Acoustic Echo Canceling in the Double-Talk Condition

Prof. Mohammad Reza Asharif*, Rui Chen*,
*Department of Information Engineering,
University of the Ryukyus
1-Senbaru, Nishihara, Okinawa, Japan
asharif@ie.u-ryukyu.ac.jp

Prof. KatsumiYamashita +
+Department of Electrical and Electronic Systems,
Graduate School of Engineering,
Osaka Prefecture University, Osaka, Japan
yamashita@comm.ees.osakafu-u.ac.jp

Abstract: In the echo canceling for hand-free set mobile radiotelephone or teleconference system, the double-talk is occurred when both the near-end and the far-end speakers talk simultaneously. The conventional adaptive digital FIR filter using algorithm such as LMS fails to track the echo path in this condition. Because the error signal is contaminated to the near-end signal to estimate the gradient correctly. The Correlation LMS (CLMS) and Extended Correlation LMS (ECLMS) algorithms have been introduced by authors to challenge the double-talk in the echo canceling system. In this paper we propose a new implementation of ECLMS algorithm in the wavelet domain called wavelet transform extended correlation LMS algorithm (WECLMS) to improve the speed of the convergence. The computer simulation results support the theoretical findings and verify the robustness of the proposed WECLMS algorithm in the double-talk situation.

Key words: Echo canceling, Adaptive digital filtering, LMS algorithm, Double-talk, Correlation function, Wavelet domain.

1 – Introduction

In hand-free mobile radiotelephone or in tele-conference system, where we have acoustic echo feedback from loudspeaker to microphone, the quality of communications is degraded severely.

Adaptive FIR filters by using the conventional LMS, BLMS, or NLMS algorithms are utilized for echo canceling. However, in the double-talk environment when both the near-end and the far-end signals are presented, the error signal used for tap adaptations will be uncorrelated with the echo signal and therefore, tap adaptations processes are severely damaged.

The conventional algorithm usually stops adaptation whenever double-talk sensor detects this condition. Stopping the tap adaptation is just a passive action to handle the double-talk condition and it causes lowering speed of adaptations and/or totally mislead when the echo path changed in the period of halting tap adaptation. Other works for challenging the problem of double-talk situation in the echo canceling can be found in [1], [2], and [3] that cause much more complexity adding to a simple LMS algorithm.

To solve the double-talk problem, correlation LMS (CLMS) algorithm and Extended CLMS (ECLMS) algorithm which utilize the correlation function of input signal instead of the input signal itself, have been proposed [4], [5], and [6]. Therefore, we can continue the tap adaptation (non-freezing) even in the double-talk situation, without misleading the estimation process. However, the convergence speed of the CLMS and the ECLMS algorithms are not so fast.

In this paper, we propose a new implementation of ECLMS algorithm in the wavelet domain called wavelet transform extended correlation LMS algorithm (WECLMS), to improve the speed of the convergence. The computer simulation results verify that the WECLMS algorithm achieves a better result compared with CLMS and ECLMS algorithms and show the robustness of the WECLMS algorithm in the double-talk condition.

2 - Double-Talk and ECLMS Algorithm

In Fig.1, the echo canceling is shown. The output of the FIR filter, $\hat{y}(n)$, is estimating the echo signal, $y(n)$, by adjusting taps, $h_i(n)$, to filter the input $x(n)$:

$$\hat{y}(n) = \sum_{i=0}^{N-1} h_i(n).x(n-i) \tag{1}$$

The echo signal is obtained from echo impulse response, r, as follows (N is the acoustic impulse response length):

$$y(n) = \sum_{i=0}^{N-1} r_i.x(n-i) \tag{2}$$

The error signal, $e(n)$, is calculated as below:

$$e(n)=d(n)-\hat{y}(n) \tag{3}$$

where $d(n)$, is microphone signal that usually contains the echo signal. The LMS algorithm [7] is as follows:

$$h_i(n+1) = h_i(n) + 2\mu_0.e(n).x(n-i) \qquad (4)$$

where μ_0, is the step size for tap coefficients adaptation.

If the near-end signal, $s(n)$, is also presented during the echo canceling, then the microphone signal contains both the echo and the near-end signals.:

$$d(n)=y(n)+s(n) \qquad (5)$$

We call this condition as double-talk. It is well known that the error signal in this case contains uncorrelated component with input and echo signals. Therefore, the algorithm in (4) is failed to track the correct echo impulse response.

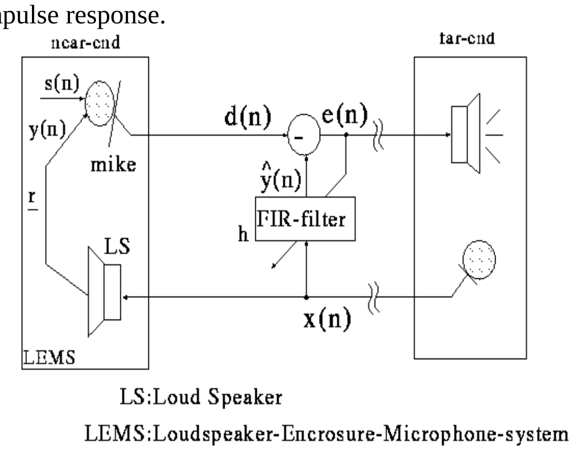

Fig.1. Echo canceller system

The ECLMS algorithm [6] is defined to handle this condition by computing the autocorrelation of the input as follows:

$$R_{xx}(n,k) = \sum_{j=0}^{n} x(j).x(j-k) \qquad (6)$$

Also the cross-correlation between the desired and the input signal is calculated as follows:

$$R_{dx}(n,k) = \sum_{j=0}^{n} d(j).x(j-k) \qquad (7)$$

Substituting from (2), (5) and (6) into (7) and assuming that there is no correlation between the far-end and the near-end signals [6] $R_{sx}(n,k) \approx 0$, the cross-correlation will be obtained as follows:

$$R_{dx}(n,k) = \sum_{i=0}^{N-1} r_i.R_{xx}(n,|k-i|) \qquad (8)$$

To estimate $R_{dx}(n,k)$, we need to process the autocorrelation values of the input by an adaptive filter and find the error, $e(n,k)$, between the real and the estimated values of the cross-correlation.

$$\tilde{R}_{dx}(n,k) = \sum_{i=0}^{N-1} \tilde{h}_i(n).R_{xx}(n,|k-i|) \qquad (9)$$

$$e(n,k) = R_{dx}(n,k) - \tilde{R}_{dx}(n,k) \qquad (10)$$

The gradient for tap coefficients adjustment in the correlation-processing filter is obtained (to minimize the MSE) as follows:

$$\nabla_j[MSE] = -2E[e(n,j).Toeplitz(R_{xx}(n,j))] \qquad (11)$$

and the ECLMS algorithm [6] is derived as below:

$$h_j(n+1) = h_j(n) + \frac{2\mu e(n,j)Toeplitz(R_{xx}(n,j))}{1+tr[Toeplitz(R_{xx}(n,j)).Toeplitz(R_{xx}(n,j))]} \qquad (12)$$

3 – Discrete Wavelet domain Algorithm

Like the Fourier series expansion, the wavelet series expansion of the previous section maps a function of a continuous variable into a sequence of coefficients. If the function being expanded is a sequence of number, like samples of a continuous function f (x), the resulting coefficients are called the discrete wavelet transform (DWT) [8] of f(x). For this case, the DWT transform can be defined as:

$$W_\phi(j_0,p) = \frac{1}{\sqrt{M}}\sum_x f(x)\phi_{j_0,p}(p) \qquad (13)$$

$$W_\varphi(j,p) = \frac{1}{\sqrt{M}}\sum_x f(x)\varphi_{j,p}(x) \qquad (14)$$

for $j \geq j_0$ and

$$f(x) = \frac{1}{\sqrt{M}}\sum_p W_\phi(j_0,p)\phi_{j_0,p}(x) + \frac{1}{\sqrt{M}}\sum_{j=j_0}^{\infty}\sum_p W_\varphi(j,p)\varphi_{j,p}(x) \qquad (15)$$

where $$\phi_{j,p}(x) = 2^{j/2}\phi(2^j x - p) \qquad (16)$$

$$\varphi_{j,p}(x) = 2^{j/2}\varphi(2^j x - p) \qquad (17)$$

Here, $W_\phi(j_0,p)$ are called the approximation or scaling coefficients; $W_\varphi(j,p)$ are called the detail or wavelet coefficients; $\phi(x)$ is called scaling function and $\varphi(x)$ is called wavelet function; p determine the position of $\phi(x)$ along the x-axis; j determine $\phi(x)$'s width – how broad or narrow it is along the x-axis. For example, $f(x) = f(x_0 + x\Delta x)$ for some x_0, Δx , and x=0,1,2...M-1. We select M to be a power of 2 (i.e., M=2^j) so that the summations are performed over x=0,1,2...M-1, j=0,1,2...J-1, and p= 0,1,2...2^j-1. We can set j_0 equal each one from 0 to J-1, thus Eq.13 and 14 define a “family” of transform that differ in starting scale j_0. The Inverter Discrete Wavelet Transform is defined as Eq.15.

To improve the speed of the convergence we propose a new implementation of ECLMS algorithm in the wavelet domain called wavelet transform extended correlation LMS algorithm (WECLMS). In Fig3, the WECLMS algorithm is shown.

As shown in the Fig.2, first, for each n we take Discrete Wavelet Transform (DWT) of the cross-correlation function and the autocorrelation function by Eq.16, 17. The two coefficients can be written as:

$$DWT\ \ (R_{dx}(n,k)) = [W_{\phi}(n,l_1), W_{\varphi}(n,l_2)] \qquad (18)$$

$$DWT\ \ (R_{xx}(n,k)) = [\widetilde{W}_{\phi}(n,l_1), \widetilde{W}_{\varphi}(n,l_2)] \qquad (19)$$

where

$$Length\ \ (W_{\phi}(j_0, p)) = Length\ \ (\widetilde{W}_{\phi}(j_0, p)) = l_1$$

$$Length\ \ (W_{\varphi}(j\ \ , p) = Length\ \ (\widetilde{W}_{\varphi}(j, p)) = l_2$$

$$l_1 + l_2 = Length\ \ (R_{xx}(n,k))$$

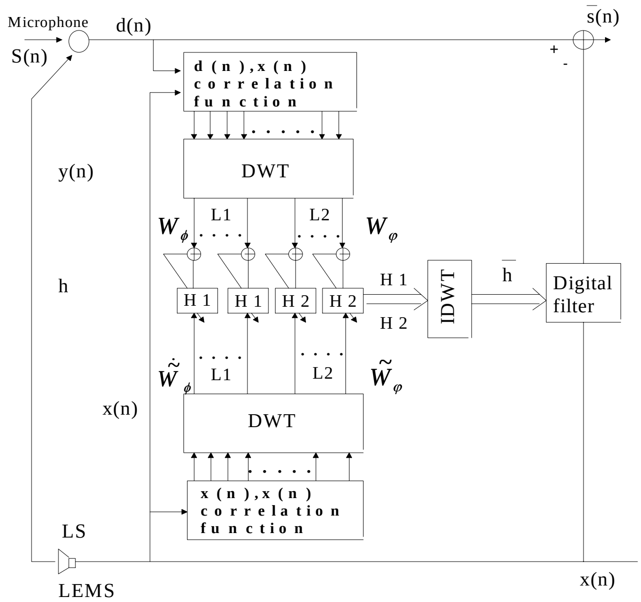

Fig.2. Echo canceller using WECLMS algorithm

As like as the ECLMS algorithm the error signal is shown by

$$e_1(n,l_1) = W_{\phi}(n,l_1) - \sum_{q=0}^{l_1} H_1(n,l_1)\widetilde{W}_{\phi}(n,l_1 - q) \qquad (20)$$

$$e_2(n,l_2) = W_{\varphi}(n,l_1) - \sum_{q=0}^{l_2} H_2(n,l_2)\widetilde{W}_{\varphi}(n,l_2 - q) \qquad (21)$$

We can update the tap coefficients is shown as

$$H_1(n+1) = H_1(n) + \frac{2\mu ToePlitz(\widetilde{W}_{\phi})e_1(n)}{1 + tr[Toeplitz(\widetilde{W}_{\phi})Toeplitz(\widetilde{W}_{\phi})]} \qquad (22)$$

$$H_2(n+1) = H_2(n) + \frac{2\mu ToePlitz(\widetilde{W}_{\varphi})e_2(n)}{1 + tr[Toeplitz(\widetilde{W}_{\varphi})Toeplitz(\widetilde{W}_{\varphi})]} \qquad (23)$$

To this end we use the H_1 and H_2 to do the Inverter Discrete Wavelet Transform (IDWT) by the Eq.15.

$$IDWT\ \ (H_1, H_2) = \widetilde{h} \qquad (24)$$

4 - Simulation Results

The acoustic echo impulse response, r_i, of the room is assumed to have exponential decaying shape that decreases to -60 dB after N samples as follows:

$$r_i = Randn\ [\exp(-8i / N)] \qquad (25)$$

To measure the performance of the convergence of the algorithm, we use the ratio of distance of weight and impulse response, DW(n), which is defined as follows:

$$DW(n) = 10\log_{10}[\sum_{i=0}^{N-1} \|r_i - \widetilde{h}_i(n)\|^2 / \sum_{i=0}^{N-1} \|r_i\|^2] \qquad (26)$$

In order to show the capability and robustness of the wavelet domain proposed WECLMS algorithm, we have performed several computer simulations. In Fig. 3, the convergence characteristics for the wavelet domain proposed WECLMS algorithm is compared with CLMS, and ECLMS algorithms in the single-talk condition. As we see from the Fig 3, the WECLMS is better than the CLMS and ECLMS, but the enough convergence is not achieved. In the Fig.4, the WECLMS algorithm is compared with those of LMS, CLMS and ECLMS algorithm in the double-talk condition. As the Fig.4 shown, the LMS algorithm cannot work in the double-talk condition. The CLMS and ECLMS reach to –4dB and –8dB, while the WECLMS, which is the best among all algorithms, converge to –16dB. In the next simulation in Fig. 5, we started with the single-talk condition. Then, at 2496-th iteration, we changed to double-talk condition. We can see that both in the single-talk and double-talk condition the WECLMS algorithm converges very fast. In the last simulation in Fig.6, we started with the single-talk condition. Then, at 4992-th iteration, we changed the echo path impulse response (by using different random number in Eq.2) and imposed the double-talk condition at the same time.

As it shown in Fig.6, the WECLMS algorithm has superior convergence characteristics comparing with the CLMS and ECLMS algorithm.

5 - Conclusion

A new implementation of the extended correlation LMS algorithm in the wavelet domain was proposed. An improvement of more than -10 dB has been obtained in performance of the proposed algorithm over the past algorithm. Also, a 16 dB convergence has been obtained as compared with other conventional algorithm, which totally does not converge in double-talk. Therefore, the proposed WECLMS algorithm is more robust than previously proposed CLMS and ECLMS algorithms. The robustness of the proposed algorithm for the echo canceling in double-talk situation was shown by computer simulation**.**

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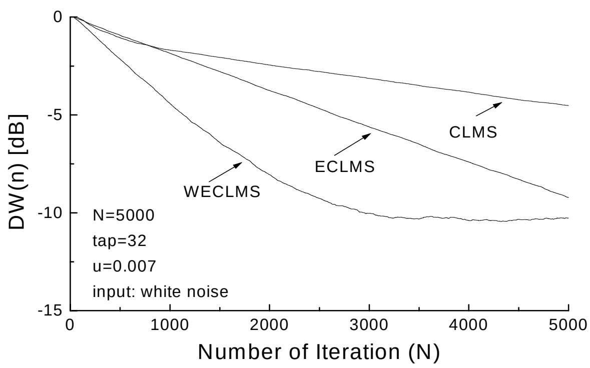

Fig.3. Comparison between LMS, CLMS, ECLMS and proposed WECLMS in single-talk

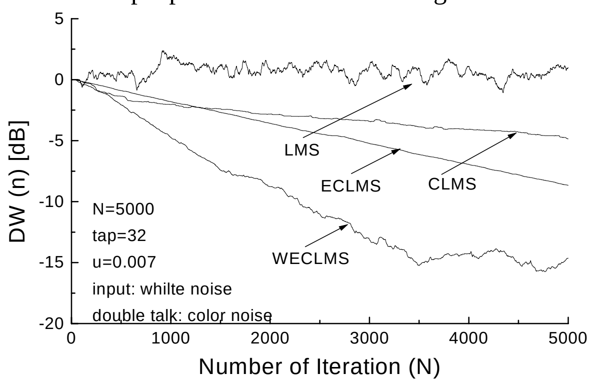

Fig.4. Comparison between LMS, CLMS, ECLMS and proposed WECLMS in double-talk

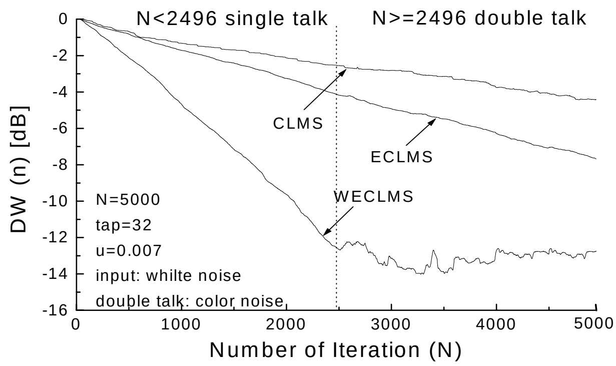

Fig.5. Switching from single to double talk with the same echo path

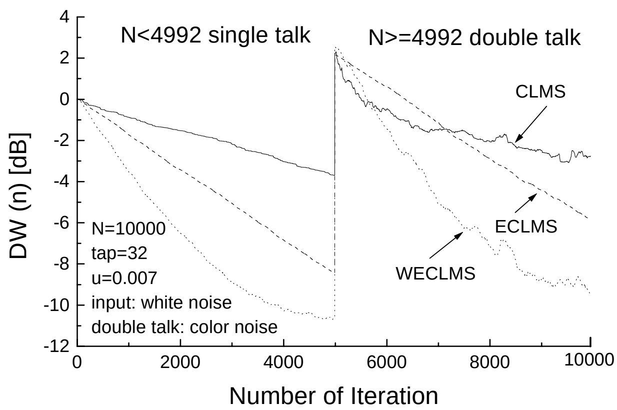

Fig.6. Switching from single to double talk with the echo path changed