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An Enhanced Noise Control Algorithm Based on the Lattice Structure

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I. INTRODUCTION

Due to its simplicity, as well as effectiveness, the filtered-x LMS algorithm has been used to solve active noise cancellation (ANC) problems where the statistics of the input process are unknown or changing with time [1,2]. However, a major drawback of the LMS algorithm is that it suffers from slow convergence speed when eigenvalues of the underlying correlation matrix of the input signal are highly diversified [3]. An effective method of overcoming this difficulty is to use a lattice filter. Because of its decoupling property, the lattice filter is capable of delivering good performance despite wide variations in the eigenvalue spread of the correlation matrix of the input data. In a practical ANC problem, however, it is physically impossible to obtain the acoustic noise or the cancellation signal directly since they are both being sensed by the same acoustic devices. Thus, it is required to employ a method of estimating the noise component from the error signal [5].

In this paper, we present an enhanced feedforward ANC algorithm based on the lattice structure. To implement the adaptive feedforward ANC, the filtered reference signal is fed into the lattice predictor whose reflection coefficients are updated so as to minimize power sums of the forward and backward prediction errors at relevant stages. The regression coefficients of the joint-process estimator are then iteratively updated over time, based on the estimation errors of each stage so that the actuator output waveform is nearly equal to the negative of the noise source as sensed by the error sensor. In the method presented, the local estimation errors are directly obtained from the signal sensed by the error microphone using the modified order-update for the estimation error. Simulation results for a round duct are presented which support the fast convergence of the lattice-based feedforward ANC algorithm. Also, the proposed algorithm is implemented in real-time using the Motorola DSP56001 microprocessor.

II. LATTICE-BASED FEEDFORWARD ANC ALGORITHM

The lattice filter offers a highly efficient structure for generating the sequence of forward prediction errors and the corresponding sequence of backward prediction errors simultaneously [4]. The backward prediction errors $\{b_i(k)\}$ produced by the various stages of a lattice predictor are orthogonal to each other. The order-update recursion for the estimation error can be expressed using the set of regression coefficients $\{\alpha_i\}$.

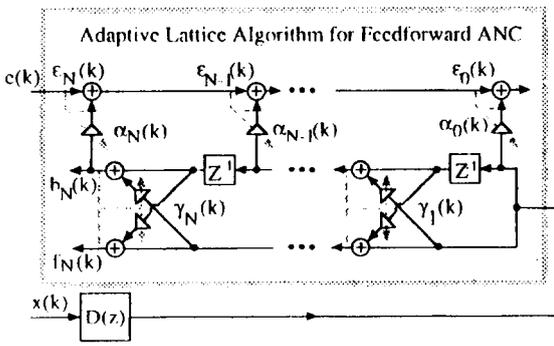


Fig. 1. Block diagram of the adaptive lattice algorithm for feedforward ANC.

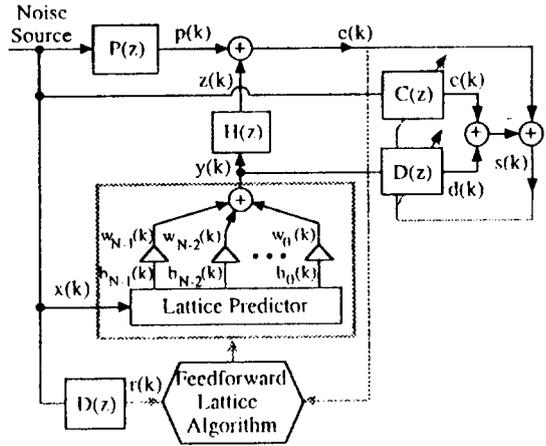


Fig. 2. Digital model of the feedforward ANC algorithm based on the lattice structure.

In a typical ANC system, a noise signal is measured at the location of the noise source with a local sensor. The same noise propagates both acoustically and structurally to the location of a second(error) sensor at which it is desired to remove the components due to the noise source. The adaptive filter derives the actuator signal necessary to minimize the noise power at the location of the error sensor. Thus, the error sensor measures the combined control actuator and primary noise outputs as propagated to the location of the error sensor. The reference signal of the adaptive filter is filtered with the transfer function of the actuator to compensate for the phase shift introduced by the actuator, and the coefficients of the adaptive filter are iteratively updated based on the output of the error sensor. The above procedure is a general framework of the filtered-x LMS algorithm. When the lattice filter is considered for implementing the feedforward ANC, it is required to estimate the primary noise signal to compute the local estimation error at relevant stage of the lattice filter. To meet this requirement, we may change the order-update recursion as follows:

$$\begin{aligned} \epsilon_{N-i-1}(k) &= \epsilon_{N-i}(k) - \alpha_{N-i} b_{N-i}(k), \quad i=0,1,\dots,N, \\ \epsilon_N(k) &= e(k), \end{aligned} \tag{2.1}$$

where $e(k)$ represents the error signal measured with the second sensor. Eq. (2.1) indicates that the local estimation errors can be computed in successive order from the error signal. Fig. 1 shows the block diagram of the lattice filter which implements the feedforward ANC. To implement the feedforward ANC the filtered reference signal is fed into the lattice predictor. In Fig. 1 the reflection coefficients are updated using the gradient adaptive lattice algorithm [4], and the normalized LMS algorithm is used to update the regression coefficients [4]. The normalized LMS algorithm is convergent in the mean-square sense if the adaptation constant μ satisfies the condition: $0 < \mu < 2$.

A digital model of the adaptive feedforward ANC based on the lattice structure is shown in Fig. 2, where the on-line system identification presented in [6] is utilized. The block $P(z)$ in Fig. 2 represents the transfer function from the noise source to the error sensor, and $H(z)$ denotes the transfer function from the adaptive filter output to the error sensor. As mentioned previously, the lattice filter produces the orthogonalized backward prediction errors at various stages, so that unlike the conventional filtered-x LMS algorithm, the convergence speed of the presented algorithm does not depend on the eigenvalue spread-ratio of the correlation matrix of the input.

III. RESULTS AND DISCUSSION

For the experiment involving the algorithm presented here, a round duct with diameter 11.6 cm and length $L=5.6$ m was used. A loudspeaker was attached to one end of the duct to generate the noise signal and the other end was closed. The secondary loudspeaker and the error microphone were placed at $0.34L$ and $0.47L$, respectively, from the first loudspeaker.

A) Computer Simulations

Computer simulations have been performed for the noise source which consists of three sinusoidal components: 100, 200, 300 Hz, with an ambient broadband noise level set at -20 dB below the signal level. Simulation results are plotted in Fig. 3 and Fig. 4, where the *a priori* estimate of $H(z)$ has been used for the 'filtered' reference. As can be seen from Figs. 3 and 4, the rate of convergence of the lattice-based ANC algorithm is superior over the transversal filtered-x algorithm. At steady-state both the lattice and transversal schemes perform in roughly the same manner as shown by the spectrums in Fig. 5. Fig. 6 shows the result of the simulation for the lattice-based adaptive feedforward ANC algorithm combined with the on-line system identification. Insofar as the rate of convergence is concerned, it has been observed that the performance of the presented scheme depends on the convergence speed of the adaptive filter performing the system identification. Also, the residual error signal is accompanied by relatively large variance at transient state, which has been observed for different cases [6].

B) Real-time Implementation

The lattice-based adaptive feedforward ANC algorithm has been programmed in assembly language on the Motorola DSP56000 ADS board, in conjunction with the Ariel ADC56000 I/O board. Fig. 7 shows the result produced by the real-time system, with the lattice-based ANC algorithm implemented. It is clear that the real-time system shows the same performance as observed in computer simulations. When the N-stage lattice controller and the M-tap system identification filter are used, the computational complexity of the lattice-based feedforward ANC algorithm is about $(544+196N+12M)$ oscillator clock cycles, while the filtered-x LMS algorithm requires $(522+28N+12M)$ cycles. Since the lattice scheme requires $2N$ divisions per iteration, the ratio of computational complexity between the lattice-based and filtered-x algorithms increases with the filter order. For $N=32$ and $M=32$, for example, the ratio of the computational complexity between both algorithms is about 4:1, but this ratio increases about 5.4:1 for $N=128$ and $M=64$.

IV. SUMMARY

In this paper, we have presented an enhanced adaptive feedforward noise control algorithm based on the lattice structure. Due to its decoupling property, the algorithm presented here is capable of delivering good performance despite wide variations in the eigenvalue spread of the correlation matrix of the input signal, which has been confirmed by experimental results.

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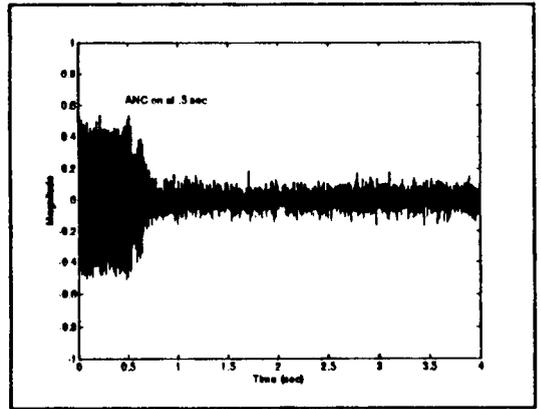
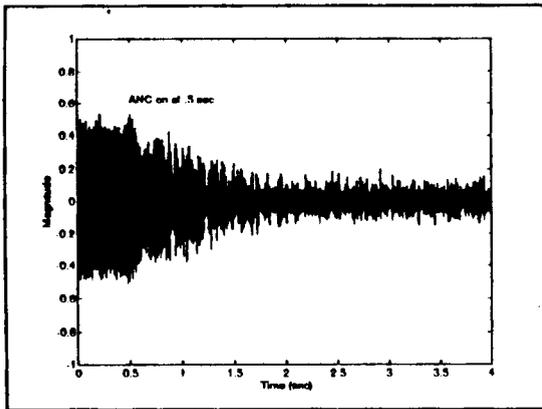


Fig. 3. Residual errors of (a) the filtered-x LMS algorithm and (b) the lattice-based feedforward ANC algorithm.

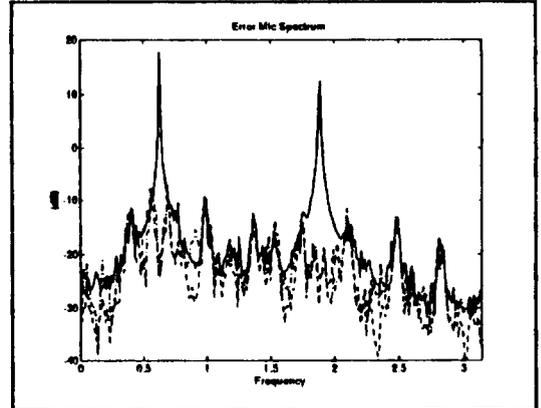
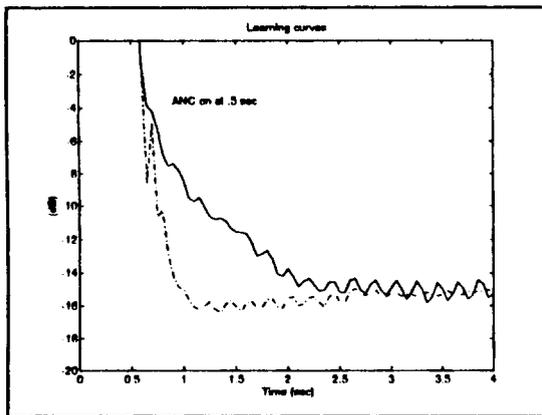


Fig. 4. Learning curves of the filtered-x LMS algorithm (solid line) and the lattice-based feedforward ANC algorithm (dashed line).

Fig. 5. Error signal spectra; ANC off (solid line), ANC on (dashed line: filter-x LMS, dashdot line: lattice-based feedforward ANC algorithm).

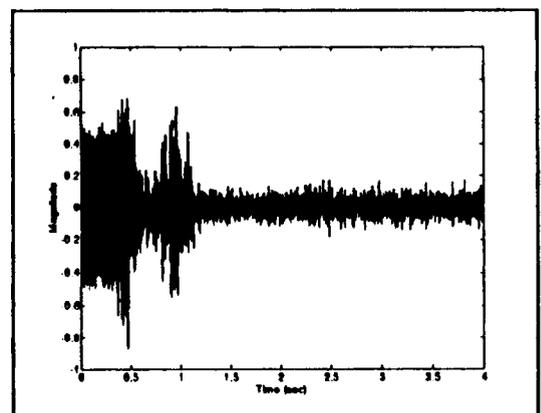
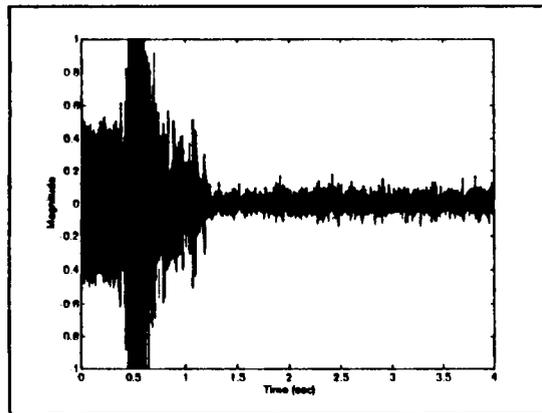


Fig. 6. Residual error signal of the lattice-based ANC algorithm combined with the on-line system id.

Fig. 7. Residual error signal for the real-time system.