Sparsity Promoting LMS for Adaptive Feedback Cancellation

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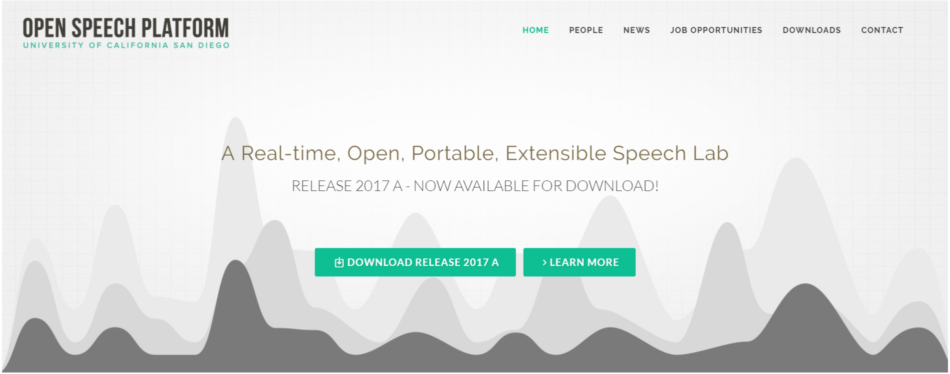
Our Project Website



- To validate real-time performance of hearing aid algorithms.
- Link: http://openspeechplatform.ucsd.edu
- Supported by NIH/NIDCD grants #1R21DC015046 and #1R01DC015436.

Problem of Acoustic Feedback

- Arises from a portion of the output sound at the receiver feeding back to the microphone and getting reinforced by the hearing aid.
- Results in annoying howling and whistling sounds which could become increasingly louder.
- Limits the maximum gain that a hearing aid device can provide.

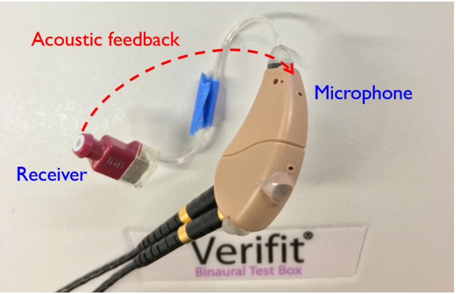


Figure: Illustration of acoustic feedback in the hearing aid.

Solution: Adaptive Feedback Cancellation (AFC)

- Framework: Prediction-Error-Method (PEM) based AFC [Spriet et al., 2008].

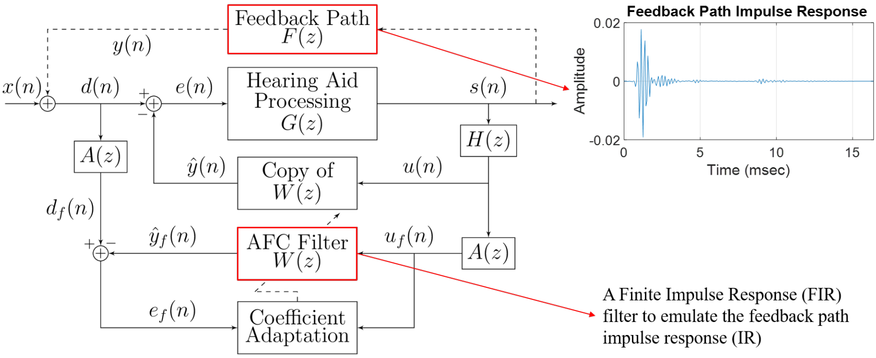


Figure: Block diagram of the AFC framework.

Adaptive Filtering

- In the coefficient adaptation stage, the **Least Mean Square** (**LMS**) algorithms are the most widely used adaptive filtering techniques in AFC.

- Advantages:
  1. computational simplicity
  2. stability

- Drawbacks:
  1. biased estimation
  2. slow convergence speed

  – Several methods have been proposed to overcome these downsides. However, few of them exploit the structural characteristics of feedback path IRs.

Coefficient Adaptation: The Baseline Algorithm

The (Modified) Normalized LMS (NLMS) [Greenberg, 1998]

Update rule:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu(n)\mathbf{u}_f(n)e_f(n). \tag{1}$$

Power-normalized step size:

$$\mu(n) = \frac{\mu}{L\hat{\sigma}^2(n) + \epsilon}. \tag{2}$$

Power estimation:

$$\hat{\sigma}^2(n) = \rho\hat{\sigma}^2(n-1) + (1-\rho)(u_f^2(n) + e_f^2(n)). \tag{3}$$

- $\mathbf{w}(n) = [w_0(n), w_1(n), ..., w_{L-1}(n)]^T$: the estimated AFC filter at time n
- $\mathbf{u}_f(n) = [u_f(n), u_f(n-1), ..., u_f(n-L+1)]^T$
- $e_f(n) = d_f(n) - \mathbf{w}^T(n)\mathbf{u}_f(n)$
- $\mu > 0$: the step size parameter
- ϵ: a small positive constant to prevent division by zero
- $0 < \rho \leq 1$: the forgetting factor

Improving Convergence Speed. How?

- Well-known fact: the trade-off between fast convergence and low steady-state error, controlled by the adaptation step size parameter.
  - $\mu \uparrow$: faster convergence , higher error
  - $\mu \downarrow$: slower convergence, lower error

- Combination of two adaptive filters with different step size parameters [Schepker et al., 2016] can improve the convergence rate without increasing the error. However, computational complexity could double.

- Goal: With only one single adaptive filter, to speed up convergence by taking advantage of the feedback path structure.

Sparse Structure of the Feedback Path

- Observe: Typical feedback path IRs are temporally (quasi-) **sparse**.

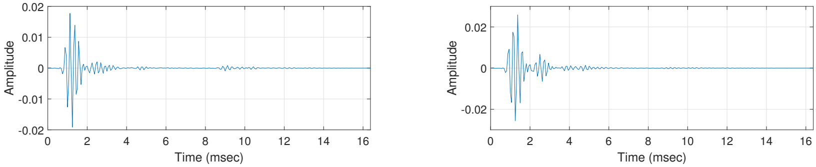


Figure: Examples of measured acoustic feedback paths.

- **Proportionate adaptation** to take advantage of the sparsity:
  - The family of the Proportionate NLMS (PNLMS) algorithms
  - **Sparsity promoting LMS** (**SLMS**) [Proposed]

Proportionate Adaptation

- The main idea:
  - Each tap of the AFC filter gets updated independently using a different step size.
  - The step size is proportional to the magnitude of the tap itself.
  - In each iteration, the step sizes are redistributed according to the magnitude of coefficients of the current AFC filter.

Proportionate Matrix (or Step Size Control Matrix)

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu(n)\mathbf{P}(n)\mathbf{u}_f(n)e_f(n). \tag{4}$$

- $\mathbf{P}(n) = diag\{p_0(n), p_1(n), ..., p_{L-1}(n)\}$ is an L-by-L diagonal matrix for assigning different weights to different taps, where $p_l(n)$ is a function of the current $w_l(n)$.
- Existing approaches: PNLMS-type algorithms – Different ways of computing $p_l(n)$.

PNLMS-Type Algorithms

PNLMS [Duttweiler, 2000]

$$p_l(n) = \frac{|w_l(n)|}{\frac{1}{L}||\mathbf{w}(n)||_1}, \tag{5}$$

where

$$||\mathbf{w}(n)||_1 = \sum_{i=0}^{L-1} |w_i(n)|. \tag{6}$$

Note: Some additional minor operations are needed to provide a mechanism for preventing the algorithm from getting stuck at zero. For simplicity the equations are now shown here.

Improved PNLMS (IPNLMS) [Benesty and Gay, 2002]

$$p_l(n) = \frac{1-\alpha}{2} + (1+\alpha)\frac{|w_l(n)|}{\frac{2}{L}||\mathbf{w}(n)||_1}, \tag{7}$$

where α is a constant between $[-1, 1]$ for different degrees of sparsity.

PNLMS-Type Algorithms (Cont'd)

IPNLMS-l_0 [Paleologu et al., 2010]

$$p_l(n) = \frac{1-\alpha}{L} + (1+\alpha)\frac{1-e^{-\beta|w_l(n)|}}{\frac{2}{L}||\mathbf{w}||_0}, \tag{8}$$

since

$$||\mathbf{w}||_0 \approx \sum_{i=0}^{L-1}[1-e^{-\beta|w_i(n)|}], \tag{9}$$

where $\alpha \in [-1, 1]$ and β is a non-negative constant. A sparser system would prefer a smaller β.

- All of the above are ad hoc and not derived from minimizing any underlying objective functions.
- No algorithms for other choices of ℓ_p norm (e.g., $p = 0.8, 1.5$).

Proposed Algorithm: SLMS

- Ordinary LMS:

$$\min_{\mathbf{w}} \quad J(\mathbf{w}) = E\left[|e_f(n)|^2\right]. \tag{10}$$

- Adding the penalty term to incorporate sparsity:

$$\min_{\mathbf{w}} \quad J(\mathbf{w}) = E\left[|e_f(n)|^2\right] + \gamma \|\mathbf{w}\|_p^p, \tag{11}$$

  where the ℓ_p norm diversity measure:

$$\|\mathbf{w}\|_p^p = \sum_{l=0}^{L-1} |w_l|^p, \quad p \in (0, 2] \tag{12}$$

  is added with a regularization parameter $\gamma > 0$ to promote sparsity in the solution $\mathbf{w}$.

- Optimization tools:
  1. Gradient of the ℓ_p norm w.r.t. $\mathbf{w}$:

$$\nabla_{\mathbf{w}} \|\mathbf{w}\|_p^p = p\,\Pi(\mathbf{w})\mathbf{w}, \tag{13}$$

     where $\Pi(\mathbf{w}) = diag(|w_l|^{p-2})$.

  2. Affine scaling transformation:

$$\mathbf{q}(\mathbf{w}) \triangleq \Pi^{\frac{1}{2}}(\mathbf{w}(n))\mathbf{w}. \tag{14}$$

     - It belongs to the family of interior-point methods.
     - Can be viewed as a mechanism to transform the original optimization problem into an equivalent one in which the current point is favorably positioned at the center of the feasible region.
     - It leads to algorithms that can support larger learning steps along the search direction, and the overall adaptation can be sped up.

Proposed Algorithm: SLMS (Cont'd)

- The use of the affine scaling transformation is the key part in deriving the SLMS. Reasons are:
    1. It makes our algorithm fundamentally different from the ones obtained by directly performing optimization in the original coefficient domain, e.g., the Zero-Attracting LMS (ZA-LMS) like algorithms [Chen et al., 2009, Taheri and Vorobyov, 2011]:
        - $\gamma > 0$ to enforce sparse solutions, at the expense of introducing bias.
        - If $\gamma = 0$, they reduce to the ordinary LMS.
    2. In our algorithm, the impact of the ℓ_p norm term on the optimal solution is removed by setting $\gamma = 0$ for the resulting algorithm.
        - It converges to the same place as the ordinary LMS; i.e., no additional bias is introduced.
        - However, it still benefits from sparsity due to the presence of the proportionate matrix.
- The algorithm does not enforce, but takes advantage of sparsity if it exists in the structure. Thus the name: "Sparsity promoting LMS (SLMS)."

Proposed Algorithm: SLMS (Cont'd)

SLMS [Proposed]

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu(n)\mathbf{P}(n)\mathbf{u}_f(n)e_f(n), \tag{15}$$

where

$$p_l(n) = \frac{|w_l(n)|^{2-p}}{\frac{1}{L}\sum_{i=0}^{L-1}|w_i(n)|^{2-p}}, \tag{16}$$

- γ is not present in the algorithm.
- p is responsible for fitting different degrees of sparsity.
  - $p = 1$ approximates the PNLMS (highly proportionate: sparse).
  - $p = 2$ recovers the NLMS (non-proportionate: dispersive).

Experimental Setup

- Computer simulations in MATLAB at a sampling rate of 16 kHz.
- The HA processing $G(z) = gz^{-d}$ with $g = 20$ and d corresponding to a delay of 8 ms.
- The feedback path IRs were measured using a behind-the-ear HA with open fitting on a dummy head and truncated to a length of 263 sample ($\approx$ 16.5 msec).
- The AFC filter length was $L = 100$ (6.25 msec) to cover the significant part of the feedback IRs.
- Metrics:
  1. Hearing-Aid Speech Quality Index (HASQI) [Kates and Arehart, 2014]
  2. normalized misalignment
  3. Added Stable Gain (ASG) [Kates, 2001]

Experiment I: Effect of p on Convergence

- Input: A speech-shaped noise sequence.
- System IRs with different sparsity levels:

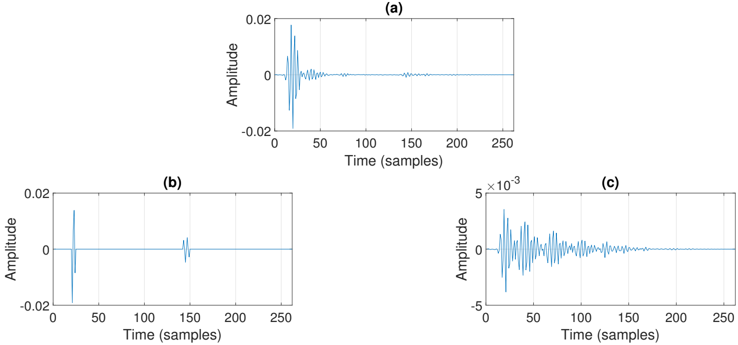


Figure: (a) a measured acoustic feedback path, (b) an artificial sparse system, (c) an artificial dispersive system.

Experiment I: Effect of p on Convergence (Cont'd)

- The resulting misalignment curves:

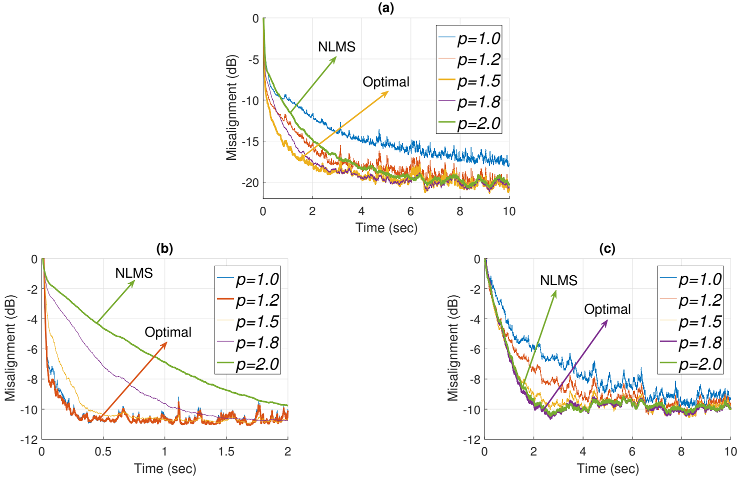


Figure: The (a) feedback path, (b) sparse, and (c) dispersive IRs.

Experiment II: Sensitivity of p

- Input: 25 male and 25 female speech files from TIMIT dataset.
- Measured acoustic feedback path IRs of 3 different scenarios:

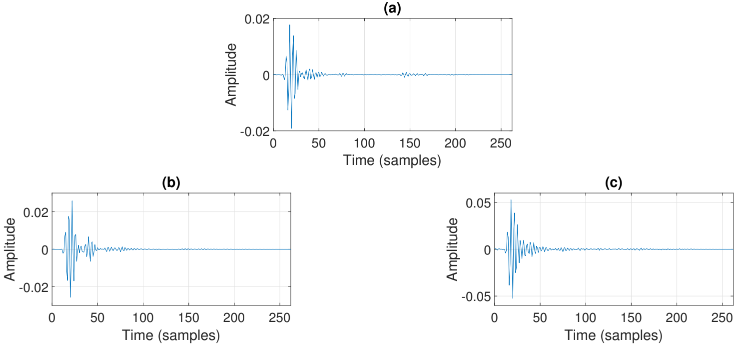


Figure: (a) f_1: no obstruction, (b) f_2: with a cellphone close to the ear, and (c) f_3: with a cellphone right on the ear.

Simulation Result II: Sensitivity of p (cont'd)

- The obtained average HASQI scores over the 50 test files:

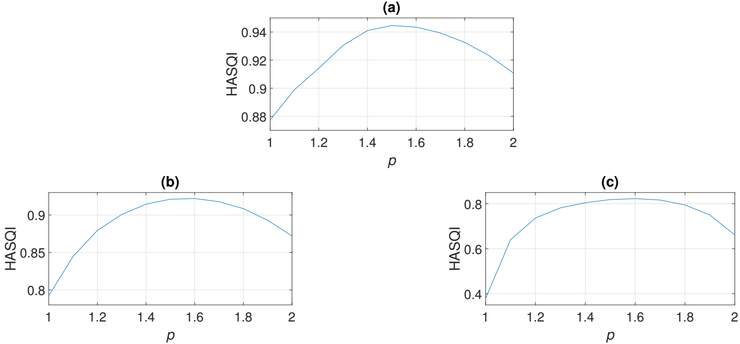


Figure: Effect of p on speech quality of SLMS for (a) f_1, (b) f_2, and (c) f_3.

- p is optimal around 1.5, corresponding to the previous result.
- p is not sensitive around its optimal value.

Experiment III: Comparison with Other Algorithms

- Input: A speech-shaped noise sequence.
- The feedback path changed from f_1 to f_2 then f_3 at 1/3 and 2/3 of the input sequence, respectively.

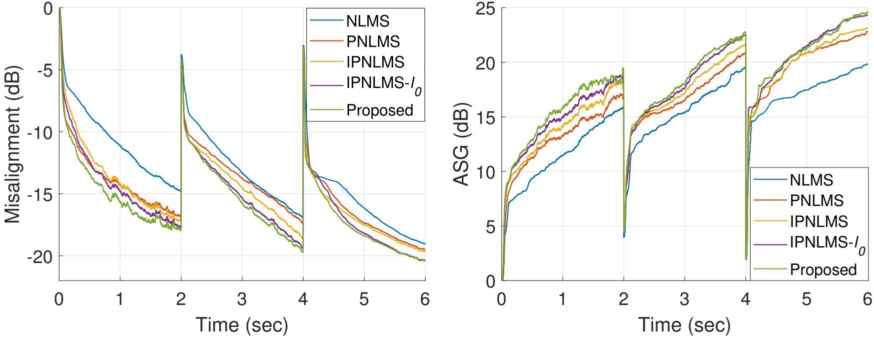


Figure: Misalignment and ASG Comparison.

Experiment IV: Quality Comparison

- Input: 25 male and 25 female speech files from TIMIT dataset.
- Obtain the average HASQI scores over the 50 test files:

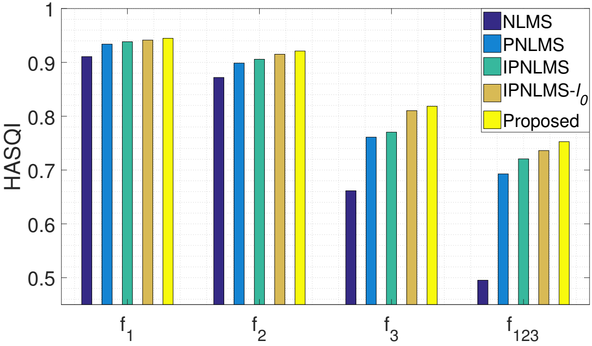


Figure: Quality comparison: The first 3 cases were fixed environments with f_1, f_2, and f_3. The last case f_{123} was the feedback path changing from f_1 to f_2 then f_3 at 1/3 and 2/3 of the input sequence, respectively.

Conclusions

- Typical acoustic feedback paths have sparse structure. We use proportionate adaptation to take advantage of it.
- SLMS: a proportionate-type LMS derived by formally minimizing an objective function with the ℓ_p norm diversity measure. p is not sensitive near its optimal value.
- Compared to the baseline NLMS, the SLMS can provide about 0.25 HASQI and 5 dB ASG improvements.
- SLMS outperforms other proportionate-type algorithms in terms of speech quality, misalignment, and ASG.

Thank You!
Questions?

Backup Slides

Techniques for Reducing the Bias

- Several methods have been proposed to address the bias issue. The main idea is to decorrelate the signals before they are used to compute the gradient for adaptation.
    1. Filtered-X LMS (FXLMS) [Hellgren, 2002, Chi et al., 2003]
    2. Prediction-Error-Method (PEM) based AFC [Spriet et al., 2008]
    3. insertion of probe noise [Guo et al., 2012a]
    4. phase modulation [Guo et al., 2012b]
    5. PEM with frequency shifting [Strasser and Puder, 2015]
    6. dual-microphone approach [Nakagawa et al., 2012]

Proposed Algorithm: SLMS

SLMS [Proposed]

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu(n)\mathbf{P}(n)\mathbf{u}_f(n)e_f(n), \tag{17}$$

with

$$p_l(n) = \frac{r_l(n)}{\frac{1}{L}\sum_{i=0}^{L-1} r_i(n)}, \tag{18}$$

where

$$r_l(n) = \left||w_l(n)| + c\right|^{2-p}. \tag{19}$$

- $c > 0$ is a small constant to prevent from getting stuck once $w_l(n)$ becomes zero.

Evaluation Metrics

- HASQI [Kates and Arehart, 2014]
    1. Compares the time-frequency envelope modulation, temporal fine structure, and long-term spectra.
    2. Measure the distortion between the feedback-compensated signal $e(n)$ and desired input $x(n)$
    3. The HASQI score ranges from 0 to 1, where the higher the score, the better the quality (less distortion).

Evaluation Metrics (Cont'd)

- Normalized misalignment:

$$\text{Misalignment} = 10\log_{10}\frac{\int_0^{\pi} |F(e^{j\omega}) - \hat{F}(e^{j\omega})|^2 d\omega}{\int_0^{\pi} |F(e^{j\omega})|^2 d\omega}, \tag{20}$$

where $F(e^{j\omega})$ and $\hat{F}(e^{j\omega})$ are the frequency responses of the measured and estimated feedback IRs, respectively.

- ASG [Kates, 2001]:

$$\begin{aligned} \text{ASG} = & \, 20\log_{10}\left(\min_{\omega}\frac{1}{|F(e^{j\omega}) - \hat{F}(e^{j\omega})|}\right) \\ & - 20\log_{10}\left(\min_{\omega}\frac{1}{|F(e^{j\omega})|}\right). \end{aligned} \tag{21}$$

Reference I

[Chen et al., 2009] Chen, Y., Gu, Y., and Hero, A. O. (2009).
Sparse LMS for system identification.
In *Proc. IEEE Int. Conf. Acoust., Speech, Signal Process. (ICASSP)*, pages 3125–3128.

[Chi et al., 2003] Chi, H.-F., Gao, S. X., Soli, S. D., and Alwan, A. (2003).
Band-limited feedback cancellation with a modified filtered-X LMS algorithm for hearing aids.
Speech Commun., 39(1-2):147–161.

[Greenberg, 1998] Greenberg, J. E. (1998).
Modified LMS algorithms for speech processing with an adaptive noise canceller.
IEEE Trans. Speech Audio Process., 6(4):338–351.

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

Reference II

[Guo et al., 2012b] Guo, M., Jensen, S. H., Jensen, J., and Grant, S. L. (2012b).
On the use of a phase modulation method for decorrelation in acoustic feedback cancellation.
In *Proc. Europ. Signal Process. Conf. (EUSIPCO)*, pages 2000–2004.

[Hellgren, 2002] Hellgren, J. (2002).
Analysis of feedback cancellation in hearing aids with Filtered-X LMS and the direct method of closed loop identification.
IEEE Trans. Speech Audio Process., 10(2):119–131.

[Kates, 2001] Kates, J. M. (2001).
Room reverberation effects in hearing aid feedback cancellation.
J. Acoust. Soc. Am., 109(1):367–378.

[Kates and Arehart, 2014] Kates, J. M. and Arehart, K. H. (2014).
The hearing-aid speech quality index (HASQI) version 2.
J. Audio Eng. Soc., 62(3):99–117.

Reference III

[Nakagawa et al., 2012] Nakagawa, C. R. C., Nordholm, S., and Yan, W.-Y. (2012).
Dual microphone solution for acoustic feedback cancellation for assistive listening.
In *Proc. IEEE Int. Conf. Acoust., Speech, Signal Process. (ICASSP)*, pages 149–152.

[Schepker et al., 2016] Schepker, H., Tran, L. T. T., Nordholm, S., and Doclo, S. (2016).
Improving adaptive feedback cancellation in hearing aids using an affine combination of filters.
In *Proc. IEEE Int. Conf. Acoust., Speech, Signal Process. (ICASSP)*, pages 231–235.

[Spriet et al., 2008] Spriet, A., Doclo, S., Moonen, M., and Wouters, J. (2008).
Feedback control in hearing aids.
Springer Handbook of Speech Process., pages 979–1000.

Reference IV

[Strasser and Puder, 2015] Strasser, F. and Puder, H. (2015).
Adaptive feedback cancellation for realistic hearing aid applications.
IEEE/ACM Trans. Audio, Speech, Lang. Process., 23(12):2322–2333.

[Taheri and Vorobyov, 2011] Taheri, O. and Vorobyov, S. A. (2011).
Sparse channel estimation with ℓ_p-norm and reweighted ℓ_1-norm penalized least mean squares.
In *Proc. IEEE Int. Conf. Acoust., Speech, Signal Process. (ICASSP)*, pages 2864–2867.