters of the desired system for a well-defined parameter estimation problem. If the observed data, i.e., the backscattered echoes, are nonlinear functions of parameters, the inverse mapping, mapping from observed signals to parameters (parameter estimation), is also non-linear and does not have an explicit solution. Second, the noise embedded in the observed signals obscures the estimation of the true value of parameters. Hence, the degradation caused by noise needs to be quantified for the resolution bounds on the estimated parameters. Third, the model order, i.e., the number of parameters (echoes), may not be known a priori. Therefore, the model order selection needs to be combined in the estimation problem.

We will examine these problems in the maximum likelihood estimation (MLE) context. First, we decompose the backscattered echoes (observation signal) in terms of model echoes. A model echo is a nonlinear function of the

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desired system parameters (echo location and amplitude). Then, we address the MLE of these parameters when the echoes are corrupted by noise. The MLE of echo parameters requires the minimization of the mean-squared error between the measured echoes and model echoes when the noise is characterized as white Gaussian noise (WGN). Iterative least squares (LS) optimization methods may address this minimization problem, but they are likely to suffer from convergence problems caused by the frequent local minima and ill-posed iterations in computations. Alternative to LS methods is the expectation maximization (EM) algorithm. EM algorithm is a computationally efficient MLE method extensively used for superimposed signal estimation. The EM method translates the complicated higher order parameter estimation problem (M-echo estimation) into lower order parameter estimation problems (one-echo estimation), hence facilitating convergence and providing computational efficiency (for additional detail, see Part I of this study). The model order selection, i.e., the determination of the number of echoes, can be incorporated in the algorithm using an information theoretic criterion. The performance of the estimation as well as the resolution bounds on the estimated parameters can be assessed using the analytical Cramer-Rao lower bounds (CRLB). The CRLB can be derived based on the underlying parametric model as was described in Part I of this paper.

In this paper, we examine the space alternating generalized EM (SAGE) algorithm [4] for deconvolution of ultrasonic echoes from localized regions where the pulse-echo wavelet, i.e., reference echo, is assumed to be invariant. This requires prior estimation of the pulse-echo wavelet in terms of Gaussian echoes. Then, the measured signal is decomposed in terms of the reference echo by estimating the locations and amplitudes (spikes) of all echoes. The estimation algorithm also determines the number of echoes by utilizing an information theoretic criterion. The performance of this algorithm is tested in high resolution NDE applications such as subsample time delay estimation and thickness measurement of thin layers.

The remainder of this paper is organized as follows. In Section II, high resolution pulse-echo wavelet (transducer impulse response or the reference echo) estimation is addressed. Section III presents the deconvolution of overlapping echoes using the estimated pulse-echo wavelet. Finally, Sections IV and V present ultrasonic NDE applications that rely on high resolution deconvolution.

II. Pulse-Echo Wavelet Estimation

The magnitude spectrum of the transducer pulse-echo wavelet has bandpass characteristics. Hence, the time domain representation of the wavelet can be modeled by a number of superimposed bandpass signals (Gaussian echo wavelets) [5]:

$$h(t) = \sum_{m=1}^{M} c_m e^{-\alpha_m (t-\lambda_m)^2} \cos\left(2\pi f_m \left(t - \lambda_m\right) + \phi_m\right) \tag{1}$$

where f_m is the center frequency, α_m is the bandwidth factor, c_m is the weight, and ϕ_m is the phase of the corresponding echo wavelet at the arrival time λ_m. Representing the parameters in parameter vectors $\theta_m = [\alpha_m \ \lambda_m \ f_m \ \phi_m \ c_m]$ and assuming a WGN in the observation, the pulse-echo wavelet can be written as

$$h(t) = \sum_{m=1}^{M} f(\theta_m; t) + \nu(t) \tag{2}$$

where $\nu(t)$ is a WGN process and $f(\theta; t)$ represents a Gaussian echo wavelet. Our objective is to estimate the 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 using the SAGE algorithm (see Part I of this paper), but the model order has been assumed to be known. We address the model order estimation, i.e., the determination of the number of echoes, using the minimum description length (MDL) principle [6]. The MDL metric for a normal distribution is given by

$$MDL(M) = (\mu M + 1) \log N + N \log \frac{E}{N} \tag{3}$$

where M is the model order, i.e., the number of Gaussian echoes; μ is the number of unknown parameters of each Guassian echo ($\mu = 5$ for the Gaussian echo model); $\mu M + 1$ is the number of free parameters in the model, including the noise parameter; N is the record length; and E denotes the mean square error (MSE) between the data and the model [6]. The MDL metric, provided that the record length is fixed, depends on the MSE and the number of parameters. Although the increased model order reduces the MSE, the number of parameters penalizes the metric, hence forcing a trade off for optimal model order at the minimum value of the MDL.

The SAGE algorithm has been presented in Part I of this study for M-superimposed echo estimation. Now, we incorporate the model order selection into the algorithm as follows.

Step 1. Start with model order one (i.e., $M = 1$).
Step 2. Make initial guesses for the parameter vectors and form $\Theta^{(0)} = \left[\theta_1^{(0)}; \theta_2^{(0)}; \ldots; \theta_M^{(0)}\right]$. Set $k = 0$ (iteration number) and $m = 1$ (signal number).
Step 3. (E-Step) Compute $\hat{\chi}_m^{(k)} = f\left(\theta_m^{(k)}\right) + \frac{1}{M}\left\{h - \sum_{l=1}^{M} f\left(\theta_l^{(k)}\right)\right\}$.
Step 4. (M-Step) Iterate the mth parameter vector using the Gauss-Newton algorithm (see Part I): $\theta_m^{(k+1)} = \arg_{\theta_m} \min \parallel \hat{\chi}_m^{(k)} - f(\theta_m) \parallel^2$ and set $\theta_m^{(k)} = \theta_m^{(k+1)}$.
Step 5. Set $m \rightarrow m+1$ and go to Step 3 unless $m > M$.
Step 6. Check convergence criterion: if $\parallel \Theta^{(k+1)} - \Theta^{(k)} \parallel \leq$ tolerance, then go to Step 8.
Step 7. Set $m = 1, k \rightarrow k+1$, and go to Step 3.

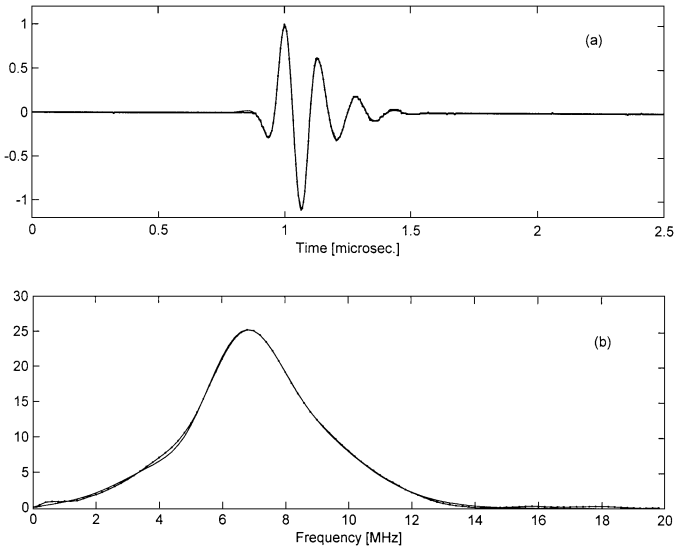

Fig. 1. The pulse-echo wavelet of a broadband transducer. The dotted line depicts the measured echo, and the solid line depicts the estimated echo in terms of a) time domain representations and b) magnitude spectra.

Step 8. Compute $MDL(M)$ and compare it with the $MDL(M-1)$.
Step 9. If MDL decreases or $M = 1$, set $M \to M+1$ and go to Step 2.
Step 10. The optimal model order is M; the estimated parameters are $\theta_1, \theta_2, \ldots, \theta_M$.

Steps 2 through 7 correspond to the original SAGE algorithm for M-superimposed echo estimation. Steps 8 through 10 carry out the model order selection. The MDL is computed for each model order and compared with the MDL of previous order. If the MDL metric decreases, the model order is increased by one. If it stays the same or higher, the current model order is said to be optimum, and the algorithm is terminated. 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 load, the estimated parameters from the previous model order can be used for initial guess in the current model order.

The SAGE algorithm just presented is applied to estimate the pulse-echo wavelet of a broadband transducer (0.5-in diameter, unfocused with a center frequency of about 7 MHz; sampling rate of 200 MHz; and an 8-bit resolution) reflected from a planar surface reflector. A steel block with a flat surface is placed in water in the far field of the transducer. The measured echo, reflected from the front surface of the steel sample, is shown in Fig. 1(a) in a dashed line. The estimated echo (the optimum model order, i.e., the number of Gaussian echoes is 3) is shown on the same figure in a solid line. The model nicely fits the measured echo where the estimated SNR is as high as 27 dB. The magnitude spectra of the measured and estimated echoes are also in good agreement [see Fig. 1(b)].

High resolution pulse-echo wavelet estimation is desirable for transducer characterization and deconvolution problems. The transducer beam field can be characterized by placing a point reflector at various points of the beam field and by estimating the measured echo at that point. Model-based estimation is sensitive to the small variations in the pulse-echo wavelet and, hence, can characterize the interaction of the beam field and the target with high resolution. In deconvolution problems, the accurate estimation of the desired system response depends on the accuracy of the pulse-echo wavelet estimation. Any slight deviation from the actual pulse-echo wavelet would yield a significant deviation in the estimation, causing inaccurate deconvolution results. High resolution pulse-echo wavelet estimation improves the resolution and accuracy of deconvolution. We present the deconvolution problem in the next section.

III. Deconvolution of Backscattered Echoes

An ultrasonic echo propagated through a frequency-independent homogeneous path and reflected from a flat surface can be represented by the model

$$s(t) = \beta h(t-\tau) \tag{4}$$

where $h(t)$ denotes the transducer pulse-echo wavelet. The time of arrival (TOA) of the echo, τ, is related to the location of the reflector as the distance from the transducer over the speed of ultrasound in the propagation path. The amplitude of the echo, β, is primarily governed by the impedance, size, or orientation of the reflector. The transducer pulse-echo wavelet, $h(t)$, can be represented by the sum of a number of Gaussian echo wavelets (see Section II). The model given in (4) may represent an echo arriving from an isolated target in a homogeneous and non-dispersive path. This model can be generalized to the M-echoes as

$$y(t) = \sum_{m=1}^{M} \beta_m h(t-\tau_m) + \nu(t) \tag{5}$$

where the reflectivity vector $\psi_m = [\tau_m \beta_m]$ represents the TOA and amplitude of the mth echo. The term $\nu(t)$ accounts for the measurement noise and can be characterized as WGN. This model may represent M echoes reflected from a localized region in the material or the reverberation echoes reflected from thin layers, provided that the transducer pulse is invariant throughout the propagation path. The determination of the parameter vectors, ψ_m, from the measured echoes can be expressed as a deconvolution problem if (5) is written in the following format:

$$y(t) = h(t) * \left\{ \sum_{m=1}^{M} \beta_m \delta(t-\tau_m) \right\} + \nu(t) \tag{6}$$

where the bracketed term (impulse train) denotes the unknown system response and $h(t)$ denotes the transducer pulse-echo wavelet. The deconvolution problem (known as the inverse problem) is to restore the desired system response given the noisy observation of echoes, $y(t)$. The

inverse problem can be better formulated using discrete notations for (6) as

$$y = Hf + \nu \tag{7}$$

where H denotes the degradation matrix (the convolution matrix whose rows contain circularly shifted samples of h); f denotes the desired system response [see the bracketed term in (6)] that contains the spikes, i.e., reflectors; and ν denotes the discrete version of the noise process $\nu(t)$. If the system response is treated as a random process with known statistics, the model given by (7) can be described by a "Bayesian linear model" [2]. If the desired system statistics are given by zero mean and covariance matrix C_f, i.e., $[C_f]_{ij} = r_{ff}(i-j$, where r_{ff} is the autocorrelation sequence of f, and the noise ν is described by WGN with variance σ^2, then the minimum mean square estimator (MMSE) for f can be written as [2]:

$$\hat{f}_{MMSE} = C_f H^T (H C_f H^T + \sigma^2 I)^{-1} y. \tag{8}$$

This estimator is also known as the Wiener filter estimator. In utilizing the Wiener filter for deconvolution, one needs to know the pulse-echo wavelet and the desired system statistics (or the power spectral density) when the noise is WGN.

In the most general case, when the desired system statistics are not known, the generalized inverse (pseudoinverse) method provides a unique LS solution with a minimum norm [1]. The pseudoinverse solution to the desired system response for the observation model given in (7) has the following form:

$$\hat{f}_{GI} = \left(H^T H\right)^{-1} H^T y. \tag{9}$$

However, the inversion of the term $(H^T H)$ is not computationally practical because of the size and potential rank deficiency of the matrix. To bypass the direct inversion, the degradation matrix H is diagonalized using the singular value decomposition (SVD). Then, the pseudoinverse solution based on the SVD is written as [7]

$$\hat{f}_{GI} = \sum_{i=1}^{r} \sigma_i^{-1} \left(u_i^T y\right) \nu_i \tag{10}$$

where u_i and ν_i are the orthonormal vectors and σ_i's are the singular values of the SVD of the degradation operator H.

More recently, the iterated window maximization (IWM) algorithm [8] has been proposed for blind deconvolution of ultrasonic traces. The method is based on the maximum a posteriori estimation (MAP) of the transducer pulse-echo wavelet and the desired system response (reflectivity) in alternating steps, using a priori statistics for both the transducer pulse-echo wavelet and reflectivity. Given the pulse-echo wavelet, the reflectivity is estimated by minimizing the MSE plus an additional term linearly dependent on the number of spikes in the iterated window to enforce the sparseness assumption, i.e., the number of spikes in the window cannot be larger than a preset parameter [8]. Although good results have been achieved with the IWM method, its optimality is questionable especially for closely spaced overlapping echoes. Moreover, the resolution of the spike estimates is limited by the sampling interval.

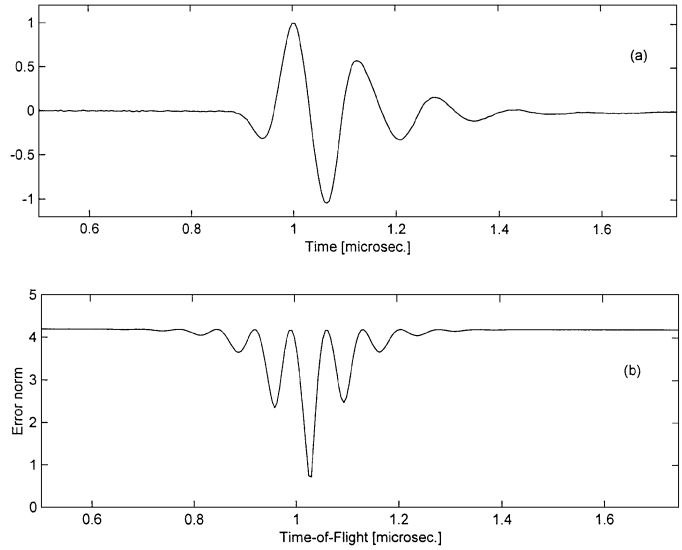

Fig. 2. a) A typical ultrasonic echo; b) the variation of error function in terms of TOF.

In this study, we address the deconvolution problem given by (6) in the context of model-based estimation. Implicit to the method is the assumption that the desired system response is a spike train with unknown amplitudes and locations. In addition, the number of spikes is considered to be unknown. Furthermore, there is no assumption or statistical knowledge imposed on the amplitude and locations of the spikes. This method is also known as model-based deconvolution [3].

Using the spike train model for the desired system response, the observed echoes can be represented by the superimposed pulse-echo wavelets corrupted by noise (5). The unknown parameters (the locations and amplitudes of spikes) can be estimated by minimizing the MSE between the measured echoes and the model, assuming the noise is WGN. The MSE is a nonlinear function of the parameters. Moreover, the model order, i.e., the number of spikes, is not known. Iterative LS optimization methods may address this nonlinear parameter estimation problem, but they are subject to local convergence because of frequent local minima. The frequent local minima are due to the oscillatory nature of the error function in terms of spike locations (for example, see Fig. 2, the MSE of a typical echo in terms of the time of flight).

An alternative to the LS method is the SAGE algorithm [5]. The SAGE algorithm translates the M-spike estimation problem into a "one spike at a time" estimation problem, providing computational versatility. However, the convergence and speed of the SAGE algorithm depend on the convergence and speed of the "one-spike estimation" algorithm. A simple Gauss Newton (GN) algorithm (see Part I) can be used for "one-spike estimation,"

but, depending on the initial starting point, the algorithm may become trapped in one of the many local minima (see Fig. 2). The local minimum is avoided by taking a prescribed step to the left and right of the estimate and reiterating the GN algorithm in the search of global minimum. Any direction that reduces the MSE is accepted; otherwise, the current minimum is said to be the global minimum. The step size is determined by inspecting the periodicity of the error function [Fig. 2(b)]. The period of the local minima is very close to the echo period, i.e., the inverse of the center frequency for a single Guassian echo or the inverse of the largest center frequency when multiple Guassian echoes are involved. Therefore, taking the step size as $1/2(f_c)_{\max}$ is practical for skipping the local minima in search of the global minimum. Note that $(f_c)_{\max}$ is the maximum center frequency among the center frequencies of multiple Gaussian echoes that compose the measured signal. This global search procedure can be coupled into the GN algorithm to ensure global convergence for one-spike estimation.

The estimation of the number of echoes can be incorporated into the algorithm using the MDL metric (3). 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 the optimum. In summary, the SAGE algorithm for restoration of the spikes from the backscattered echoes is implemented in the following steps.

Step 1. Start with model order one (i.e., $M = 1$).
Step 2. Make initial guesses for reflectivity vectors and form $\Psi^{(0)} = \left[\psi_1^{(0)}; \psi_2^{(0)}; \ldots; \psi_M^{(0)}\right]$.
Set $k = 0$ (iteration number) and $m = 1$ (spike number).
Step 3. Expectation Step. Compute $\hat{\chi}_m^{(k)} = s\left(\psi_m^{(k)}\right) + \frac{1}{M}\left\{y - \sum_{l=1}^{M} s\left(\psi_l^{(k)}\right)\right\}$, where $\psi_m = [\beta_m \tau_m]$ and $s(\psi_m) = \beta_m h(t - \tau_m)$, where $h(.)$ is given by (1).
Step 4. (Maximization Step) Iterate the mth parameter vector using the GN algorithm coupled with the global search procedure: $\psi_m^{(k+1)} = \arg_{\psi_m} \min \parallel \hat{\chi}_m^{(k)} - s(\psi_m) \parallel^2$ and set $\psi_m^{(k)} = \psi_m^{(k+1)}$.
Step 5. Set $m \to m + 1$ and go to Step 3 unless $m > M$.
Step 6. Check convergence criterion: if $\parallel \Psi^{(k+1)} - \Psi^{(k)} \parallel \leq$ tolerance, then go to Step 8.
Step 7. Set $m = 1, k \to k + 1$, and go to Step 3.
Step 8. Compute $MDL(M)$ and compare it with the $MDL(M - 1)$.
Step 9. If MDL decreases or $M = 1$, set $M \to M + 1$ and go to Step 2.
Step 10. The model order is M, and the estimated parameters are $\psi_1, \psi_2, \ldots, \psi_M$.

In this algorithm, making a good initial guess is important to achieving the optimal solution with the least number of iterations. When the model order is one ($M = 1$), a reasonable initial guess for TOF would be in the middle of the echo, and a good guess for the amplitude is a value close to the peak value of the echo. As the model order is increased, e.g., M, initial guesses have to be made for the M parameter set. The initial guesses for the M-1 parameter set can simply be a set equal to the estimated parameter set of the previous model order, M-1. The initial guess for the new parameter set can be made based on the most recent estimated parameter set. The initial guess for amplitude would be the estimated amplitude for the most recent echo, and the TOF would be the time of flight estimate for the most recent echo plus a displacement. The displacement is determined using the time difference of arrivals of the most recent two echoes. This initial guess procedure produces good results for overlapping echoes.

To demonstrate the performance of the algorithm, three overlapping echoes in the presence of noise are generated according to

$$y(t) = \sum_{m=1}^{3} \beta_m h(t - \tau_m) + \nu(t)$$

where $h(t)$ is the estimated pulse-echo wavelet (Section I). The amplitudes of the echoes are given by $\beta_1 = 1, \beta_2 = -0.83$, and $\beta_3 = -0.17$, and their TOF are given by $\tau_1 = 0.523, \tau_2 = 0.623$, and $\tau_3 = 0.723\ \mu s$. The WGN process, $\nu(t)$, is added to the echoes to generate a signal with SNR = 5 dB. The echoes are closely spaced in time to simulate reverberation echoes from a thin layer [Fig. 3(a)]. Then, the SAGE algorithm is performed to estimate the positions and amplitudes of these echoes [Fig. 3(e)]. For comparison, the Wiener filter (8), pseudoinverse deconvolution (10), and IWM deconvolution [8] (see acknowledgment) results are also shown in Fig. 3(b, c, and d, respectively). It can be observed that the SAGE algorithm can recover the spikes with high accuracy and resolution where the Wiener filter and pseudoinverse methods blur the spike locations and amplitudes. The IWM solution comes close to optimal, but the resolution of spike location is limited by the sampling interval. The SAGE method improves the resolution of the spike location within the sampling interval, offering a better solution. In fact, the resolution bounds on the spike locations and amplitudes can be obtained from the analytical CRLB (see Part I of this paper). We also note that the model order selection has been carried out successfully using the MDL principle in the algorithm (Table I). Starting from model order one, we estimate the parameters for each model order, then compute the MDL and estimation SNR. The MDL metric decreases until the model order 3; hence, the optimal model order is said to be 3.

The next section presents some applications of the model-based estimation method when high resolution and accurate system restoration are essential.

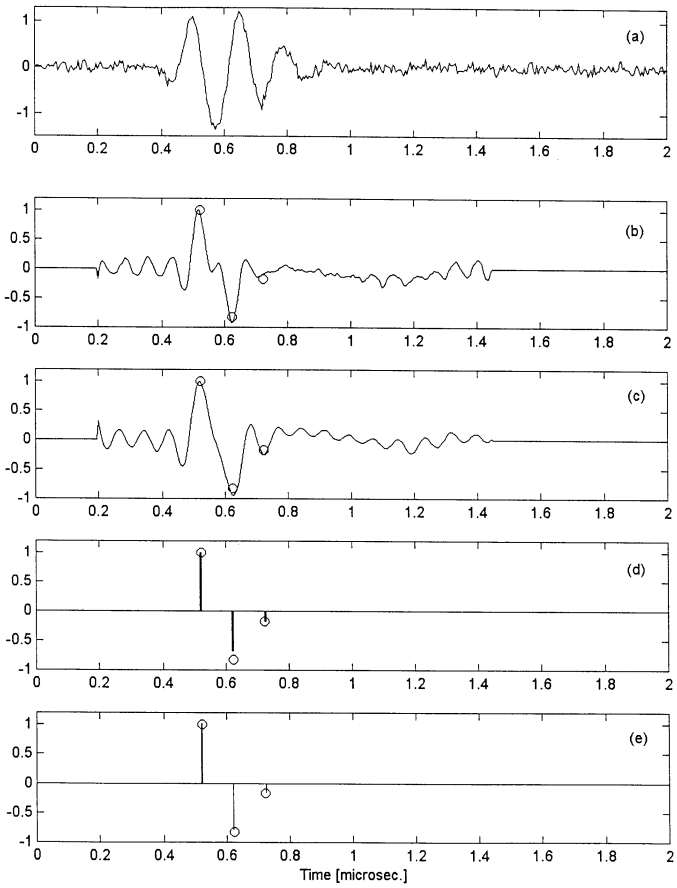

Fig. 3. a) Three overlapping echoes simulated using the estimated pulse-echo wavelet in Fig. 1(a) (circles represent the actual spikes used in simulation), b) the Wiener filter deconvolution result, c) the pseudoinverse deconvolution result, d) the IWM deconvolution result, and e) the SAGE deconvolution result.

TABLE I
THE VARIATION OF THE MDL METRIC IN TERMS OF MODEL ORDER FOR THE THREE OVERLAPPING ECHOES SHOWN IN FIG. 3(A).

Model Order (M)	Estimation SNR [dB]	MDL
1	6.54	−1576
2	12.29	−2036
3	**12.82**	**−2071**
4	12.72	−2050

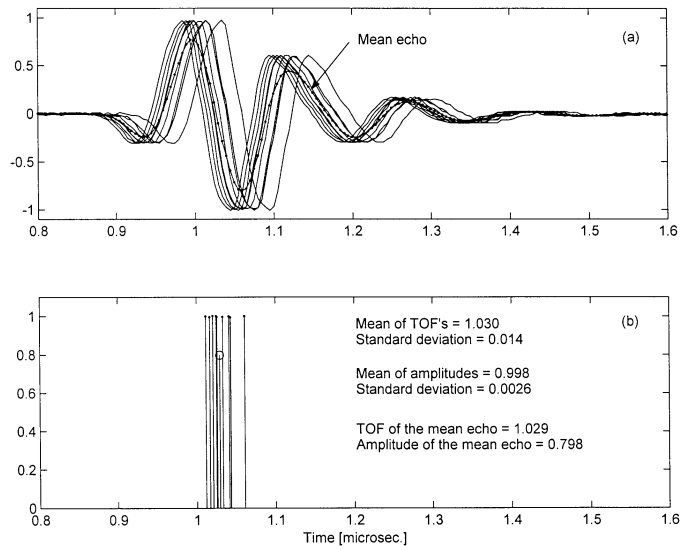

Fig. 4. a) Ten repetitive measurements of an ultrasonic signal. The dotted line depicts the mean of the 10 ensembles without any synchronization. b) The TOF and amplitude estimates of the 10 ensembles and the mean echo (the circled bar) using the SAGE method.

IV. Subsample Time Delay Estimation

In certain NDE applications, repetitive measurements of the ultrasonic signal are acquired and averaged to improve the SNR. However, subsample time delays arise between the ensembles because of the triggering phenomena in the measurement system or the fluctuations in the propagation medium, e.g., heat, air disturbances, etc. The time delays of all of the measurements need to be estimated so that the signals can be aligned on the time axis for improved averaging [9]. Subsample time delay estimation is also necessary to improve the accuracy of TOF estimation. For example, in airborne ultrasonic applications, the velocity of sound in air is sensitive to temperature changes and disturbances, making the TOF vary for different measurements of the echo. An average TOF is necessary, but the direct signal averaging introduces shape distortion caused by the misaligned echoes, distorting the actual TOF of the echo.

In this study, we represent a subsample echo by the model given in (4), which is the time-delayed and amplitude-scaled replica of the transducer pulse-echo wavelet. One of the ensembles is used as a reference echo to compute the transducer pulse-echo wavelet by the method described in Section I. Then, the TOFs and amplitudes of the subsample echoes are estimated using the SAGE algorithm, by fixing the model order to one.

To demonstrate the performance of the method, the following experimental setup is used. A steel block with a planar surface is placed in the water, perpendicular to the transducer beam field. Ten measurements of the front surface echo are recorded. These echoes are shown in Fig. 4(a). Although the echo shapes are similar, some variations exist in their TOFs. The TOFs and amplitudes of these echoes, as well as the TOF and amplitude of the mean echo (the average of the 10 ensemble echoes), are estimated using the SAGE algorithm. One of the ensemble echoes is used to compute the transducer pulse-echo wavelet. The estimated spikes for ensemble echoes are shown in Fig. 4(b). Several observations can be made based on the estimation results. First, the average of the estimated TOFs differs from the TOF of the mean echo. It is important to point out that the direct averaging of time-shifted echoes introduces shape distortion, contributing to inaccuracy in the TOF estimation. Second, subsample time delays can be a fraction, as well as real multiples of the sampling interval.

This suggests that the resolution of the subsample time delay estimation is not limited by the sampling interval. Third, the amplitude estimations of the subsample echoes are consistent, suggesting an accurate TOF estimation.

V. Thin Layer Thickness Measurement

The thickness and ultrasound velocity estimation of thin layers is a challenging task in NDE because of the bandlimited characteristics of the transducer pulse-echo wavelet. When ultrasonic testing is applied to a thin layer, two or more reflections of the pulse-echo wavelet can be observed, often overlapping. The first echo comes from the front surface, and the second echo comes from the back surface. The rest are the reverberation echoes between the two boundaries. The time-difference of arrivals (TDOA) of these multiple reflections can be used to determine the thickness or ultrasonic velocity of the sample. On the other hand, the amplitudes of reflections can be used to calculate the acoustic impedance of the layer reference to that of the propagation path.

Thin layer thickness measurement is addressed in [10] using a homomorphic deconvolution method based on the recovery of the layer impulse response, but only two reflections are assumed. However, reverberant structures, e.g., metal thin layers, may exhibit many more reflections. The classical LS deconvolution methods cannot recover closely spaced overlapping echoes within the desired resolution (see the discussion for the results shown in Fig. 3). This problem can be addressed effectively using the model-based deconvolution method. The backscattered echoes from a thin layer in a homogeneous propagation path, e.g., water, can be represented by the model [11]:

$$r(t) = \rho h(t) + \varsigma_{12}\varsigma_{21} \sum_{m=1}^{\infty} (-\rho)^{2m-1} h(t - 2m\Delta T) \tag{11}$$

where $h(t)$ denotes the transducer pulse-echo wavelet; ρ denotes the reflection coefficient from the propagation path to layer; ς_{12} and ς_{21} denote the transmission coefficients from the propagation path to layer and layer to the propagation path respectively; and ΔT denotes the TDOA of the successive reverberation echoes.

The analytical model for reverberation echoes (11) can be represented by the superimposed echo model (5) with unknown locations, amplitudes, and model order (M). The model order M represents the number of most significant echoes in (11) so that they can be estimated by the algorithm with a reasonable accuracy. The transducer pulse-echo wavelet, $h(t)$, is assumed to be invariant in the model as it travels back and forth between the two boundaries. But, the model order M is assumed to be unknown. It is possible to determine various properties (thickness, acoustic impedance, and density) of the layer if the parameters of the superimposed echoes can be estimated accurately from the measured echoes. However, the estimation of the echo parameters could be a challenging task for highly reverberant thin layers because of the closely spaced reverberations and noise (for example, see Fig. 6, the reverberation echoes from a thin steel sample).

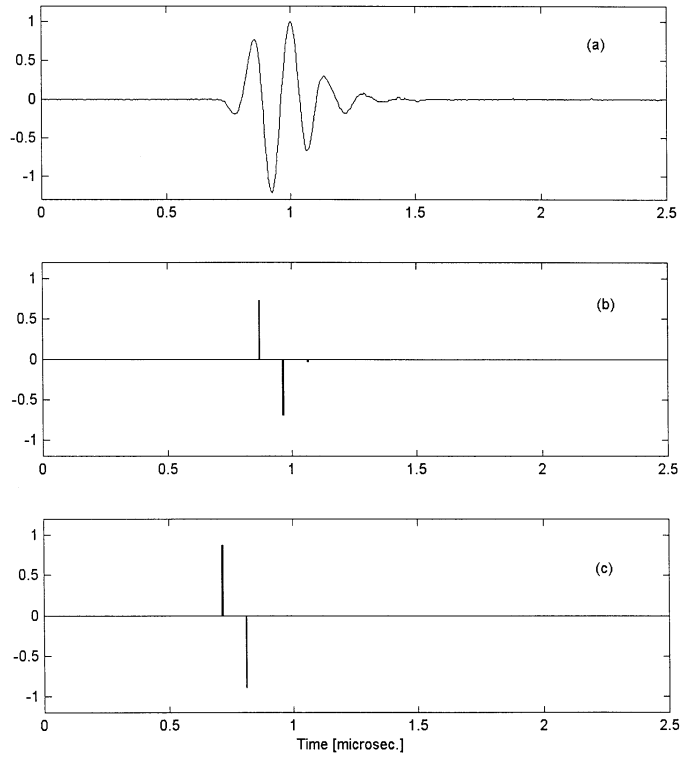

Fig. 5. a) The reflected echoes from a transparency film (0.1 mm thick), b) the reflectivity estimates using the SAGE method, and c) the reflectivity estimates using the IWM method.

We test the performance of the model-based estimation method on the experimental echoes reflected from thin layers. The transducer pulse-echo wavelet estimation is performed prior to the actual thickness measurement as described in Section I. First, we acquired experimental echoes from a thin transparency film (0.1 mm) using the broadband transducer whose impulse response is shown in Fig. 1(a). The measured echoes from the thin film are shown in Fig. 5(a). The estimated spike locations and amplitudes are shown in Fig. 5(b) using the SAGE method and in Fig. 5(c) using the IWM method. Note that the IWM method assumes the start of the echo as its TOF. The negative amplitudes represent the phase-inverted echoes and agree with the theoretical model. Our 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 IWM method fails to capture the third echo. The average difference in TOF can be related to the thickness, and the amplitudes can be related to the reflection and transmission coefficients of the layer [11].

To demonstrate the reverberation echoes, a thin steel sample (0.3 mm) is tested using the same transducer. The measured echoes are shown in Fig. 6(a). The estimated spikes associated with the reverberation echoes are shown

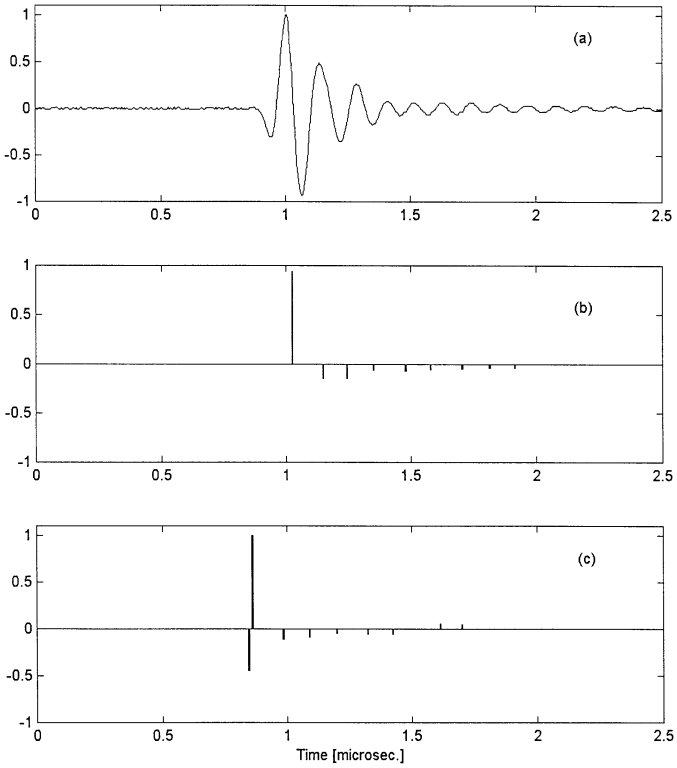

Fig. 6. a) The reverberation echoes from a thin steel layer (0.3 mm), b) the reflectivity estimates using the SAGE method, and c) the reflectivity estimates using the IWM method.

in Fig. 6(b) using the SAGE method and in Fig. 6(c) using the IWM method. Contrary to the transparency film, the steel sample causes many reflections because of the greater impedance mismatch with respect to that of water. The SAGE algorithm is able to capture the reverberation echoes with a reasonable accuracy; the IWM method produces a solution that is not consistent with the theoretical expectation as described in the analytical model (11).

VI. Conclusions

In this study, we address the deconvolution of ultrasonic echoes backscattered from localized regions using a model-based estimation method. The method is based on the reconstruction of the shifted and attenuated copies of the pulse-echo wavelet in the ultrasonic data trace, assuming the pulse-echo wavelet is invariant. First, the transducer pulse-echo wavelet has been modeled and estimated in terms of Gaussian echo wavelets. Then, the backscattered echoes are modeled as the convolution of the pulse-echo wavelet with a spike train. The spike train represents the desired system response, i.e., the actual backscattering characteristics of a medium under ultrasonic test. The estimation of spike locations and amplitudes is addressed using the SAGE algorithm. The SAGE algorithm is coupled with model order selection using the MDL principle to estimate the number of spikes. The algorithm has been compared with classical deconvolution methods and the IWM method for closely spaced overlapping echoes. The SAGE algorithm is superior to its alternatives in several points. First, it offers a high resolution solution for the desired system response, i.e., it can estimate the location of a spike within a fraction of the sampling interval. Second, the optimality of the estimated parameters associated with the desired system response can be verified using analytical methods. In other words, the model-based estimation provides its own analytically well-defined performance measures. Third, the algorithm is able to resolve closely spaced overlapping echoes that cannot be resolved by its alternatives. The shortcoming of the model-based estimation algorithm is that it is relatively slow and computationally intensive, although it can be improved by applying computational procedures such as downsampling and divide-and-conquer (data segmentation) methods.

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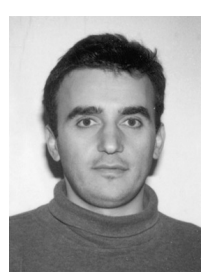

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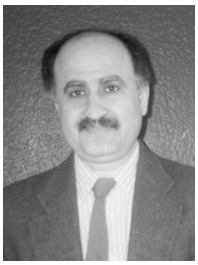

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