World Academy of Science, Engineering and Technology
International Journal of Electronics and Communication Engineering
Vol:3, No:9, 2009

Nonlinear Acoustic Echo Cancellation Using Volterra Filtering with a Variable Step-Size GS-PAP Algorithm

J. B. Seo, K. J. Kim, and S. W. Nam

Open Science Index, Electronics and Communication Engineering Vol:3, No:9, 2009 publications.waset.org/13166/pdf

***Abstract*—**In this paper, a nonlinear acoustic echo cancellation (AEC) system is proposed, whereby 3rd order Volterra filtering is utilized along with a variable step-size Gauss-Seidel pseudo affine projection (VSSGS-PAP) algorithm. In particular, the proposed nonlinear AEC system is developed by considering a double-talk situation with near-end signal variation. Simulation results demonstrate that the proposed approach yields better nonlinear AEC performance than conventional approaches.

***Keywords*—**Acoustic echo cancellation (AEC), Volterra filtering, variable step-size, GS-PAP.

I. Introduction

ACOUSTIC echo cancellation (AEC) is a classical application of adaptive filters to cancellation of acoustic echoes appearing in communication channels as depicted in Fig. 1. In particular, AEC is very effective in cancelling the acoustic echoes in such systems as telecommunications, internet telephony and audio and video conferencing system. However, since acoustic echoes can be produced from the open-air acoustic path between a loudspeaker and a microphone in hands-free full-duplex communication systems, communication quality may be severely degraded due to those echoes [1,2]. For that purpose, some AEC systems have been increasingly proposed recently. Furthermore, computationally efficient adaptive algorithms also have been developed to reduce computational cost of the corresponding AEC systems. For example, affine projection (AP) algorithms were reported, which yield faster convergence speed than the least-mean squares (LMS) methods and also requires much lower computational complexity than the recursive least-squares (RLS) method [3-5]. However, if the AP order increases, higher computational burden can be required for a matrix inversion or even stability problems may occur [4]. To solve those problems, the Gauss-Seidel pseudo affine projection (GS-PAP) algorithm was suggested in [5]. However, the performance of the GS-PAP algorithm may not be so good particularly when a non-unity step-size is chosen. In [7], a GS-PAP with variable step-size, called variable step-size PAP (VSS-PAP) algorithm, was proposed for linear AEC systems. Also, the variable step-size Gauss-Seidel pseudo affine projection (VSSGS-PAP) algorithm was reported [9], being robust to near-end signal variations in a double-talk situation.

J.B. Seo is with the Department of Electronics and Computer Engineering, Hanyang University, Seoul, 133-791, Korea (phone: +82-2-2281-0588; e-mail: jbseo@hanyang.ac.kr).

K.J. Kim is with the Department of Electronics and Computer Engineering, Hanyang University, Seoul, 133-791, Korea (phone: +82-2-2281-0588; e-mail: kjkim@hanyang.ac.kr).

S.W. Nam is with the Department of Electronics and Computer Engineering, Hanyang University, Seoul, 133-791, Korea (phone: +82-2-2220-0346; e-mail: swnam@hanyang.ac.kr).

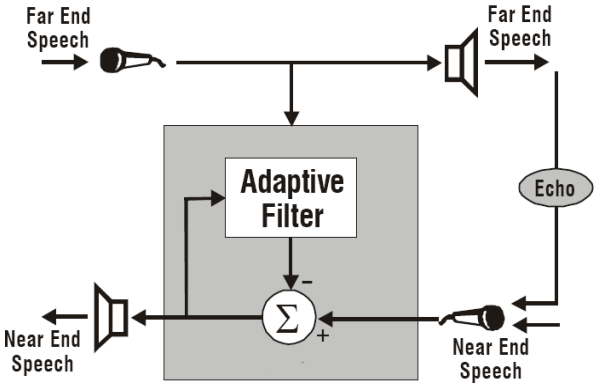


Fig. 1 AEC scheme using an adaptive filter

In case of nonlinear AEC systems, Volterra filtering approaches were suggested [10,11], whereby the linear relation between system kernels and the system output is utilized, making it possible to extend conventional linear approaches further to nonlinear AEC [12-15].

In this paper, we propose a new nonlinear AEC, employing adaptive 3rd-order Volterra filtering with a VSSGS-PAP algorithm. The proposed approach is robust even to near-end signal variations, yielding stable nonlinear AEC performance and faster convergence than conventional Volterra AEC methods.

This paper is organized as follows: In Section II, the Volterra nonlinear AEC methods are discussed. In Section III, the proposed nonlinear AEC is presented by employing Volterra filtering with a VSSGS-PAP algorithm. Also, simulation results are provided in Section IV, and finally, Section V concludes this work.

II. Volterra Nonlinear AEC System

The linear theory can be directly applied to Volterra filtering for nonlinear AEC systems [10-11] since the output of the

Open Science Index, Electronics and Communication Engineering Vol:3, No:9, 2009 publications.waset.org/13166/pdf

Volterra filter is linear with respect to Volterra kernels. In particular, a block diagram for a nonlinear AEC using adaptive Volterra filtering is described in Fig. 2, where $x[n]$ is a far-end signal as in Fig. 1.

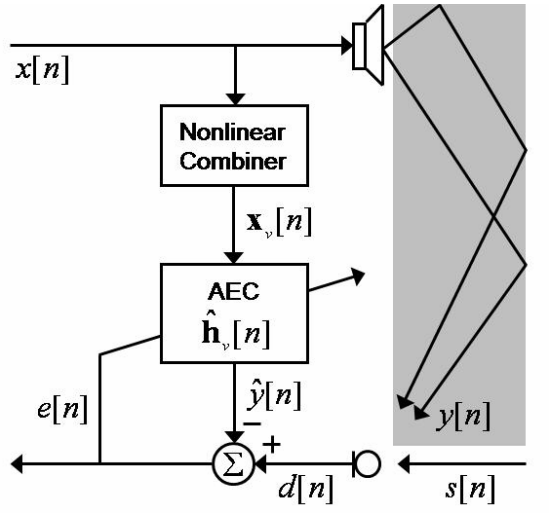


Fig. 2 Nonlinear AEC system

Also, $h[n]$ is an impulse response of an echo path. The input-output relation of a 3rd-order Volterra model can be expressed by [13]

$$\hat{y}[n] = \sum_{m_1=0}^{N-1} \hat{h}_1[m_1]x[n-m_1] + \sum_{m_1=0}^{N-1}\sum_{m_2=0}^{N-1} \hat{h}_2[m_1,m_2]x[n-m_1]x[n-m_2] + \sum_{m_1=0}^{N-1}\sum_{m_2=m_1}^{N-1}\sum_{m_3=m_2}^{N-1} \hat{h}_3[m_1,m_2,m_3]x[n-m_1]x[n-m_2]x[n-m_3], \quad (1)$$

Furthermore, (1) can be simplified by adopting a matrix form as follows:

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

In (2), $\mathbf{x}_v[n]$ is a Volterra input vector, and $\hat{\mathbf{h}}_v[n]$ is a Volterra kernel vector defined by

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

$$\hat{\mathbf{h}}_v[n] = [\hat{h}_1[0],\ldots,\hat{h}_1[N-1],\hat{h}_2[0,0],\ldots,\hat{h}_2[0,N-1],\hat{h}_2[1,1],\ldots,\hat{h}_2[1,N-1], \hat{h}_2[2,2],\ldots,\hat{h}_2[N-1,N-1],\hat{h}_3[0,0,0],\ldots,\hat{h}_3[0,0,N-1],\ldots, \hat{h}_3[0,0,N-1],\ldots,\hat{h}_3[N-1,N-1,N-1]]^T \quad (4)$$

As the difference between a real acoustic echo signal $y[n]$ and a Volterra filter output $\hat{y}[n]$, the following error signal $e[n]$ is defined as:

$$e[n] = d[n] - \hat{\mathbf{h}}_v^T[n]\mathbf{x}_v[n] \quad (5)$$

In (5), $d[n]$ is a desired signal. If a near-end speech signal $s[n]$ or a background noise signal $v[n]$ exists, $d[n]=y[n]+s[n]+v[n]$, and if not, $d[n]=y[n]+v[n]$.

III. Nonlinear AEC using a VSSGS-PAP Algorithm

The AP algorithm may have some problems in calculating the inversion of matrices causing the numerical unstability along with increased computational complexity [4-5]. To solve those problem, the GS-PAP algorithm [5] (i.e., an improved version of the AP algorithm) can be utilized by using the Gauss-Seidel method [5]. Thus, it enables us to obtain the matrix inverse in a more stable and efficient way. However, the performance of the GS-PAP algorithm can be degraded when a non-unity step-size is chosen [7]. Also, the VSSGS-PAP algorithm [9] recently reported for the *linear* AEC solves the step-size problem of the conventional GS-PAP algorithm, whereby the error signal filtered by linear prediction coefficients [7] and the near-end signal variations [8,9] are further considered.

The modified VSSGS-PAP algorithm proposed for the *nonlinear* AEC system can be expressed as follows:

$$\mathbf{R}_v[n]\mathbf{p}[n] = \mathbf{b}, \quad (6)$$

$$\mathbf{u}[n] = \frac{1}{p_0}\mathbf{X}_v[n]\mathbf{p}[n], \quad (7)$$

$$\bar{e}[n] = \frac{1}{p_0}\mu[n]\mathbf{p}^T[n]\,\mathbf{e}[n], \quad (8)$$

$$\hat{\mathbf{h}}[n+1] = \hat{\mathbf{h}}[n] + \frac{\bar{e}[n]}{\|\mathbf{u}[n]\|_2 + \delta}\mathbf{u}[n], \quad (9)$$

In (6)-(7), $\mathbf{R}_v[n]$ is the autocorrelation matrix of the Volterra input vector, $\mathbf{X}_v[n]$ is a Volterra input matrix (i.e. $\mathbf{X}_v[n] = [\,\mathbf{x}_v[n]\ \mathbf{x}_v[n-1]\ldots\ \mathbf{x}_v[n-M+1]]$), M is the affine projection order, and $\mathbf{b}$ is an $M \times 1$ vector with only one unity at the top (i.e., $\mathbf{b} = [1\ 0\ldots 0]^T$). In (8), $\mathbf{e}[n]$ is an $M \times 1$ error signal vector (i.e., $\mathbf{e}[n] = [\,e[n]\ e[n-1]\ldots\ e[n-M+1]]^T$), and $\mathbf{p}[n]$ is the optimal linear prediction coefficient obtained by the Gauss-Seidel (GS) method [5]. In (9), δ is the regularization factor which avoids division by zero, and $\mathbf{u}[n]$ and $\bar{e}[n]$ are an approximated decorrelation vector and a filtered error vector, respectively.

Note that the following variable step-size $\mu[n]$ can be obtained by modifying the results of [9]:

$$\mu[n] = \left[1 - \sqrt{\frac{\left|\sigma_d^2[n] - \sigma_{\hat{y}}^2[n]\right|}{\sigma_e^2[n]}}\right] \quad (10)$$

$$\sigma_e^2[n] = \lambda \sigma_e^2[n-1] + (1-\lambda)\sigma_e^2[n] \quad (11)$$

$$\sigma_d^2[n] = \lambda \sigma_d^2[n-1] + (1-\lambda)\sigma_d^2[n] \quad (12)$$

$$\sigma_{\hat{y}}^2[n] = \lambda \sigma_{\hat{y}}^2[n-1] + (1-\lambda)\sigma_{\hat{y}}^2[n] \quad (13)$$

In (10)-(13), $\sigma_d^2[n]$ and $\sigma_{\hat{y}}^2[n]$ correspond to the expected powers of the desired signal and an adaptive filter output signal, respectively. $\sqrt{|\sigma_d^2[n] - \sigma_{\hat{y}}^2[n]|}$ in (10) denotes the near-end signal variation. Also, $\sigma_e^2[n]$ is the variance of the error signal and λ is a forgetting factor close to 1. If the adaptive filter converges, both the near-end signal variation and the standard deviation $\sigma_e[n]$ of the error signal become similar. Then, the step-size value is close to 0. If the adaptive filter does not converge, then the step-size becomes close to 1 [8-9]. The proposed approach is expected to yield faster convergence and lower misalignment even in case of near-end signal variations than conventional algorithms.

IV. Simulation Results

To demonstrate the performance of the proposed approach, the following impulse response of an echo path is considered as in [13]:

$$f(x[n]) = 1.01333x[n] - 0.01333x^3[n] \quad (14)$$

For the quantitative performance measure in the proposed approach, the following Echo Return Loss Enhancement (ERLE) is adopted:

$$ERLE = 10\log_{10}\frac{E\{y^2[n]\}}{E\{e^2[n]\}} \quad (15)$$

In (15), $y[n]$ and $e[n]$ denote the echo signal and the error signal, respectively, in case that the near-end signal is suppressed or cancelled. Note that the undistorted error signal $e[n]$ can be written as

$$e[n] = d[n] - \hat{y}[n] \quad (16)$$

In (16), $\hat{y}[n]$ is the echo replica. The far-end speech, the near-end speech, and the background noise signals (sampled at 8 kHz) for the simulation are shown in Fig. 3. In the simulation, (i) the single-talk situation is in 0-0.1sec, (ii) the interval (0.1 sec – 0.5sec) is in the double-talk situation, and (iii) the system finally returns to the single-talk situation at 0.5 sec. A white Gaussian noise with 20dB is added as the background noise.

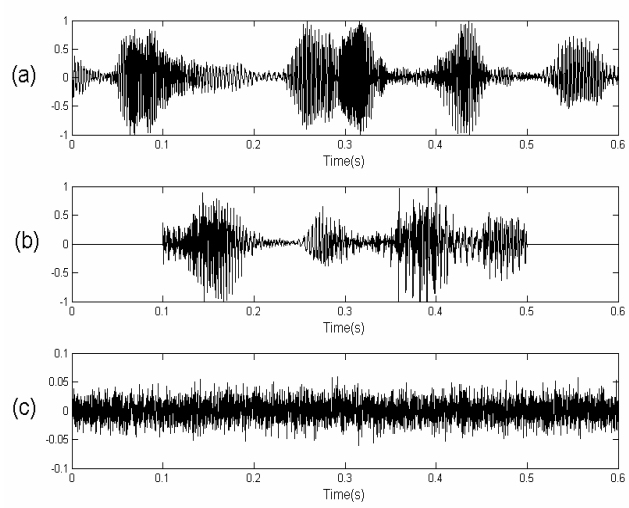


Fig. 3 (a) Far-end speech signal, (b) near-end speech signal, and (c) Background noise signal

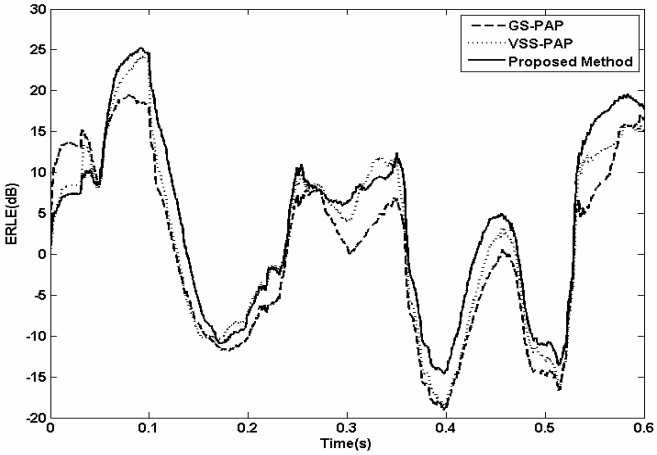


Fig. 4 ERLE curves for the nonlinear echo cancellation

The simulation results (obtained by applying the GS-PAP, VSS-PAP, and VSSGS-PAP methods) are shown in Fig. 4. More specifically, the curve, depicted by the *solid line*, denotes the ERLE value obtained by applying the proposed approach (i.e., VSSGS-PAP), and the *dashed line* denotes the ERLE value obtained by employing the GS-PAP. Finally, the *dotted line* denotes the ERLE value obtained by using the VSS-PAP algorithm. It can be seen from Fig. 4 that the proposed nonlinear echo cancellation approach provides better AEC performance even in a noisy environment.

V. Conclusion

In this paper, a nonlinear AEC approach is proposed, whereby a 3rd-order Volterra filtering with a VSSGS-PAP algorithm is employed. In particular, the proposed approach provides faster convergence and better AEC performance even in a double-talk situation with near-end signal variation, compared with the conventional AEC methods.

Open Science Index, Electronics and Communication Engineering Vol:3, No:9, 2009 publications.waset.org/13166/pdf

ACKNOWLEDGMENT

This work was supported by the Joint Technology Development Consortium Business 2009 among Industry (Dasan Cousultants Co., Ltd.), Academy and Research Institute (Hanyang University) of the Small and Medium Business Administration, Republic of Korea.

REFERENCES

[1] S. Haykin, Adaptive filter theory, Prentice-Hall Information and System Sciences. Englewood Cliffs, NJ: Prentice-Hall, 1986.
[2] V. Pahor and A. Carini, "A Variable step-size control of adaptation for acoustic echo cancellation filters," European Transactions on Telecommunications, vol. 13, no. 2, pp. 85-93, Mar.-Apr. 2002.
[3] K. Oseki and T. Umeda, "An adaptive algorithm using an orthogonal projection to an affine subspace and its properties," Electronics and Communications in Japan, vol. 67-A, no. 5, pp. 19-27, 1984.
[4] S.L. Gray and S. Tavathia, "The fast affine projection algorithm," Proc. of ICASSP1995, Detroit (MI), vol. 5, pp. 3023-3026, May 1995.
[5] F. Albu and A. Fagan, "The Gauss-Seidel pseudo affine projection algorithm and its application for echo cancellation," Proc. of Asilomar Conf., Asilomar Grove, CA, U.S.A, pp. 1303-1306, Nov. 2003.
[6] H.C. Shin, A.H. Sayed and W.J. Song, "Variable step-size NLMS and affine projection algorithms," IEEE Signal Processing Lett., vol. 11, no. 2, pp. 132-135, Feb. 2004.
[7] J. Lee, Y.C. Park, and D.H. Youn, "Robust pseudo affine projection algorithm with variable step-size," IEE Electronics Lett., vol. 44, no. 3, pp. 250-251, Jan. 2008.
[8] C. Paleologu, J. Benesty, and S. Ciochina, "A variable step-size affine projection algorithm designed for acoustic echo cancellation," IEEE Trans. on Audio, Speech, Language Processing, vol. 16, no. 8, pp. 1466-1478, Nov. 2008.
[9] F. Albu and C. Paleologu, "The variable step-size Gauss-Seidel pseudo affine projection algorithm," Proc. of WASET, vol. 37, pp. 642-645, Jan. 2009.
[10] V.J. Mathews and G.L. Sicuranza, Polynomial Signal Processing, John Wiley & Sons, Inc., 2000.
[11] A. Borys, Nonlinear Aspects of Telecommunications: Discrete Volterra Series and Nonlinear Echo Cancellation, CRC Press LLC, 2001.
[12] A. Guerin, G. Faucon, and R.L. Bouquin-Jeannes, "Nonlinear acoustic echo cancellation based on Volterra filters," IEEE Trans. Speech and Audio Processing, vol. 11, no. 6, pp. 672-683, Nov. 2003.
[13] K.Y. Ahn, D.H. Kim, and S.W. Nam, "Nonlinear echo cancellation using an expanded correlation LMS algorithm," Proc. of ISCAS 2005, vol. 4, pp. 3371-3374, May 2005.
[14] A. Fermo, A. Carini, and G.L. Sicuranza, "Analysis of different low complexity nonlinear filters for acoustic echo cancellation," J. of Computing and Information Technology, vol. 8, no. 4, pp. 333-339, Dec. 2000.
[15] A. Fermo, A. Carini and G.L. Sicuranza, "Low complexity nonlinear adaptive filters for acoustic echo cancellation in GSM hand-set receivers," European Trans. on Telecommunications, vol. 14, no. 2, pp. 161-169, Mar./Apr. 2003.

Open Science Index, Electronics and Communication Engineering Vol:3, No:9, 2009 publications.waset.org/13166/pdf