A PEM-BASED FREQUENCY-DOMAIN KALMAN FILTER FOR ADAPTIVE FEEDBACK CANCELLATION

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ABSTRACT

Adaptive feedback cancellation (AFC) algorithms are used to solve the problem of acoustic feedback, but, frequently, they do not address the fundamental problem of loudspeaker and source signal correlation, leading to an estimation bias if standard adaptive filtering methods are used. Loudspeaker and source signal prefiltering via the prediction-error method (PEM) can address this problem. In addition to this, the use of a frequency-domain Kalman filter (FDKF) is an appealing tool for the estimation of the adaptive feedback canceler, given the advantages it offers over other common techniques, such as Wiener filtering. In this paper, we derive an algorithm employing a PEM-based prewhitening and a frequency-domain Kalman filter (PEM-FDKF) for AFC. We demonstrate its improved performance when compared with standard frequency-domain adaptive filter (FDAF) algorithms, in terms of reduced estimation error, achievable amplification and sound quality.

***Index Terms*—** Adaptive feedback cancellation (AFC), prediction-error method (PEM), Kalman filter, source signal modeling

1. INTRODUCTION

Acoustic feedback represents a detrimental phenomenon that can affect different kinds of acoustic systems. The feedback problem occurs when there exists an (unwanted) acoustic coupling between loudspeaker(s) and microphone(s) of an acoustic system, causing the transition from an open-loop to a closed-loop system. Closed-loop systems can become unstable even when the different components within the loop are individually stable and the result of such instability, when dealing with acoustic signals, is the well-known howling artifact. This artifact can often lead to perceptual annoyance due to the distortions produced on the desired signal and must therefore be limited. Applications reducing these artifacts are found, e. g., in sound reinforcement systems [1] and hearing aids [2].

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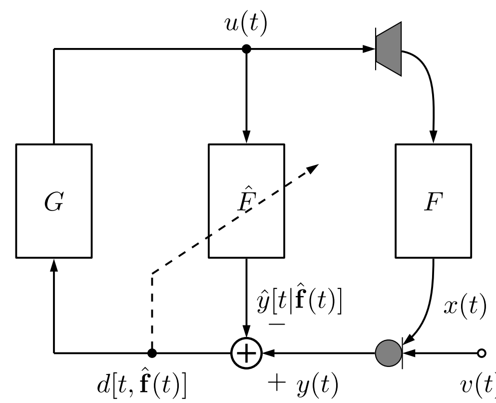

Fig. 1. General adaptive feedback cancellation.

A useful approach to tackle the feedback problem is based on adaptive filtering, leading to the so-called adaptive feedback cancellation (AFC), see Fig. 1. The scheme in the figure depicts a typical acoustic scenario affected by feedback where the microphone signal $y(t)$, t being the discrete-time index, is given by the sum of the source signal $v(t)$, i. e. the signal to be amplified, and the unwanted feedback component $x(t)$. In the AFC, the adaptive filter $\hat{\mathbf{f}}(t)$ estimates, at time t, the linear and of finite order n_F (assumed to be known) true acoustic feedback path $\mathbf{f} = [f_0 \quad f_1 \quad \dots \quad f_{n_F-1}]^{\mathrm{T}}$ to remove the prediction $\hat{y}[t|\hat{\mathbf{f}}(t)]$ of $x(t)$ from the microphone signal $y(t)$. The closed-loop transfer function (TF) $C_{\mathrm{TF}}(q)$ of the system, i. e. from $v(t)$ to $u(t)$, is easily found as:

$$C_{\mathrm{TF}}(q) = \frac{G(q)}{1 - G(q)\left[F(q) - \hat{F}(q)\right]}, \tag{1}$$

where q^{-1} represents the delay operator used to define the polynomial TFs $G(q)$, $F(q)$ and $\hat{F}(q)$ of the forward path, the feedback path and the estimated feedback path, respectively. The Nyquist stability criterion [1] defines the maximum (frequency-dependent) gain the system can sustain without becoming unstable. From Eq. (1) we see that if the estimate $\hat{F}(q)$ approximates well enough (ideally equals) $F(q)$, the closed-loop frequency response approximates the forward path $G(q)$, i. e. the open-loop frequency response.

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Unfortunately, classic adaptive filter theory is not optimal for closed-loop systems, because of the correlation existing between the reference signal and the noise signal (represented, in AFC, by loudspeaker and source signal, respectively) leading to an estimation bias if standard adaptive filtering methods are used. Decorrelation between the loudspeaker and source signal can be achieved using a whitening prefilter, estimated via the prediction-error method (PEM), on both of the signals [1]. Additionally, setting some of the critical parameters, such as the stepsize for the AFC update, is not always a trivial task [3]; for instance, compared to other common adaptive filtering procedures, such as adaptive echo cancellation (AEC), the choice of the stepsize in a feedback system is much more involved, since the adaptive filter has to operate in a continuous so-called "double-talk" situation [1].

This paper presents an AFC algorithm capable of dealing with such problems by means of a PEM-based prewhitening stage in combination with an optimal feedback canceler, estimated using a frequency-domain Kalman filter (FDKF). The approach allows to address both the reduction of the estimation bias, caused by the correlation between loudspeaker and source signal, and the choice of the stepsize, which is tuned adaptively.

The paper is structured as follows: in Section 2, we give a brief description of different definable minimization criteria for AFC; in Section 3, we show how to exploit Kalman-filter theory, using a "slow" time-variability assumption for the feedback path, to adaptively estimate the feedback canceler; in Section 4, we show some simulation results that highlight the faster convergence of the new algorithm as well as the improved stability; finally, the conclusions are given in Section 5.

2. DIFFERENT MINIMIZATION CRITERIA IN ADAPTIVE FEEDBACK CANCELLATION

The extended version of the AFC in Fig. 1 that we are going to use is shown in Fig. 2. Time variability is now assumed for all the polynomial TFs, e. g. $F(q) \rightarrow F(q,t)$. This AFC exploits the benefits deriving from the source signal modeling through a PEM-based prewhitening [1], which strongly reduces the correlation between loudspeaker and source signal. This reduced correlation allows to lower the bias of the feedback path estimate and hence to obtain a more efficient feedback cancellation. Some new quantities are introduced in Fig. 2: $H(q,t)$ is assumed to be a monic, inversely stable, time-varying model of the source signal $v(t)$ fed with the white noise sequence $e(t)$; $y_a[t, \hat{\mathbf{a}}(t)]$ and $u_a[t, \hat{\mathbf{a}}(t)]$ are, respectively, the microphone and loudspeaker signal filtered with the estimated inverse source signal model $\hat{A}(q,t) = \hat{H}^{-1}(q,t)$, and, finally, $\varepsilon[t, \hat{\mathbf{a}}(t), \hat{\mathbf{f}}(t)]$ is the prediction error signal. For the sake of clarity, the dependencies of the signals on $\hat{\mathbf{a}}(t)$, and $\hat{\mathbf{f}}(t)$ will be dropped.

The impulse response (IR) $\mathbf{f}(t)$ is assumed to completely model the feedback path so that the microphone signal $y(t)$ can be expressed as the sum of the source signal $v(t)$ and the feedback signal $x(t)$, i. e. $y(t) = v(t) + x(t) = v(t) + \mathbf{f}^{\mathrm{T}}(t)\mathbf{u}(t)$, with the loudspeaker signal vector defined as $\mathbf{u}(t) = [u(t) \quad u(t-1) \quad \dots \quad u(t-n_F+1)]^{\mathrm{T}}$. An alternative representation of the filtering operation can be given using the polynomial TF $F(q,t)$, i. e. $\mathbf{f}^{\mathrm{T}}(t)\mathbf{u}(t) = F(q,t)u(t)$.

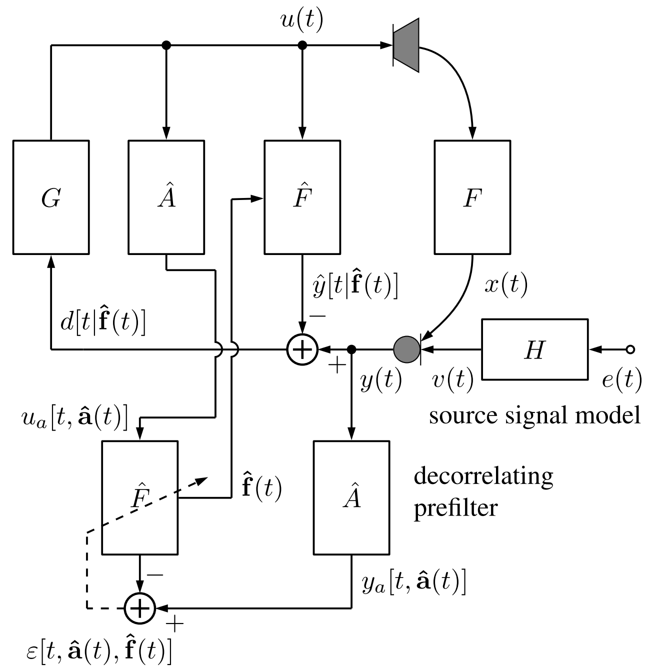

Fig. 2. Complete adaptive feedback cancellation algorithm.

To estimate the unknown vector $\mathbf{f}(t)$, different optimization criteria can be defined. Introducing $\mathbb{E}\{\cdot\}$ as expectation operator, a common criterion, widely used in adaptive filter theory [3], is given as

$$\min_{\hat{\mathbf{f}}(t)} \mathbb{E}\left\{\left|y(t) - \hat{\mathbf{f}}^{\mathrm{T}}(t)\mathbf{u}(t)\right|^2\right\} \tag{2}$$

where $\hat{\mathbf{f}}(t)$ minimizes the power of the error signal $d(t)$. It can be shown that the solution of the estimation problem in Eq. (2) is unbiased if $\mathbb{E}\{\mathbf{u}(t)v(t)\} = \mathbf{0}$, which is not the common case in AFC, due to the closed-loop nature of the system [2].

The bias of the estimate can be reduced, ideally eliminated [1], by modifying Eq. (2) into

$$\min_{\hat{\mathbf{f}}(t)} \mathbb{E}\left\{\left|y_a(t) - \hat{\mathbf{f}}^{\mathrm{T}}(t)\mathbf{u}_a(t)\right|^2\right\}, \tag{3}$$

where both the loudspeaker signal vector and the microphone signal are prefiltered via $\hat{A}(q,t)$, the estimated inverse of the source signal model $H(q,t)$, i. e.

$$\mathbf{u}_a(t) = \begin{bmatrix} \hat{A}(q,t)u(t) \\ \vdots \\ \hat{A}(q,t)u(t-n_F+1) \end{bmatrix} \tag{4a}$$

$$y_a(t) = \hat{A}(q,t)y(t). \tag{4b}$$

The argument of the expected value in Eq. (3) can be seen to match the power of the prediction error signal $\varepsilon(t)$, cf. Fig. 2.

A less widespread optimization criterion, e. g. used in the work by Enzner and Vary [4], considers the mean-square error (MSE) between the signals $v(t)$ and $d(t)$, i. e.

$$\min_{\hat{\mathbf{f}}(t)} \mathbb{E}\left\{|v(t) - d(t)|^2\right\}, \tag{5}$$

and, in AFC, the choice of this criterion is rather appealing considering the very definition of the feedback cancellation goal, i. e. the reproduction of the amplified source signal in the loudspeaker, without distortions due to the feedback coupling between $u(t)$ and $y(t)$. Minimizing the difference between the error signal $d(t)$ and the (unknown) source signal $v(t)$, indeed leads to the set goal in a more intuitive way, when compared with the other criteria. Unfortunately, the statistical behavior of the resulting estimate has been studied only for the AEC case and further analysis is needed for an extension to the AFC case.

Finally, a different and straightforward criterion considers the MSE between the true and estimated IR

$$\min_{\hat{\mathbf{f}}(t)} \mathbb{E}\left\{\left\|\mathbf{f}(t) - \hat{\mathbf{f}}(t)\right\|^2\right\}. \tag{6}$$

Such a criterion is motivated by statistical properties [5,6] and, similar to the criterion in Eq. (5), corresponds to very intuitive condition. A modified version of the optimization problem in Eq. (6) is the one we are aiming to solve with the algorithm proposed in this paper, which will be introduced in Section 3.

It is important to notice that both the criteria in Eqs. (5) and (6) require a shift from a deterministic to a stochastic framework, since both rely on the use of unknown quantities, respectively $v(t)$ and $\mathbf{f}(t)$. Therefore, these quantities should be treated as two stochastic processes described by some available prior knowledge; in particular, for the case of $\mathbf{f}(t)$, this leads to a Bayesian framework.

A common model for the source signal $v(t)$ is a random process with zero mean and autocorrelation $\varphi_{\mathrm{vv}}(t,n) = \mathbb{E}\{v(t)v(t+n)\}$ [4, 5]. A similar model could be chosen for the unknown feedback path $\mathbf{f}(t)$. However, it is reasonable to assume that the dynamical behavior of the feedback path is characterized by smooth transitions; therefore, we could use a less erratic model than a simple random vector process. The same idea was applied in AEC [4], where the "slow" echo path variability was modeled by means of a random walk, i. e. a first-order Markov process. The inclusion of this model in the optimization problem defined in Eq. (6) leads to the derivation of a solution based on the Kalman filter.

3. PEM-BASED FREQUENCY-DOMAIN KALMAN FILTER (PEM-FDKF)

As mentioned in the previous section, the estimation of the unknown feedback path can be tackled using an approach similar to that proposed by Enzner and Vary [4] for AEC, where the echo path is modeled using a first-order Markov model and the estimation process is carried out via a frequency-domain Kalman filter (FDKF) with some additional simplifications. However, some changes must be introduced in order to adapt such a framework to AFC. In particular, the previously discussed correlation between loudspeaker and source signal must be reduced, or eliminated, by means of a PEM-based prewhitening filter addressing such an issue. Although the proposed algorithm differs from the standard PEM, the acronym PEM was retained since the update equations of the Kalman filter rely on the frequency-domain version of $\varepsilon(t)$.

The choice of a frequency-domain approach has several advantages: not only does it allow a lower computational complexity, it also reinforces the role of the prefilters due to the good (although not perfect) decorrelation properties of the discrete Fourier transform [7]. Additionally, the formulation of the problem as a Kalman filter modeling allows to optimally estimate the frequency-dependent stepsize of the adaptive procedure [4], leading to a significantly improved convergence.

To correctly formulate the problem in the frequency domain [7], we must first move from the discrete time t to the discrete time-frame index k and introduce the discrete frequency index l. This allows to introduce the several frame-based quantities playing a role in the model, starting from the M-samples loudspeaker signal frame at time $k \in \mathbb{Z}$,

$$\mathbf{u}(k) = [u(kR - M + 1) \quad \ldots \quad u(kR-1) \quad u(kR)]^{\mathrm{T}}, \tag{7}$$

where R denotes the frame shift. Following a common approach found in literature [2, 5], the model $H(q,t)$ generating the source signal $v(t)$ is assumed to be time-varying and autoregressive (AR); the AR model coefficients $\hat{\mathbf{h}}(k)$ are then estimated using the Levinson-Durbin algorithm [3, pp. 254-264]. Using the estimate $\hat{A}(q, t-1)$, the prefiltered version of the loudspeaker signal frame is defined as

$$\mathbf{u}_a(k) = \begin{bmatrix} \hat{A}(q,t-1)u(kR) \\ \vdots \\ \hat{A}(q,t-1)u(kR-M+1) \end{bmatrix} \tag{8a}$$

$$= [u_a(kR - M + 1) \quad \ldots \quad u_a(kR-1) \quad u_a(kR)]^{\mathrm{T}}. \tag{8b}$$

The frequency-domain version of the prefiltered loudspeaker signal can be expressed by introducing the discrete Fourier transform matrix $\mathbf{F}_{\mathrm{M}}$ of size $M \times M$ and deriving the associated diagonal matrix via the $\mathrm{diag}\{\cdot\}$ operator

$$\mathbf{U}_a(k) = \mathrm{diag}\{\mathbf{F}_{\mathrm{M}}\mathbf{u}_a(k)\}. \tag{9}$$

The frequency-domain version of the feedback path $\mathbf{f}(t)$ requires a frame-based representation as well, and to do so we need to assume the finite IR (FIR) nature of $f(t)$:

$$\mathbf{f}(k) = [f(0,k) \quad f(1,k) \quad \ldots \quad f(M-R-1,k)]^{\mathrm{T}} \tag{10a}$$

$$\mathbf{F}(k) = \mathbf{F}_{\mathrm{M}} \begin{pmatrix} \mathbf{f}(k) \\ \mathbf{0} \end{pmatrix}. \tag{10b}$$

The parameters R and M should be chosen properly, taking into consideration the length of the true feedback path; a reasonable choice is $R = n_F$ and $M = 2R$ [7, 8].

Finally, we introduce the R-samples prefiltered microphone signal and source signal frame at time $k \in \mathbb{Z}$, i. e.

$$\mathbf{y}_a(k) = [y_a(kR - R + 1) \quad \ldots \quad y_a(kR-1) \quad y_a(kR)]^{\mathrm{T}} \tag{11a}$$

$$\mathbf{e}(k) = [e(kR-R+1) \quad \dots \quad e(kR-1) \quad e(kR)]^{\mathrm{T}}, \tag{11b}$$

and their corresponding frequency-domain versions:

$$\mathbf{Y}_a(k) = \mathbf{F}_{\mathrm{M}}\mathbf{Q}\mathbf{y}_a(k) \tag{12a}$$

$$\mathbf{E}(k) = \mathbf{F}_{\mathrm{M}}\mathbf{Q}\mathbf{e}(k), \tag{12b}$$

with $\mathbf{Q} = \begin{pmatrix}\mathbf{0} & \mathbf{I}_{\mathrm{R}}\end{pmatrix}^{\mathrm{T}}$ being the projection matrix of size $M \times R$ to be used together with $\mathbf{F}_{\mathrm{M}}$ to obtain the suitable frequency domain versions of $\mathbf{y}_a(k)$ and $\mathbf{e}(k)$.

From the equations introduced so far, we can combine a linear model for $\mathbf{Y}_a(k)$ together with the Markov model for the feedback path, and define the following state-space representation:

$$\mathbf{F}(k+1) = A \cdot \mathbf{F}(k) + \mathbf{N}(k) \tag{13a}$$

$$\mathbf{Y}_a(k) = \mathbf{C}_a(k)\mathbf{F}(k) + \mathbf{E}(k), \tag{13b}$$

where $\mathbf{C}_a(k) = \mathbf{F}_{\mathrm{M}}\mathbf{Q}\mathbf{Q}^{\mathrm{T}}\mathbf{F}_{\mathrm{M}}^{-1}\mathbf{U}_a(k)$ is the linear transformation of $\mathbf{U}_a(k)$ allowing to correctly compute the linear convolution between $\mathbf{u}_a(k)$ and $\mathbf{f}(k)$, $\mathbf{N}(k)$ is the noise process representing the unpredictability of the feedback path and A is the transition factor accounting for the time-variability of the feedback path model [4]. The estimation of $\mathbf{N}(k)$ is based on the model equation (13a) and exploits the assumption that the feedback path statistics has a much slower rate of change than the source signal statistics [4]. The value of the transition factor A should be chosen to be $0 \ll A < 1$ [4,9].

The state space-model in Eq. (13) employs prefiltered variables and, in this way, approximates the assumed decorrelation between loudspeaker and source signal; this assumption is needed when using a Kalman filter to estimate $\mathbf{F}(k)$. Kalman-filter theory allows to obtain a linear minimum MSE (MMSE) estimate of the state $\mathbf{F}(k)$ given the model defined in Eq. (13), i. e. solving the optimization problem [6, ch. 13]

$$\min_{\hat{\mathbf{F}}^+(k)} \mathbb{E}\left\{\left\|\mathbf{F}(k) - \hat{\mathbf{F}}^+(k)\right\|^2\right\}, \tag{14}$$

similar to the Bayesian optimization problem in Eq. (6).

For implementation purposes, we use the same approximations introduced by Enzner and Vary [4], allowing to address both the problem of high computational complexity and ill-posedness of the solution via diagonal operations, to modify the standard FDKF expression accordingly. The complete set of equations describing the algorithm update is as follows:

$$\hat{\mathbf{F}}(k+1) = A \cdot \hat{\mathbf{F}}^+(k) \tag{15a}$$

$$\mathbf{P}(k+1) = A^2 \cdot \mathbf{P}^+(k) + \mathbf{\Psi}_{nn}(k) \tag{15b}$$

$$\hat{\mathbf{F}}^+(k) = \hat{\mathbf{F}}(k) + \mathbf{F}_{\mathrm{M}}(\mathbf{I}_{\mathrm{M}} - \mathbf{Q}\mathbf{Q}^{\mathrm{T}})\mathbf{F}_{\mathrm{M}}^{-1}\mathbf{K}(k) \times \underbrace{\mathbf{F}_{\mathrm{M}}\mathbf{Q}\left[\mathbf{y}_a(k) - \mathbf{Q}^{\mathrm{T}}\mathbf{F}_{\mathrm{M}}^{-1}\mathbf{U}_a(k)\hat{\mathbf{F}}(k)\right]}_{\boldsymbol{\mathcal{E}}(k)} \tag{15c}$$

$$\mathbf{P}^+(k) = \left[\mathbf{I}_{\mathrm{M}} - \frac{R}{M}\mathbf{K}(k)\mathbf{U}_a(k)\right]\mathbf{P}(k) \tag{15d}$$

$$\mathbf{K}(k) = \mathbf{P}(k)\mathbf{U}_a^{\mathrm{H}}(k)\left[\mathbf{U}_a(k)\mathbf{P}(k)\mathbf{U}_a^{\mathrm{H}}(k) + \mathbf{\Psi}_{\mathrm{ee}}(k)\right]^{-1}, \tag{15e}$$

where $\mathbf{P}(k)$ is the frequency-domain estimation error covariance matrix, $\mathbf{K}(k)$ is the frequency-domain Kalman gain, the superscript $^+$ indicates a posteriori estimates and, finally, $\mathbf{\Psi}_{\mathrm{ee}}(k)$ and $\mathbf{\Psi}_{nn}(k)$ are the estimated covariance matrices of $\mathbf{E}(k)$ and $\mathbf{N}(k)$ [4], respectively. More details about the initialization of the algorithm parameters are provided in the following section. As mentioned earlier, the use of the frequency-domain prediction error $\boldsymbol{\mathcal{E}}(k)$, cf. Eq. (15c), motivates the name of the proposed algorithm.

4. SIMULATION RESULTS

We now show some simulation results in order to assess the performance of the proposed algorithm. The algorithms (novel and baselines) are compared in terms of three measures, assessing the estimation error, the achievable amplification that they can provide, and the sound quality.

The first measure is the misadjustment (Mis), defined as the normalized distance between the true and estimated IR:

$$\mathrm{Mis}(k)[\mathrm{dB}] = 20\log_{10}\|\mathbf{f}(k) - \hat{\mathbf{f}}(k)\|/\|\mathbf{f}(k)\|. \tag{16}$$

The second measure is the added stable gain (ASG) which is based on the so-called maximum stable gain (MSG), i. e. the maximum gain achievable at a given time without compromising the system stability and assuming a spectrally flat $G(k,l)$, and on the K_{MSG}, i. e. the maximum stable gain of the system when no feedback canceller is included:

$$\mathrm{ASG}(k) = \mathrm{MSG}(k) - K_{\mathrm{MSG}}. \tag{17}$$

Finally, the sound quality is assessed by means of an objective measure called frequency-weighted log-spectral signal distortion (SD), a distance measure proven to correlate quite well with subjective data in feedback cancellation tasks [10].

As baseline algorithms, we use two frequency-domain adaptive filter (FDAF) feedback cancellation algorithms based on the normalized least mean squares (NLMS) algorithm, with and without the inclusion of prefilters (PEM-FDAF [8] and FDAF [7], respectively). The two baseline algorithms are compared with the proposed FDKF implementations, with and without the prefiltering stage (PEM-FDKF and FDKF, respectively). The source signal $v(k)$ is a clean speech signal sampled at $f_{\mathrm{s}} = 8000$ Hz while $F(k,l)$ is taken from a database of recorded hearing aids feedback paths. The order of the estimated AR model for $v(k)$ was fixed to 25 and the constants of the different algorithms are as follows: the NLMS algorithm step size $\mu = 0.02$, the regularization constant $\alpha = 5 \times 10^{-5}$, and the forgetting factor $\lambda = 0.85$ (used to recursively calculate the loudspeaker signal power) for both FDAF and PEM-FDAF. These three parameters are all involved in the calculation of the feedback estimate adopting a recursive updating procedure. Furthermore, the frame shift was $R = 80$ and the FFT size was $M = 160$. Both FDKF algorithms use the initialization value $\mathbf{P}(0) = 5 \times 10^{-2}\mathbf{I}_{\mathrm{M}}$ and a transition factor $A = 0.99999$.[1] Although the Markov model in Eq. (13a) assumes a time-varying feedback path, no

[1]The value of $\mathbf{P}(0)$ is chosen from prior knowledge on the amplitude of the true feedback path (e. g. initial fitting measurements in hearing aids AFC).

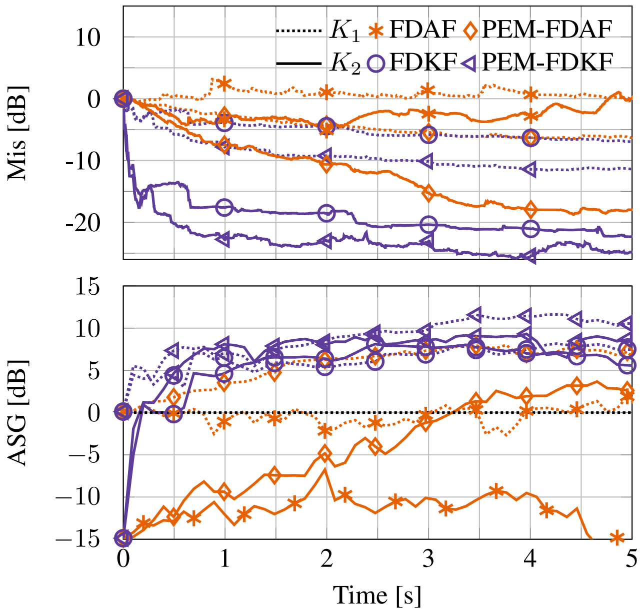

Fig. 3. Mis and ASG performance over time of the different algorithms for the two tested gains.

time variability was included in the simulations; this was done to show that the choice of A is not extremely critical.

In the first simulated case, the transfer function $G(k, l)$ is fixed to a constant gain of 3 dB below the value of the K_{MSG} (from now on referred to as K_1) with an 80-samples delay, i. e. $\geq R$.[2] Smaller delays can be achieved using a partitioned-block frequency domain approach [2]. Mis and ASG are shown using dotted lines in Fig. 3. The simple FDAF does not work properly in this case, but including the PEM-based prewhitening improves the performance by roughly 6 dB for both the metrics. The FDKF provides slightly better performance than the FDAF algorithms, by exploiting the good convergence properties of the Kalman filter. Finally, the PEM-FDKF returns the best results thanks to the decorrelating properties of the PEM-based prewhitening.

In the second simulated case, shown with solid lines in Fig. 3, a similar situation is considered where only the forward path gain is increased by 15 dB compared to the previous case; this value is referred to as K_2 in the figure. In such a scenario, the convergence of the algorithms is sped up and the Mis is reduced because of the higher gain. However, both FDAF and PEM-FDAF exhibit prolonged instability, as pointed out by the negative ASG values. Both FDKF implementations, instead, retrieve stability rather quickly; namely, in less than 0.5 s.

Finally, the sound quality results, in terms of mean and maximum SD, are reported in Table 1 for both of the tested gains. Both FDKF algorithms perform better than the FDAF algorithms in the two tested scenarios. Again, the PEM-FDKF returns the best results suggesting that the extremely limited signal distortion between loudspeaker and source signals also from an objective point of view.

[2]The 3 dB margin is usually chosen to avoid audible ringing effects [1].

Table 1. Mean and maximum SD values of the different algorithms for the two tested gains. In brackets, the results from the last second of simulation (4-5 s), achieving better convergence.

	mean(SD)		max(SD)	
	K_1	K_2	K_1	K_2
FDAF	3.21	31.97 (31.53)	8.19	58.92 (42.16)
PEM-FDAF	1.66	2.27 (2.12)	4.50	5.98 (4.36)
FDKF	1.46	1.48 (1.26)	4.45	4.77 (2.15)
PEM-FDKF	1.06	1.23 (1.19)	3.76	5.32 (2.04)

5. CONCLUSIONS

In this paper, we have presented a novel algorithm for AFC. By using a state-space model to represent the time-varying acoustic feedback path combined with a PEM-based prewhitening approach, an approximation of the FDKF was used to provide an optimal adaptive estimator of the unknown feedback path.

Simulation results have shown the improved performance exhibited by the presented algorithm compared to two simpler FDAF implementations, in terms of estimation error, added stable gain and sound quality.

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