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NONLINEAR ECHO CANCELLATION USING A CORRELATION RLS ADAPTATION SCHEME

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Abstract: - Adaptive algorithms have been widely used to reduce or cancel undesired echo signals in acoustic communication systems. In particular, in a double-talk scenario, fluctuations in the estimation of echo path parameters and nonlinear distortion in a hybrid system may result in significant performance degradation. In this paper, the use of nonlinear echo cancellation via a correlation RLS (CRLS) algorithm is proposed to compensate for nonlinear distortion in the echo path and to solve the double-talk problem. Simulation results, showing fast convergence and robustness, are provided to illustrate the validity and performance of the proposed approach.

Key-Words: - Nonlinear echo cancellation, Correlation RLS, Volterra filter

1. Introduction

In voice and data transmission systems (e.g., hands-free and teleconference systems), communication quality may be severely degraded due to echo signals. To cancel or suppress such undesirable echoes, the normalized LMS (NLMS) algorithms have been widely utilized as an underlying adaptation algorithm [1,10,12-15]. However, it may lead to slow asymptotic convergence and/or divergence when the noise is strong as in a double-talk situation. To overcome this problem and achieve double-talk echo cancellation in a linear telephone network, adaptive schemes based on recursive least square (RLS) and fast affine projection (FAP) have been studied [5,10-15]. For example, (i) when a double-talk is detected, the divergence of the adaptive filter coefficients is inhibited by setting the step-size to zero [12]; (ii) subband echo cancellation is used [13]; (iii) a novel adaptation scheme with variable step sizes is formulated by comparing the powers of input and error signals [14]; (iv) a correlation RLS (CRLS) or correlation LMS (CLMS) algorithms is studied [9,11]. However, in practice, nonlinear distortions [2-9] may also occur in the echo path, due to (i) impedance mismatch in two-to-four wire hybrid circuits [1,2], (ii) digital-to-analog converter (DAC) and analog-to-digital converter (ADC) [3,4], (iii) imbalance in the positive and negative pulses transmitted, (iv) saturation in transformers of hybrids in a full-duplex digital subscriber loop, or (v) loudspeaker nonlinearities. Thus, it is necessary to take into account the effects of nonlinear distortions to achieve better nonlinear echo cancellation or suppression. For this purpose, several approaches, including adaptive Volterra filtering [2-9], have been proposed. However, the performances of these conventional echo cancellation approaches may be severely degraded in a double-talk situation, since the error signal contains not only a near-end signal but also a nonlinear echo signal. Accordingly, a new nonlinear echo cancellation approach is proposed in this paper, where an adaptive Volterra filter with a CRLS adaptation scheme is employed to compensate for nonlinear distortions in the echo path and.

This paper is organized as follows: In the next section, Volterra series modeling and nonlinear echo cancellation are introduced. In Section 3, Volterra filtering is discussed along with a correlation RLS algorithm. To illustrate the performance of the proposed nonlinear echo cancellation, some simulation results are provided in Section 4. Finally, conclusions are given in Section 5.

2. Volterra Series Modeling and Nonlinear Echo Cancellation

2.1 Discrete Volterra Series

Discrete Volterra series has been used to model many nonlinear systems in engineering and science [2-8]. In particular, linear filter theory can be used for the analysis of such systems, since output of the latter is linear with respect to the system kernels. Furthermore, the DAC of a hybrid telephone network can be modelled as the following third-order Volterra system [3]:

$$\begin{aligned} y[n] &= \sum_{i=0}^{N-1} h_1[i]x[n-i] + \sum_{i=0}^{N-1}\sum_{j=i}^{N-1} h_2[i,j]x[n-i]x[n-j] \\ &+ \sum_{i=0}^{N-1}\sum_{j=i}^{N-1}\sum_{k=j}^{N-1} h_3[i,j,k]x[n-i]x[n-j]x[n-k] \end{aligned} \quad (1)$$

where $h_1[i]$, $h_2[i,j]$, and $h_3[i,j,k]$ are first-, second-, and third-order Volterra kernels, respectively, and N denotes the memory size. Also, nonlinear kernels (i.e., $h_2[i,j]$ and $h_3[i,j,k]$) can be assumed to be symmetric. (1) can also be expressed in a vector form:

$$y[n] = \mathbf{h}_v^T[n]\mathbf{x}_v[n] \quad (2)$$

where the Volterra kernel vector $\mathbf{h}_v[n]$ consists of linear, quadratic, and cubic kernels, and the Volterra input vector $\mathbf{x}_v[n]$ consists of linear, quadratic, and cubic inputs:

$$\begin{aligned} \mathbf{x}_v[n] = [\ & x[n], \ldots, x[n-N+1], x^2[n], x[n]x[n-1], \ldots, \\ & x[n]x[n-N+1], x^2[n-1], \ldots, x[n-1]x[n-N+1], \\ & x[n-2]x[n-2], \ldots, x^2[n-N+1], x^3[n], \ldots, x^2[n]\cdot \\ & x[n-N+1], \ldots, x^3[n-N+1]\ ]^T \end{aligned} \quad (3)$$

$$\begin{aligned} \mathbf{h}_v[n] = [& h_1[0], \ldots, h_1[N-1], h_2[0,0], h_2[0,1], \ldots, h_2[0,N-1], \\ & h_2[1,1], \ldots, h_2[1,N-1], h_2[2,2], \ldots, h_2[N-1,N-1], \\ & h_3[0,0,0], \ldots, h_3[0,0,N-1], \ldots, h_3[N-1,N-1,N-1]]^T \end{aligned}$$

(4)

2.2. Nonlinear Echo Cancellation

The conventional structure for nonlinear echo cancellation [2-4] is shown in Fig. 1, where the echo replica $\hat{y}[n]$ is the output of the third-order Volterra model, and the error signal $e[n]$ is defined as the difference between the echo signal $y[n]$ and $\hat{y}[n]$.

$$e[n] = y[n] - \hat{y}[n] \quad (5)$$

The Volterra filter coefficients can be updated in an adaptive way by employing the normalized LMS algorithm:

$$\mathbf{h}_v[n+1] = \mathbf{h}_v[n] + \mu e[n]\frac{\mathbf{x}_v[n]}{\|\mathbf{x}_v[n]\|^2} \quad (6)$$

3. Adaptive Volterra Filtering With A CRLS Algorithm

In a double-talk situation, a near-end signal $s[n]$ becomes the error signal $e[n]$ as in Figs. 2 and 3. Thus, a large error signal may give rise to faulty adaptation of filter coefficients which may diverge. To overcome this problem and achieve fast convergence, a correlation RLS algorithm is employed in this paper for efficient nonlinear echo cancellation under a double-talk scenario. In a previous work, such an algorithm has been found to be robust for linear echo cancellation in a hands-free telephone system [9], even when double-talk is present. The correlation RLS algorithm utilizes the fact that a far-end signal is not correlated with a near-end signal, and, accordingly, the residual error for tap adaptation can be relatively small, compared with that in the conventional normalized LMS algorithm. More specifically, in the correlation RLS approach, the auto-correlation input vector is used as a canceller input, rather than the input vector itself. Thus, the input auto-correlation vector $\mathbf{\Phi}_{x\mathbf{x}_v}[n]$ and the cross-correlation $\phi_{dx}[n]$ between the desired value and input signals are now given by

$$\mathbf{\Phi}_{x\mathbf{x}_v}[n] = \mathbf{x}_v[n]x[n] \quad (7)$$

$$\phi_{dx}[n] = \sum_{i=0}^{n} d[i]x[i] \quad (8)$$

Note that $\mathbf{\Phi}_{x\mathbf{x}_v}[n]$ is an auto-correlation vector of the Volterra input, and $\phi_{dx}[n]$ is the cross-correlation between the desired signal $d[n]$ and the system input $x[n]$. Also, the desired signal $d[n]$ consists of the echo signal $y[n]$ and the near-end signal $s[n]$.

$$d[n] = y[n] + s[n] \quad (9)$$

Since the far-end signal $x[n]$ is uncorrelated with the near-end signal $s[n]$, the cross-correlation becomes

$$\begin{aligned} \phi_{dx}[n] &= \phi_{sx}[n] + \sum_{i=0}^{n} y[i]x[i] \\ &\cong \sum_{i=0}^{n} y[i]x[i] \end{aligned} \quad (10)$$

Furthermore, the echo signal $y[n]$ is the output of the echo path r_i when excited by the input $x[n]$ so that,, with $\phi_{x\mathbf{x}_v}[n,i]$ being the *i-th* element of $\mathbf{\Phi}_{x\mathbf{x}_v}[n]$, the cross-correlation $\phi_{dx}[n]$ can be expressed as

$$\phi_{dx}[n] \cong \sum_i r_i \phi_{x\mathbf{x}_v}[n,i] \quad (11)$$

An estimate of the desired cross-correlation signal $\phi_{dx}[n,i]$ can then be obtained from

$$\hat{\phi}_{dx}[n] = \sum_i h_v[n,i]\phi_{x\mathbf{x}_v}[n,i] \quad (12)$$

where $h_v[n,i]$ is the *i-th* element of $\mathbf{h}_v[n]$.

Just as in adaptive linear filter theory, the nonlinear echo path can be estimated by updating the Volterra filter coefficients (or $\mathbf{h}_v[n]$), where the error signal $e[n]$ for the tap adaptation in the correlation RLS algorithm can be calculated by

$$e[n] = \phi_{dx}[n] - \hat{\phi}_{dx}[n] \tag{13}$$

In addition, the cost function $J[n]$ can be defined by the following sum of weighted least squares errors as in the CRLS algorithm [9]:

$$J[n] = \sum_{p=1}^{n} \lambda^{n-p} \left| e[p] \right|^2 \tag{14}$$

At time n, the optimal kernel vector $\mathbf{h}_v[n]$, obtained by minimizing the cost function $J[n]$, can be expressed in a matrix form of the Wiener-Hopf equation:

$$\mathbf{\Psi}_{x\mathbf{x}_v}[n]\mathbf{h}_v[n] = \mathbf{\Psi}_{dx}[n] \tag{15}$$

$$\mathbf{\Psi}_{x\mathbf{x}_v}[n] = [\varphi_0^T[n], \varphi_1^T[n], \ldots, \varphi_{N-1}^T[n]]^T \tag{16}$$

$$\mathbf{\Psi}_{dx}[n] = [\psi[n,0], \psi[n,-1], \ldots, \psi[n,-N+1]]^T \tag{17}$$

for $k = 0, 1, \ldots, N-1$ (N : the filter length)

$$\varphi_k[n] = \sum_{p=1}^{n} \lambda^{n-p} \phi^*_{x\mathbf{x}_v}[p,k] \mathbf{\Phi}^H_{x\mathbf{x}_v}[p] \tag{18}$$

$$\psi[n,-k] = \sum_{p=1}^{n} \lambda^{n-p} \phi^*_{x\mathbf{x}_v}[p,k] \phi_{dx}[p] \tag{19}$$

Using the Kalman recursion method and the matrix inverse lemma, the following filter coefficient adaptation algorithm can be derived:

$$\mathbf{P}[n] = \lambda^{-1}\mathbf{P}[n-1] - \lambda^{-1}\mathbf{k}[n]\mathbf{\Phi}^H_{x\mathbf{x}_v}[n]\mathbf{P}[n-1] \tag{20}$$

$$\mathbf{k}[n] = \frac{\lambda^{-1}\mathbf{P}[n-1]\mathbf{\Phi}_{x\mathbf{x}_v}}{1 + \lambda^{-1}\mathbf{\Phi}^H_{x\mathbf{x}_v}\mathbf{P}[n-1]\mathbf{\Phi}_{x\mathbf{x}_v}} \tag{21}$$

$$\xi[n] = \phi_{dx}[n] - \mathbf{h}_v^H[n-1]\mathbf{\Phi}_{x\mathbf{x}_v}[n] \tag{22}$$

$$\mathbf{h}_v[n] = \mathbf{h}_v[n-1] + \mathbf{k}[n]\xi^*[n] \tag{23}$$

Finally, to estimate in an adaptive way the auto-correlation and cross-correlation, the following formulas can be used:

$$\phi_{x\mathbf{x}_v}[n,i] = (1-\alpha)\phi_{x\mathbf{x}_v}[n-1,i] + \alpha x[n] x_v[n,i] \tag{24}$$

$$\phi_{dx}[n] = (1-\beta)\phi_{dx}[n-1] + \beta d[n] x[n] \tag{25}$$

where $x_v[n,i]$ is the *i-th* element of $\mathbf{x}_v[n]$.

4. Simulation Results

To demonstrate the performance of the proposed approach, the following DAC in a hybrid network is considered: The echo signal generated by impedance mismatch of the hybrid system in a telephone network is transmitted with nonlinear distortion, with the distortion obtained from passing the echo signal through a nonlinear system. Also, the echo path model consists of a distorted nonlinear path in the DAC and a simple exponentially decreasing linear echo path. Here, the following impulse response of the simple linear path is considered:

$$r_i = \exp(-0.8 * i) \tag{26}$$

Also, the nonlinear charateristics of the DAC can be modelled by the following third-order polynomial system, which is the cause for the nonlinear component of the system,

$$f(x) = 1.01333x - 0.01333x^3 \tag{27}$$

As a quantitative performance measure for the proposed approach, the following Echo Return Loss Enhancement (ERLE) is adopted

$$ERLE = 10\log_{10}\frac{E\{y^2[n]\}}{E\{e^2[n]\}} \tag{28}$$

Here, $y[n]$ and $e[n]$ are the echo and error signals when the near-end signal is suppressed or cancelled. Note that the undistorted error signal $e[n]$ is

$$e[n] = y[n] - \hat{y}[n] \tag{29}$$

where $\hat{y}[n]$ is the echo replica. In the simulation, (i) the echo impulse response is changed at 0.1 sec as in Fig. 3; (ii) a double-talk scenario is then activated at 0.1 sec,; and (iii) the system finally returns to the single-talk situation at 0.5 sec. Three sets of results, obtained by using the correlation RLS, Gauss-Seidel FAP [10], and correlation LMS [11] methods, are shown in Fig. 4. More specifically, the solid line shows the ERLE obtained by applying the proposed approach, the dashed line indicates the ERLE obtained by employing the Gauss-Seidel FAP, and the dotted line denotes the ERLE value from the correlation LMS algorithm. It can be seen that the proposed nonlinear echo cancellation approach provides better performance and more robustness even when the echo path is changed or the double-talk is enforced as shown in Fig. 3.

5. Conclusion

In this paper, a nonlinear echo cancellation algorithm has been proposed and investigated to compensate for nonlinear distortion in echo paths.. The algorithm uses third-order adaptive Volterra filtering with a correlation RLS adaptation scheme. In addition, the input auto-correlation is used as a canceller input, and the canceller output is compared with the cross-correlation between input and desired signals. Simulation results show that the proposed approach is able to yields better echo cancellation performance even in a double-talk situation.

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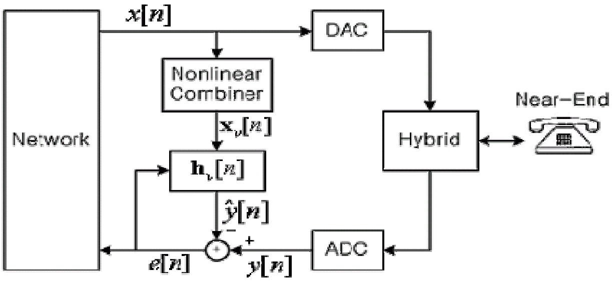

Fig. 1. The conventional nonlinear line echo canceller.

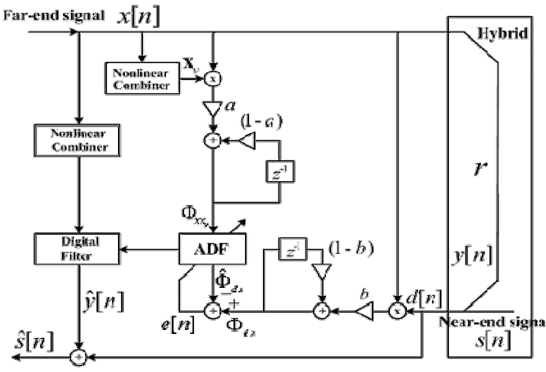

Fig. 2. The proposed nonlinear echo cancellation system.

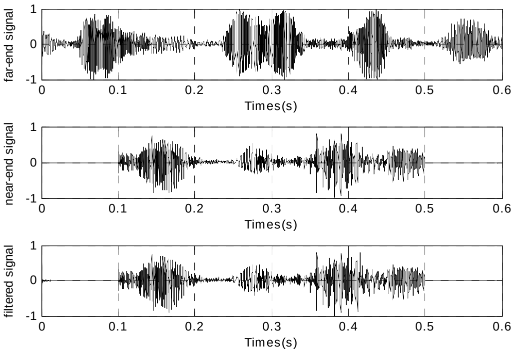

Fig. 3. Far-end, near-end, and filtered signals.

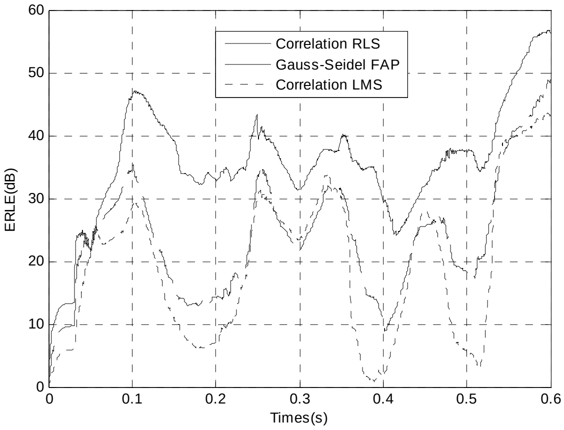

Fig. 4. ERLE curves for the nonlinear echo cancellation