

A NOISE-ROBUST STOCHASTIC GRADIENT ALGORITHM WITH AN ADAPTIVE STEP-SIZE SUITABLE FOR MOBILE HANDS-FREE TELEPHONES

Akihiro Hirano and Akihiko Sugiyama

Information Technology Research Laboratories, NEC Corporation
1-1, Miyazaki 4-Chome, Miyamae-Ku, Kawasaki, Kanagawa 216, Japan

ABSTRACT

This paper proposes a new noise-robust adaptive FIR filtering algorithm with an adaptive step-size which takes non-stationarity of speech signals into account. The proposed algorithm controls the step-size based on the reference input signal power and the estimated noise power. Implementation of an acoustic echo canceller based on this algorithm using digital signal processors is also described. Computer simulation results using a real speech signal show that the proposed algorithm improves the ERLE (echo return loss enhancement) by more than 10 dB compared with conventional noise-robust adaptive-step algorithms. The implemented echo canceller achieves 25 dB of the ERLE, which agrees with the computer simulation results.

1. INTRODUCTION

Acoustic echo cancellers are used in many communication systems such as TV conferencing and hands-free telephones to reduce echoes which disturb comfortable conversation. In acoustic echo cancellation, robustness against disturbing signals is important because adaptation should be performed under disturbance by a room noise and a near-end speech. Such robustness is more essential in mobile hands-free telephones which will be used in noisy vehicles.

For echo cancellers, stochastic gradient algorithms[1-3] are widely used. The learning identification method (known as the normalized LMS algorithm, NLMS)[1] is the most popular example. Though NLMS is simple and easy to implement, it is not so robust as to reduce echoes in noisy environments. In order to cope with a noise, some noise-robust adaptive step-size algorithms[2-3] have been proposed. However, these algorithms do not incorporate non-stationarity of speech signals and cannot operate properly if the input signal is a speech and a large additive noise exists.

This paper proposes a new noise-robust adaptive FIR filtering algorithm with an adaptive step-size which takes non-stationarity of speech signals into account. Section 2 briefly describes normalized LMS algorithm and some conventional noise-robust adaptive step-size algorithms. A new adaptive step-size algorithm which controls the step-size based on the reference input signal power and the noise power is proposed in Section 3. An acoustic echo canceller based on the proposed algorithm implemented using digital signal processors (DSP's) is described followed by computer simulations and performance evaluation using the hardware.

2. CONVENTIONAL ALGORITHMS

2.1. Normalized LMS

In stochastic gradient algorithms, the filter coefficient vector $\mathbf{W}(t)$ is updated by

$$\mathbf{W}(t+1) = \mathbf{W}(t) + \mu(t)e(t)\mathbf{X}(t) \quad (1)$$

where $\mathbf{X}(t)$ is the reference input signal vector, $e(t)$ is the error signal. The step-size $\mu(t)$ in NLMS is inversely proportional to the reference input signal power $P_X(t)$ and is calculated by

$$\mu_{NLMS}(t) = \frac{\mu_0}{P_X(t)} \quad (2)$$

In (2), μ_0 is a positive constant which controls both the convergence speed and robustness against noise.

Using the optimum filter coefficient vector \mathbf{H} and the additive noise $n(t)$, adaptation of $\mathbf{W}(t)$ is given by

$$\begin{aligned} \mathbf{W}(t+1) = \mathbf{W}(t) + & \frac{\mu_0 \{\mathbf{H} - \mathbf{W}(t)\}^T \mathbf{X}(t) \mathbf{X}(t)}{P_X(t)} \\ & + \frac{\mu_0 n(t) \mathbf{X}(t)}{P_X(t)} \end{aligned} \quad (3)$$

where superscript T means transpose of a vector. Normalization by $P_X(t)$ makes the contribution of the coefficient error $\mathbf{H} - \mathbf{W}(t)$ to adaptation independent of $P_X(t)$.

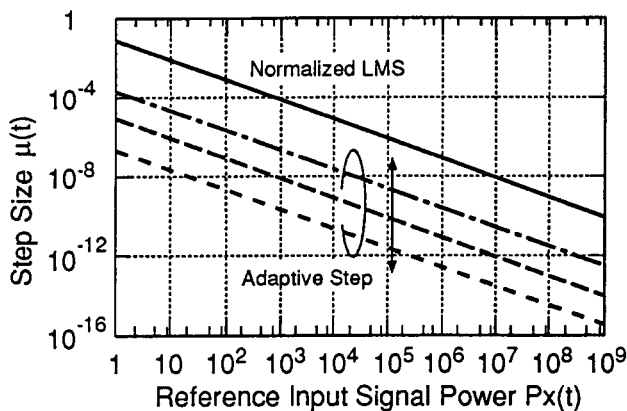


Fig. 1. Comparison of step-size in conventional adaptive step-size algorithms

However, the influence of the noise $n(t)$ becomes too large for small $P_X(t)$. This is why NLMS cannot update filter coefficients correctly if the reference input signal is non-stationary and the additive noise exists.

2.2. Noise-Robust Adaptive Step-Size Algorithms

Some noise-robust adaptive step-size algorithms[2-3] have been proposed. The normalized stochastic gradient algorithm with a gradient adaptive and limited step-size (NSG-GALS)[2] controls its step-size based on the gradient of the squared error with respect to the step-size. An adaptive limit on the modification amount of the step-size is introduced for stable control of the step-size. The step-size of the time-varying step-size NLMS (TVS-NLMS)[3] is inversely proportional to the additive noise power. To enhance the tracking speed for echo path changes, larger step-size is used after echo path changes.

Figure 1 compares the step-sizes of the conventional algorithms. The step-size of the adaptive-step algorithms becomes smaller for a larger noise. However, these algorithms pay no attention to the relation between the reference input signal power and the influence of the noise. Disturbance by the noise is still large if the reference input signal is small. Therefore, the performance of these algorithms should be degraded for non-stationary inputs.

3. PROPOSED ALGORITHM

In order to reduce the influence of the additive noise, the proposed algorithm uses smaller step-size for smaller reference input signal power $P_X(t)$. Figure 2 demonstrates step-size control in the proposed algorithm. The step-size $\mu_{Prop}(t)$ becomes larger for a larger $P_X(t)$ until $P_X(t)$ reaches a threshold $P_{th}(t)$. For $P_{th}(t) < P_X(t)$, $\mu_{Prop}(t)$ becomes smaller.

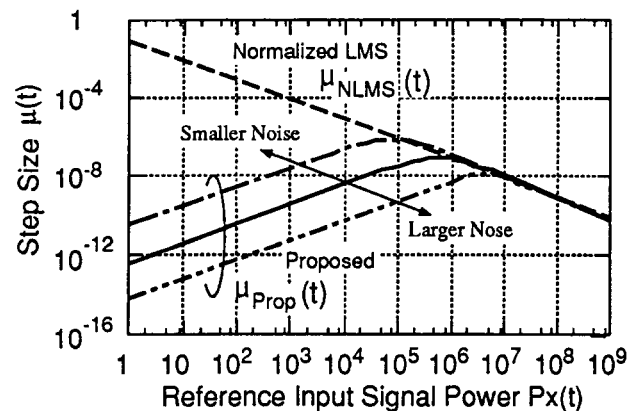


Fig. 2. Step-size in proposed algorithm.

Such a step-size is obtained by

$$\mu_{Prop}(t) = \frac{\mu_0 P_X(t)}{P_X^2(t) + P_{th}^2(t)} \quad (4)$$

The threshold $P_{th}(t)$ is controlled using the estimated noise power $P_N(t)$ by

$$P_{th}(t) = \alpha P_N(t). \quad (5)$$

To avoid the influence of the residual echo on the noise power estimation, $P_N(t)$ is updated by

$$P_N(t+1) = \beta P_N(t) + (1-\beta)e^2(t) \quad (6)$$

only if the error signal power is greater than the filter output power. Note that this algorithm requires only a few additional operations to NLMS.

4. DSP IMPLEMENTATION

An acoustic echo canceller based on the proposed algorithm has been implemented by using multiple DSP system[4]. The block diagram of the implemented echo canceller is shown in Fig. 3. Four NEC's 32-bit floating point DSP μ PD77230s[5] are installed and are connected via a 16-bit shared bus. One-chip μ -law CODEC's are used for analog-to-digital and digital-to-analog conversion. The sampling frequency is 8 kHz. Data transmission between a DSP and a CODEC is carried out through serial-data communication lines.

The proposed algorithm has been realized simply by appending the noise power estimator and replacing the step-size calculator of the NLMS. The implemented echo canceller has 512 taps, which is sufficient for typical mobile hands-free telephones. Each DSP performs 128-tap FIR filtering and coefficient adaptation. DSP#0 estimates the noise power and controls the step-size. Figure 4 illustrates the implemented echo canceller.

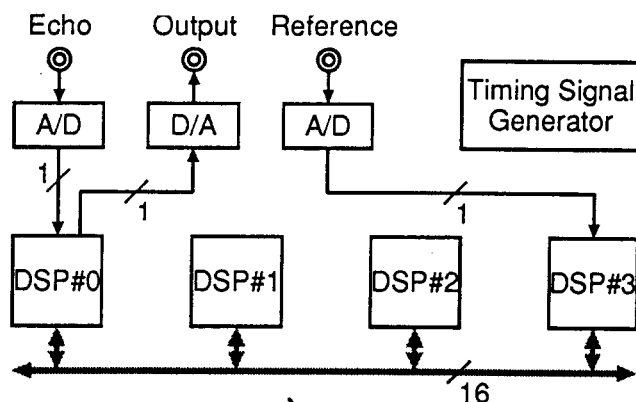


Fig. 3. Block diagram of echo canceller.

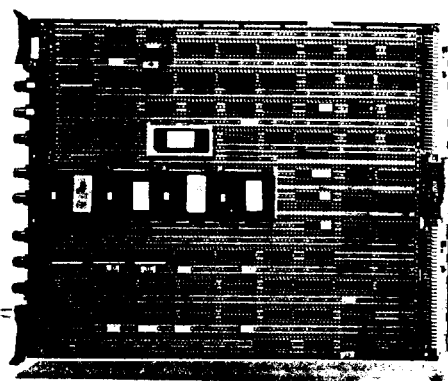


Fig. 4. Implemented echo canceller.

5. PERFORMANCE EVALUATION

The performance of the proposed algorithm has been evaluated by computer simulations and measurements using the hardware. Evaluations have been carried out for an acoustic echo canceller in a mobile hands-free telephone. A reference input signal is a female speech signal. An echo and noises have been recorded in a car with a noisy diesel engine. These signals have been sampled at 8 kHz. In the computer simulations, the signals have been converted into 16-bit integer. The 8-bit μ -law format has been used for the measurements.

Figure 5 shows the reference input signal power and the noise power. Noise1 is an engine noise in an idle state. The echo is clearly audible for Noise1. Noise2 has been recorded in a moving car and contains an engine noise, a wind noise and also brake noises. The echo-to-noise ratio is almost always less than 0 dB for Noise2.

In the computer simulations, NSG-GALS, TVS-NLMS and the proposed algorithm have been compared. All calculations have been performed in double precision floating point. The parameters for each algorithm have

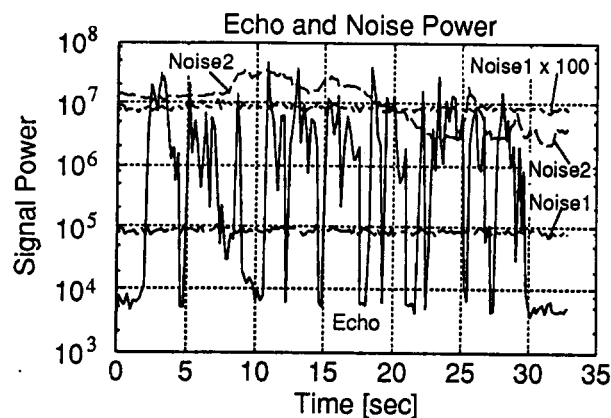


Fig. 5. Echo power and noise power.

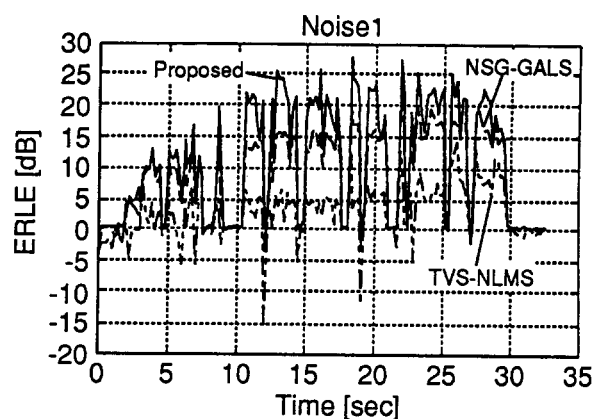


Fig. 6. ERLE for Noise1.

been optimized for Noise1. The parameters have been chosen as $\mu_0 = 0.1$, $\rho = 1.0 \times 10^{-4}$, $\alpha = 2.0 \times 10^{-5}$ and $\beta = 0.0001$ for NSG-GALS, $\rho = 0.01$ and $\epsilon = 1.0 \times 10^6$ for TVS-NLMS and $\mu_0 = 0.2$, $\alpha = 50.0$ and $\beta = 0.9984$ for the proposed algorithm. The number of taps is 512.

Figure 6 compares the ERLE (Echo Return Loss Enhancement) for Noise1. The proposed algorithm achieves almost 25 dB of ERLE, which is 10 dB higher than NSG-GALS and 20 dB higher than TVS-NLMS. Tracking capability for noise level variation have been examined by using an amplified version of Noise1 (Noise1 \times 100), which is 100 times larger in power, and Noise2. Figures 7 and 8 compare the performance for Noise1 \times 100 and Noise2. The proposed algorithm reduces echoes by more than 10 dB while two conventional algorithms amplify them.

Performance of the hardware has been measured using the speech and Noise1. At the beginning of measurements, the filter coefficients have been initialized to 0.

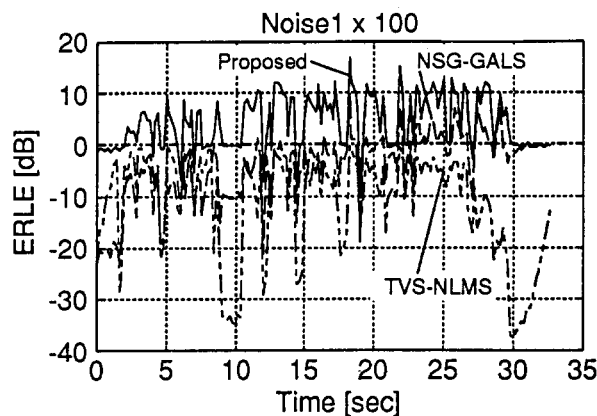


Fig. 7. ERLE for Noise1 \times 100.

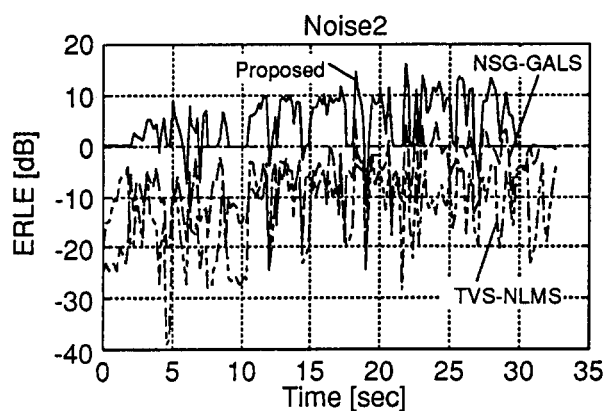


Fig. 8. ERLE for Noise2.

After 18 seconds of adaptation, the power spectrum of the echo canceller output has been measured by an FFT spectrum analyzer. The power spectrum have been averaged for 16 seconds. Figure 9 shows the power spectrum of the echo canceller output. 25 dB of the ERLE, which agrees with the computer simulation results, is achieved.

6. CONCLUSION

A new noise-robust adaptive FIR filtering algorithm, which takes non-stationarity of speech signals into account, has been proposed. It controls the step-size based on the reference input signal power and the estimated noise power. An echo canceller using this algorithm has been implemented by DSP's. The performance of the proposed algorithm has been evaluated by computer simulations and measurement using the hardware. Computer simulation results using real speech and noise show that the proposed algorithm improves the ERLE by more than 10 dB compared with the conventional noise-robust adaptive-step algorithms. The implemented echo canceller

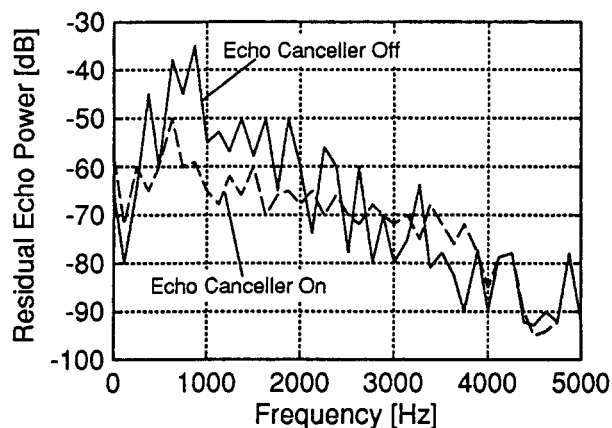


Fig. 9. Residual echo power.

reduces echoes by 25 dB for measured signals. The measurement results using the hardware agree with the computer simulation results.

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