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ACOUSTIC SIGNAL PROCESSING AND COMPUTER SIMULATION

Reflectivity Function Reconstruction Using Adaptive Lattice Deconvolution Technique[1]

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Abstract—Deconvolution of ultrasonic echo signals improves resolution and quality of ultrasonic images. The problem of reconstructing the reflectivity of a biological tissue is examined by adaptive lattice deconvolution of the echo ultrasound signals. The simulation of the signal formation process in an ultrasonic-echo scan line in noisy conditions is estimated. The reflectivity of a biological tissue is estimated as cross-correlation coefficients between forward and backward predication errors in each stage of the adaptive lattice filter.

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INTRODUCTION

The use of deconvolution technique for both range and later resolution enhancement in ultrasonic application has been subject to widespread investigation and is well documented in the literature [1–4]. In this paper, the lattice adaptive deconvolution algorithm has been used to enhance axial resolution in an ultrasonic system by suitable processing of the received output. This approach offers several advantages over the transversal structure. First, the lattice structure orthogonalizes the input signal stage-by-stage, which leads to fast convergence and efficient tracking capabilities when used in an adaptive environment. Second, the various stages are decoupled from each other, so it is relatively easy to increase the prediction order if required. The effect of convergence parameters and filter length on the performance of the adaptive algorithm has been investigated.

In practice it is well accepted that, one scan line of the received pulse-echo signal, $y(t)$ at time t, can be represented as [5]

$$y(t) = w(t)*u(t) + n(t), \tag{1}$$

where $u(t)$ is the medium response or the reflectivity function [6], $w(t)$ is the ultrasound system response [7], $n(t)$ is the zero-mean Gaussian noise, and * represents convolution. Deconvolution attempts to remove the effect of the input function $w(t)$ from the output $y(t)$ to achieve some close approximation to the original medium impulse response $u(t)$.

[1] The article is published in the original.

ADAPTIVE LATTICE FILTER

The adaptive lattice filter algorithm [8] discussed in this paper are implemented with FIR filter structure. The unknown system is modeled by an FIR filter with adjustable coefficients. Both the unknown time-variant system and FIR filter model are excited by an input sequence. The adaptive FIR filter output is compared with the unknown system output to produce an estimation error. The estimation error is then used as the input to an adaptive control algorithm which corrects the individual tap weights of the filter. This process is repeated through several stages until the estimation error becomes sufficiently small. The resultant FIR filter response now represents that of the previously unknown system. Figure 1 shows the stages of a lattice filter structure. The following equations represent a set of recursive equations describing the lattice filter as derived from Fig. 1 [9].

$$f_0(n) = b_0(n) = y(n), \tag{2}$$

$$f_m(n) = f_{m-1}(n) - K_m(n)b_{m-1}(n-1), \tag{3}$$

$$b_m(n) = b_{m-1}(n-1) - K_m(n)f_{m-1}(n), \tag{4}$$

where $f_m(n)$, $b_m(n)$ are the forward and backward single predication residuals at the mth stage output and $K_m(n)$ is the reflection coefficient. An adaptive gradient algorithm for estimation of these coefficients is given by [9]

$$K_m(n+1) = K_m(n) + \alpha_m[f_m(n)b_{m-1}(n-1) + f_{m-1}(n)b_m(n)], \tag{5}$$

where a_m a convergence factor. The average power level of the input trace can be calculated as the

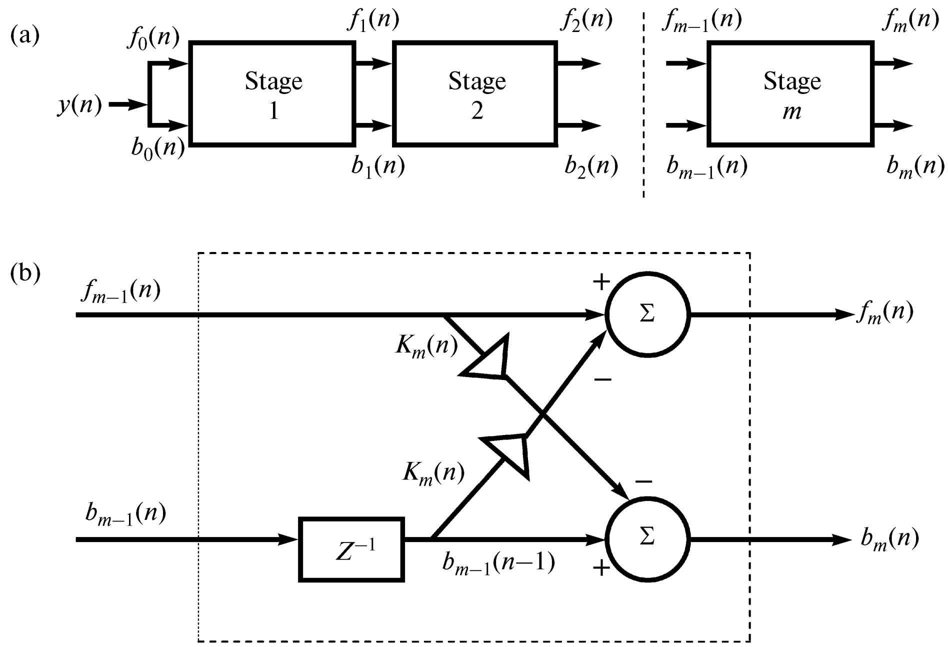

Fig. 1. Lattice structure (a) stages of lattice filters (b) m stage of lattice filter.

weighted summation of the previous value and the square of the current data point the energy for adaptive lattice implementation can be written as [10]

$$\sigma(n) = \beta\sigma(n-1) + (1-\beta)[(f(n))^2 + (b(n-1))^2], \tag{6}$$

where β is a weight factor ($0 < \beta < 1$). Equation (6) can be used to smooth out the actual noisy gradient.

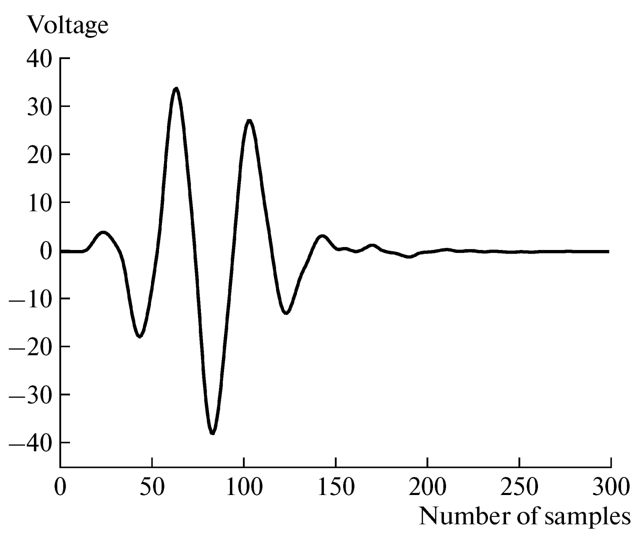

Fig. 2. Time domain pulse-echo response of 5 MHz transducer.

RESULTS

The results are derived for a representative range of simulated ultrasonic data, obtained using the modeling of ultrasonic piezoelectric transducers described in reference [11]. The simulation was applied using typical data for transducer constructed with medium damping materials applied to the back face [12]. The transmitter response was applied for 10 mm diameter pulse-echo transducer of 5 MHz center frequency. It should be noted that the wavelength corresponding to the frequency of pulse-echo transducer is about 0.3 mm, which may be quite feasible when soft tissues are imaged [13]. In order to investigate the combined effects of the transducer, transient acoustic field response [14] and absorption filter on scanning system performance the simulation was applied to a medium of soft biological tissue with an absorption coefficient of 1 dB MHz cm. consequently, assuming the tissue properties to be uniform in the plane perpendicular to the scanning beam. The simulation were carried out by multiplying the transfer functions of the two transducer responses by the transient acoustic field response, transfer function of the transmission medium and the reflector sequence of the tissue in the frequency domain [15]. The simulation was carried out at an effective sampling time of 5 ns. Figure 2 shows the simulation of a 5 MHz pulse-echo transducer. The artificial reflector sequence of biological tissue is shown in Fig. 3 corresponding to seven point targets in the tissue which distributed randomly in position and amplitude. The pulse-echo response of the transducer has been combined with the tissue reflector sequence, transient diffraction acoustic field

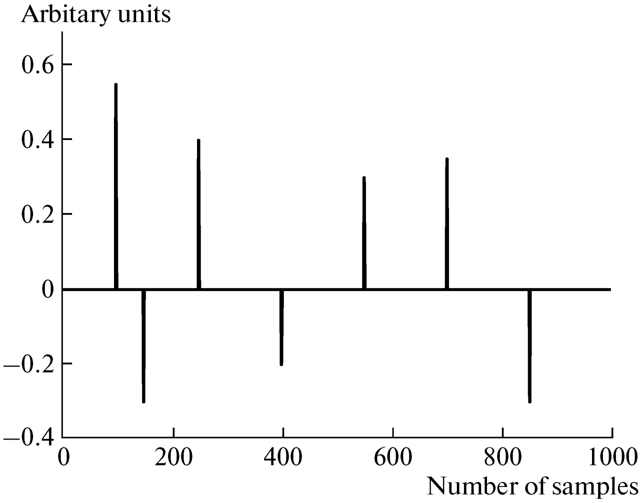

Fig. 3. The impulse reflector series of tissue.

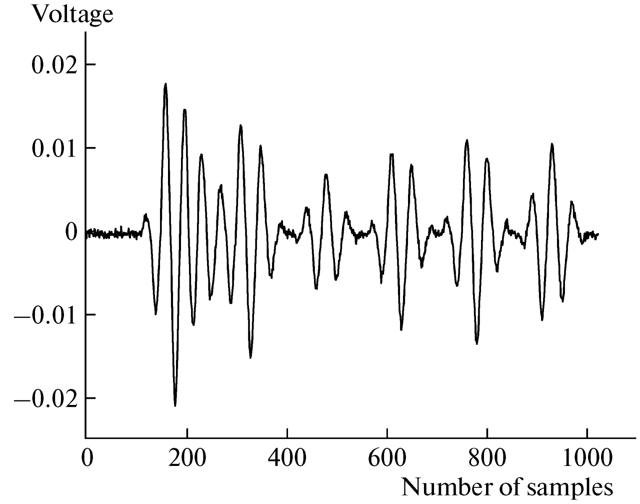

Fig. 4. The overall simulation of pulse-echo 5 MHz after propagation 5 cm in soft tissue with signal to noise level 25.

and medium absorption response for a depth 5 cm in biological tissue. The most common type of noise and the one that we are most interested in, is Gaussian noise. In many situations, the noise that is present within an image can be modeled as the sum of many independent noise sources. Under this situation, Gaussian noise can be used to model the noise present in an A-scan, consequently. An uncorrelated Gaussian noise can be simply added to the overall time-domain response.

The simulation signal-to-noise ratio values presented here used the average power values for signal and noise in which the average values are obtained by averaging over the time range of interest. Figure 4 shows the overall time-domain response at the receiver terminal at signal-to-noise level of 25 dB. The squared error norm between the true reflectivity and the predicted reflectivity output from deconvolution algorithm was computed to obtain the optimum parameter of filter length, α and β. Our result shows that the optimum parameter for adaptive lattice deconvolution takes the values $\alpha = 1.7$, $\beta = 0.97$ and filter length equal to 36. The deconvolution results for A-scan ultrasonic data at different signal to noise ratio are shown in Fig. 5. From this figure, it can be seen that the first and second responses overlapping in the reconstruction function due to the time sequence between them equal to 0.375 μs. The alternating sign of the reconstructed function is very close to the initial pulse. The relative Amplitudes of the responses are equal to the relative initial amplitudes, and their locations look like real locations. It is clear from these figures that the results are promising for improving resolution and minimizing noise. The deconvolution

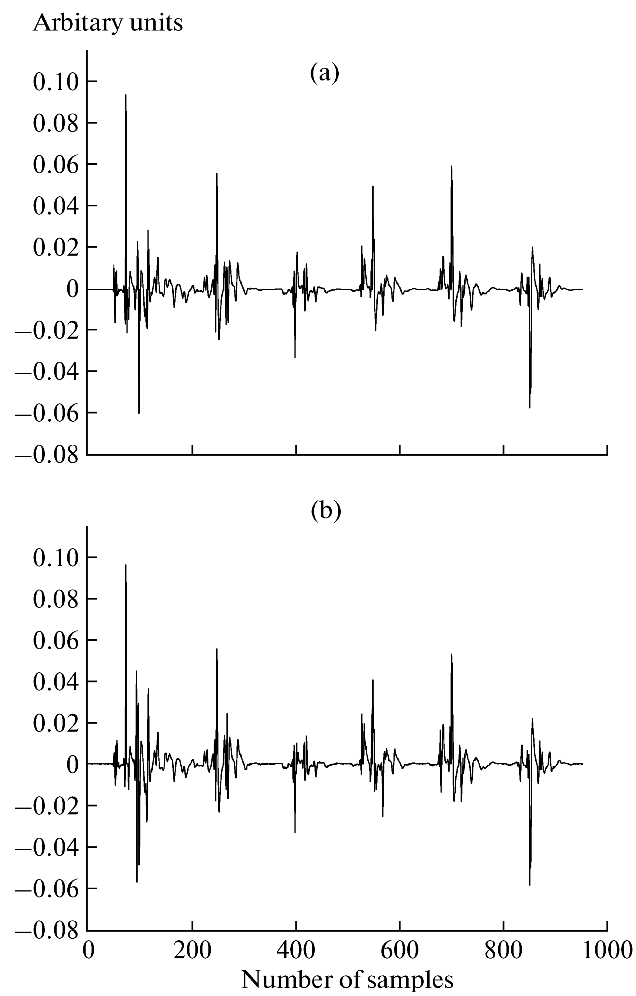

Fig. 5. Deconvolution processor for estimated reflectivity functions at signal to noise ratio (a) 25 dB, (b) 45 dB.

results presented are in good agreement with the true reflectivity function.

CONCLUSIONS

This paper has described a method for ultrasound deconvolution based on adaptive lattice filter. We have presented an adaptive lattice deconvolution technique to process ultrasound echo signals in order to obtain a better estimation of the reflectivity function. The success of this technique is dependent on the convergence parameter, the weight factor and filter length. The algorithm can be used effectively in real time application particularly two and three dimensional images. Further work in this direction should, however, develop techniques which exploit the sparse nature of the reflection sequences.

REFERENCES

1. J. F. Synnevag, A. Austeng, and S. Holm, IEEE Trans. Ultrason. Ferroelectr. Freq. Control **54**, 1606 (2007).
2. Fuji Kensaku, Tanaka Masaaki, Sasaoka Naoto, and Itoh Yoshio, Acoust. Sci. Technol. **28**, 98 (2007).
3. S. Haykin, *Blind Deconvolution* (Prentice-Hall, New Jersey, 1994).
4. A. E. Bazulin and E. G. Bazulin, Acoust. Phys. J. **55**, 832 (2009).
5. T. Taxt and G. V. Frolva, IEEE Trans. Ultrason. Ferroelect. Freq. Contr. **46**, 291 (1999).
6. O. Michailovich and D. Adam, IEEE Int. Symp. Biomed. Imag., pp. 1055–1058 (2002).
7. D. Adam and O. Michailovich, IEEE Trans. Biomed. Eng. **49**, 118 (2002).
8. S. Haykin, *Adaptive Filter Theory*, 4th ed. (Prentice-Hall, 2002).
9. A. K. Mahalanabis, Rurendra Prasad, and K. P. Mohandas, IEEE Trans. Acoust. Speech Signal Process. **31**, 591 (1983)
10. Sophocles J. Orfanidis, *Optimum Signal Processing, An Introduction*, 2th ed. (McGraw-Hill, 2007).
11. M. G. S. Ali and A. Raouf Mohamed, Ultrasonic **30**, 311 (1992).
12. M. A. Grigor'ev, A. V. Tolstikov, and Yu. N. Navrotskaya, Acoust. Phys. J. **49**, 409 (2003).
13. Acoust. Phys. J. **55**, 538 (2009).
14. P. R. Stepanishen, J. Acoust. Soc. Am. **49**, 1629 (1971).
15. M. G. S. Ali, J. Sound Vibrat. **236**, 609 (2000).