# CONTROLLING THE ADAPTATION OF FEEDBACK CANCELLATION FILTERS – PROBLEM ANALYSIS AND SOLUTION APPROACHES

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**ABSTRACT**

Feedback is an inherent problem to all hearing aid applications. The compensation approach, i.e. modelling the feedback path with an adaptive FIR filter is a method which allows avoiding feedback without effecting the desired signal. However, this approach is hard to be realized. Due to the correlation of the input and feedback signals, the adaptation is crucial and has to be controlled sophistically. In the paper, a detailed analysis of the feedback compensator structure is given and compared to the echo cancellation structure. It will be shown that classical control methods which have proven to be powerful for echo cancellation, cannot be applied for feedback cancellation and alternative control methods will be introduced and evaluated.

## 1. INTRODUCTION

One major problem when designing hearing aids is feedback which occurs due to the closed assembly of the hearing aid receiver's output and the hearing aid microphone(s) in combination with the usually high hearing aid amplification.

The usual approach, which allows to cancel feedback without attenuating or disturbing the desired signal, is to place an adaptive FIR filter, which models the external feedback path, in parallel to the hearing aid. The structure of such a hearing aid is depicted in Fig. 1.

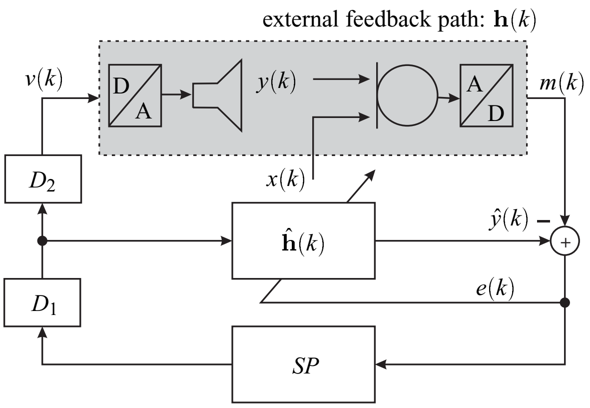


Figure 1: General setup of a feedback cancellation system with *SP* modeling the hearing aid signal processing, $\mathbf{h}(k)$ the external feedback path, $\hat{\mathbf{h}}(k)$ the adaptive filter, and $D_1$, $D_2$ adjustable delays.

The external feedback path, $\mathbf{h}(k)$, comprises the D/A and A/D converters, the loudspeaker and microphone characteristics, and the acoustic feedback path. All the signal processing inherent to typical state of the art hearing aids is combined in the *SP* block in Fig. 1.

Usually, this signal processing involves some kinds of noise reduction to reduce ambient noise and AGC (automatic gain control) blocks in different frequency bands. The AGC equalizes level dependent effects of hearing loss (recruitment). The last component of the *SP* block is a peak limiter to avoid overload of the D/A converters. The AGC and peak limiters involve some kinds of non-linear signal processing.

In the following, the structures for echo compensation and hearing aids as shown in Fig. 1 are compared. Speaking in echo cancellation terminology, $x(k)$ is the local speaker located in the loudspeaker enclosure microphone (LEM) environment whereas $v(k)$ is the signal coming from the far-end speaker and $e(k)$ is the signal going back to the far-end speaker. In the hearing aid context, however, this signal is the hearing aid input which is fed back to the hearing aid loudspeaker. Thus, the system is permanently in the state which is known as "double-talk" for echo cancellation. Additionally, the usually assumption that the feedback signal $y(k)$ and input signal $x(k)$ are uncorrelated does not hold.

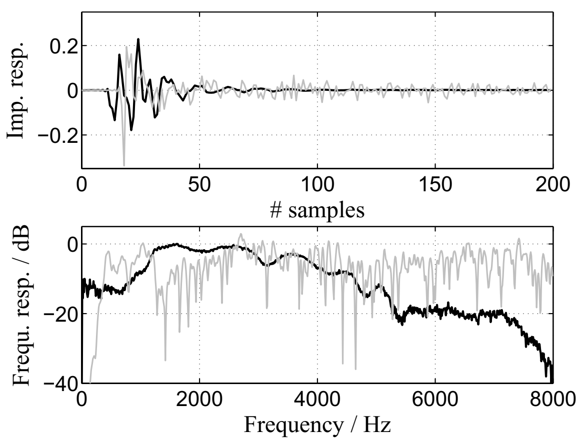


Figure 2: Impulse (above) and frequency (below) responses of hearing aid feedback path (dark) and echo path of a hands-free car phone (light) sampled at 16 kHz.

In Fig. 2, a typical feedback path for hearing aids worn behind the ear (BTE) is compared to a LEM impulse response of a car. Two major differences can be observed: On the one hand, feedback impulse responses are much shorter than LEM impulse responses. This, because nearly only reflections around the ear contribute to the feedback impulse responses. On the other hand, the feedback channels exhibit a band-pass characteristic. Typically, these channels show the lowest attenuation for frequency components between 1 and 4 kHz. As in contrast, typical input signals, $x(k)$, such as speech or music exhibit large components below 1 kHz, the feedback signal, $y(k)$, to input signal, $x(k)$, power ratio is very small below 1 kHz. Adapting only the frequency components of the filter $\hat{\mathbf{h}}(k)$ above 1 kHz may cancel strong components disturbing the adaptation [2, 3].

However, the major problem is the adaptation of the system for permanent "double-talk". Additionally, the system structure of feedback cancellation involves the problem that the adaptive filter converges to a setting that not only cancels feedback but distorts the desired signal. The analysis of this problem is described in Section 2. The effect of this problem on the step-size control is considered in Section 3. Especially methods will be analyzed which proved their suitability for echo cancellation but unfortunately only their restrictive application is possible for the control of feedback cancellation filters. In Section 4, alternative control approaches are investigated before concluding the paper in Section 5.

## 2. PROBLEM DESCRIPTION

Looking at the structure of the complete feedback cancellation system according to Fig. 1 with $D_1 = D_2 = 0$, the only criterion for the adjustment of the filter coefficients $\hat{\mathbf{h}}(k)$ is the minimization of the mean square of the error signal $e(k)$. Writing $e(k)$ as

$$e(k) = x(k) + \sum_{l=0}^{N-1} [h_l(k) - \hat{h}_l(k)]\, v(k-l), \quad (1)$$

where the adaptive filter is assumed to model the complete feedback path of length $N$, and deriving the mean square error $\mathrm{E}\{e^2(k)\}$ with respect to $\hat{h}_l(k)$, one obtains the following relation known as orthogonality theorem:

$$\mathrm{E}\{v(k-l)\, e(k)\} \overset{!}{=} 0 \quad l \in [0, N-1]. \quad (2)$$

Writing Eqn. 1 in vector notation as

$$e(k) = x(k) + [\mathbf{h}(k) - \hat{\mathbf{h}}(k)]^T \mathbf{v}(k) \quad (3)$$

with $\mathbf{v}(k) = [v(k), \ldots, v(k-N+1)]^T$, $\hat{\mathbf{h}}(k) = [\hat{h}_0(k), \ldots, \hat{h}_{N-1}(k)]^T$ and $\mathbf{h}(k) = [h_0(k), \ldots, h_{N-1}(k)]^T$ and deriving the mean square error with respect to $\hat{\mathbf{h}}(k)$, one obtains the following equation:

$$\mathbf{r}_{x\mathbf{v}}(k) + \mathbf{R}_{\mathbf{vv}}(k)\, [\mathbf{h}(k) - \hat{\mathbf{h}}(k)] = [0, \ldots, 0]^T, \quad (4)$$

with the cross-correlation vector $\mathbf{r}_{x\mathbf{v}}(k) = \mathrm{E}\{x(k)\, \mathbf{v}(k)\}$ and the autocorrelation matrix $\mathbf{R}_{\mathbf{vv}}(k) = \mathrm{E}\{\mathbf{v}(k)\mathbf{v}^T(k)\}$, respectively.

Resolving this equation with respect to $\hat{\mathbf{h}}(k)$, it becomes obvious that the optimum solution which minimizes the mean square error is a bias of the true feedback path:

$$\hat{\mathbf{h}}_{opt}(k) = \mathbf{h}(k) + \mathbf{R}_{\mathbf{vv}}^{-1}(k)\, \mathbf{r}_{x\mathbf{v}}(k). \quad (5)$$

The second term $\mathbf{R}_{\mathbf{vv}}^{-1}(k)\, \mathbf{r}_{x\mathbf{v}}(k)$ distorts the input signal $x(k)$ as the signal $v(k)$ is filtered such that all predictable components of $x(k)$ are subtracted, i.e. $x(k)$ is whitened. For an alterantive derivation of correlation effects, see e.g. [5].

To demonstrate the relations, simulations were performed where the *SP* block of Fig. 1 was simply set to a gain $g$. The filter $\hat{\mathbf{h}}(k)$ was adapted under three different conditions:

1. for a white input signal,
2. for a colored input signal with the external feedback path turned to zero: $\mathbf{h} = [0, \ldots, 0]^T$, and
3. for a colored input signal with an activated model of the external feedback path.

For the feedback path, a very simple model was used with $\mathbf{h} = [1\ -0.6\ 0.1\ -0.3\ -0.2]^T$ and $D_2$ was set to 3. The colored input signal was generated by a MA (moving average) process: $x(k) = u(k) + \sum_{l=0}^{L} b(l)\, u(k-l-1)$, with a white signal $u(l)$ and $L = 20$.

The results are depicted in Fig. 3. For the white input signal, the filter $\hat{\mathbf{h}}(k)$ adapts – as desired – to the feedback path (upper graph). When the feedback path is turned off and the colored signal is used as input, however, the filter acts as a decorrelation filter: If the *SP* block simply is a gain $g = 1$ the filter coefficients model the coefficients $b(l)$ of the input signal's model (middle graph). The result, which is obtained for the case when a colored signal is used to identify the feedback path, shows the superposition of both, the true feedback path and the FIR model of the input signal (lower graph).

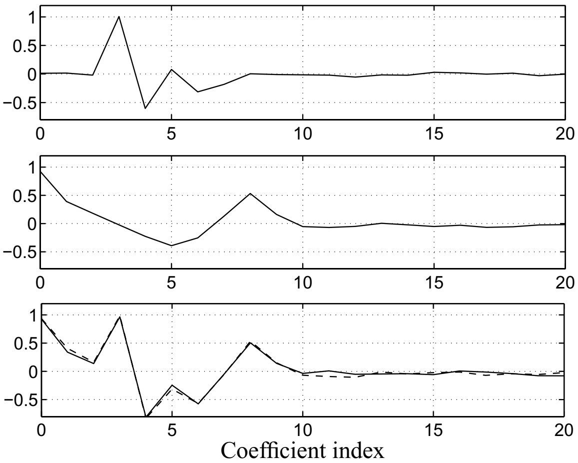


Figure 3: Results for $\hat{\mathbf{h}}(k)$ for white (above) and colored excitation with external feedback path off (middle) and on (below). In the lower graph it is shown that the filter (solid line) nearly converges to the sum of the upper and middle graph (dashed line).

Unfortunately, the last case corresponds to the general application for which the decorrelating effect of the feedback cancellation filter can hardly be avoided. The impact on the control of this filter, especially on the suitability of the control methods utilized for echo cancellation, will be shown in the next section.

## 3. ANALYSIS OF THE METHODS UTILIZED IN ECHO CANCELLATION FOR THE CONTROL OF FEEDBACK CANCELLATION

Unfortunately, the property that the feedback cancellation filter decorrelates the input signal has large impact on the control of the feedback cancellation filter: Most of the methods for estimating the convergence rate of the adaptive system – which is the most challenging problem when controlling adaptive filters – that give good results for echo cancellation cannot be applied.

### 3.1 Optimal step-size for feedback cancellation

Before going into details, a short review of the derivation of the optimal step-size for echo cancellation when utilizing the normalized LMS adaptation procedure according to [4] is given. The derivation of the optimal step-size for the feedback cancellation application can be performed identically up to the step when the optimal step-size is noted as:

$$\alpha_{opt}(k) = \frac{\mathrm{E}\{e(k)\, \varepsilon(k)\}}{\mathrm{E}\{e^2(k)\}}, \quad (6)$$

with $\varepsilon(k) = [\mathbf{h}(k) - \hat{\mathbf{h}}(k)]^T \mathbf{v}(k)$ being the error signal due to filter mismatch, the so-called undisturbed error. Thus, $e(k) = x(k) + \varepsilon(k)$.

Since $\varepsilon(k)$ and $x(k)$ are, in contrast to echo cancellation, not uncorrelated, the numerator of $\alpha_{opt}(k)$ has to be written as follows:

$$\mathrm{E}\{e(k)\, \varepsilon(k)\} = \mathrm{E}\{\varepsilon^2(k)\} + \mathrm{E}\{x(k)\, \varepsilon(k)\}. \quad (7)$$

Supposing the filter $\hat{\mathbf{h}}(k)$ is adapted to the biased solution $\hat{\mathbf{h}}_{opt}(k)$ according to Eqn. 5, one can easily determine that in this case $\mathrm{E}\{e(k)\, \varepsilon(k)\} = 0$. Thus, $\mathrm{E}\{x(k)\, \varepsilon(k)\}$ is a negative value that compensates the value $\mathrm{E}\{\varepsilon^2(k)\}$ which is – due to the bias of $\hat{\mathbf{h}}_{opt}(k)$ – a non-zero and positive quantity.

Neglecting the term $\mathrm{E}\{x(k)\, \varepsilon(k)\}$ and choosing

$$\alpha_{opt}(k) = \frac{\mathrm{E}\{\varepsilon^2(k)\}}{\mathrm{E}\{e^2(k)\}} \quad (8)$$

which is the optimum step-size known from echo cancellation, results in a too large step-size for non-white, i.e. colored input signals.

The larger the bias of $\hat{\mathbf{h}}_{opt}(k)$, the larger is the error when choosing the step-size according to Eqn. 8 instead according to Eqn. 6.

Two effects of the choice of the step-size can be observed:

1. For colored input, the too large step-size impedes the filter to convert closely to the (biased) filter values $\hat{\mathbf{h}}_{opt}(k)$. As they differ from the true feedback path anyway, this choice of the step-size has no real negative impact.
2. Whenever the filter $\hat{\mathbf{h}}(k)$ has been chosen to $\mathbf{h}(k)$, e.g. because of a rather white input signal in the past, the step-size according to Eqn. 8 stays low and avoids or at least delays the adaptation to the biased solution according to Eqn. 5, whenever the input signal's correlation properties change.

Concluding, the choice of the step-size according to Eqn. 8 is rather advantageous, than showing a negative impact. The dominant problem, however, still is the filter bias for non-white input signals. Therefore, additional to the optimum step-size, further means (s. Section 4) are required to avoid or reduce erroneous adaptation. In the following, methods will be analyzed to obtain an estimate of the step-size according to Eqn. 8.

### 3.2 Determining the optimal step-size

As the undisturbed error signal is not available, its power has to be estimated based other available signals. An efficient method proposed in [4] is the product of the mean power of the filter excitation signal and the system distance:

$$\mathrm{E}\{\varepsilon^2(k)\} \approx \mathrm{E}\{v^2(k)\} \cdot \mathrm{E}\{\| \mathbf{h}(k) - \hat{\mathbf{h}}(k) \|^2\}. \qquad (9)$$

### 3.3 Estimating the system distance

Corresponding to [4], the most powerful methods for the echo cancellation application for estimating the system distance $\mathrm{E}\{\| \mathbf{h}(k) - \hat{\mathbf{h}}(k) \|^2\}$ are the estimation of the coupling factor and the delay coefficient method.

#### *3.3.1 Estimation with the coupling factor*

The determination of the coupling factor requires periods of "single talk", i.e., periods without presence of a signal which disturbs the adaptation. In our case, this is equivalent to $x(k) = 0$. Unfortunately, for the feedback cancellation application, $x(k)$ is the only excitation signal – the "signal talk" situation is never present. Thus, the coupling factor cannot be utilized for controlling the adaptation of the feedback cancellation filter.

#### *3.3.2 Estimation with the delay coefficient method*

The delay coefficient method inserts a delay in the signal path denoted as $D_2$ in Fig. 1. This delay has to be modeled by the adaptive filter. For white input $x(k)$ or for the echo cancellation application, the coefficients modeling the delay (in the following: delay coefficients) ideally converge to zero and their mean deviation from zero can be utilized for extrapolating to the estimation of the filter convergence [6]. However, for feedback cancellation and the usual non-white input, the delay coefficients additionally model the input spectrum as shown in the lower graph of Fig. 3. Thus, for feedback cancellation, the delay coefficients are not representative for the filter convergence.

Concluding, the two major filter control methods usually applied for echo cancellation cannot be used for the control of feedback cancellation filters.

#### *3.3.3 Shadow filter approach*

However, not all detection methods which show a good performance are irrelevant for feedback cancellation. The shadow filter approach [4] also provides helpful information for the feedback filter control. Here, a second, usually shorter filter is put in parallel to the adaptive filter (reference filter). For this filter, also, the error signal is determined, but not for the use as output, only for control purposes.

Usually, if this error signal is in mean smaller than the error of the reference filter, the shadow filter is better converged. However, this is not always true for feedback cancellation. The reason is that the feedback cancellation filter also decorrelates the input signal. Thus, for strongly correlated input signals, i.e. signals with a slowly decreasing autocorrelation, the converged reference filter may give a larger output than the misadjusted shadow filter which is misadjusted to the feedback path but well adjusted to the input signal. Though the shadow filter approach cannot directly be utilized for detecting a badly converged reference filter, a lower error signal of the shadow filter indicates that either the feedback path has changed or a strongly correlated input signal is present. Thus, additional methods are required which differentiate between these two cases because they require a high (feedback path change) or a low (correlated input signal) step-size, respectively.

## 4. ALTERNATIVE ADAPTATION AND CONTROL APPROACHES

In the previous section, traditional control approaches known from echo cancellation were analyzed for the application to feedback cancellation. Unfortunately, the correct adaptation of the filter is a very sophisticated task mainly due to the correlated input.

### 4.1 Decorrelation Filters

As for white input signals the adaptation works well, an adaptive decorrelation filter for the input signal $x(k)$ could solve the adaptation problem. Unfortunately, the signal $x(k)$ is not available. Alternatively, the decorrelation filter may be put at the input of the hearing aid signal processing as indicated in Fig. 4. However, adapting the decorrelation filter based on $m(k)$, not on $x(k)$ decorrelates the sum of $x(k)$ and the feedback signal $y(k)$. Thus, when feedback is present, the decorrelation filter adapts to a kind of notch filter that mainly attenuates the frequency components where feedback is present. Unfortunately, this impedes the adaptive filter to adapt the feedback frequency components and to quickly cancel feedback. This problem may be reduced, e.g. by constraining the filter not to adapt to the type of a notch filter. However, for this rather complicated control methods are required.

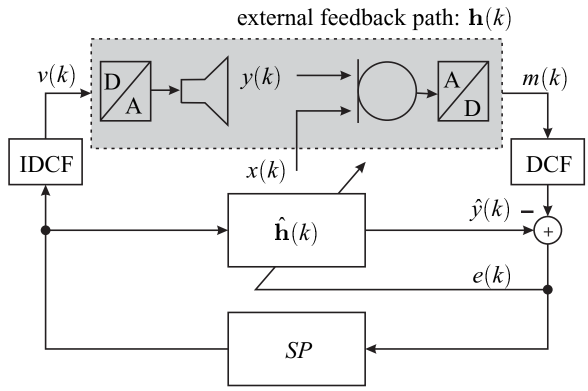


Figure 4: Feedback cancellation system with decorrelation (DCF) and inverse decorrelation (IDCF) filters.

### 4.2 Decorrelating the signals $x(k)$ and $v(k)$

The bias of the filter coefficients is given in Eqn. 5 and is dependent on the correlation of $x(k)$ and $v(k)$. This correlation can be reduced by reducing the correlation of $e(k)$ and $v(k)$ in the *SP* block with later explained signal processing methods. The correlations are related as follow: Supposing the adaptive filter being set to some (not optimum) value $\hat{\mathbf{h}}(k)$, the bias term can be noted as:

$$\mathbf{R}_{\mathbf{vv}}^{-1}(k)\,\mathbf{r}_{x\mathbf{v}}(k) = \mathbf{R}_{\mathbf{vv}}^{-1}(k)\,\mathbf{r}_{e\mathbf{v}}(k) - [\mathbf{h}(\mathbf{k}) - \hat{\mathbf{h}}(k)]. \qquad (10)$$

| Signal | Ben. $\alpha = 0.5$ | Ben. $\alpha = 2$ | agc |
|---|---|---|---|
| $\overline{\gamma^2}_{ev,dB}$ | -0.3 / -2.5 | -1.1 / -4.8 | -1 / -0.3 |
| **Signal** | abs | half wave rectifier | |
| $\overline{\gamma^2}_{ev,dB}$ | -10 / -12 | -2.2 / -6.5 | |

Table 1: Mean square coherence function for different non-linear signal processing methods applied on speech / music signal.

Supposing also that $\hat{\mathbf{h}}(k)$ is fixed at the current time index, i.e. $\mathbf{h}(\mathbf{k}) - \hat{\mathbf{h}}(k) =$ const, then reducing the correlation between $e(k)$ and $v(k)$ directly reduces the bias. When the adaptation is then freed, according to Eqn. 5, $\hat{\mathbf{h}}(k)$ can better converge to $\mathbf{h}(k)$.

#### 4.2.1 Delaying the output signal

Delaying the signal $v(k)$ by setting $D_1 > 0$ may also reduce the term $\mathbf{r}_{e\mathbf{v}}(k)$. An explanation is as follows: If the block *SP* was a gain with $g = 1$, $\mathbf{r}_{e\mathbf{v}}(k) = \mathbf{r}_{e\mathbf{e}_d}(k)$ with $\mathbf{e}_d(k) = [e(k-1-D_1), \ldots, e(k-N-D_1)]^T$. Thus, the vector $\mathbf{r}_{e\mathbf{e}_d}(k)$ covers different sections of the autocorrelation of $e(k)$. Since for usual signals the autocorrelation values decrease significantly, the term $\mathbf{r}_{e\mathbf{v}}(k)$ reduces with increasing delay $D_1$.

For strongly correlated input signals, e.g. music, however, the decrease of the autocorrelation values may be low. Thus, the bias term may stay high. Additionally, the delay should not be too high in order to avoid comb filter effects appearing due to the superposition with the acoustic signal which bypasses the hearing aid.

#### 4.2.2 Non-linear signal processing

A more general mean to reduce the term $\mathbf{r}_{e\mathbf{v}}(k)$ is to perform a non-linear processing in the *SP* block. Different decorrelation means may be utilized for this non-linear processing, such as the "Benesty" non-linearity [1], which in the simplest form adds a portion of the half-wave rectifier signal $rect(e(k))$: $\tilde{v}(k) = e(k) + \alpha\, rect(e(k))$.

Some decorrelation may also be achieved, due to the non-linear processing performed in standard hearing aid *SP* blocks, i.e. the AGC and the peak limiter.

To investigate the decorrelation properties of the different non-linear signal processing methods, ideally the term $\mathbf{R}^{-1}_{\mathbf{vv}}(k)\,\mathbf{r}_{e\mathbf{v}}(k)$ should be determined. However, for real signals with rapidly changing correlation properties, only short-term estimations of these quantities are available, which may result in large estimation errors, especially due to the matrix inversion. Therefore, we investigate the non-linear processing methods with the standard coherence function. Looking at the obtained mean square values:

$$\begin{aligned} \overline{\gamma^2}_{ev,dB} &= 10\log\left(\int_{-\pi}^{\pi} \gamma^2_{ev}\, d\Omega\right) \\ &= 10\log\left(\int_{-\pi}^{\pi} \frac{|S_{ev}(\Omega)|^2}{S_{ee}(\Omega)\,S_{vv}(\Omega)} d\Omega\right) \qquad (11) \end{aligned}$$

given in Tab. 1, is gets obvious that the decorrelation of the hearing aid's and the "Benesty's" non-linearity is very limited, especially when it should be inaudible. For comparison, the results of extreme non-linearities such as the absolute value or the pure half-wave rectifier are also depicted.

### 4.3 Adding artificial noise

Adding artificial noise – ideally a pseudo noise sequence $v_{PN}(k)$ – behind the *SP* block and determining the cross-correlation between this noise sequence and the input signal $m(k)$ of the hearing aid, the feedback path can be determined. The problem is that both, the input signal $x(k)$ and the feedback signal $y(k)$ are disturbing the estimation of the cross-correlation to the noise sequence. As the noise should be inaudible, long-term averaging is necessary to estimate the cross-correlation. Let $R$ denote the ratio (in dB) of the artificial noise and all other signal components of the signal $m(k)$ where $R$ is strongly negative for inaudible noise. Thus, when determining the cross-correlation, of $v_{PN}(k)$ and $m(k)$, at least an averaging of $L_{PN} = 10^{-R/10}$ samples is necessary to detect correlated components of $v_{PN}(k)$. Experiments showed that for this an averaging of approximately 2.5 to 5 seconds is necessary. Thus, the estimate can only follow very slowly changing feedback paths.

Alternatively, based on the correlation of $v_{PN}(k)$ and $e(k)$ feedback path changes may be detected. The detection result may be utilized in combination with the shadow filter approach (s. Section 3.3.3).

Another aspect of adding noise is to use it as a tool for decorrelation. Let the resulting output signal be $\tilde{v}(k) = v(k) + v_{PN}(k)$. As the input $x(k)$ is orthogonal to $v_{PN}(k)$, the filter coefficient's bias changes to $\mathbf{R}^{-1}_{\tilde{\mathbf{v}}\tilde{\mathbf{v}}}(k) \cdot r_{\mathbf{v}x}(k)$, having the effect that the larger normalization term reduces the bias. However, the artificial noise power has to be chosen much smaller than the mean output signal power $\sigma^2_{v_{PN}}(k) \ll \sigma^2_v(k)$. Thus, $\mathbf{R}_{\tilde{\mathbf{v}}\tilde{\mathbf{v}}}(k)$ is only slightly larger than $\mathbf{R}_{\mathbf{vv}}(k)$ and the filter coefficient's bias reduction due to artificial noise is negligible.

Concluding this section, it was shown that there are some methods for improving the adaptation of feedback filters. However, none of them is able to solve the problem alone. Nevertheless, combining them intelligently still offers potential. E.g., although one is not able to steadily identify the feedback path with artificial noise, this method may be utilized as rescue detector for compensating long-term deficiencies of other detecting methods or for delivering the distinction of feedback path changes and correlated input signals required for the shadow filter approach.

## 5. SUMMARY

In this paper we analyzed the feedback cancellation problem and showed that the used adaptive filter usually converges to a biased solution. The optimum step-size known from echo cancellation may also be applied for feedback cancellation. However, most of the methods known from echo cancellation for estimating this step-size cannot be utilized. Additional procedures are necessary, especially to avoid the bias of the adaptive filter. Here, some methods, such as non-linearities and the addition of artificial noise were analyzed. Although they still show large deficiencies, in combination they offer the potential for adaptation improvements.

## REFERENCES


[1] J. Benesty, D. R. Morgan: *A Better Understanding and an Improved Solution to the Specific Problems of Stereophonic Acoustic Echo Cancellation,* Transactions on Speech and Audio Processing, vol. 6, no. 2, pp. 156-165, March, 1998

[2] H. F. Chi, S. X. Gao, S. D. Soli: *A Novel Approach of Adaptive Feedback Cancellation for Hearing Aids,* Proc. IEEE ISCAS, pp. 187-190, 1999

[3] J. Hellgren: *Analysis of Feedback Cancellation in Hearing Aids With Filtered-X LMS and the Direct Method of Closed Loop Identification,* Transactions on Speech and Audio Processing, vol. 10, no. 2, pp. 119-131, February, 2002

[4] A. Mader, H. Puder, and G.U. Schmidt: *Step-Size Control for Acoustic Echo Cancellation Filters - An Overview,* Signal Processing, vol. 80, no 9, pp. 1697-1719, September, 2000

[5] M. G. Siqueira, A. Alwan: *Steady-State Analysis of Continuous Adaptation in Acoustic Feedback Reduction Systems for Hearing-Aids,* Transactions on Speech and Audio Processing, vol. 8, no. 4, pp. 443-453, July, 2000

[6] S. Yamamoto, S. Kitayama: *An Adaptive Echo Canceller With Variable Step Gain Method,* The Transactions of the IECE of Japan, vol. E 65, no. 1, pp. 1-8, 1982