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Conference Paper · May 1993

DOI: 10.1109/ICASSP.1993.319503 · Source: IEEE Xplore

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SELF IMPROVED ERROR REFERENCE FOR ADAPTIVE ECHO CANCELLATION IN FULL-DUPLEX BASEBAND DATA COMMUNICATIONS

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ABSTRACT

This work presents a new adaptive echo canceller for baseband data communications working with PAM signals. The goal is to gain advantage of the *a priori* knowlegde of the signal statistic to improve the error reference of the adaptive algorithm in situations of an advanced convergence state. In these cases, when the incoming signal level is clearly above the residual echo level, the adaptive algorithm can not correctly "see" the right error reference, the residual echo, thus slowing down the convergence. Here, we use a strategy to selfcancellate the masking effect produced by the incoming signal that speed up the overall convergence of the algorithm. We use a modified LMA (Least Mean Absolute) algorithm to maintain low the computational burden.

I INTRODUCTION

Nowadays, one of the biggest drawbacks in conventional adaptive schemes for echo cancellation (EC) on the Digital Subscriber Line (DSL) lies in the interfering and undesired additive effect caused by the incoming signal $y(n)$ (and intersymbol interference $u(n)$) on the residual echo $e(n)-\hat{e}(n)$ (see Figure 1). This mainly takes relevance in advanced stages of convergence where the residual echo is in essence smaller than the total incoming signal (usually <–10 dB). In such stages, the incoming signal masks the "natural" error reference of the adaptive algorithm, the residual echo, forcing the algorithm to slow down the convergence towards its steady state value (in the ISDN typically selected to get a BER of 10^{-7}, that is, approx. –25 dB).

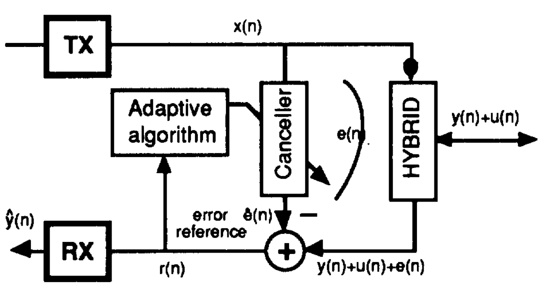

Figure 1

To avoid this undesired behavior during an important period of the convergence time, some new schemes based on the improvement of the error reference are found in the literature [1, 2, 3, 4, 5]; e.g., namely: a) adding an uncorrelated dithering signal to the error reference, b) removing (part of) the incoming signal (or estimations) from the error reference (decision-directed schemes) [4] c) implementation of a double-talk detector for analog voice applications, d) training periods in a semiduplex start-up phase, and e) exploiting some statistical characteristics of the incoming signal to alleviate the effect of its presence in the error reference.

In this work, we will present a new adaptive scheme for PAM line codes derived from scheme e) (Binary bipolar and 2B1Q data). The technique tries to gain advantage of the symmetrical (2 or 4 levels) nature of the incoming signal around zero to improve the error reference signal that guides the adaptive algorithm. The adaptive scheme uses a modified LMA algorithm to maintain low the total computational burden. The idea, first introduced in [5] and extended in [6], is supported by the fact that the received signal, sampled at the symbol rate (with the correct sampling phase) fall in the vicinity of a reduced number of zero-symmetric values ([1 –1] for the bipolar case and [+3 +1 –1 –3] for the 2B1Q) with relative high probabilities. Therefore, a delayed (not too retarded) sample of the reference signal $r(n)$ might be a good replica of the current sample level (at least statistically speaking), thus offering the possibility of cancelling, by simply addition (or subtraction), the masking effect in the old error reference (see Figure 2) and, therefore, providing a new and cleaner error reference. This procedure is not, of course, totally free of risk, since the delayed sample plus (or minus) the *old* error reference may, even deteriorate the *new* one in, at least, 50% or 75% (depending on the considered line code) of the total working time. However, accepting the fact that the masking effect is only meaningful when the residual echo is small enough, the benefit obtained by its total cancellation the rest of the time, counterbalances the loss of amplifying the masking disturbance in such advanced stages of convergence.

In the present work, we will extend the theoretic analysis carried out in [6] for Binary bipolar data to the case of 2B1Q line code too using new strategies of signal selfcancellation in the error reference. The main modification to [5] presented here introduces a *sign control* (see Figure 3) to command the delayed sample sign. It exploits, at the current time, the knowlegde of the sign in the previous delayed data. This modification is very useful since the use of a data-dependent sign control in the new error reference can increase the rate of selfcancellation of the incoming discrete levels, thus outperforming the case with a fixed and deterministic sign ($\oplus = +$ or $-$). Furthermore, the use of a sign control, other than a fix sign, minimizes the convergence dependence on the correlation's sign between the residual exho samples (current and delayed) [6].

In summary, the second order analysis here presented assumes Binary bipolar and 2B1Q data contaminated with an independent residual Gaussian intersymbol interference (or background noise) in a DSL. The usual hypotheses of joint stationarity and stochastic independence among the involved processes and random variables are assumed. The analysis

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introduces a new perspective on the choice of a constant adaption step that guarantees the convergence for any given initial tap settings (initial crosscorrelation between the two samples of involved residual echoes) and power of intersymbol interference towards a desired steady state value. Moreover, a function concerning the speed of convergence versus the residual echo variance is also defined. The results of our analysis will show how the use of this scheme, in those stages where the residual echo and input powers are similar, improve considerably the global convergence provided by its corresponding (similar steady state values) LMS algorithm. Some computer simulations will be also presented.

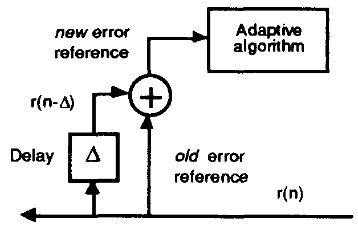

Figure 2

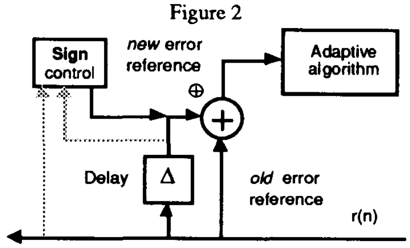

Figure 3

II THE ADAPTIVE ALGORITHM

Let us assume a situation of advanced convergence with no background noise where the residual echo is negligible against the incoming signal level. Here, we are going to use a new non-deterministic sign as $\oplus = -\mathrm{sign}(y_0 y_1)$, where y_0 and y_1 are the current and delayed far-end signals respectively, $y(n)$ and $y(n-\Delta)$. This choice always forces the algorithm to selfcancellate the effect of the previous signal with independence of its sign. Thus, with this new sign, the new probability distribution for the interfering signal (let us call it z) present in the error reference, $z = y_0 - \mathrm{sign}(y_0 y_1) y_1$, is depicted in Figure 4. That is, the 4-level distribution, for the 2B1Q line code, modifies into a ternary one with a zero-level of probability 0.5, while the 2-level Binary case modifies into a deterministic situation of a zero-valued signal. This new error references are interference-free half of the overall time for the 2B1Q case and the complete time for the Binary case, thus clearly outperforming the behavior in the algorithm with a fixed sign (+ or –).

The new strategy here proposed introduces (as in [5, 6]) some difficulties in the convergence analysis of the adaptive algorithm, since the new observed error reference is a function of both, the current and delayed residual echoes. However, assuming a pertinent advanced convergence state and a joint Gaussian distribution with controlled crosscorrelation for the residual echoes, the theoretical second order analysis is still feasible.

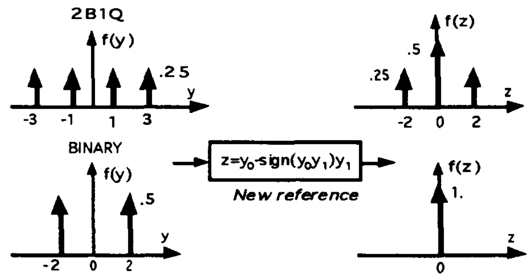

Figure 4

Thus, considering that we have selected the LMA as our adaptive algorithm for operational and ease of implementation reasons, the final expression that updates the echo canceller coefficients is as follows:

$$\mathbf{c}(n+1) = \mathbf{c}(n) + \mu\,\mathrm{sign}[r(n) - \mathrm{sign}(r(n)r(n-\Delta))r(n-\Delta)]\mathbf{x}(n) \qquad (1)$$

or equivalently, by rearranging the sign(•) function

$$\mathbf{c}(n+1) = \mathbf{c}(n) + \mu\,\mathrm{sign}[r(n)] \times \mathrm{sign}[|r(n)| - |r(n-\Delta)|]\mathbf{x}(n) \qquad (2)$$

where $\mathbf{c}(n)$ is the current canceller vector (N taps), $\mathbf{x}(n)$ the input vector, $r(n)$ and $r(n-\Delta)$ the current and delayed error references and μ the adaption step (assumed a positive constant). The algorithm's format presented in (2) modifies the standard LMA algorithm only in an additional sign operation, that is, introducing $\mathrm{sign}[|r(n)| - |r(n-\Delta)|]$. It represents a moderate increment in the overall computational burden per iteration with respect to the standard LMA algorithm.

III CONVERGENCE ANALYSIS

In order to continue with the second order analysis of the adaptive algorithm introduced in (2), we will use the following usual hypotheses:

h1) x(n), y(n) and u(n) are zero-mean, white, stationary and independent processes.

h2) $x(n)$ and $y(n)$ are Binary or 2B1Q and $u(n)$ Gaussian random processes.

h3) $x(n)$ and $\mathbf{c}(n)$ are (approx.) independent processes. It is obviously not true, but assumable since μ is usually small even for this new error reference.

h4) the residual delayed echoes are jointly Gasussian and independent of $x(n)$. It is also a realistic assumption at least for long transversal filters (N>>1) and advanced stages of convergence.

h5) Considering the delay Δ short enough, the covariance matrix for the residual delayed echoes is assumed to be

$$\mathbf{C}(n) = \begin{bmatrix} \sigma_\varepsilon^2(n) & \rho(n)\sigma_\varepsilon^2(n) \\ \rho(n)\sigma_\varepsilon^2(n) & \sigma_\varepsilon^2(n) \end{bmatrix} \qquad (3)$$

that is, identical variances and $\rho(n)$ the time-dependent correlation coefficient. It is usually unknown and depends on the initial settings of $\mathbf{c}(0)$. In steady state, it goes to zero, $\rho(\infty)=0$, that is, the residual echo process is uncorrelated.

Considering hypotheses h3 and h4, and denoting the residual echo as

$$\varepsilon(n)=e(n)-\hat{e}(n)=[\mathbf{c}_p-\mathbf{c}(n)]^t\mathbf{x}(n)=\mathbf{v}^t(n)\mathbf{x}(n) \quad (4)$$

where $\mathbf{c}_p$ is the tap vector for the hybrid, we can approximate the current residual echo variance (here, it equals its quadratic mean value) by the following formula:

$$\sigma_\varepsilon^2(n)=E\{\varepsilon^2(n)\}=E\left\{[\mathbf{v}^t(n)\mathbf{x}(n)]^2\right\}=$$
$$=E\left\{\left[\sum_{j=0}^{N-1}v_j(n)x(n-j)\right]^2\right\}=\sigma_x^2\sum_{j=0}^{N-1}E\{v_j^2(n)\}= \quad (5)$$
$$=\sigma_x^2E\{\mathbf{v}^t(n)\mathbf{v}(n)\}$$

thus, directly from (2), subtracting $\mathbf{c}_p$, transposing and multiplying by itself yields

$$\mathbf{v}^t(n+1)\mathbf{v}(n+1)=\mathbf{v}^t(n)\mathbf{v}(n)-$$
$$-2\mu\,\text{sign}[r(n)]\text{sign}[|r(n)|-|r(n-\Delta)|]\varepsilon(n)+ \quad (6)$$
$$+\mu^2\mathbf{x}^t(n)\mathbf{x}(n)$$

where taking expectations and multiplying both sides by σ_x^2, we finally obtain:

$$\sigma_\varepsilon^2(n+1)=\sigma_\varepsilon^2(n)\left[1-\mu S_1(n)+\mu^2S_2(n)\right] \quad (7)$$

a recursive equation for the residual echo variance, $\sigma_\varepsilon^2(n)$, where $S_1(n)$ and $S_2(n)$ are given by

$$S_1(n)=\frac{2\sigma_x^2}{\sigma_\varepsilon^2}E\left\{\varepsilon(n)\text{sign}[r(n)]\text{sign}(|r(n)|-|r(n-\Delta)|)\right\} \quad (8)$$

$$S_2(n)=\frac{N\sigma_x^4}{\sigma_\varepsilon^2} \quad (9)$$

They are two time–dependent expected values of the current and delayed random variables and, therefore, functions of their second order statistics. In particular, solving (8) for a symmetrical, 2M-level, PAM signal results [7]

$$S_1=\frac{1}{4M^2}\sum_{i=1}^{2M}\sum_{j=1}^{2M}T(i,j,\rho)+T(i,j,-\rho)-$$
$$-\frac{\sqrt{2}}{2M}\sum_{i=1}^{2M}T\left(\sqrt{2}i,\sqrt{2}M+\frac{1}{\sqrt{2}},0\right) \quad (10)$$

$$T(i,j,\rho)=\frac{2(1+\rho)\sigma_x^2}{\sqrt{\pi}\sqrt{\sigma_\varepsilon^2(1+\rho)+\sigma_n^2}}\times$$
$$\times\exp\left[-\frac{3(i-j)^2\sigma_y^2}{(2M-1)(2M+1)\left(\sigma_\varepsilon^2(1+\rho)+\sigma_n^2\right)}\right] \quad (11)$$

with M=1,2 for the Binary and 2B1Q line codes respectively. The dependency of $T(i,j,\rho)$ on the correlation coefficient ρ is not critical in most of the operational cases.

From (7) the second order convergence is guaranteed if $\sigma_\varepsilon^2(n+1)<\sigma_\varepsilon^2(n)$,$\forall n$, that is

$$(0)<\mu<\frac{S_1(n)}{S_2(n)}\ ,\forall n \quad (12)$$

the positive and constant adaption step μ is upper bounded by a dynamic value dependent on the convergence state. Then, assuming a convergent transient and since it can be shown that last quotient is a monotonic increasing function with σ_ε^2 [7], the necessary adaption step to converge towards a desired steady state value, $\sigma_\varepsilon^2(\infty)$, is obtained by

$$\mu=\frac{S_1\left[\sigma_\varepsilon^2(\infty)\right]}{S_2\left[\sigma_\varepsilon^2(\infty)\right]}=\min\left[\frac{S_1(n)}{S_2(n)}\right],\ \forall n \quad (13)$$

In particular, assuming $\sigma_\varepsilon^2(\infty)<<\sigma_y^2,\sigma_n^2<<\sigma_y^2$, and $\rho(\infty)$=0 in the steady state we have for a generic symmetrical 2M-PAM

$$\mu=\frac{2\sigma_\varepsilon^2(\infty)}{NM\sigma_x^2\sqrt{\pi\left(\sigma_\varepsilon^2(\infty)+\sigma_n^2\right)}} \quad (14)$$

Paying now attention to expression (7), it is simple to define a convergence speed function, dependent on σ_ε^2, for any given μ value (or equivalently, any given steady state value). It will be helpful to know the convergence regi ons where the proposed algorithm outperforms some other classical algorithms as, for instance, the standard LMS. This function is defined as

$$v(n)=-10\log_{10}\left[\frac{\sigma_\varepsilon^2(n+1)}{\sigma_\varepsilon^2(n)}\right]=$$
$$=-10\log_{10}\left[1-\mu S_1(n)+\mu^2S_2(n)\right]\ \text{(dB / iteration)} \quad (15)$$

Figures 5 and 6 show the evolution of the speed of convergence for two different settings and algorithms (improved LMA and LMS). In both cases we have used the statistic of a 2B1Q line code. They correspond to two different and representative situations of $\sigma_\varepsilon^2(\infty)=-35$dB or $\sigma_\varepsilon^2(\infty)=-25$dB with a background interference of $\sigma_n^2=-30$dB. These choices try to show the performance of the proposed algorithm in a situation of residual echo buried in background noise, $\sigma_\varepsilon^2(\infty)<\sigma_n^2$, and an opposite situation of relatively clean residual echo $\sigma_\varepsilon^2(\infty)>\sigma_n^2$. Observe that the modified LMA algorithm outperforms the standard LMS in the region where the residual echo variance $\sigma_\varepsilon^2<\approx 3$ dB. This algorithm suffer much more the background noise and masking effect than the corresponding modified LMA. Observe also the relaltive large decrement in speed for the LMS algorithm when using a smaller adaption step to obtain a 10 dB smaller steady state value. In this line of considering the effect of the interferences, the curves for the proposed algorithm are much less affected. They present a clear increment in the speed of convergence in the vicinity of –10 dB, reaching their maximum speed values in regions very close to the selected steady state values. These curves were plotted for ρ=0. In general, although not shown in the work, they present a strong insensivity to moderate zero-deviations of ρ.

IV SIMULATION RESULTS

To show the validity of our approximatted theoretical analysis, we have run some computer simulations. The key parameters for the simulation are: a) A N=10 tap transversal hybrid with coefficientes c_i=0.3i (i=1,...,10); b) background noise of power –30 dB, incoming and outgoing 2B1Q signal of powers $\sigma_y^2=\sigma_x^2=1$; c) 2 different choices for μ to obtain steady state values of –25 and –35 dB respectively, the same situations of figures 5 and 6; d) a starting setting of $\mathbf{c}(0)=\mathbf{0}$ that forces a $\rho(0)\approx0.2$.

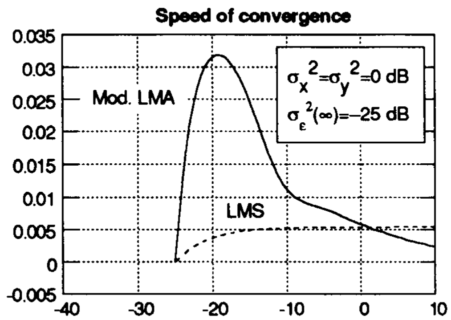

Figure 5

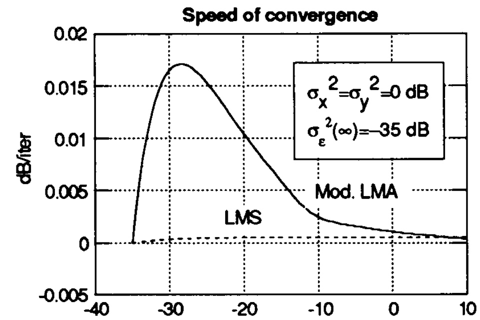

Figure 6

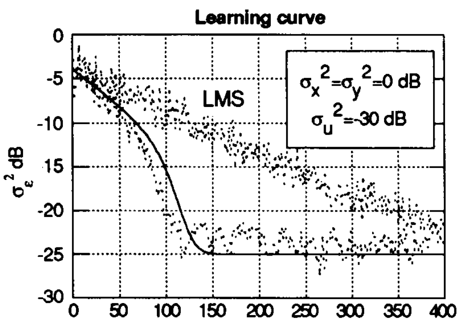

Figure 7

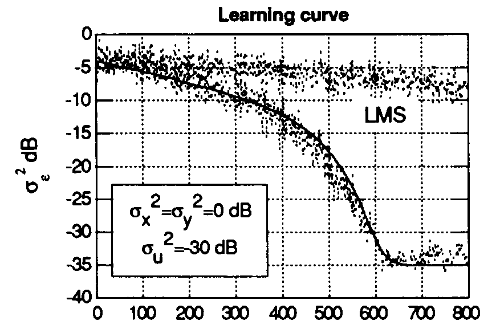

Figure 8

Figures 7 and 8 show the simulation results for both algorithms and conditions when using the ideal scheme of figure 1. They prsents the residual echo power vs. the iteration number (normalized by the filter length N). All dotted lines were obtained by averaging 6 single realizations. The solid lines represent the theoretical residual echo power under identical conditions. Observe the good fit with the corresponding simulated results. In both situations the modified LMA algorithm outperform the LMS. However, whereas in figure 7 the LMS reachs the steady state value four times later than the LMA, in figure 8, this fact occurs not before than ten times later (not shown in the graphics). It means that the LMS algorithm is being affected by the "masking effect" of the far-end signal, $y(n)$, much more than the modified LMA algorithm does.

As final conclusion, we could say that the modified LMA algorithm exploits both, the statistical knowlegde of the line code and the good properties of the sign function, to improve the error signal that guides the adaptive algorithm. The consequence is a faster convergence towards the desired steady stste value (usually below –25 dB for the ISDN). Furthermore, the overall increment in the computational burden per iteration is still reduced, thus allowing a single/chip VLSI implementation of a U-interface incorporating echo cancellation.

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