CLOSED-LOOP FEEDBACK CANCELLATION UTILIZING TWO MICROPHONES AND TRANSFORM DOMAIN PROCESSING

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ABSTRACT

In this paper we are studying the use of two microphones for acoustic feedback cancellation in hearing aids. With the two microphones approach, an additional microphone is employed to provide added information about the signals which is then utilized to obtain an incoming signal estimate. This estimate is removed from the error signal prior to adapting the canceler, thus removing the undesired signal correlation. In this paper, we propose to use orthogonal transforms with the two microphones approach. The discrete Fourier transform and the discrete cosine transform are implemented to transform the adaptive filter signals. Also, a bank of adaptive filters is employed, each adapting to different portions of the spectrum for a finer control of the adaptation process. Simulation results based on real measured feedback paths and speech signals show improved convergence rates and stable solutions.

Index Terms—Acoustic feedback, bias problem, feedback cancellation, hearing aids, two microphones

I. INTRODUCTION AND CONTRIBUTION

Sound reinforcement systems such as public address systems and hearing aids suffer from acoustic feedback problems. Acoustic feedback results from the acoustic coupling between the loudspeaker and microphone. The microphone(s) picks up the loudspeaker's signal and re-amplifies it creating an acoustic loop. For each round trip the signal traveling around this loop gets re-amplified potentially causing system instability. The feedback problem limits the maximum stable gain (MSG) achievable, it deteriorates the sound quality by producing a distortion of the incoming signal, and it is a cause of instability in acoustic systems working in closedloop [1].

The use of acoustic feedback cancelers (AFC) is currently a preferred option in feedback control techniques [2]. The purpose of AFC is essentially to identify a model of the feedback path and to estimate the feedback signal. The feedback estimate is then subtracted from the microphone signal. However one of the challenges with feedback cancelers, as a result of the closed-loop signals, is the bias problem where the canceler's coefficients become biased when the correlation between the loudspeaker and incoming signal is non-zero [1], [3]. This correlation generally leads to a poor system performance and in the worst-case scenario, it may cause the cancellation system to fail. Different techniques have been proposed to reduce this correlation including phase modification, frequency shifting, decorrelating pre-filters, adaptive

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filters in tandem, use of synthesized signals, and probe noise injection [2]–[10]. The use of orthogonal transforms to transform the adaptive filter signals can also be used to reduce signal correlation. Originally, the use of orthogonal transform was proposed to increase convergence rates in stochastic gradient algorithms such as the least mean squares (LMS) algorithm [11]–[13]. In [14] the discrete cosine transform (DCT) is applied to the prediction error method (PEM) to boost the PEM performance for acoustic echo cancellation (AEC) and AFC. In [15], an additional microphone was employed to provide added information which was utilized to obtain an incoming signal estimate. This estimate is removed from the error signal prior to adapting the canceler, thus removing the undesired signal correlation. We refer to this method as the two microphone acoustic feedback canceler (TM-AFC).

In this paper, we propose to use orthogonal transforms with the TM-AFC method. The discrete Fourier transform (DFT) and the DCT are implemented to transform the adaptive filter signals. The intention is to further enhance the overall TM-AFC performance. In this work, the transform is not only applied to the input signal of the canceler as in [14], but also to the error signal. Another differentiator is that a bank of adaptive filters is employed, each adapting to different portions of the spectrum. This enables for a finer control of the adaptation process. The full band filter's coefficients are synthesized and used to provide the necessary signal estimates. The proposed structure is similar to delayless subband filtering but without decimation [16], [17]. Furthermore, this work does not make use of probe signal injection as in [15] which benefits signal quality [3]. From the simulation results, we see improvements in convergence rates and stable solutions using real speech signals.

This paper is structured as follows. First, we review the TM-AFC approach. Then, the proposed transform domain with filtered error version of the TM-AFC method is presented followed by simulation results.

II. REVIEW TM-AFC

Fig. 1 illustrates a feedback canceler for an hearing aid with a single microphone. The feedback path between the loudspeaker and the microphone is assumed to be a discrete-time finite impulse response (FIR) filter with coefficient vector $\mathbf{g}_1 = [g_{10} \dots g_{1L_g-1}]^T$ with filter length L_g which is represented as a polynomial transfer function $G_1(q)$ in q as $G_1(q) = \mathbf{g}_1^T \mathbf{q}$ with $\mathbf{q} = [1 \ q^{-1} \dots q^{-L_g+1}]^T$. This representation allows the following notation, for the filtering of y(n) by G(q), $G_1(q)y(n) = \mathbf{g}_1^T(n)\mathbf{y}(n)$ [18]. Column vectors are emphasized using lower letters in bold, the superscript T denote vector transpose, the discrete-time index is denoted by n, and the symbol q^{-1} denotes the



Fig. 1: General AFC set-up.

discrete-time delay operator $q^{-1}u(n) = u(n-1)$. All signals are real-valued, and we denote all signals as discrete-time signals with time index n for convenience. The forward path K(q) represents the regular signal processing path of the device. In this paper, K(q)has a delay $d_k \ge 1$ and provides the system with a constant gain i.e., $K(q) = q^{-d_k}K$. The adaptive filter $\hat{G}_1(q)$, with coefficient vector $\hat{\mathbf{g}}_1 = \begin{bmatrix} \hat{g}_{1_0} & \dots & \hat{g}_{1_{L_g-1}} \end{bmatrix}^T$ and filter length $L_{\hat{g}} = L_g$, identifies and tracks changes to the feedback path by producing an estimate f(n) of the feedback signal f(n). The loudspeaker and microphone signals are y(n) and $m_1(n)$, respectively. The incoming signal is denoted by $u_1(n)$ and the feedback signal is denoted by $f_1(n) = G_1(q)y(n)$. The estimate $\hat{f}_1(n)$ is subtracted from the microphone signal $m_1(n)$. The error signal $e_1(n)$ is used to update the canceler's coefficients and is also amplified by the forward path and played out through the loudspeaker. As a result of the non-zero correlation between the incoming and loudspeaker signal, the canceler's optimal solution is biased [3].

To remove the undesired signal correlation in the canceler's optimal solution an additional microphone was used in [15] to obtain an incoming signal estimate, which is subtracted from the error signal prior to adapting the feedback canceler. The two microphones are placed rather close but not in the same position which means that the received signals have high correlation. The TM-AFC configuration is presented in Fig. 2. We write the relationship between the incoming signals $u_1(n)$ and $u_2(n)$ as

$$u_1(n) = H(q)u_2(n) + \zeta(n)$$
 (1)

where $\zeta(n)$ is the part of $u_1(n)$ that is not predictable from $u_2(n)$ and H(q) is a FIR filter with length L_h . The delay d_m in the first microphone signal path is to avoid having a non-causal system. $\hat{H}(q)$ is an adaptive FIR filter of length $L_{\hat{h}} \ge L_h + d_m$ which filters the second microphone signal $m_2(n)$ producing the incoming signal estimate $\hat{u}_1(n)$ which is subtracted from the error signal $e_1(n)$.

It is required that $|G_1(q)| > |G_2(q)|$. A possible location for the microphones would be to have one microphone in the ear canal and an additional microphone behind the ear, for instance, refer to Fig. 3. The microphone in the ear canal is the main microphone, which signal is amplified and played out through the loudspeaker. By having such an arrangement, the natural position for signal pick-up is maintained providing the user with a more natural hearing [19]. Thus, having the main microphone scenario, such placement may limit the amount of gain possible due to a stronger coupling between the loudspeaker and microphone signals. For higher gains, the microphone may be placed behind the ear. This may affect the



Fig. 3: Proposed microphone location.

auditory cues and natural hearing. Thus, by using the TM-AFC approach, natural hearing and higher gains can be obtained.

A challenge with the TM-AFC approach is the presence of a second feedback channel $G_2(q)$. In [15] it was shown that $G_2(q)$ introduces a bias to the solution. However, with the proposed microphone arrangement, it can be assumed that $|G_2(q)|$ is weak.

III. TRANSFORM DOMAIN FILTERED ERROR TM-AFC

In this section we present an extended version of the TM-AFC. The intention in using orthonormal transformation is to further improve on the performance of the TM-AFC approach.

The orthonormal transformations, **T**, used in this paper are the DFT and DCT. The $M \times M$ DCT and DFT matrix coefficients $\mathbf{T}_{\text{DCT}}[k, l]$ and $\mathbf{T}_{\text{DFT}}[k, l]$ are given as in (2)-(3), respectively. Note that there may be several other orthogonal transforms suitable for adaptive filtering algorithms, please refer to [12].

$$\mathbf{T}_{\text{DCT}}[k,l] = \begin{cases} \frac{1}{\sqrt{M}}, & k = 0 \& l = 0 \dots M - 1\\ \left(\frac{2}{M}\right)^{\frac{1}{2}} \cos\frac{\pi(2l+1)k}{2M}, & (2)\\ k = 1 \dots M - 1 \& l = 0 \dots M - 1. \end{cases}$$

$$\mathbf{T}_{\text{DFT}}[k,l] = \frac{1}{\sqrt{M}} e^{-2\pi k l/M}, \, k, \, l = 0 \dots M - 1.$$
(3)



Fig. 4: Proposed TD-Fe-TM-AFC method.

We refer to this proposed approach as the transform domain (TD) with filtered error (Fe) TM-AFC and is presented in Fig. (4). The inputs y(n) and $m_2(n)$, of $\hat{G}_1(q)$ and $\hat{H}(q)$, respectively, are transformed by **T**, which can be any suitable orthogonal transform. The transform matrix **T** can be thought of as a bank of M parallel filters tuned to different portions of the spectrum of the input sequence [12]. The components of the transformed input vectors appear to be approximately decorrelated with one another. Moreover, an appropriate power normalization can convert the input autocorrelation matrix to a normalized matrix whose eigenvalue spread will be smaller than that of the original input signal, thereby improving the convergence behavior of the system in the transform domain [12], [14]. A difference between the proposed approach and the one used in [14], to improve the PEM, is that the error signal is also filtered by **T** and a bank of adaptive filters is used.

M adaptive filters (AF) are used to adapt the different portions of the spectrum. Then, the full band filters, $\hat{G}_1(q)$ and $\hat{H}(q)$, are synthesized by adding the estimated coefficients of the M filters together. The feedback estimate $\hat{f}_1(n)$ is produced by filtering the loudspeaker signal y(n) by this full band feedback canceler $\hat{G}_1(q)$. The same procedure is applied to $\hat{H}(q)$. This structure is similar to delayless subband filtering but without decimation [16], [17].

The improvement in performance comes at the cost of an increase in computational complexity. Three transform domain operations are required as well as an additional M - 1 adaptive filters for each identification. Nevertheless, when the DFT is used, we can make use of the complex conjugate symmetry to reduce complexity, thus reducing the number of filters used (only M/2 + 1 filters are required). Also, fast versions of the algorithm for the DCT and DFT are available, which reduces the complexity from $O(M^2)$ to $O(M \log M)$ operations [20], [21].



Fig. 5: Feedback paths' characteristics.

IV. SIMULATION RESULTS

In order to perform simulations, experiments were first conducted to obtain the feedback path's characteristics and variations. Measurements were conducted in a recording studio using a Brüel & Kjær (B&K) head and torso simulator type 4128C. Fig. 5 presents the feedback path's characteristics with a normal fit in the ear with and without obstruction. Obstruction refers to a flat surfaced object placed very close to the ear to simulate the use of a mobile phone. In our simulations this will be used to simulate a path change to analyze the tracking performance of the algorithm. Note that the second feedback path's magnitude response is much weaker than the first feedback path. Speech signals were also recorded using the two microphones. The input sequence used for the speech signals was real speech segments from NOIZEUS database which contains 30 IEEE sentences spoken by 3 male and 3 female speakers [22]. The speech signals were concatenated together and played out back to back.

To assess the performance of the algorithm, the misalignment between the true and estimated feedback path and the added stable gain (ASG) measures are used. The misalignment is used to represent the accuracy of the feedback path estimation and is defined as

Misalignment =
$$20 \log_{10} \frac{\int_0^\pi \left\| G(\omega) - \hat{G}(\omega) \right\|_2 d\omega}{\int_0^\pi \|G(\omega)\|_2 d\omega}.$$
 (4)

To quantify the added achievable amplification the ASG is defined as

$$ASG = MSG - 20 \log_{10} \left[\min_{\omega} \frac{1}{|G(\omega)|} \right]$$
(5)

where MSG is defined as

$$\mathbf{MSG} = 20 \log_{10} \left[\min_{\omega} \frac{1}{\left| G(\omega) - \hat{G}(\omega) \right|} \right].$$
(6)

The MSG and ASG is determined by the frequency where the mismatch between the actual and estimated path is greatest. However, the system will only be unstable when the phase at that frequency equals a multiple of 2π .

In the simulations the following parameters were used. The length of the actual feedback path is $L_g = 32$ samples. The simulation run lasts for 80 seconds with a instantaneous change of feedback path occurring at time 40 seconds. Speech is used as the incoming signal. The complex normalized least mean squares



Fig. 6: Instantaneous misalignment and ASG plots for varying M.

(NLMS) algorithm is used for adapting the M filters for $\hat{G}_1(q)$ and $\hat{H}(q)$ with step size $\mu = 0.0001$. The filter length for $\hat{H}(q)$ is $L_{\hat{h}} = 8$ with $d_m = 3$. The sampling frequency is 16 kHz, and the forward path gain K = 30 dB with a forward path delay of $d_k = 32$ samples.

Fig. 6 presents the misalignment and ASG curves for varying values of M. We compare the transform domain version of the algorithms with the two microphone NLMS (TM-NLMS) with a step-size which gives similar initial convergence. The TD-Fe method is also applied to the traditional NLMS filter and is labeled TD-Fe-NLMS-DFT. Figs. 6a-6b presents the case where M = 2. With M = 2, both the DCT and DFT transform result in similar performance in terms of misalignment and ASG. The step size $\mu_{\text{TM-NLMS}} = 2\mu$ is used to give similar initial convergence. In Figs. 6c-6d M = 4, and $\mu_{\text{TM-NLMS}} = 5\mu$. Finally, in Figs. 6e-6f M = 8, and $\mu_{\text{TM-NLMS}} = 10\mu$.

As the value of M is increased, the convergence rate is improved

at the cost of higher complexity. It is interesting to note that for higher values of M, the DFT transform starts to give greater improvements in performance than the DCT. Also note that TD-Fe-NLMS is very sensitive to the incoming signal, whereas, the TM-NLMS and TD-Fe-TM-NLMS methods are more robust to the incoming signal variations.

V. CONCLUSION

In this paper we extended the TM-AFC method. We proposed to improve on the TM-AFC performance by utilizing orthogonal transforms. Both the adaptive filter's input and error signals are transformed and a bank of adaptive filters used. The full band filter's coefficients are then synthesized and used to provide the necessary signal estimates. Simulation results based on real measured feedback paths and speech signals showed improved convergence rates and stable solutions.

VI. REFERENCES

- A. Spriet, S. Doclo, and M. Moonen, "Feedback control in hearing aids," Springer handbook of speech processing, 2008.
- [2] 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.*, vol. 20, no. 9, pp. 2549– 2563, 2012.
- [3] T. van Waterschoot and M. Moonen, "Fifty years of acoustic feedback control: state of the art and future challenges," *Proc. IEEE*, no. 99, pp. 1–40, 2011.
- [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, pp. 3749–3763, Oct. 2005.
- [5] J. Hellgren, "Analysis of feedback cancellation in hearing aids with Filtered-x LMS and the direct method of closed loop identification," *IEEE Trans. Speech Audio Process.*, vol. 10, no. 2, pp. 119–131, 2002.
- [6] C. R. C. Nakagawa, S. Nordholm, and W.-Y. Yan, "New Insights Into Optimal Acoustic Feedback Cancellation," *IEEE Signal Process. Lett.*, vol. 20, pp. 869–872, Sept. 2013.
- [7] C. R. C. Nakagawa, S. Nordholm, and W.-Y. Yan, "Feedback Cancellation With Probe Shaping Compensation," *IEEE Signal Process. Lett.*, vol. 21, pp. 365–369, Mar. 2014.
- [8] M. Guo, S. H. Jensen, J. Jensen, and S. L. Grant, "On the Use of a Phase Modulation Method for Decorrelation in Acoustic Feedback Cancellation," in *Eur. Signal Process. Conf.*, 2012.
- [9] M. T. Akhtar and A. Nishihara, "Acoustic feedback neutralization in digital hearing aids - A two adaptive filters-based solution," in 2013 IEEE Int. Symp. Circuits Syst., pp. 529–532, IEEE, May 2013.
- [10] G. Ma, F. Gran, F. Jacobsen, and F. T. Agerkvist, "Adaptive Feedback Cancellation With Band-Limited LPC Vocoder in Digital Hearing Aids," *IEEE Trans. Audio. Speech. Lang. Processing*, vol. 19, pp. 677–687, May 2011.
- [11] S. Narayan and A. Peterson, "Frequency domain least-meansquare algorithm," *Proc. IEEE*, vol. 69, no. 1, pp. 124–126, 1981.
- [12] B. Farhang-Boroujeny and S. Gazor, "Selection of orthonormal transforms for improving the performance of the transform domain normalised LMS algorithm," *IEE Proc. F Radar Signal Process.*, vol. 139, no. 5, p. 327, 1992.
- [13] J. J. Shynk, "Frequency-domain and multirate adaptive filtering," *IEEE Signal Process. Mag.*, vol. 9, no. 1, pp. 14–37, 1992.
- [14] J. M. Gil-Cacho, T. van Waterschoot, and M. Moonen, "Transform Domain Prediction Error Method for Improved Acoustic Echo and Feedback Cancellation," in *Eur. Signal Process. Conf.*, pp. 2422–2426, Aug. 2012.
- [15] C. R. C. Nakagawa, S. Nordholm, and W.-Y. Yan, "Dual microphone solution for acoustic feedback cancellation for assistive listening," in 2012 IEEE Int. Conf. Acoust. Speech Signal Process., pp. 149–152, IEEE, Mar. 2012.
- [16] J. Huo, S. Nordholm, and Z. Zang, "New weight transform schemes for delayless subband adaptive filtering," in *Glob. Telecommun. Conf. 2001. GLOBECOM'01. IEEE*, vol. 1, pp. 197–201 vol. 1, IEEE, 2001.

- [17] D. Morgan and J. Thi, "A delayless subband adaptive filter architecture," *IEEE Trans. Signal Process.*, vol. 43, no. 8, pp. 1819–1830, 1995.
- [18] L. Ljung, System Identification Theory for the User. Prentice-Hall, 1999.
- [19] J. Blauert, Spatial hearing: the psychophysics of human sound localization. MIT press, 1997.
- [20] D. F. Elliott and K. R. Rao, Fast transforms: algorithms, analyses, applications. Academic press New York, 1982.
- [21] P. Duhamel and M. Vetterli, "Fast fourier transforms: A tutorial review and a state of the art," *Signal Processing*, vol. 19, pp. 259–299, Apr. 1990.
- [22] P. C. Loizou, Speech enhancement: theory and practice. CRC press, 2007.