The Hybrid Simplified Kalman Filter for Adaptive Feedback Cancellation

Felix Albu
Department of ETEE
Valahia University of Targoviste
Targoviste, Romania
felix.albu@valahia.ro

Linh T.T. Tran, Sven Nordholm
Faculty of Science and Engineering
Curtin University
Perth, Australia
t.tran57@postgrad.curtin.edu.au,
S.Nordholm@curtin.edu.au

***Abstract*— Numerous adaptive feedback cancellation (AFC) algorithms are used in open-fitting and in-ear hearing aid devices (HADs) in order to avoid the possible annoying howling sounds. Recently, a hybrid AFC (H-AFC) scheme that shortened the recovering time from howling was proposed. It consists of a switched combination adaptive filter controlled by a stability detector that chooses either the standard normalized least mean squares (NLMS) algorithm or the prediction-error method (PEM) NLMS algorithm. In this paper a hybrid simplified Kalman filter (H-SKF) that uses a modified stability detector and a switch between NLMS and (PEM) SKF algorithms is proposed. It is shown that the proposed approach improves the convergence properties and shortens the howling periods for both speech and music signals compared with the hybrid NLMS (H-NLMS) algorithm.**

Keywords—adaptive feedback cancellation; hearing aids; hybrid normalized LMS algorithms; simplified Kalman filter;

I. Introduction

In the hearing aid devices (HADs) the microphone signals are amplified and played back through loudspeakers [1]-[3]. Annoying artifacts such as reverberation echoes or howling can be generated sometimes due to the acoustic feedback loops. The feedback problem in HADs is an increasingly issue due to the use of small-sized HADs as well as open-fitting HADs [4]. There are broadly two solutions for the feedback problem: feedforward suppression and feedback cancellation algorithms [1]-[2]. An example of feedforward suppression algorithms is the notch-filtering [4]. In adaptive feedback cancellation (AFC) an adaptive filter identifies the time-varying acoustic feedback path [5]-[6]. Unfortunately, mismatches in the estimate of correlation properties of the incoming signal can lead to a biased solution. Several techniques have been proposed to reduce this bias, such us frequency shifting [7], non-linear processing [8], probe noise injection [9], two microphones solution [10]-[13], etc. One of the most promising techniques is the prediction-error-method AFC (PEM-AFC) [14]. In PEM-AFC, the inverse of the estimated all-pole filter is used to pre-filter the loudspeaker signal and the microphone signal prior to adapting the feedback canceler. A significant practical challenge is to improve the AFC performance when there are fast changes in the acoustic feedback path or when howling occurs. In [15] the recovery from a howling period using AFC has been investigated. The hybrid NLMS (H-NLMS) algorithm was proposed. It combines the strength of the NLMS and PEM-NLMS algorithms. The former provides a fast re-convergence from a howling period [1], while the latter provides a low misalignment (MIS) and a low bias solution [14]. The H-NLMS algorithm was controlled by a stability detector using a soft-clipper. When instability is detected, the standard NLMS algorithm is used, otherwise the PEM-NLMS algorithm is used. It was also shown that the H-NLMS algorithm outperformed the PEM-NLMS algorithm both during the initial convergence as well as during re-convergence after a feedback path change [15].

The Kalman filter has been used in many practical applications such as active noise control (ANC) [16], acoustic echo cancellation (AEC) [17], etc. In [17] the simplified Kalman filter (SKF) has been proposed. Its relationship with NLMS and similar behavior with the variable step-size (VSS) adaptive filter have been proved. The VSS schemes were successfully used to improve the performances of the AEC [18] and AFC systems [19], respectively. However, the SKF performance for AFC systems has not been investigated yet.

In this paper, we propose a hybrid algorithm combining the PEM-SKF algorithm and the standard NLMS algorithm using a modified stability detector based not only on soft-clipping as in [15] but also on the variance of the consecutive filter coefficients estimates. It is shown that the proposed algorithm called the hybrid SKF (H-SKF) algorithm can achieve better performance in terms of added stable gain (ASG) and MIS than the H-NLMS algorithm and can reduce the howling time at the price of a small numerical complexity increase.

The paper is structured as follows. Section II presents the proposed algorithm. The simulation results are presented in Section III. Finally, the conclusions are given.

II. The Proposed Algorithm

A. *The H-NLMS algorithm*

Fig.1 illustrates the scheme of the proposed method. It is based on the scheme from [15], the difference is that the

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stability detector output depends on the filter update parameters too.

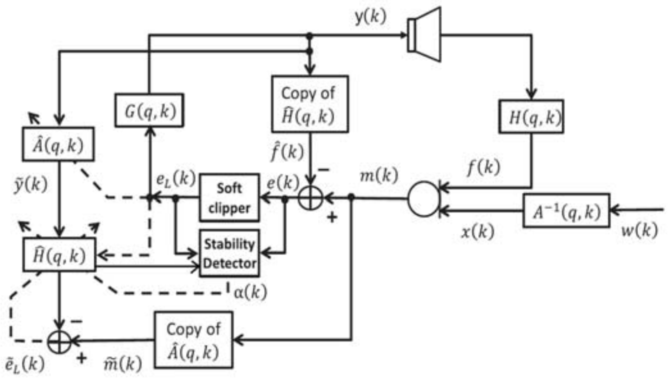

Fig. 1. Block diagram of the used AFC scheme

The microphone signal is given by:

$$m(k) = H(q,k)y(k) + x(k) \tag{1}$$

where $H(q,k) = \mathbf{h}^T(k)\mathbf{q}$, $\mathbf{h}(k) = \left[h_0(k),...,h_{L_h-1}(k)\right]^T$ is the impulse response (IR) of the feedback path having L_h coefficients, $\mathbf{q} = \left[1\ q^{-1}\ ...\ q^{-L_h+1}\right]^T$, q^{-1} is the delay operator and $x(k)$ is the incoming signal.

The error signal is:

$$e(k) = \left[H(q,k) - \hat{H}(q,k)\right]y(k) + x(k), \tag{2}$$

where $\hat{H}(q,k)$ is an estimate of $H(q,k)$ and $y(k)$ is the input of the adaptive filter.

In the PEM-AFC approach, the incoming signal is modeled as an auto-regressive (AR) model [14], i.e.,

$$x(k) = A^{-1}(q,k)w(k), \tag{3}$$

with $A(q,k)$ a stable polynomial transfer function and $w(k)$ white Gaussian noise. The AR coefficients are usually found by the Levinson-Durbin method. In the H-AFC approach, the pre-filtered error signal is defined as follows [15]:

$$\tilde{e}_L(k) = \tilde{m}(k) - \hat{H}(q,k)\tilde{y}(k), \tag{4}$$

where $\tilde{y}(k) = \hat{A}(q,k)y(k)$ and $\tilde{m}(k) = \hat{A}(q,k)m(k)$.

The NLMS algorithm has the well-known update equation [15] as:

$$\hat{\mathbf{h}}(k+1) = \hat{\mathbf{h}}(k) + \frac{\mu\mathbf{y}(k)e_L(k)}{\left\|\mathbf{y}(k)\right\|_2^2 + \delta}, \tag{5}$$

where $\hat{\mathbf{h}}(k)$ is an estimate of $\mathbf{h}(k)$, $\hat{\mathbf{h}}(k) = \left[\hat{h}_0(k),...,\hat{h}_{L_{\hat{h}}}(k)\right]^T$ with $L_{\hat{h}}$ coefficients, $\|\bullet\|_2$ is the l^2-norm, μ is the step size and δ is a small regularization factor, and the vector $\mathbf{y}(k)$ collect previous $L_{\hat{h}}$ samples of $y(k)$, i.e. $y(k-i)$, $i = 0 : L_{\hat{h}} - 1$.

The PEM-NLMS updating equation [14]-[15] is given by:

$$\hat{\mathbf{h}}(k+1) = \hat{\mathbf{h}}(k) + \frac{\mu\tilde{\mathbf{y}}(k)\tilde{e}_L(k)}{\left\|\tilde{\mathbf{y}}(k)\right\|_2^2 + \delta}, \tag{6}$$

where $\tilde{\mathbf{y}}(k) = \left[\tilde{y}_0(k),...,\tilde{y}_{L_{\hat{h}}-1}(k)\right]^T$.

These coefficients are copied to the feedback canceller as seen in Fig. 1. When a soft-clipping is used with PEM-NLMS the algorithm is termed as PEMSC-NLMS [15].

It is known that the NLMS algorithm is able to quickly recover the unstable system [1], while PEM-NLMS is not working very well in these situations [14]. Therefore, in [15], the Hybrid NLMS (H-NLMS) algorithm that combines the NLMS and PEMSC-NLMS algorithms was proposed.

The H-NLMS update is given by [15]:

$$\begin{aligned}\hat{\mathbf{h}}(k+1) = \hat{\mathbf{h}}(k) &+ \left[1-\alpha(k)\right]\mu_1(k)\tilde{\mathbf{y}}(k)\tilde{e}_L(k) \\ &+ \alpha(k)\mu_2(k)\mathbf{y}(k)e_L(k),\end{aligned} \tag{7}$$

where $\mu_1(k) = \mu_1 / \left(\left\|\tilde{\mathbf{y}}(k)\right\|_2^2 + \delta\right)$, μ_1 is the step size of the PEMSC-NLMS algorithm, $\mu_2(k) = \mu_2 / \left(\left\|\mathbf{y}(k)\right\|_2^2 + \delta\right)$, μ_2 is the step size of the NLMS algorithm and $\alpha(k)$ is a binary control signal [15].

The soft clipping detector operates on the error signal [15]:

$$\alpha(k) = I\left\{\left|e(k) - e_L(k)\right| < \gamma\right\}, \tag{8}$$

where I is a binary function depending on the γ threshold and

$$e_L(k) = \beta\tanh\left(e(k)/\beta\right), \tag{9}$$

where β is a parameter providing the amount of nonlinear distortion [15]. It was also shown in [15] that β should be chosen such that $x(k)$ lies in the linear range of the tanh-function.

B. *The Hybrid Simplified Kalman algorithm for AFC*

In [15] the simplified Kalman algorithm (SKF) was proposed. It was shown that it behaves like a variable step-size filter with proper parameters. Its fast convergence and low misadjustment were proved for an acoustic echo cancellation (AEC) application. The SKF algorithm performance has not been tested on the AFC case. However, our simulations have shown that, in some cases, the SKF algorithm leads to howling periods, particularly at the beginning of convergence or when a feedback path change.

The SKF algorithm has an initialization phase, i.e. $\hat{\mathbf{h}}(0) = \mathbf{0}_{L_{\hat{h}}\times 1}$, $\hat{\sigma}_w^2(0) = 0$, $r_{\boldsymbol{\mu}}(0) = \varepsilon > 0$. Also, the noise power σ_v^2 is known in advance or estimated [20].

Using notations from Fig. 1 the SKF equations are adapted as follows:

$$r_{\mathbf{m}}(k) = r_{\boldsymbol{\mu}}(k-1) + \hat{\sigma}_w^2(k) \tag{10}$$

$$\delta(k) = \sigma_v^2 / r_{\mathbf{m}}(k) \tag{11}$$

$$\hat{\sigma}_{\tilde{y}}^2(k) = \tilde{\mathbf{y}}^T(k)\tilde{\mathbf{y}}(k) \tag{12}$$

$$s(k) = \frac{1}{\hat{\sigma}_{\tilde{y}}^2(k) + \delta(k)} \tag{13}$$

$$r_{\boldsymbol{\mu}}(k) = \left[1 - s(k)\hat{\sigma}_{\tilde{y}}^2(k)/L\right] r_{\mathbf{m}}(k) \tag{14}$$

$$\mathbf{u}(k) = s(k)\tilde{\mathbf{y}}(k)\tilde{e}_L(k) \tag{15}$$

$$\hat{\sigma}_w^2(k) = \mathbf{u}^T(k)\mathbf{u}(k)/L \tag{16}$$

$$\hat{\mathbf{h}}(k+1) = \hat{\mathbf{h}}(k) + \mathbf{u}(k) \tag{17}$$

As shown in [15], when the SKF algorithm starts to converge or there is a feedback change, the parameter $\hat{\sigma}_w^2(k)$ takes high values that leads to fast convergence. Our simulations have shown that, during these periods, there is also a risk of howling occurrence. Therefore, it would help to allow some NLMS iterations during these detected periods [1], [15]. We propose to use a switched combination of the NLMS and the SKF algorithm controlled by the stability detector whose binary decision is given not only by the soft-clipping as in [15] but also by the $\hat{\sigma}_w^2(k)$ value. The NLMS algorithm is selected when instability is detected, while the SKF algorithm is selected otherwise. We can achieve this by modifying the control operator as follows:

$$\alpha_1(k) = \alpha(k) \cup \left(\hat{\sigma}_w^2(k) > \theta\right), \tag{18}$$

where $\cup$ is the binary OR operator and θ is a carefully chosen threshold. Its value is chosen depending on the AFC scheme parameters (σ_v^2, β, γ) such that the stability margin [15] on a test speech file is smaller than 3 dB.

Therefore, the proposed Hybrid SKF (H-SKF) update is given by

$$\hat{\mathbf{h}}(k+1) = \hat{\mathbf{h}}(k) + \left[1 - \alpha_1(k)\right]\mathbf{u}(k) + \alpha_1(k)\mu_2(k)\mathbf{y}(k)e_L(k). \tag{19}$$

where $\mu_2(k)$ is the same as defined in Eq. 7.

III. Simulation Results

The performance of the H-NLMS, the SKF and the H-SKF algorithms was investigated using the same feedback path characteristics measured for both scenarios of normal and closest feedback paths (see Fig. 2) from [21]. The incoming signal were a concatenated male and female speech from NOIZEUS database and a music signal (the song "Imagine" by John Lennon). Fig. 2 shows the amplitude responses of the measured acoustic feedback paths, where the first acoustic feedback path ($H_1(f)$) and the second acoustic feedback path ($H_2(f)$) were measured in free-field and with a telephone receiver placed close to the ear, respectively [21]. The incoming signals were a concatenated male and female speech from NOIZEUS database and a music signal (the song "Imagine" by John Lennon). The signals were 50s long and the tracking behavior was examined by switching after 25s from the normal path to the closest feedback path.

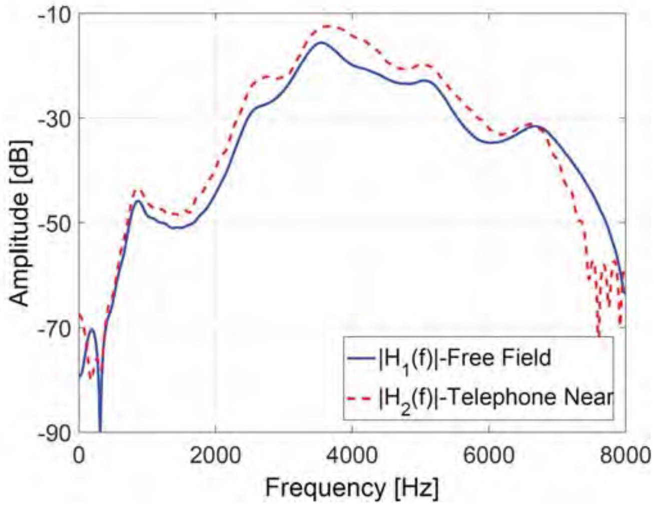

Fig. 2. Characteristics of measured feedback paths [21]

The ASG and misalignment (MIS) are used to evaluate the performance of the AFC system. They are defined as follows [14]

$$\text{MIS} = 10\log_{10}\left(\frac{\int_0^{\pi}\left|H(\Omega) - \hat{H}(\Omega)\right|^2 d\Omega}{\int_0^{\pi}\left|H(\Omega)\right|^2 d\Omega}\right) \tag{20}$$

$$\text{ASG} = 10\log_{10}\frac{1}{\max_{\Omega}\left|H(\Omega) - \hat{H}(\Omega)\right|^2} - 10\log_{10}\frac{1}{\max_{\Omega}\left|H(\Omega)\right|^2}, \tag{21}$$

where $H(\Omega)$ and $\hat{H}(\Omega)$ are the frequency response of the measured and estimated acoustic feedback paths at the normalized frequency Ω, respectively [15]. We've also computed the average values of both MIS and ASG over the 50s signals and the perceptual evaluation of speech quality (PESQ) measure for entire signal [21]. The PESQ measure is recommended by ITU-T for speech quality assessment of narrow-band handset telephony and speech codecs [22].

The prediction-error filter has an order of 20 and the Levinson-Durbin method was made on blocks of 100 ms. As in [15], $L_{\hat{h}} = 64$, the gain in the forward path G_0 is 45 dB, d_G corresponds to a 6 ms delay in the forward path and one sample delay is in the feedback canceller path. Other parameters were: $\gamma = 0.15$, $\beta = 2$, $\mu_1 = 0.001$, $\varepsilon = 10^{-4}$, $\mu_2 = 0.2$, and $\sigma_v^2 = 0.05$.

In the first experiment, the influence of θ value on the ASG performance is examined. Three cases were considered: no θ, i.e. in Eq. 19 $\alpha(k)$ replaces $\alpha_1(k)$, $\theta = 10^{-10}$ and $\theta = 10^{-13}$.

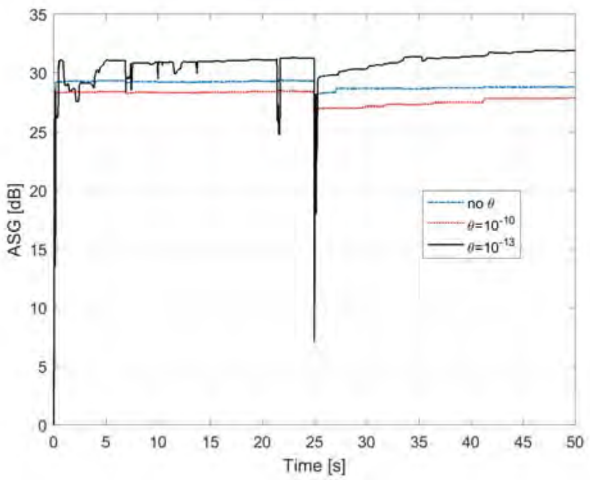

Fig. 3. ASG Performance of the H-SKF algorithm for different θ values.

It can be seen from Fig. 3 that the choice of θ has an important effect on the ASG performance. The best performance is obtained for $\theta = 10^{-13}$ while the worst is obtained for $\theta = 10^{-10}$. Therefore, a proper choice of θ can lead to improved performance of the H-SKF algorithm. The value of $\theta = 10^{-13}$ is used for the following experiments.

In Fig. 4 a comparison of the MIS and ASG performance of the H-SKF and the H-NLMS algorithms is made when the incoming signal is speech at 0 dB volume level. It can be noticed that the proposed algorithm obtains better MIS and ASG performance, have a faster convergence and better tracking abilities. Also, the PESQ score of the H-SKF was 3.90 while the PESQ score of the H-NLMS was 3.53.

Fig. 5 presents the control signals for the H-SKF algoritm ($\alpha_1(k)$ and $\alpha(k)$, respectively). The contribution of the term $\hat{\sigma}_w^2(k) > \theta$ of Eq. 18 can be noticed by comparing the control variables from Fig. 5.

Figure 6 shows the loudspeakers output signals for speech incoming signals at 0 dB signal level. It can be seen that the H-SKF algorithm is able to reduce the howling periods. It can be noticed from Fig. 6 that the H-SKF obtains better MIS than the H-NLMS (an average misalignment reduction of 1.1 dB). Also, the average ASG increase is about 0.3 dB. The PESQ score of the H-SKF is 3.63, while the PESQ score of the H-NLMS is 3.38.

In Fig. 7 the MIS and ASG performance of the investigated algorithms for the same parameters as above is made when the volume level of incoming speech signal is at -6 dB. By comparing Fig. 7 and Fig. 4, it is obvious that the volume level of incoming speech signal has an influence of the performances of both investigated algorithms.

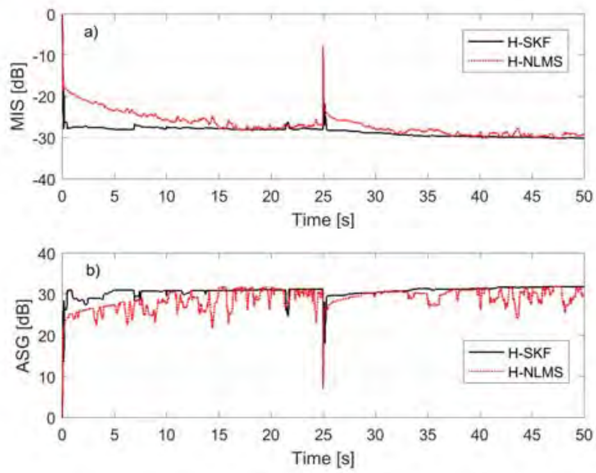

Fig. 4. Performance comparison of the H-SKF and the H-NLMS algorithms for 0 dB speech volume level; a) MIS; b) ASG.

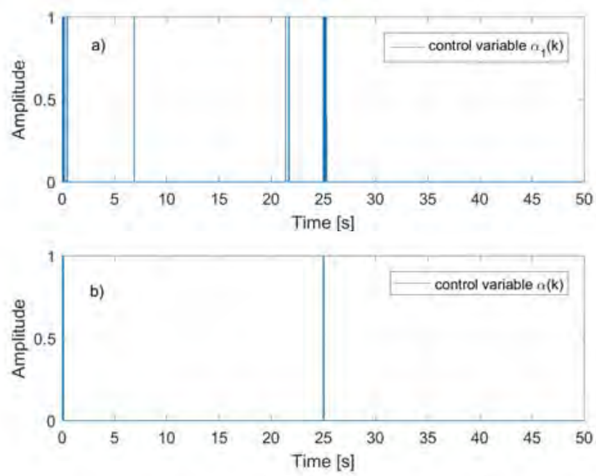

Fig. 5. Control signals for 0 dB volume level of incoming speech signal; a) $\alpha_1(k)$; b) $\alpha(k)$

For this volume level, the control signals are shown in Fig. 8 and the loudspeaker output signals are plotted in Fig. 9.

In the following simulation, the performance of the H-SKF and H-NLMS algorithms for incoming music signal is investigated. The results are like those obtained for speech. Fig. 10 compares the ASG and the MIS of the H-SKF algorithm and the H-NLMS algorithm for incoming music signal, while Fig. 11 illustrates the loudspeaker output signals. The improvement in terms of ASG and MIS is around 2 dB.

It is obvious that the howling periods for the H-SKF algorithm are fewer and shorter than those of the H-NLMS algorithm. It can be seen from Fig. 12 that the control signal of H-SKF matches the howling periods of the loudspeaker signal of Fig. 11.

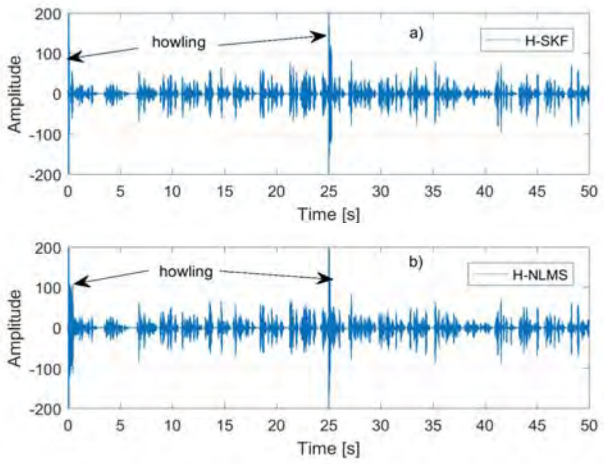

Fig. 6. Loudspeaker output signals for 0 dB volume level of incoming speech signal; a) H-SKF; b) H-NLMS

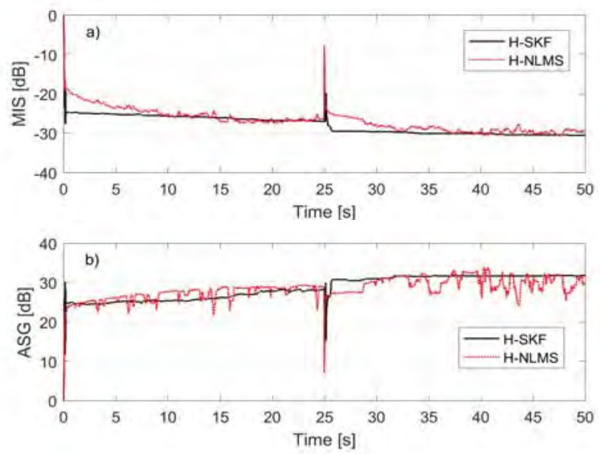

Fig. 7. Performance comparison of the H-SKF and the H-NLMS algorithm for -6 dB speech volume level; a) MIS; b) ASG.

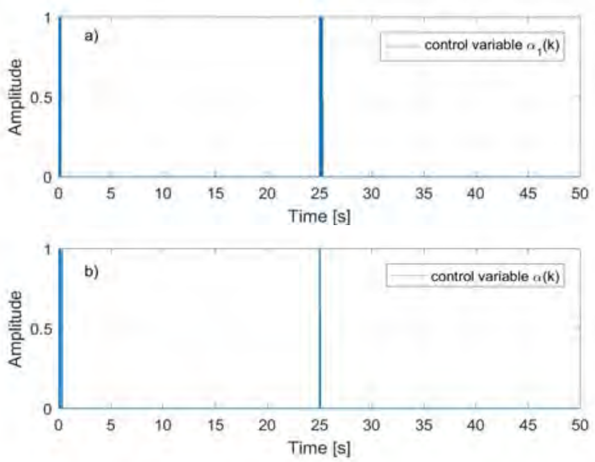

Fig. 8. Control signals for -6 dB speech volume level; a) H-SKF; b) H-NLMS

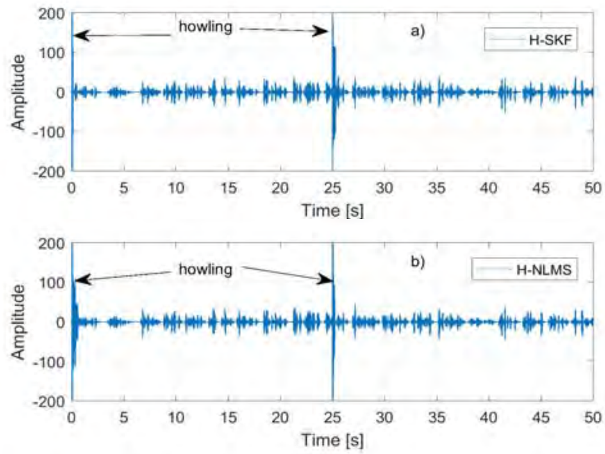

Fig. 9. Loudspeaker output signals for -6 dB speech volume level; a) H-SKF; b) H-NLMS

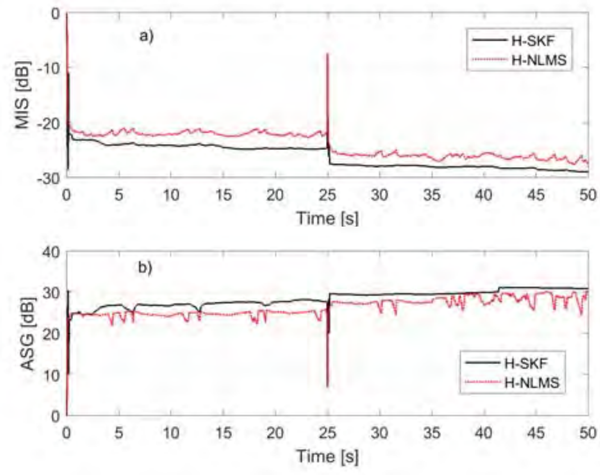

Fig. 10. Performance comparison of H-SKF and H-NLMS algorithm for 0 dB music volume level; a) MIS; b) ASG.

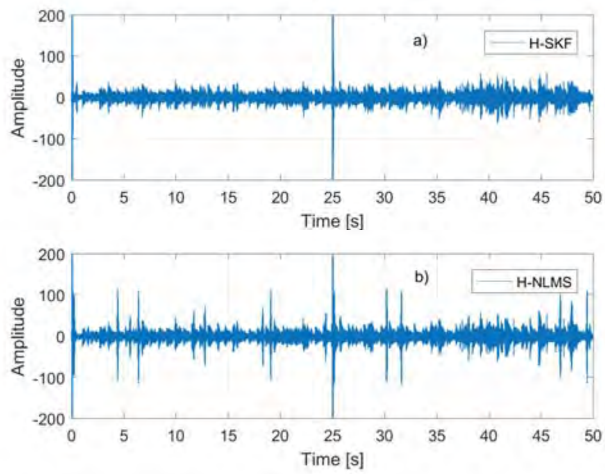

Fig. 11. Loudspeaker output signals for 0 dB music volume level; a) H-SKF; b) H-NLMS

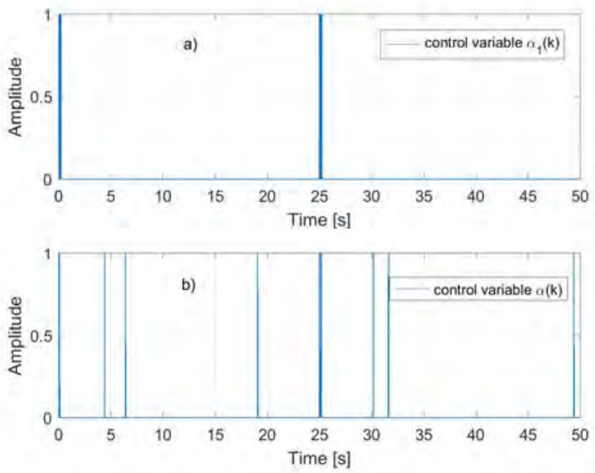

Fig. 12. Control signals for 0 dB music volume level; a) H-SKF; b) H-NLMS

It can be concluded that the performance of the H-SKF algorithm is much better than that of the H-NLMS algorithm for incoming music signals.

IV. Conclusions

In this paper a hybrid simplified Kalman filtering AFC algorithm for HADs has been proposed. It uses a combined previously proposed soft-clipping-based stability detector with a comparison of an internal algorithm parameter with a threshold. The simulations suggest that, for the current parameter set-up, improved results can be obtained by the proposed H-SKF algorithm over those of the H-NLMS algorithm for both incoming speech and music signals and a changing acoustic feedback path.

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References

[1] A. Spriet, S. Doclo, M. Moonen, and J. Wouters, “Feedback control in hearing aids,” in Springer Handbook of Speech Processing (Springer-Verlag, Berlin Heidelberg, pp. 979–1000, 2008.

[2] T. van Waterschoot and M. Moonen, “Fifty years of acoustic feedback control: State of the art and future challenges,” in Proc. IEEE, pp. 1–40, Feb. 2011.

[3] S. Doclo, W. Kellermann, S. Makino, and S. E. Nordholm, “Multichannel signal enhancement algorithms for assisted listening devices: Exploiting spatial diversity using multiple microphones,” IEEE Signal Process. Mag. 32(2), pp. 18–30, Mar. 2015.

[4] T. van Waterschoot and M. Moonen, “Comparative evaluation of howling detection criteria in notch-filter-based howling suppression,” J. Audio Eng. Soc. 58(11), pp. 923–940, Nov. 2010.

[5] J. M. Kates, “Constrained adaptation for feedback cancellation in hearing aids,” J. Acoust. Soc. Am. 106(2), pp. 1010–1019, Aug. 1999.

[6] E. Greenberg, P. M. Zurek, and M. Brantley, “Evaluation of feedback reduction algorithms for hearing aids,” J. Acoust. Soc. Am. 108(5), pp. 2366–2376, Nov. 2000.

[7] M. Guo and B. Kuenzle, “On the periodically time-varying bias in adaptive feedback cancellation systems with frequency shifting,” in Proc. of ICASSP 2016, pp. 539–543, March 2016.

[8] D. J. Freed, “Adaptive feedback cancellation in hearing aids with clipping in the feedback path,” J. Acoust. Soc. Am. 123(3), pp. 1618–1626, Mar. 2008.

[9] M. Guo, S. H. Jensen, and J. Jensen, “Novel acoustic feedback cancellation approaches in hearing aid applications using probe noise and probe noise enhancement,” IEEE Trans. Audio, Speech Lang. Process. 20(9), pp. 2549–2563, Jun. 2012.

[10] C. R. C. Nakagawa, S. Nordholm, and W.-Y. Yan, “Dual microphone solution for acoustic feedback cancellation for assistive listening,” in Proc. of ICASSP 2012, pp. 149–152, Mar. 2012.

[11] C. R. C. Nakagawa, S. Nordholm, F. Albu and W.-Y. Yan, “Closed-loop feedback cancellation utilizing two microphones and transform domain processing,” in Proc. of ICASSP 2014, pp. 3645–3649, May 2014,

[12] F. Albu, R. Nakagawa, and S. Nordholm, “Proportionate algorithms for two-microphone active feedback cancellation,” in Proc. 23rd Eur. Signal Process. Conf., 2015, pp. 290–294, Aug. 2015.

[13] S. Pradhan, N.V George, F. Albu and S. Nordholm, "Two microphone acoustic feedback cancellation in digital hearing aids: A step size controlled frequency domain approach", Applied Acoustics 132, 142-151, March 2018.

[14] A. Spriet, I. Proudler, M. Moonen, and J. Wouters, “Adaptive feedback cancellation in hearing aids with linear prediction of the desired signal,” IEEE Trans. Signal Process. 53(10), pp. 3749–3763, Oct. 2005.

[15] S. Nordholm, H. Schepker, L.T.T. Tran, S. Doclo, “Stability-controlled hybrid adaptive feedback cancellation scheme for hearing aids,” J. Acoust. Soc. Am. 143(1), pp. 150-166, Jan. 2018.

[16] P. A. C. Lopes and M. S. Piedade, “A Kalman filter approach to active noise control,” in Proc. of Eusipco, pp. 1-5, Sept. 2000.

[17] C. Paleologu, J. Benesty, and S. Ciochina, “Study of the general Kalman filter for echo cancellation,” IEEE Trans. Audio Speech Lang. Process. 21 (8), pp. 1539–1549, Aug. 2013.

[18] F. Albu, C. Paleologu and S. Ciochina, “New variable step size affine projection algorithms,” in Proceedings of IEEE COMM 2012, pp. 63–66, 2012.

[19] F. Albu, L. T. T. Tran and S. Nordholm, "A Combined Variable Step Size Strategy for Two Microphones Acoustic Feedback Cancellation using Proportionate Algorithms," in Proc. of APSIPA ASC 2017, Dec. 2017.

[20] M. A. Iqbal and S. L. Grant, “Novel variable step size NLMS algorithm for echo cancellation,” in Proc. of ICASSP 2008, pp. 241–244, Apr. 2008.

[21] T. Sankowsky-Rothe, M. Blau, H. Schepker, and S. Doclo, “Reciprocal measurement of acoustic feedback paths in hearing aids,” J. Acoust. Soc. Am., 138(4), pp. 399–404, Oct. 2015.

[22] ITU-R BS-1387, “Method for objective measurements of perceived audio quality,” International Telecommunications Union, Geneva, Switzerland, 100 pp, 1998.