NONLINEAR ACOUSTIC ECHO CANCELLATION WITH 2ND ORDER ADAPTIVE VOLTERRA FILTERS

A. Stenger, L. Trautmann, and R. Rabenstein

University of Erlangen-Nürnberg, Telecommunications Laboratory
Cauerstr. 7, D-91058 Erlangen, Germany
stenger@nt.e-technik.uni-erlangen.de

ABSTRACT

Acoustic echo cancellers in today's speakerphones or video conferencing systems rely on the assumption of a linear echo path. Low-cost audio equipment or constraints of portable communication systems cause nonlinear distortions, which limit the echo return loss enhancement achievable by linear adaptation schemes. These distortions are a superposition of different effects, which can be modelled either as memoryless nonlinearities or as nonlinear systems with memory. Proper adaptation schemes for both cases of nonlinearities are discussed. An echo canceller for nonlinear systems with memory based on an adaptive second order Volterra filter is presented. Its performance is demonstrated by measurements with small loudspeakers. The results show an improvement in the echo return loss enhancement of 7 dB over a conventional linear adaptive filter. The additional computational requirement for the presented Volterra filter is comparable to that of existing acoustic echo cancellers.

1. INTRODUCTION

The typical setup for acoustic echo cancellation is shown in Fig. 1. The linear part of the echo path is represented by $h[k]$, the digital counterpart of the echo path's impulse response. The microphone signal $y[k]$ contains the linear echo $d[k] = x[k] * h[k]$ and additional signal components of different nature, denoted by $n[k]$. Irrespective of their nature, the adaptive filter $\hat{h}[k]$ can be adjusted such that $d[k]$ is cancelled arbitrarily well, e.g. with the NLMS algorithm [1]. Then the transmitted signal $e[k]$ closely resembles $n[k]$.

If $n[k]$ contains not only local speech but also nonlinear echo components, caused by distortions of the audio equipment, then additional adaptation measures have to cancel these echo components, as they cannot be cancelled by the linear filter $\hat{h}[k]$. These measures depend on the kind of nonlinearities encountered in the transmission chain shown in Fig. 2.

The main source of nonlinearities is found in part (B), since the loudspeaker and the power amplifier are operated

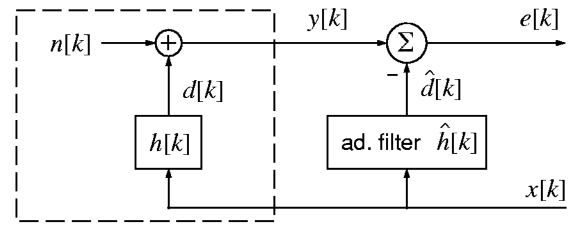

Figure 1: linear adaptive filter for acoustic echo cancellation

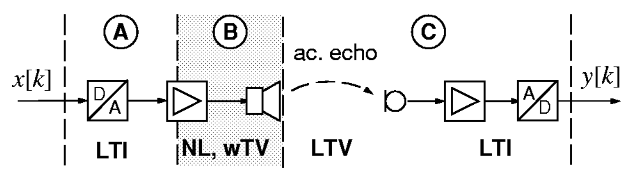

Figure 2: nonlinear echo path

at the highest signal level of the transmission chain. This part of the system is assumed to be weakly time-variant (wTV), e.g. due to temperature drift. The acoustic echo path (C) is known to be linear and time-variant (LTV), while the microphone and the amplifier (C) can be modeled as LTI systems because of their low signal amplitudes. Also the nonlinear quantization of the A/D and D/A converters can be neglected in this context.

If nonlinear distortions are mainly caused by an overdriven amplifier, they are approximately memoryless and can be modeled by a saturation curve [1, 2]. Two existing approaches, which are specialized on this type of nonlinearity, are discussed in section 2.

Another kind of nonlinearity is caused by the loudspeaker [3]. Due to the long time constants of the electro-mechanical system, the memory of this nonlinear behaviour cannot be neglected, see section 3.2. When the speaker is operated at its power limit, the nonlinear distortions will impair echo cancelling by linear filters. In [4] a neural network is used as nonlinear system with memory. With a cascade of a time-delay neural network and an adaptive FIR filter, considerable improvement of nonlinear echo reduction is achieved. A disadvantage is the need for a second reference microphone to provide an error signal for the adaptive neural network. In [8] adaptive Volterra filters have been proposed for line echo cancelling. However, due to their high numerical complexity they have not been used in practical systems yet.

In this paper, we develop an acoustic echo canceller with a second order adaptive Volterra filter and propose a method that keeps the computational complexity modest. After reviewing some fundamentals of adaptive Volterra filters in section 3.1, we discuss in section 3.2 how to reduce the number of Volterra coefficients required to model systems as shown in Fig. 2. Based on measurements with small loudspeakers, in section 3.3 we propose a nonlinear acoustic echo canceller structure with reduced complexity. Finally experimental results with a small loudspeaker and a one-chip amplifier are presented in section 3.4.

2. ACOUSTIC ECHO CANCELLERS WITH MEMORYLESS NONLINEAR MODEL

Acoustic echo cancellers consisting of a cascade of linear systems and memoryless nonlinear systems have already been proposed.

In [2], parts (A) and (C) of Fig. 2 are modelled with adaptive FIR filters and part (B) is realized by a saturation curve with one adaptive parameter. The adaptation of part (A) costs $O(N^2)$ multiplications, N being the number of coefficients. Local minima of the error surface cause problems, but with a special inititalization of the adaptive coefficients, as much as 8 dB ERLE improvement over a linear adaptive filter are reported.

In [1] part (A) is modelled as a delay, part (B) is represented by a 7th order polynomial with time-invariant coefficients, and part (C) is a standard NLMS adaptive filter. With only 14 additional multiplications per sample an ERLE improvement of 4 dB is obtained, without affecting convergence properties of the adaptive filter.

With both systems, the good results can only be obtained if the major cause of nonlinearities is a clipping amplifier. In many non-portable applications, like PC telephones or videophones, the power amplifier is not necessarily overdriven, but it is still desirabe to operate a small, cheap speaker at its power limit. Therefore we propose a nonlinear echo canceller which works well in this case.

3. ACOUSTIC ECHO CANCELLER FOR NONLINEARITIES WITH MEMORY

3.1. Adaptive Volterra Filters

In [5] the representation of nonlinear systems by truncated volterra series expansions is discussed and adaptation algorithms for second order Volterra filters are given. An N-th order discrete Volterra filter with input $x[k]$, output $y[k]$ and memory length M can be described as

$$\begin{aligned} y[k] &= \sum_{r=1}^{N}\sum_{\kappa_1=0}^{M}\cdots\sum_{\kappa_r=\kappa_{r-1}}^{M} h_r[\kappa_1,\cdots,\kappa_r]\cdot \\ &\qquad \cdot x[k-\kappa_1]\cdots x[k-\kappa_r]\,, \qquad (1) \end{aligned}$$

where h_r are the r-th order volterra kernels. [6] shows that Volterra kernels are symmetric, which is exploited in (1) by considering only coefficients with non-decreasing indices κ_r, i.e. $\kappa_r \geq \kappa_{r-1}$. With the vectors

$$\mathbf{x}_1[k] = (x[k], x[k-1], \cdots, x[k-M+1])$$

and

$$\hat{\mathbf{h}}_1 = (\hat{h}_1[0], \hat{h}_1[1], \cdots, \hat{h}_1[M-1])$$

for the first order volterra kernel, and

$$\begin{aligned} \mathbf{x}_2[k] &= (x^2[k], x[k]x[k-1], \cdots, x[k]x[k-M+1], \\ &\quad x[k-1]x[k-1], \cdots, \\ &\quad x[k-M+1]x[k-M+1]) \end{aligned}$$

and

$$\begin{aligned} \hat{\mathbf{h}}_2 &= (\hat{h}_2[0,0], \hat{h}_2[0,1], \cdots, \hat{h}_2[0,M-1], \\ &\quad \hat{h}_2[1,1], \cdots, \hat{h}_2[M-1,M-1]) \end{aligned}$$

for the second order volterra kernel, the LMS adaptive Volterra filter can be formulated as

$$e[k] = y[k] - \hat{\mathbf{h}}_1[k]\mathbf{x}_1{}^T[k] - \hat{\mathbf{h}}_2[k]\mathbf{x}_2{}^T[k] \qquad (2)$$

$$\hat{\mathbf{h}}_1[k+1] = \hat{\mathbf{h}}_1[k] + \mu_1\, e[k]\mathbf{x}_1[k] \qquad (3)$$

$$\hat{\mathbf{h}}_2[k+1] = \hat{\mathbf{h}}_2[k] + \mu_2\, e[k]\mathbf{x}_2[k] \qquad (4)$$

As in the linear NLMS algorithm, we normalize the stepsize with respect to the power of the input vectors $\mathbf{x}$, and obtain

$$\mu_1 = \frac{\alpha_1}{||\mathbf{x}_1[k]||_2^2} \qquad \mu_2 = \frac{\alpha_2}{||\mathbf{x}_2[k]||_2^2}\,. \qquad (5)$$

with stepsize parameters α_1 and α_2. If symmetry is exploited, the second order kernel has $\frac{1}{2}M(M+1)$ elements. Thus the computational complexity of the second order kernel is $\frac{3}{2}M^2 + \frac{3}{2}M + 2$ multiplications per sample, if it is adapted by the NLMS algorithm, while a linear NLMS adaptive filter costs $2M + 2$ multiplications per sample.

3.2. Discussion of second order memory length

As we do not use a cascade of nonlinear and linear systems, the memory length of the Volterra kernels is determined by the whole transmission chain in Fig. 2. As known from linear acoustic echo cancellers, it is typically several hundred taps. Due to the complexity of $O(N^2)$, the memory length of the second order Volterra kernel must be much less in a practical application.

For analog audio systems where the linear component dominates, the envelope of the higher order kernels is determined by the envelope of the impulse response [7]. As the envelope of room impulse responses typically has a peak and exponentially decays, we could ignore all coefficients, which have a time index being "too far away" from the peak of the impulse response. That this assumption is true for an acoustic echo path with a highly excited small loudspeaker shows the following measurement in an anechoic chamber. The first 50 taps of the impulse response, measured with linear NLMS adaptive filter, is shown in Fig. 3. Fig. 4 shows the second order Volterra kernel $\hat{\mathbf{h}}_2[\kappa_1, \kappa_2]$, which was identified using equations (2), (3) and (4) with $M = 50$.

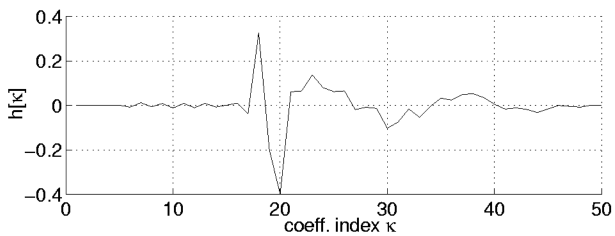

Figure 3: Linear FIR system with memory length 50

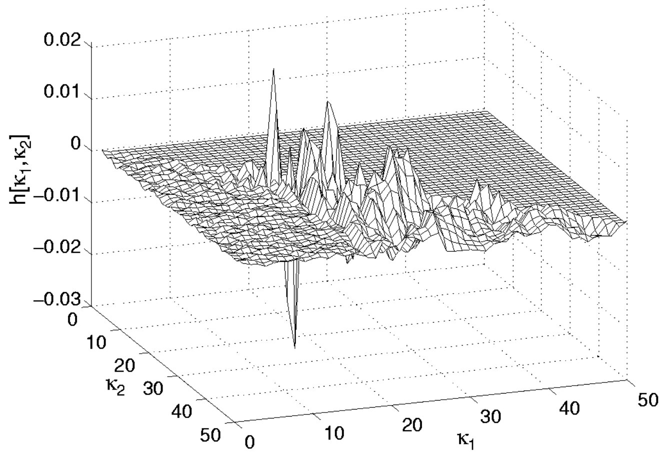

Figure 4: Second order Volterra kernel adapted from a small loudspeaker

The zero elements in the upper half have not been used for symmetry reasons. As expected, especially the first coefficients with time indices, at which the impulse response is small, too, carry little information. Towards higher coefficient indices κ_1 or κ_2, the envelope of the volterra elements decays in a similar way as the one of the impulse response, but has relatively smaller values. Therefore the second order kernel may be truncated to shorter memory length than the linear kernel causing the same error power in the output signal.

3.3. Proposed structure

Fig. 4 suggestes to ignore the first elements of the second order volterra kernel until near the first peak in both dimensions, i.e. $\kappa_1 \leq \Delta, \kappa_2 \leq \Delta$. In the example of Fig. 3 and Fig. 4 a good choice would be $\Delta = 17$. This leads to a modified second order Volterra representation with different menory length M_1 and M_2:

$$y[k] = \sum_{\kappa=0}^{M_1-1} h_1[\kappa]x[k-\kappa] + \sum_{\kappa_1=\Delta}^{M_2+\Delta-1} \sum_{\kappa_2=\kappa_1}^{M_2+\Delta-1} h_2[\kappa_1,\kappa_2]x[k-\kappa_1]x[k-\kappa_2] \,. \tag{6}$$

An adaptive Volterra filter of the above kind is shown in Fig. 5. The NLMS adaptation algorithm for the linear filter is given in (3) with $M = M_1$. For the second order Volterra kernel it is given in (4), where the vector $\mathbf{h}_2$ must be truncated to $M = M_2 - \Delta$ and $\mathbf{x}_2$ must be delayed by Δ.

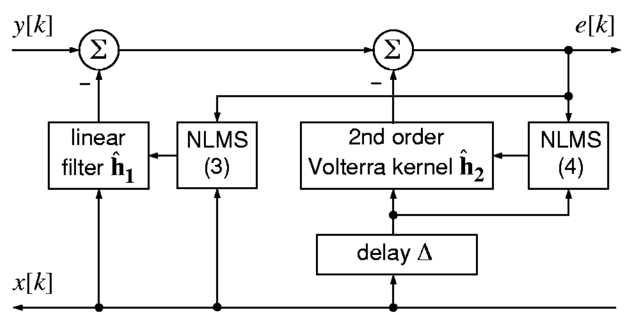

Figure 5: New nonlinear acoustic echo canceller

3.4. Experimental results

The new system has been tested with different low cost speakers between 0.1 and 0.4 Watts and a one-chip amplifier placed in an enclosure with low reverberation. As excitation $x[k]$ white Gaussian noise was used. The amplitude was chosen so that the amplifier is not highly overdriven and loudspeaker nonlinearities dominate over saturation effects. For performance evaluation of the new acoustic echo canceller we use the Echo Return Loss Enhancement

$$\text{ERLE} = \frac{\mathcal{E}\{y^2[k]\}}{\mathcal{E}\{e^2[k]\}} \,.$$

3.4.1. Convergence behaviour

Fig. 6 shows a comparision between a conventional linear acoustic echo canceller with NLMS algorithm (1) and the new system (2). The parameters of the linear system were chosen such that the excess ERLE is determined only by nonlinear echo components. As in the test room no local noise was present, this is achieved with $M = 250$ filter coefficients and a stepsize $\alpha = 0.1$. The parameters of the new system were $M_1 = 250$, $\alpha_1 = 0.1$, $M_2 = 25$, and $\alpha_2 = 0.05$.

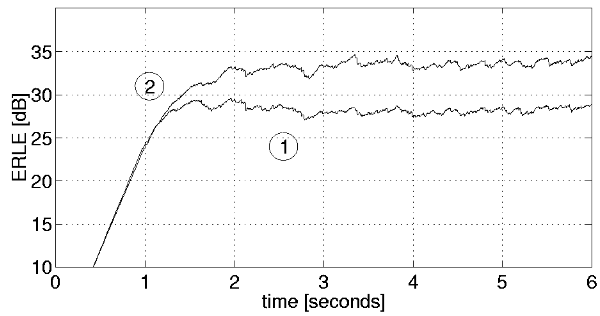

Figure 6: ERLE with linear NLMS (1) and second order Volterra filter (2)

The curves show, that convergence speed is not lowered through the additional second order kernel, and steady state ERLE is by 5.5 dB higher. With the same experimental setup, the memoryless nonlinear acoustic echo canceller [1] could gain less than 1 dB the echo reduction over a conventional linear echo canceller.

3.4.2. Complexity Considerations

As the complexity of the second order volterra kernel is $O({M_2}^2)$, its memory length M_2 should be kept as small as possible. The appropriate memory length depends on the decay characteristics of the impulse response of the echo path, the power of the nonlinear echo components, and the desired ERLE gain. Table 1 compares different memory lengths M_2 in terms of their complexity and the ERLE gain achieved for the system examined above.

Table 1: ERLE gain with different memory lengths M_2

M_2	5	10	15	20	**25**	30	35
ERLE gain [dB]	1.3	1.9	3.3	4.8	**5.5**	6.4	6.9
mult./sample	47	167	362	632	**977**	1397	1892

The third line shows the additional compexity (see section 3.1) for the second order adaptive Volterra filter with NLMS algorithm. The results show that second order Volterra filters are appropriate to model small speakers operated at high output power.

Today's linear acoustic echo cancellers require 500-1000 multiplications per sample. With additional costs in the same order of magnitude, about 5 dB ERLE improvement can be achieved. With some more computational power up to 7 dB are gained.

4. SUMMARY

The performance of linear acoustic echo cancellers is limited by nonlinear components in the echo path. Acoustic echo cancellers for memoryless nonlinearities, which are specialized on saturation effects, have already been proposed. However, loudspeaker nonlinearities cannot be modelled without memory. The theory for adaptive Volterra filters, which can model nonlinearities with memory, is well known, but those filters have not been applied sucessfully to acoustic echo cancellation.

We propose a second order adaptive Volterra filter for echo cancellation and a design rule for the choice of the relevant coefficients. Practical implementations of systems with different small loudspeakers operated at thier power limit have been investigated. With modest computational complexity an echo reduction improvement up to 7 dB over linear adaptive filters can be achieved.

5. REFERENCES

[1] A. Stenger, R. Rabenstein, "An Acoustic Echo Canceller With Compensation of Nonlinearities," *Proc. EUSIPCO 98*, Isle of Rhodes, Greece, September 1998, pp ...

[2] Bryan S. Nollet, Douglas L. Jones "Nonlinear Echo Cancellation For Hands-Free Speakerphones," *Proc. NSIP'97*, September 8-10, 1997, Michigan USA

[3] Franklin X.Y. Gao, W. Martin Sbelgrove, "Adaptive Linearization of a Loudspeaker," *Proc. ICASSP 91*, pp. 3589-3592.

[4] A. N. Birkett, R. A .Goubran, "Acoustic Echo Cancellation Using NLMS-Neural Network Structures", *Proc. ICASSP 1995, Detroit, MI*, pp. 2035-3038

[5] V. John Mathews, "Adaptive Polynomial Filters," *IEEE Signal Processing Magazine*, 8(3), pp.10-26, July 1991

[6] Martin Schetzen, "The Volterra and Wiener Theories of Nonlinear Systems," *Wiley and Sons*, New York, 1980

[7] Martin J. Reed, Malcom O. Hawksford, "Practical Modelling of Nonlinear AudioSystems Using the Volterra Series," *100th covention of AES*, Copenhagen, May 11-14, 1996, Preprint 4264 (R-2)

[8] E.J. Thomas, "Some considerations on the application of the Volterra representation of nonlinear networks to adaptive echo canceller," *Bell Systems Technicl Journal*, Vol 50, No. 8, October 1971, pp 2797-2905.