Improved Practical Variable Step-Size Algorithm For Adaptive Feedback Control in Hearing Aids

Linh T. T. Tran*, Henning Schepker†, Simon Doclo†, Hai H. Dam* and Sven Nordholm*
*Faculty of Science and Engineering, Curtin University, Perth, Australia
Email: t.tran57@postgrad.curtin.edu.au, H.Dam@exchange.curtin.edu.au, S.Nordholm@curtin.edu.au
†Signal Processing Group, Department of Medical Physics and Acoustics and the Cluster of Excellence "Hearing4All",
University of Oldenburg, Oldenburg, Germany
Email: {henning.schepker,simon.doclo}@uni-oldenburg.de

***Abstract*—Variable step-size (VSS) schemes are popular to use in acoustic echo cancellation (AEC) contexts. However, their effective implementation in adaptive feedback cancellation (AFC) for hearing aids is still challenging due to the correlation between microphone and loudspeaker signals. We propose an improved practical VSS algorithm (IPVSS) which uses a variable step-size with upper and lower limits to control the update equation of an adaptive filter. The proposed algorithm is implemented for feedback cancellation using the prediction error method. As a result, the overall system has a fast convergence rate, a high tracking rate and a low steady-state error. The performance of the proposed approach has been evaluated for both speech and music incoming signals. The simulation results show that the proposed approach outperforms a system which only utilizes either the lower or the upper fixed step-size used in the IPVSS.**

***Index Terms*—adaptive feedback cancellation, prediction error method, hearing aids, NLMS, PVSS, IPVSS.**

I. Introduction

Acoustic feedback, which is produced by the acoustic channel between a loudspeaker signal and a microphone, is one of the major problems limiting the stable gain in hearing aids. Furthermore, acoustic feedback degrades the perceived quality, which often presents itself as "howling" when the system is unstable or close to instability. To reduce the adverse effects of the feedback path, an acoustic feedback cancellation (AFC) method which employs an adaptive filter to estimate the true feedback path is commonly used. Unlike an acoustic echo cancellation (AEC) system, the AFC system is a closed loop system. Thus the incoming and loudspeaker signals in an AFC system are correlated, resulting in a biased solution in the feedback path's estimate [1]–[3].

In order to reduce the bias the so-called acoustic feedback cancellation with prediction error method (PEM) has been proposed [4]–[6]. Assuming that the input signal can be modelled as an AR-process, the PEM estimates the inverse filter to pre-whiten the input. It can be shown that the PEM allows for an unbiased estimation of the acoustic feedback path.

This work was supported in part by the Research Unit FOR 1732 "Individualized Hearing Acoustics" and the Cluster of Excellence 1077 "Hearing4All", funded by the German Research Foundation (DFG) and project 57142981 "Individualized acoustic feedback cancellation" funded by the German Acadamic Exchange Service (DAAD).

To improve the convergence speed of the adaptive algorithm, while maintaining a low steady-state error, several solutions have been proposed. These include the affine combination of two adaptive filters with different step-sizes [7]–[9] as well as variable step-size (VSS) methods [10]–[15]. The applications of affine combination and VSS methods have been widely used in AEC [16]–[20], but their applications to AFC are still limited due to the correlation between the incoming and the loudspeaker signals. To reduce this correlation, a (white) background noise [12] or a probe noise signal [21] was added. In [22] subband filtering in conjunction with frequency shifting and pre-filtering techniques were used, resulting in a significant increase in the implementation complexity. Other VSS approaches employ affine projection algorithm instead of NLMS, but increase computational complexity [23]–[25]. Most existing acoustic feedback cancellation methods using VSS (AFC-VSS) have only considered white noise, speech-shaped noise, and speech as incoming signals, while only the approach in [22] has been validated with music signals.

In this paper, we propose a new VSS algorithm called improved practical variable step-size (IPVSS) which is developed based on the practical variable step-size algorithm (PVSS). The PVSS algorithm has been successfully implemented for AEC [18], [20], but our simulations show that the PVSS algorithm is not suitable for AFC applications. The proposed IPVSS algorithm has been applied to the PEM, forming a new AFC method called PEM-IPVSS. In this method, pre-whitening filters are used to reduce the correlation, while the step-size control is restricted between an upper step-size (μ_1) and a lower step-size (μ_2), in order to control the convergence behaviour. Simulation results, which use measured acoustic feedback paths from a two-microphone behind-the-ear hearing aid, show that the proposed system outperforms a system using either the upper or the lower step-size, as well as the VSS algorithm in [12] for both speech and music incoming signals.

II. Proposed PEM-IPVSS

The proposed AFC system is illustrated in Fig. 1. The microphone signal $x(k)$ is the sum of the feedback signal $v(k) = \mathbf{f}^T(k)\,\mathbf{y}(k)$ and the incoming signal $u(k)$, i.e.,

$$x(k) = u(k) + v(k), \tag{1}$$

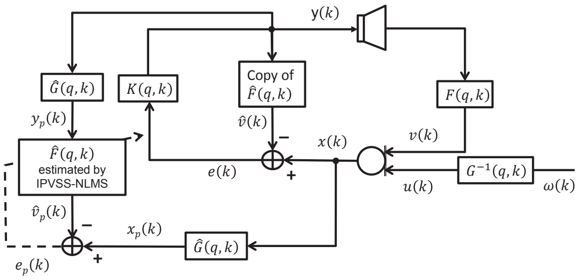


Fig. 1: The proposed AFC system.

where $\mathbf{f}(k) = \left[f_0(k), f_1(k), \ldots, f_{L_f-1}(k)\right]^T$ is the L_f-length impulse response (IR) vector of the true feedback path and $\mathbf{y}(k)$ is the L_f-length vector of the loudspeaker signal, $\mathbf{y}(k) = \left[y(k), y(k-1), \ldots, y(k-L_f+1)\right]^T$. Subtracting the estimate of feedback signal from the microphone signal results in an error signal $e(k)$,

$$e(k) = x(k) - \hat{\mathbf{f}}^T(k)\,\mathbf{y}(k), \tag{2}$$

where the $L_{\hat{f}}$-length vector $\hat{\mathbf{f}}(k)$ is an estimate of $\mathbf{f}(k)$. Then the error signal is delayed and amplified using the forward path, resulting in the loudspeaker signal, i.e.,

$$y(k) = K(q,k)\,e(k). \tag{3}$$

Assuming that the forward path is defined as $K(q,k) = |K|\,q^{-d_k}$, where $|K|$ is the broadband gain and d_k is the delay. The delay is selected such that $d_k \geqslant 1$.

We assume that the incoming signal can be modeled by filtering a white Gaussian noise sequence $w(k)$ with an all-pole filter $G^{-1}(q,k)$, i.e.,

$$u(k) = G^{-1}(q,k)\,w(k). \tag{4}$$

In the proposed AFC system, pre-whitening filters are employed to whiten the loudspeaker and microphone signals before the adaptive process, i.e., $x_p(k) = \hat{G}(q,k)\,x(k)$ and $y_p(k) = \hat{G}(q,k)\,y(k)$, where $\hat{G}(q,k)$ is an estimate of $G(q,k)$ with $G(q,k)$ the inverse of the incoming signal model. Thus the whitened error signal is computed as

$$e_p(k) = x_p(k) - \hat{v}_p(k), \tag{5}$$

where $\hat{v}_p(k) = \hat{\mathbf{f}}^T(k)\,\mathbf{y}_p(k)$ and $\mathbf{y}_p(k) = \left[y_p(k), y_p(k-1), \ldots, y_p\left(k - L_{\hat{f}} + 1\right)\right]^T$. The coefficients of $\hat{G}(q,k)$ are estimated from the error signal $e(k)$ by using the Levinson-Durbin algorithm [26]. Commonly, the estimated feedback path is updated using NLMS algorithm as follows

$$\hat{\mathbf{f}}(k) = \hat{\mathbf{f}}(k-1) + \frac{\mu}{(||\mathbf{y}_p(k)||_2^2 + \delta)}\mathbf{y}_p(k)\,e_p(k), \tag{6}$$

where μ is a fixed step-size and δ is a regularization parameter. Assuming that (4) is satisfied, the pre-whitened signals $y_p(k)$ and $u_p(k)$ are uncorrelated [4]. Hence,

$$E\left\{x_p^2(k)\right\} = E\left\{v_p^2(k)\right\} + E\left\{u_p^2(k)\right\}, \tag{7}$$

where $E\{.\}$ represents mathematical expectation, $u_p(k) = \hat{G}(q,k)\,u(k)$, and $v_p(k) = \mathbf{f}^T(k)\,\mathbf{y}_p(k)$. When the adaptive filter has converged close to the optimal value, we have

$$E\left\{\hat{v}_p^2(k)\right\} \approx E\left\{v_p^2(k)\right\}. \tag{8}$$

As a result, the incoming signal power can be approximated as

$$\hat{\sigma}_{u_p}^2(k) \approx \hat{\sigma}_{x_p}^2(k) - \hat{\sigma}_{\hat{v}_p}^2(k). \tag{9}$$

Practically, the powers of the microphone signal, the estimated feedback signal and the error signal can be recursively estimated, i.e.,

$$\hat{\sigma}_{x_p}^2(k) = \alpha\hat{\sigma}_{x_p}^2(k-1) + (1-\alpha)\,x_p^2(k) \tag{10}$$

$$\hat{\sigma}_{\hat{v}_p}^2(k) = \alpha\hat{\sigma}_{\hat{v}_p}^2(k-1) + (1-\alpha)\,\hat{v}_p^2(k) \tag{11}$$

$$\hat{\sigma}_{e_p}^2(k) = \alpha\hat{\sigma}_{e_p}^2(k-1) + (1-\alpha)\,e_p^2(k), \tag{12}$$

where α is a weighting factor which is chosen such that α is close to 1.

In [18], [20] the fixed step-size in (6) was replaced by a practical variable step-size ($\mu_{PVSS}(k)$) which was defined as

$$\mu_{PVSS}(k) = \left|1 - \frac{\sqrt{\left|\hat{\sigma}_{x_p}^2(k) - \hat{\sigma}_{\hat{v}_p}^2(k)\right|}}{\hat{\sigma}_{e_p}(k) + \xi}\right|, \tag{13}$$

where ξ is a small positive value added to avoid division by zero. Note that the PVSS algorithm has been only applied in AEC but not for AFC. Our simulations show that the PVSS algorithm does not perform well in AFC (see Fig. 3 in section III). The reason is that the step-size in (13) fluctuates over a large range, resulting in high variations in misalignment and ASG.

To reduce those fluctuations in $\mu_{PVSS}(k)$ an improved PVSS algorithm is proposed. The IPVSS algorithm employs a limiter [12] to modify the PVSS algorithm. This limiter employs upper and lower limits on the step size to control the step-size range. This constraint of the step-size means that the algorithm will have properties that are contained in that set. Thus, if we compare the performance with the upper limit and lower limit we know that the algorithm falls within that set. The step-size of the proposed IPVSS algorithm is defined as

$$\mu_{IPVSS}(k) = \begin{cases} \mu_1 & if\ \ \mu_c(k) > \mu_1 \\ \mu_2 & if\ \ \mu_c(k) < \mu_2 \\ \mu_c(k) & otherwise, \end{cases} \tag{14}$$

where

$$\mu_c(k) = \mu_1 * \gamma(k), \tag{15}$$

with $\gamma(k) = \mu_{PVSS}(k)$. The estimated feedback path is then computed as

$$\hat{\mathbf{f}}(k) = \hat{\mathbf{f}}(k-1) + \frac{\mu_{IPVSS}(k)}{(||\mathbf{y}_p(k)||_2^2 + \delta)}\mathbf{y}_p(k)\,e_p(k). \tag{16}$$

By selecting suitable values for μ_1 and μ_2, the variation range of the step-size $\mu_{PVSS}(k)$ is bounded to a smaller range.

Thus the fluctuations of the step-size are reduced and as a consequence, less variations in the performance measures are observed, i.e., misalignment and ASG compared to the PVSS algorithm. The main difference between our proposed algorithm and the variable step-size modified decorrelation NLMS algorithm (VSS-MDNLMS) [12] is in the definition of the term $\gamma(k)$. In [12] this term was defined as

$$\gamma_{VSS-MDNLMS}(k) = \left|1 - \frac{\hat{\sigma}_{x_p}(k)}{\hat{\sigma}_{e_p}(k) + \xi}\right|. \quad (17)$$

In the following we analyse the effect of this term for the adaptive algorithm performance in two scenarios of with or without an added (white) background noise. In each scenario, two cases, the adaptive feedback canceler has converged close to the optimal value and the feedback system is (close to) unstable, have been considered.

Scenario 1: No (white) background noise is added into the incoming signal.

Case 1: The feedback cancellation filter has converged close to the optimal value, i.e., $\hat{\mathbf{f}}(k) \rightarrow \mathbf{f}(k)$, hence $\hat{\sigma}^2_{e_p}(k) \approx \hat{\sigma}^2_{u_p}(k)$:

Eq. (17) can be rewritten as $\gamma_{VSS-MDNLMS}(k) \approx \left|1 - \sqrt{1 + \frac{\hat{\sigma}^2_{v_p}(k)}{\hat{\sigma}^2_{u_p}(k)}}\right| = |1 - \beta_1(k)|$, where $\beta_1(k) = \sqrt{1 + \frac{\hat{\sigma}^2_{v_p}(k)}{\hat{\sigma}^2_{u_p}(k)}} > 1$. It can be seen that $\gamma_{VSS-MDNLMS}(k)$ (so step-size of the VSS-MDNLMS algorithm, $\mu_{VSS-MDNLMS}(k)$) depends on the feedback to (incoming) signal ratio (FSR). The larger this ratio is, the larger $\beta_1(k)$ and thus the larger value of $\mu_{VSS-MDNLMS}(k)$ is obtained, resulting in high steady-state error.

In contrast, in the IPVSS algorithm $\gamma(k) = \mu_{PVSS}(k) = |1 - \beta_2(k)|$, where $\beta_2(k) = \frac{\sqrt{|\hat{\sigma}^2_{x_p}(k) - \hat{\sigma}^2_{\hat{v}_p}(k)|}}{\hat{\sigma}_{e_p}(k)} \approx 1$, hence $\gamma(k) \approx 0$, and $\mu_{IPVSS}(k) = \mu_2$ (the lower bound). As a result, the proposed algorithm achieves a lower steady-state error compared to the VSS-MDNLMS algorithm when the system has converged. Note that the value μ_2 can be set such that the desired misalignment is achieved. Without the lower limit the step size can be zero and the adaptive filter can lock-up and be insensitive to learning data.

Case 2: The system is (close to) unstable, e.g in the initialization phase and when the feedback path changes:

Eq. (8) and (9) are not held. In $\beta_i(k)$, with $i = 1, 2$, the nominator increases faster than the denominator, i.e., $\beta_i(k) > 1$. Therefore, the variable step-sizes of both algorithms tends to take large values, which drive the the weights of the feedback canceler to converge faster.

Scenario 2: A (white) background noise is added into the incoming signal. In this case the incoming signal plus noise ($u^n(k)$) is an addition of the incoming signal ($u(k)$) with a white background noise ($n(k)$), i.e.,

$$u^n(k) = u(k) + n(k). \quad (18)$$

Then the pre-filtered incoming signal plus noise can be defined as

$$u^n_p(k) = u_p(k) + n_p(k), \quad (19)$$

where $n_p(k)$ is the pre-filtered (white) noise. The incoming signal and the added noise are uncorrelated, so that

$$\hat{\sigma}^2_{u^n_p}(k) = \hat{\sigma}^2_{u_p}(k) + \hat{\sigma}^2_{n_p}(k). \quad (20)$$

Eqs. (1), and (5) can be rewritten as

$$x^n_p(k) = u^n_p(k) + v^n_p(k), \quad (21)$$

$$e^n_p(k) = x^n_p(k) - \hat{v}^n_p(k), \quad (22)$$

where $v^n_p(k)$ and $\hat{v}^n_p(k)$ are the true and the estimated feedback signals (with noise) defined in a manner analogous to $v_p(k)$ and $\hat{v}_p(k)$, respectedly. The terms $\beta_1(k)$ and $\beta_2(k)$ in the scenario 1 can be redefined as follows

$$\beta^n_1(k) = \frac{\hat{\sigma}_{x^n_p}(k)}{\hat{\sigma}_{e^n_p}(k)}, \quad (23)$$

$$\beta^n_2(k) = \frac{\sqrt{\left|\hat{\sigma}^2_{x^n_p}(k) - \hat{\sigma}^2_{\hat{v}^n_p}(k)\right|}}{\hat{\sigma}_{e^n_p}(k)}. \quad (24)$$

Case 1:

For the VSS-MDNLMS algorithm, the term $\beta^n_1(k) = \sqrt{1 + \frac{\hat{\sigma}^2_{v^n_p}(k)}{\hat{\sigma}^2_{u_p}(k) + \hat{\sigma}^2_{n_p}(k)}} > 1$, which depends on the the feedback to (incoming) signal plus noise ratio (FSNR). By selecting a background noise with large power compared to incoming signals (speech/music) such that $\beta^n_1(k) < \beta_1(k)$, the VSS-MDNLMS algorithm tends to get smalller step-size values, resulting in a lower steady-state error. However, the simulations in [12] showed that with signal to (background) noise ratio $SNR = 20dB$ the $\mu_{VSS-MDNLMS}(k)$ still fluctuates between the values μ_1 and μ_2 according to the change of FSNR.

For the IPVSS algorithm, the term $\beta^n_2(k)$ behaves in a similar manner to $\beta_2(k)$ in the case 1 (scenario 1), i.e., the (white) background noise have small or no impact on the result.

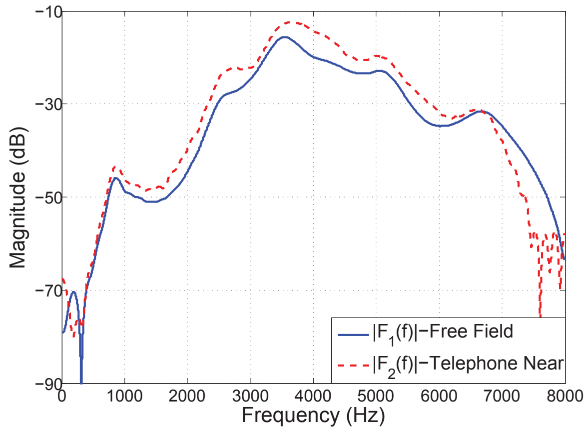
Case 2:

In this case, similar conclusions as case 2 (scenario 1) can be drawn.

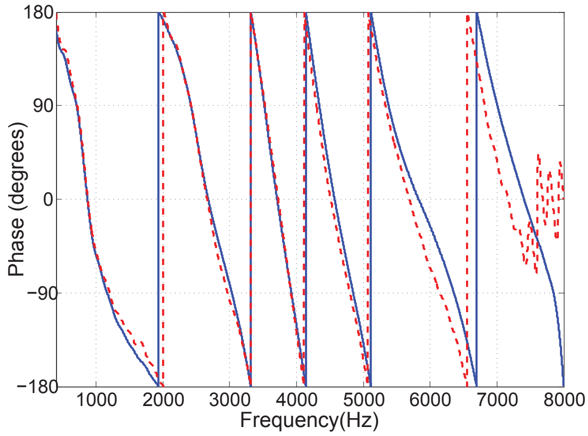
Note that the VSS-MDNLMS algorithm needs a noisy input signal to work well and that is not conducive for a well working algorithm.

III. Simulation Results

In this section, the proposed PEM-IPVSS is evaluated for both speech and music incoming signals and compared with the PEM using the VSS-MDNLMS algorithm (PEM-VSS-MDNLMS). Two measured acoustic feedback paths using a two-microphone behind-the-ear hearing aid as described in [27] were used, where the first feedback path $(F_1(f))$ was measured in free-field and the second feedback path $(F_2(f))$ was measured with a telephone receiver close to the ear. Fig. 2 shows the magnitude and phase responses of the measured feedback paths. The length of the measured feedback paths was $L_f = 100$ and the sampling frequency was $f_s = 16$kHz. The speech incoming signal was constructed

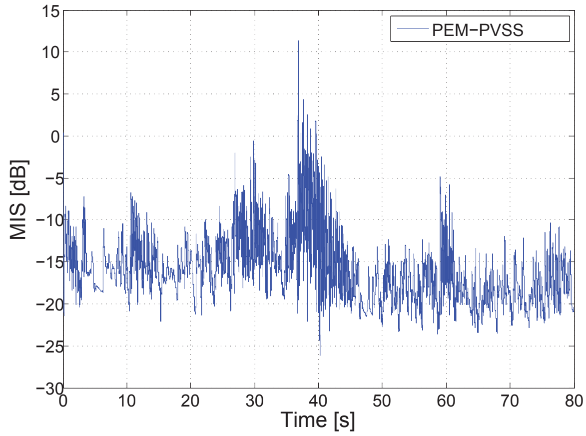


(a)



(b)

Fig. 2: Characteristics of measured feedback paths: a) Magnitude response, b) Phase response.



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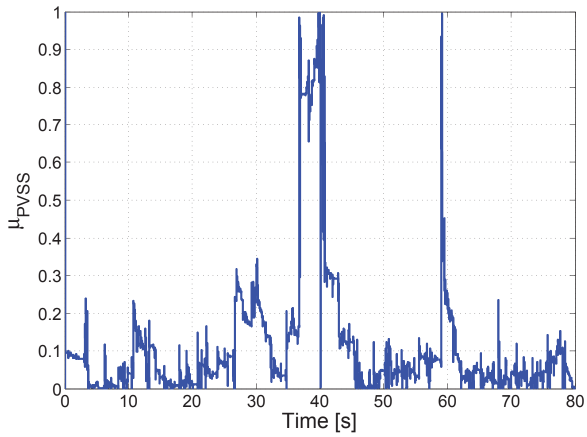


(b)

Fig. 3: a) Misalignment of the PEM-PVSS; b) μ_{PVSS}, speech incoming signal.

by concatenating real male and female speech as used in [3], while the music incoming signal is the John Lennon's Imagine. All simulations have $80s$ lengths with a sudden change from the free-field to the telephone-near feedback path after $40s$. No background noise has been added into the incoming signals in all simulations. We used the normalized misalignment (MIS) and the added stable gain (ASG) to evaluate the performance of all AFC methods. The normalized misalignment (MIS) is computed as

$$MIS = 10\log_{10}\left(\frac{||\mathbf{f} - \hat{\mathbf{f}}||_2^2}{||\mathbf{f}||_2^2}\right), \tag{25}$$

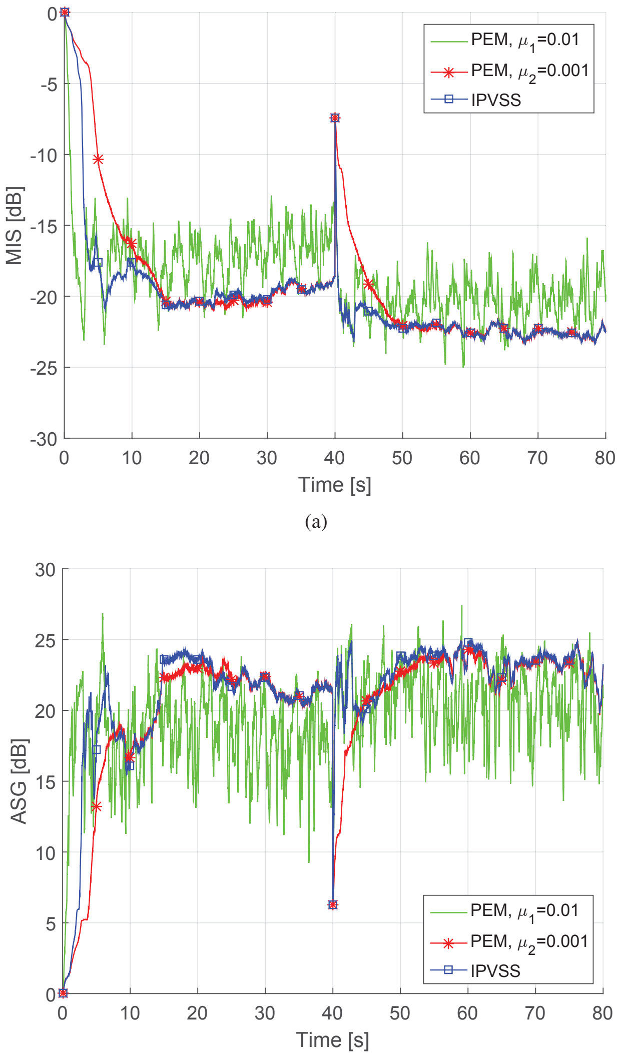
while ASG is defined as [6], [28]

$$\begin{aligned} \text{ASG} &= 10\log_{10}\frac{1}{\max_\Omega |F(\Omega) - \hat{F}(\Omega)|^2} \\ &- 10\log_{10}\frac{1}{\max_\Omega |F(\Omega)|^2}, \end{aligned} \tag{26}$$

where $\hat{F}(\Omega)$ and $F(\Omega)$ are the frequency responses of estimated and measured acoustic feedback paths at the normalized frequency Ω, respectively. The following parameters were set for all simulations. The forward path gain and the delay of the hearing aid were $|K| = 30\,dB$ and $d_k = 6ms$, respectively. The delay in the feedback canceller path was 1 sample. The length of the adaptive filter $L_{\hat{f}} = 64$, the step-sizes $\mu_1 = 0.01$, $\mu_2 = 0.001$, and $\alpha = 0.9999$, $\xi = 10^{-6}$, $\delta = 10^{-10}$ were chosen. The Levinson-Durbin algorithm was used to update the prediction-error filter $\hat{G}(q,k)$ of order 20 every 10 ms.

Fig. 4 shows the simulation results for the proposed method with the speech incoming signal. The PEM-IPVSS solution outperforms the PEM which only employs either the upper or the lower step-size used in the IPVSS algorithm. It also provides much better misalignment and added stable gain than the PEM-VSS-MDNLMS described in Fig. 8. Especially, when the feedback path changes from the free-field to the telephone-near feedback path, the proposed method tracks the change almost as quick as the case of the PEM using the upper step-size $\mu_1 = 0.01$, while remaining similar steady-state error to the case of the PEM with the lower step-size $\mu_2 = 0.001$.

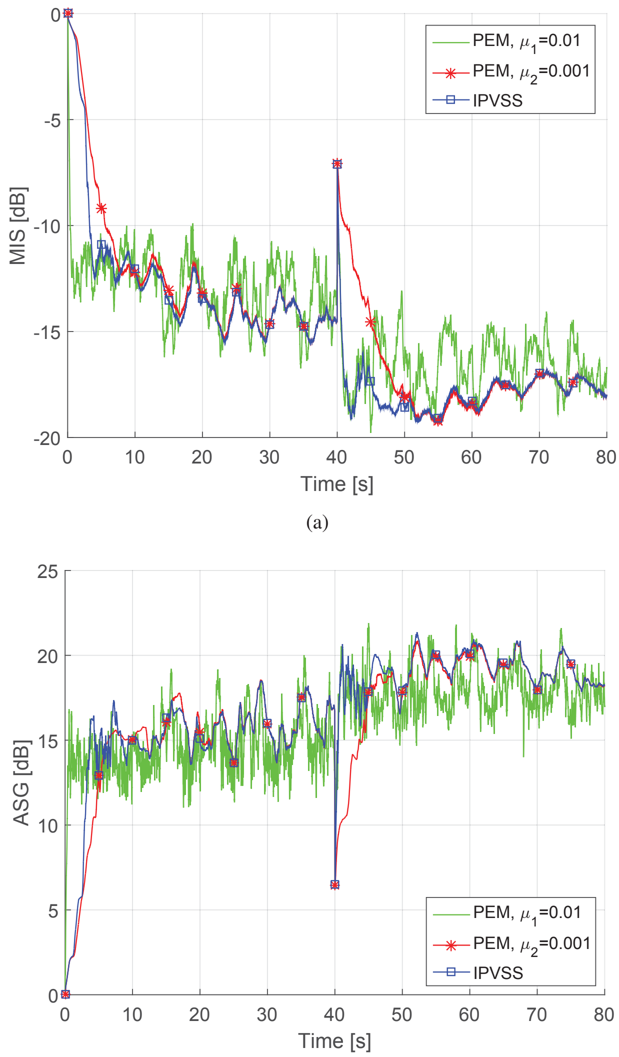
Fig. 5 illustrates the results for the proposed method with the



(a)

(b)

Fig. 4: (a) Misalignment, (b) Added Stable Gain of the PEM using NLMS and IPVSS algorithms with speech incoming signal.



(a)

(b)

Fig. 5: (a) Misalignment, (b) Added Stable Gain of the PEM using NLMS and IPVSS algorithms with music incoming signal.

music incoming signal. The simulations show that the PEM-IPVSS has significant improvements in convergence rate as well as tracking rate compared to the PEM with the lower step-size $\mu_2 = 0.001$, while providing much lower steady-state error than the PEM with the upper step-size $\mu_1 = 0.01$. The proposed method also outperforms the PEM-VSS-MDNLMS represented in Fig. 9.

Fig. 6-7 show that "howling" occurs in the beginning and when the feedback path changes. For the PEM with $\mu_2 = 0.001$ the howling periods are much longer than the case of the PEM with $\mu_1 = 0.01$. The reason is that the larger step size makes the system converge faster, i.e., a shorter howling period is observed, but it also provides a larger steady-state error as well as larger variations in the performance and vice versa. For both speech and music incoming signals, the proposed method provides a compromise solution, i.e., it can significantly reduce the howling periods, improve convergence rate and tracking rate while lowering steady-state error.

Fig. 6(d) and Fig. 7(d) represent the variable step-sizes for the PEM-IPVSS with speech and music incoming signals, respectively. For both cases, the variations of the step-sizes match with the description in the scenario 1, i.e., they are larger when the system is unstable, e.g. in the beginning of simulation and at the change of the feedback path, and smaller when the system is converged.

Fig. 10 shows the behaviour of $\mu_{VSS-MDNLMS}(k)$, which matches with the analysis in Scenario 1. When the incoming signal is speech, this step-size seems to get the maximum value almost time, resulting in high convergence rate and high steady-state error. When the incoming signal is music,

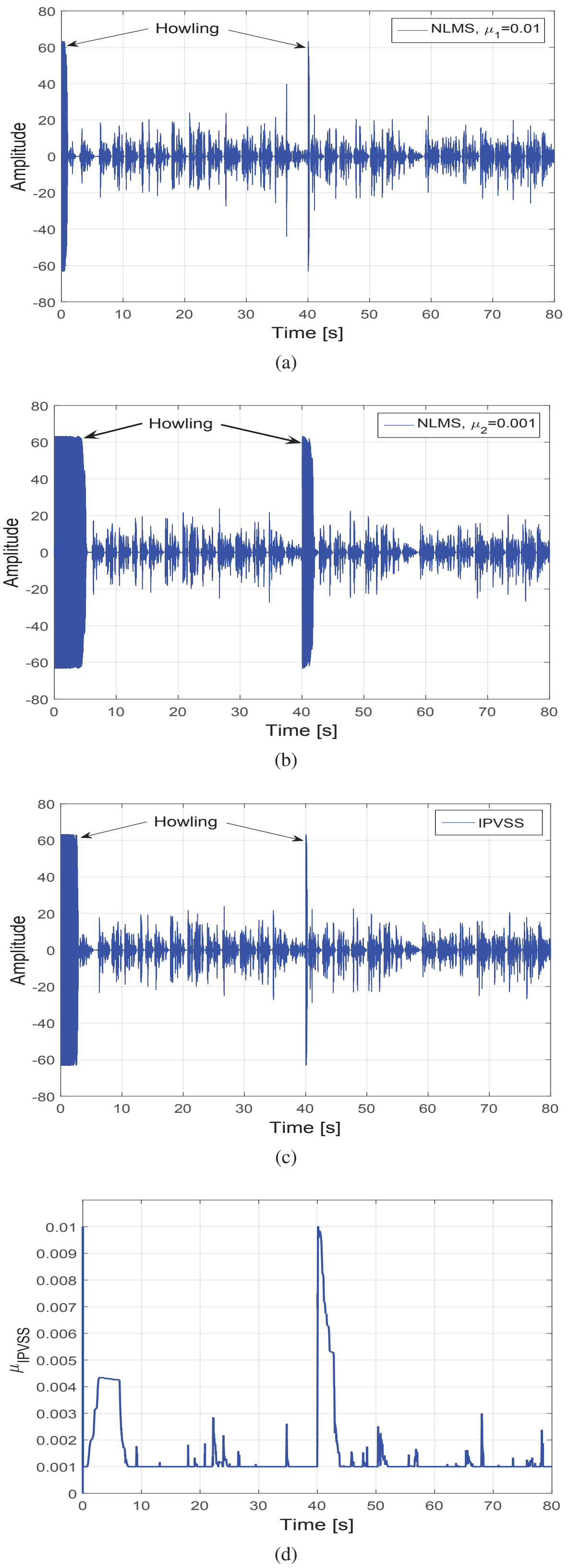


Fig. 6: Loudspeaker signals for the case of speech incoming signal: a) and b) PEM with $\mu_1 = 0.01$, $\mu_2 = 0.001$, respectively; c) PEM-IPVSS, and d) μ_{IPVSS}.

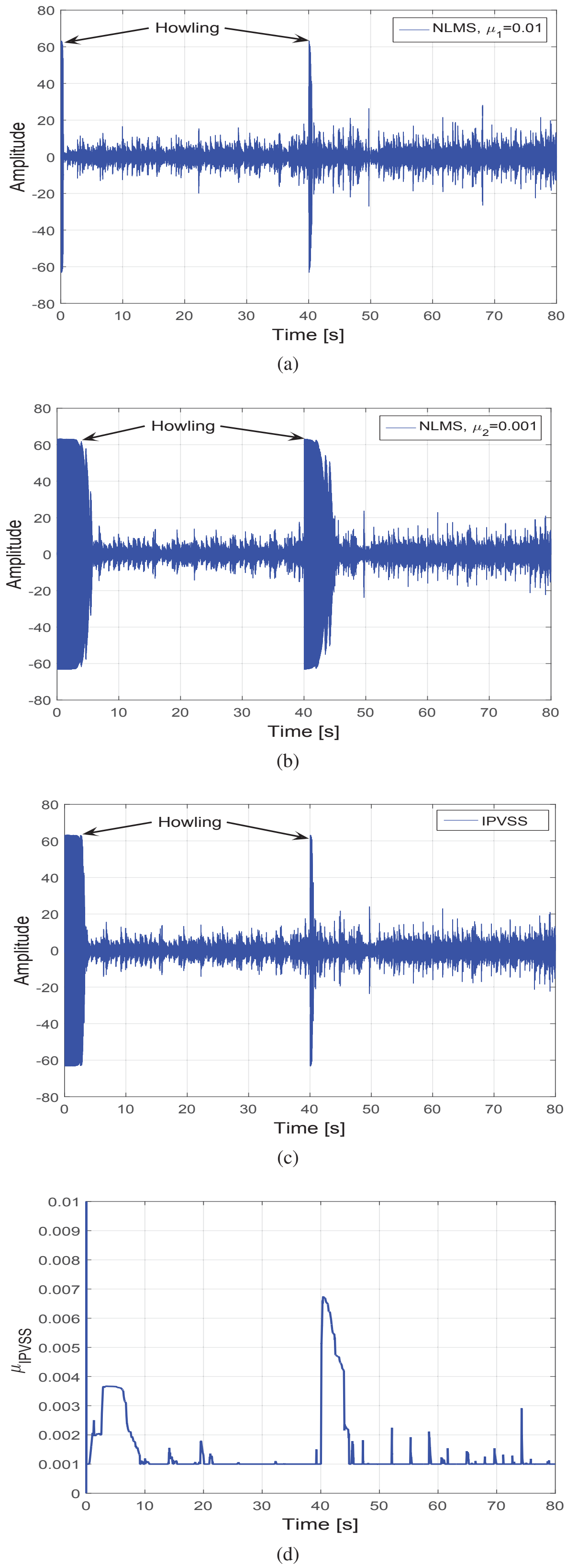
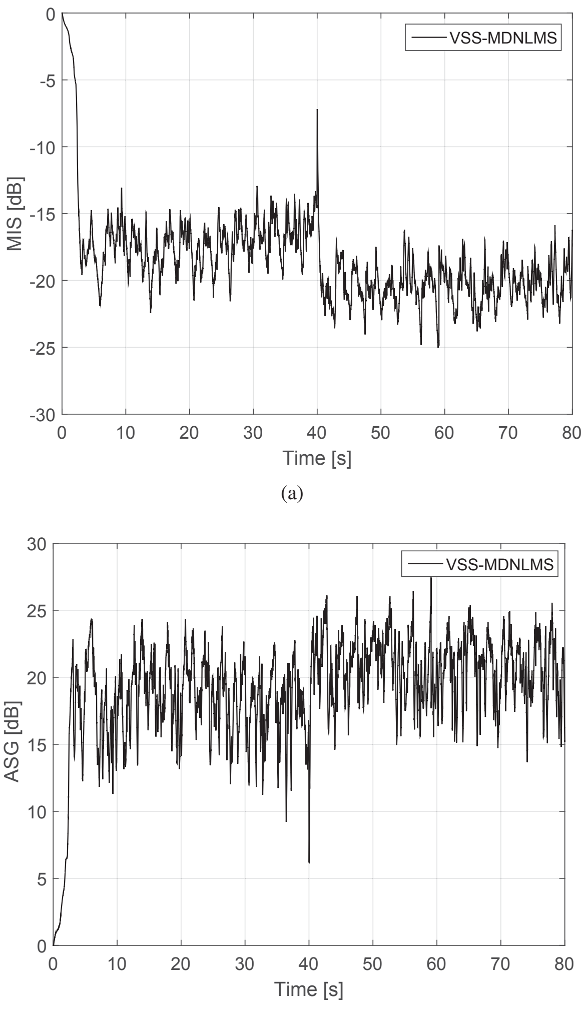


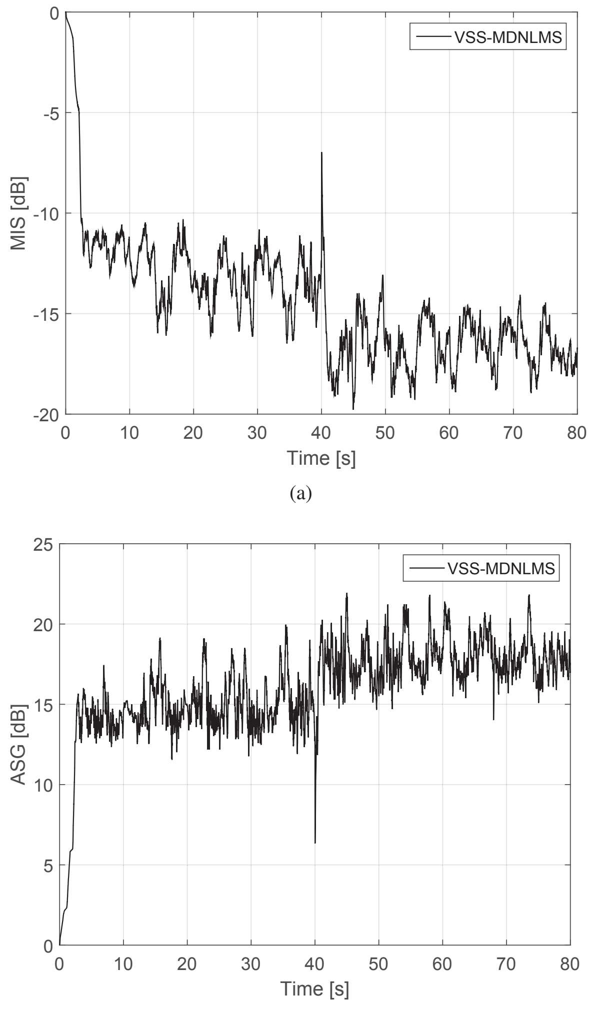
Fig. 7: Loudspeaker signals for the case of music incoming signal: a) and b) PEM with $\mu_1 = 0.01$, $\mu_2 = 0.001$, respectively; c) PEM-IPVSS, and d) μ_{IPVSS}.



(a)

(b)

Fig. 8: (a) Misalignment, (b) Added Stable Gain of the PEM using VSS-MDNLMS algorithms with speech incoming signal.



(a)

(b)

Fig. 9: (a) Misalignment, (b) Added Stable Gain of the PEM using VSS-MDNLMS algorithms with music incoming signal.

this step-size fluctuates quickly in the first 40s and gets the maximum value after the feedback path changes, thus high variations in the performance of the system are observed. In fact, the PEM-VSS-MDNLMS performance is similar to that of the PEM with upper step-size, except it has a slower convergence rate in the initial phase.

IV. Conclusion

In this paper, we proposed a new variable step-size algorithm (IPVSS) for NLMS in the context of adaptive feedback control using PEM. The proposed PEM-IPVSS outperforms the PEM when employing either the upper or the lower step-size used as the limits in the IPVSS algorithm, as well as the PEM-VSS-MDNLMS. Hence, a reduction of the howling period is achieved, while still providing a low steady-state error. Moreover, the PEM-IPVSS works well for both speech and music incoming signals, even for the case without an added (white) background noise.

References

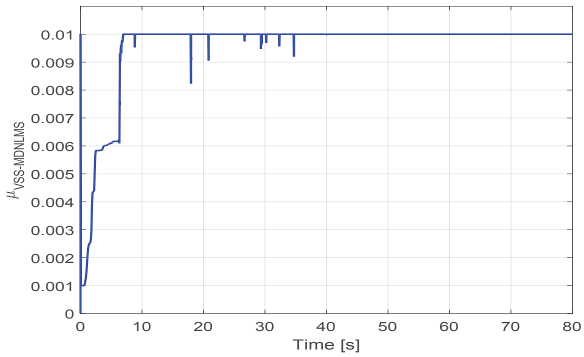
[1] M. G. Siqueira and A. Alwan, "Steady-state analysis of continuous adaptation in acoustic feedback reduction systems for hearing-aids," *IEEE Trans. Speech, Audio Process.*, vol. 8, no. 4, pp. 443–453, 2000.

[2] T. van Waterschoot and M. Moonen, "Fifty years of acoustic feedback control: State of the art and future challenges." *Proc. IEEE*, vol. 99, no. 2, pp. 288–327, 2011.

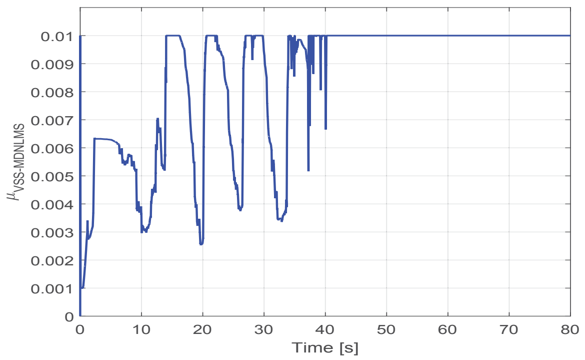
[3] C. R. C. Nakagawa, S. Nordholm, and W.-Y. Yan, "New insights into optimal acoustic feedback cancellation," *IEEE Signal Process. Lett.*, vol. 20, no. 9, pp. 869–872, 2013.

[4] 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.*, vol. 53, no. 10, pp. 3749–3763, 2005.

[5] G. Rombouts, T. Van Waterschoot, and M. Moonen, "Robust and efficient implementation of the pem afrow algorithm for acousic feedback cancellation," *J. Audio Eng. Soc.*, vol. 55, no. 11, pp. 955–966, 2007.



(a)



(b)

Fig. 10: The variable step-size $\mu_{VSS-MDNLMS}$: a) with speech incoming signal and b) with music incoming signal.

[6] A. Spriet, S. Doclo, M. Moonen, and J. Wouters, "Feedback control in hearing aids," in *Springer Handbook of Speech Processing*. Springer, 2008, pp. 979–1000.

[7] J. Arenas-García, A. R. Figueiras-Vidal, and A. H. Sayed, "Mean-square performance of a convex combination of two adaptive filters," *IEEE Trans. Signal Process.*, vol. 54, no. 3, pp. 1078–1090, 2006.

[8] R. Candido, M. T. Silva, and V. H. Nascimento, "Transient and steady-state analysis of the affine combination of two adaptive filters," *IEEE Trans. Signal Process.*, vol. 58, no. 8, pp. 4064–4078, 2010.

[9] H. Schepker, L. T. T. Tran, S. Nordholm, and S. Doclo, "Improving adaptive feedback cancellation in hearing aids using an affine combination of filters," in *IEEE Int. Conf. Acoust., Speech, Signal Process. (ICASSP)*, 2016.

[10] R. H. Kwong and E. W. Johnston, "A variable step size lms algorithm," *IEEE Trans. Signal Process.*, vol. 40, no. 7, pp. 1633–1642, 1992.

[11] J. Benesty, H. Rey, L. Rey Vega, and S. Tressens, "A nonparametric vss nlms algorithm," *IEEE Signal Process. Lett.*, vol. 13, no. 10, pp. 581–584, 2006.

[12] M. Rotaru, F. Albu, and H. Coanda, "A variable step size modified decorrelated nlms algorithm for adaptive feedback cancellation in hearing aids," *Proc of ISETC. Timisoara*, pp. 263–266, 2012.

[13] H.-C. Shin, A. H. Sayed, and W.-J. Song, "Variable step-size nlms and affine projection algorithms," *IEEE Signal Process. Lett.*, vol. 11, no. 2, pp. 132–135, 2004.

[14] H.-C. Huang and J. Lee, "A new variable step-size nlms algorithm and its performance analysis," *IEEE Trans. Signal Process.*, vol. 60, no. 4, pp. 2055–2060, 2012.

[15] J. M. Gil-Cacho, T. Van Waterschoot, M. Moonen, and S. H. Jensen, "Wiener variable step size and gradient spectral variance smoothing for double-talk-robust acoustic echo cancellation and acoustic feedback cancellation," *Signal Processing*, vol. 104, pp. 1–14, 2014.

[16] C. Paleologu, J. Benesty, and S. Ciochina, "A variable step-size affine projection algorithm designed for acoustic echo cancellation," *IEEE Trans. Audio, Speech, Lang. Process.*, vol. 16, no. 8, pp. 1466–1478, 2008.

[17] M. A. Iqbal and S. L. Grant, "Novel variable step size nlms algorithms for echo cancellation," in *in Proc. 2008 IEEE Int. Conf. Acoust., Speech, Signal Process. (ICASSP)*. IEEE, 2008, pp. 241–244.

[18] C. Paleologu, S. Ciochină, and J. Benesty, "Variable step-size nlms algorithm for under-modeling acoustic echo cancellation," *IEEE Signal Process. Lett.*, vol. 15, pp. 5–8, 2008.

[19] F. Albu, C. Paleologu, and S. Ciochina, "New variable step size affine projection algorithms," in *9th IEEE Int. Conf. Communications (COMM)*, 2012, pp. 63–66.

[20] C. Paleologu, J. Benesty, S. L. Grant, and C. Osterwise, "Variable step-size nlms algorithms designed for echo cancellation," in *2009 Conf. Record of the Forty-Third Asilomar Signals, Systems, Computers*. IEEE, 2009, pp. 633–637.

[21] S. Thipphayathetthana and C. Chinrungrueng, "Variable step-size of the least-mean-square algorithm for reducing acoustic feedback in hearing aids," in *the 2000 IEEE Asia-Pacific Conf. Circuits and Systems (APCCAS)*, 2000, pp. 407–410.

[22] F. Strasser and H. Puder, "Adaptive feedback cancellation for realistic hearing aid applications," *IEEE/ACM Trans. Audio, Speech, Lang. Process.*, vol. 23, no. 12, pp. 2322–2333, 2015.

[23] Y.-S. Kim, J.-h. Song, S.-K. Kim, and S. Lee, "Variable step-size affine projection algorithm based on global speech absence probability for adaptive feedback cancellation," *J. Central South University*, vol. 21, no. 2, pp. 646–650, 2014.

[24] L. T. T. Tran, S. Nordholm, H. Dam, W. Yan, and C. Nakagawa, "Acoustic feedback cancellation in hearing aids using two microphones employing variable step size affine projection algorithms," in *2015 IEEE Int. Conf. Digital Signal Process. (DSP)*, 2015, pp. 1191–1195.

[25] G. Panda, N. Puhan *et al.*, "A vss sparseness controlled algorithm for feedback suppression in hearing aids," in *2015 IEEE Int. Symp. Signal Process., Information Technology (ISSPIT)*, 2015, pp. 151–156.

[26] J. R. Deller Jr, J. G. Proakis, and J. H. Hansen, *Discrete time processing of speech signals*. Prentice Hall PTR, 1993.

[27] T. Sankowsky-Rothe, M. Blau, H. Schepker, and S. Doclo, "Reciprocal measurement of acoustic feedback paths in hearing aids," *J. Acoust. Soc. Am.*, vol. 138, no. 4, pp. EL399–EL404, 2015.

[28] J. Hellgren and U. Forssell, "Bias of feedback cancellation algorithms in hearing aids based on direct closed loop identification," *IEEE Trans. Speech and Audio Process.*, vol. 9, no. 8, pp. 906–913, 2001.