

SUB-BAND FEEDBACK CANCELLATION WITH VARIABLE STEP SIZES FOR MUSIC SIGNALS IN HEARING AIDS

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ABSTRACT

Standard adaptive feedback cancellation algorithms in hearing aids suffer from a biased adaptation if the input signal is spectrally colored, as it is for tonal signals, like music. Due to that, distortion artifacts (entrainment) are generated. In this paper, a sub-band feedback cancellation system is presented combined with an adaptation control to deal with those signals. Two control concepts for determining the variable step sizes [1, 2], known from general adaptive filter algorithms, are theoretically and practically analyzed and evaluated for an application to feedback cancellation. For feedback cancellation the control is combined with known methods to reduce the bias, such as prediction error filtering or frequency shifting. Based on this combination, a completely new setup for feedback cancellation is proposed. It relies entirely on signals accessible in real systems, shows a low computational complexity, and therefore has a strong practical relevance.

Index Terms— Adaptive feedback cancellation, NLMS filter adaptation, adaptation control, hearing aids

1. INTRODUCTION

Acoustic feedback is a well-known phenomenon in hearing aids. It causes, under certain conditions, the so-called howling effect, which is highly annoying for the hearing aid user and his environment. Moreover, the acoustic feedback limits the maximum amplification that can be used in hearing aids. Many solutions to this problem have been proposed, cf. [3]. The most promising and common approach to avoid acoustic feedback is the adaptive feedback cancellation (AFC) algorithm, as depicted in Fig. 1. The forward path, which represents the signal processing part of the hearing aid, is denoted by $G(\Omega)$. The acoustic feedback path between the loudspeaker and the microphone is $F(\Omega)$. The loudspeaker signal is denoted by $u(n)$ and the microphone signal by $y(n)$. The adaptation error signal $e(n)$ is the estimate of the desired input signal $x(n)$. The AFC algorithm estimates the feedback path $\hat{F}(\Omega)$ adaptively. The common choice for the adaptation

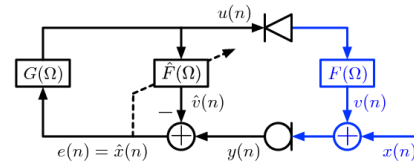


Fig. 1. Block diagram of a common AFC system with the forward path $G(\Omega)$, the acoustic feedback path $F(\Omega)$, the estimated feedback path $\hat{F}(\Omega)$, the loudspeaker signal $u(n)$, the microphone signal $y(n)$, the desired sound signal $x(n)$ and the error signal $e(n)$.

is the well-known normalized least mean square (NLMS) algorithm. Due to the correlation between $x(n)$ and $u(n)$, a bias of $\hat{F}(\Omega)$ occurs during the adaptation, cf. [3–5]. This bias becomes very large if the input signal $x(n)$ is spectrally colored, which is the case especially for tonal signals. Due to the bias, distortion artifacts (entrainment) are generated. Most of the known methods to reduce this bias have focused on speech signals [6–8]. However, those methods do not cope with music, since the tonality and correlation are much stronger for such signals. In this paper, a sub-band processing system is presented that is able to deal with those highly correlated signals. The sub-band processing reduces the computational complexity and allows a frequency selective adaptation and control. This increases the performance of the NLMS significantly, cf. [9, 10]. Two concepts for the adaptation control [1, 2] are theoretically and practically compared. Their advantages and drawbacks are denoted, and, most importantly, their usability in real systems is discussed. Finally, the better one is chosen for the proposed system. In order to use this concept, one has to find an estimate for the power of the input sound signal without feedback. Therefore, a method proposed in [11] is used, which we adjusted to our AFC problem. To improve the performance of the system, common methods such as prediction error filters (PEFs) [12–14] and a frequency shift (FS) [15, 16], which are successfully used in full-band systems, are integrated in our sub-band system. The method finally proposed in this paper consists of sub-band processing NLMS adaptation controlled by variable step sizes combined

with PEFs and FS. It allows the cancellation of feedback even for critical signals such as music. Additionally, the approach allows an application for real systems since it only relies on signals that are accessible and shows a limited computational complexity.

Our paper is organized as follows: First, we describe the system in Sec. 2, including two concepts for adaptation control and a method to estimate the power of $x(n)$, which is important to determine the adaptation control based on accessible signals. That is followed by simulations to demonstrate the behavior of the proposed system in Sec. 3. In Sec. 4 we conclude our work.

2. PROPOSED SYSTEM

A block diagram of the proposed system is depicted in Fig. 2. The adaptation is realized in sub-bands using an NLMS adaptation rule [17]:

$$\hat{\mathbf{f}}_k(n) = \hat{\mathbf{f}}_k(n-1) + \mu_k(n) \frac{e_k(n) \mathbf{u}_k^*(n)}{\|\mathbf{u}_k(n)\|^2}, \quad (1)$$

where the index k denotes the k -th sub-band and ** the conjugate complex operation. The sub-band indexes are omitted in the following. The vector $\hat{\mathbf{f}}(n)$ represents the N adaptive filter coefficients at time index n and the vector $\mathbf{u}(n)$ contains the current and the previous $N-1$ samples of the loudspeaker signal. The scalar $\mu(n)$ is known as step size and controls the adaptation.

Two methods, successfully applied in full-band processing, are integrated in the sub-band setup. The first is a FS, cf. [3], which is applied to the output signal before the loudspeaker. This nonlinear operation reduces the correlation, and therefore the adaptation bias, but it also leads to roughness for tonal music. Hence, one can only perform a small FS, which limits the benefit of the method. The other method is to pre-whiten the microphone and loudspeaker signals of the hearing aid with a PEF denoted by $A(\Omega)$. For the PEF, we apply a one tap filter in each sub-band calculated based on the error signal $e(n)$ [12]. Using $e(n)$ instead of $y(n)$ allows a better decorrelation of the input signal. Even though the frequency shift and the prediction error filter both reduce the bias of the adaptation, artifacts are still created for adaptations with constant step sizes. Hence, we suggest using variable step sizes (VSS) to improve the performance of the system. In the following, we present two concepts applied for variable step sizes, compare them theoretically and practically and select the best.

2.1. Variable Step Sizes

To control the adaptation in each band, we consider two different methods to determine a variable step size for the NLMS algorithm. A first concept [1] determines the optimal step size based on the minimization of the mean system mismatch

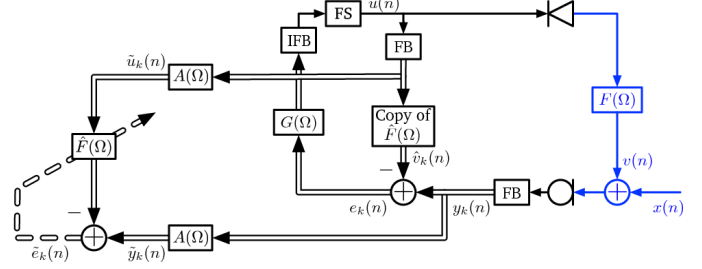


Fig. 2. Block diagram of the proposed sub-band processing system. In addition to Fig. 1, it contains filter banks (FB), inverse filter banks (IFB), a frequency shift (FS) and prediction error filters (PEF) denoted by $A(\Omega)$. The index k stands for the k -th frequency band and \sim indicates the pre-whiten signals.

$F(\Omega) - \hat{F}(\Omega)$ as follows:

$$\mu_{opt}(n) = \frac{\sigma_{e_u}^2(n)}{\sigma_e^2(n)}, \quad (2)$$

where $\sigma_{e_u}^2(n)$ and $\sigma_e^2(n)$ denote the power of different error signals. The signal $e_u(n)$ is the so-called undisturbed error given by $e_u(n) = \mathbf{u}^H(n)[\mathbf{f}(n) - \hat{\mathbf{f}}(n-1)]$ and $e(n)$ is the error signal given by $e(n) = e_u(n) + x(n)$. The major drawback of this optimal step size is that it was derived for echo cancellation where $x(n)$ and $u(n)$ are uncorrelated. In the following, we will analyze how far PEF and FS can compensate for this difference of the setup.

The second method to determine the step sizes is the nonparametric variable step size (NPVSS) by Benesty et al. [2]. Here, a step size is found in a way that

$$E\{|\epsilon(n)|^2\} = E\{|x(n)|^2\}, \quad \forall n \quad (3)$$

holds, where $\epsilon(n)$ is the *a posteriori* error signal $\epsilon(n) = \mathbf{u}^H(n)[\mathbf{f}(n) - \hat{\mathbf{f}}(n)] + x(n)$. Eq. (3) is deduced from the desired behavior of a feedback canceler $\epsilon(n) \stackrel{!}{=} x(n)$. The derivation, cf. [2], results in the step size

$$\mu_{NPVSS}(n) = 1 - \frac{\sigma_x(n)}{\sigma_e(n)}. \quad (4)$$

No assumption is made during the derivation of the NPVSS. Therefore, this step size should also be optimal for correlated signals. Nevertheless, since the signal $x(n)$ is not assessable in reality, it is not trivial to estimate $\sigma_x(n)$. Unfortunately, Benesty et al. [2] give no solution to this problem, which we will address in the following.

2.2. Estimation of the Input Signal Power

For the estimation of σ_x we use a method proposed by Huang and Lee [11] in the context of adaptation control:

$$\hat{\sigma}_x^2(n) = \sigma_e^2(n) - \frac{1}{\sigma_u^2(n)} \hat{\mathbf{r}}_{eu}^H(n) \hat{\mathbf{r}}_{eu}(n), \quad (5)$$

where $\hat{\mathbf{r}}_{eu}(n)$ is the estimated cross correlation between $\mathbf{u}(n)$ and $e(n)$. It is calculated by

$$\hat{\mathbf{r}}_{eu}(n) = \alpha \hat{\mathbf{r}}_{eu}(n-1) + (1-\alpha) \mathbf{u}^*(n) e(n), \quad (6)$$

with a smoothing parameter α and the output signal vector $\mathbf{u}(n)$, which has the same length as the adaptive filter. The concept of Eq. (5) is to subtract the power of the undisturbed error signal $e_u(n)$ from the power of the error signal $e(n)$ to estimate the power of the input signal $x(n)$. Hence, it is assumed that the following equation is reasonable:

$$\hat{\sigma}_{e_u}^2(n) = \frac{1}{\hat{\sigma}_u^2(n)} \hat{\mathbf{r}}_{eu}^H(n) \hat{\mathbf{r}}_{eu}(n). \quad (7)$$

But one can show that this result is only obtained in the case $u(n)$ is a white signal. For non-white signals one gets

$$\sigma_{e_u}^2(n) = \mathbf{r}_{eu}^H(n) \mathbf{R}_{uu}^{-1} \mathbf{r}_{eu}(n), \quad (8)$$

where \mathbf{R}_{uu} denotes the autocorrelation matrix of $\mathbf{u}(n)$. For AFC, we need to assume that $u(n)$ is a non-white signal. Even if $x(n)$ was a white signal, $u(n)$ would be colored due to the spectral shape of $G(\Omega)$. For that reason, we suggest an adjustment of Eq. (5) to

$$\hat{\sigma}_x^2(n) = \hat{\sigma}_e^2(n) - \hat{\mathbf{r}}_{eu}^H(n) \mathbf{R}_{uu}^{-1} \hat{\mathbf{r}}_{eu}(n). \quad (9)$$

However, Eq. (8) is only true if one assumes $x(n)$ and $u(n)$ to be uncorrelated – which we know is not the case. Nevertheless, just as for the OSS method applying PEF and FS may overcome this issue.

To summarize, we discussed different configurations of our system, which differ in the adaptation control method. The configurations, which will be evaluated in Sec. 3, are the following:

- CSS - constant step size of 0.25
- OSS - optimal step size, cf. Eq. (2);
 $\sigma_{e_u}^2(n)$ is based on $e_u(n)$ (not available in real systems)
- NPVSS 1 - nonparametric variable step size, cf. Eq. (4);
 $\sigma_x(n)$ is based on $x(n)$ (not available in real systems)
- NPVSS 2 - practical modification of NPVSS 1;
 $\sigma_x(n)$ is estimated as given in Eq. (9)

Also, we differentiate between systems with and without additional PEFs and FS. NPVSS 2 with PEFs and FS is our proposed system, as it is the only one to provide good results for music signals and to use accessible signals at the same time.

3. SIMULATION RESULTS

In this section, we show some simulation results. First, we note that all power values are estimated by smoothing the

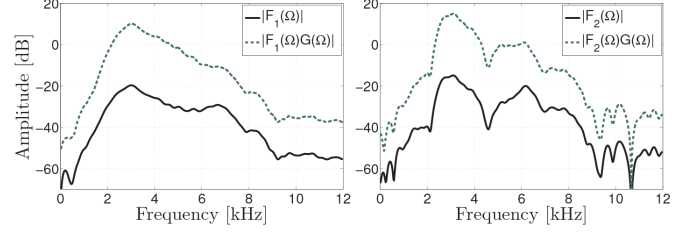


Fig. 3. The recorded feedback paths $F_1(\Omega)$ and $F_2(\Omega)$ are shown together with the closed loop given by $F(\Omega)G(\Omega)$. $F_1(\Omega)$ is a typical feedback path for hearing aids. For $F_2(\Omega)$ a hand is placed near the ear (distance ≈ 15 cm).

square of the corresponding signal, if the signal is accessible. As an example, the power of $e(n)$ is estimated by

$$\hat{\sigma}_e^2(n) = \gamma \hat{\sigma}_e^2(n-1) + (1-\gamma) |e(n)|^2, \quad (10)$$

where the smoothing constant γ is chosen for all simulations to 0.99 at a sampling frequency of 24 kHz, as well as α in Eq. (6). For the simulations, 48 sub-bands are used. The adaptive filter length for each band is set to 3, which is sufficient for obtaining a feedback reduction of approximately 28 dB. The frequency shift is set to 12 Hz. Both variable step sizes are limited to 0.25. We used three different music signals. The first one is a bell, which is chimed once, the second one is a piano signal, and the third one is a flute signal. To simulate two different feedback situations, we recorded two feedback paths at our audio lab using a behind-the-ear hearing aid with open fitting and a KEMAR dummy. For the forward path, a hearing aid processing unit with automatic gain control is used. The gain is chosen such that the closed loop is approximately 10 dB overcritical for the first feedback path and for the second one approximately 15 dB. Fig. 3 shows the recorded feedback paths and the closed loop given by $F(\Omega)G(\Omega)$. To evaluate the performance, we calculated the maximum effective closed loop gain during the adaptation, i.e., $\max\{|F_\Delta(\Omega)G(\Omega)|\}$ in dB, where $F_\Delta(\Omega) = F(\Omega) - \hat{F}(\Omega)$ is the system mismatch. Whenever 0 dB is exceeded, entrainment occurs at least at one frequency.

First, we want to demonstrate the improvement of the estimated $\hat{\sigma}_x^2(n)$ if we use our proposed Eq. (9) instead of Eq. (5) proposed in [11]. Fig. 4 shows $\sigma_x^2(n)$ based on $x(n)$ and the two estimates for each frequency band over time. The sound signal is the bell and we used $F_1(\Omega)$ as feedback path. By using Eq. (5), $\sigma_x^2(n)$ is highly overestimated in the critical frequency bands 10 – 20, while our proposed method Eq. (9), provides a good estimate of $\sigma_x^2(n)$.

In the second simulation, we used the same sound signal and feedback path as before. Fig. 5 shows the performance of all configurations of the system. The problem of the system to deal with music signals using a CSS, even though PEFs and FS are applied, is illustrated. Also one can observe that the OSS is only able to handle the music signal if we add the PEFs and FS, while the NPVSS 1 is stable without addi-

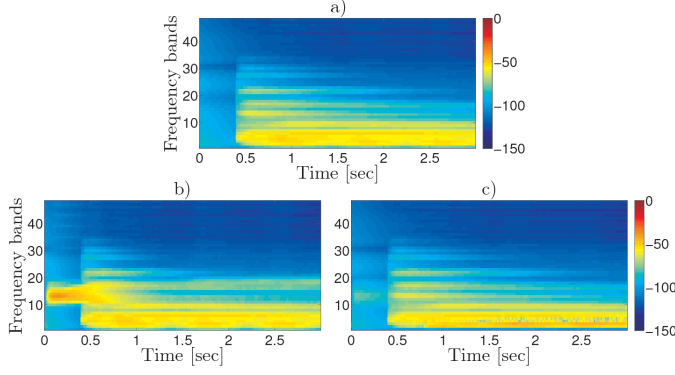


Fig. 4. a): $\sigma_x^2(n)$ based on $x(n)$ (reference). b): $\hat{\sigma}_x^2(n)$ obtained by Eq. (5). c): $\hat{\sigma}_x^2(n)$ obtained by Eq. (9). The estimate in b) is overestimated in the frequency bands 10 – 20, while our proposed approach in c) provides a good estimate.

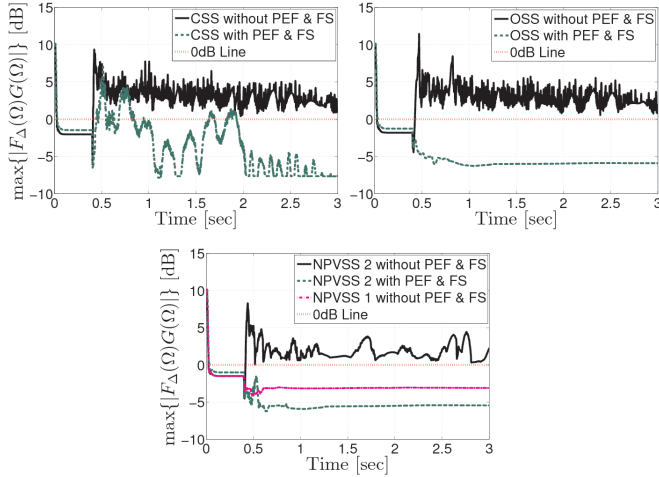


Fig. 5. The graphs show the maximum effective closed loop gain, $\max\{|F_{\Delta}(\Omega)G(\Omega)|\}$, in dB over time for one fixed feedback path and for different configurations: CSS, OSS, NPVSS 1, and NPVSS 2. For values above 0 dB entrainment occurs. CSS is not able to deal with this signal (with and without PEFs and FS). OSS and NPVSS 2 create no entrainment if PEFs and FS are applied. NPVSS 1 can deal with music signals without additional PEFs and FS. However, our proposed method NPVSS 2 is the only method of the last three that uses only accessible signals.

tional methods. Due to the assumption used for the estimate $\sigma_x(n)$, NPVSS 2 requires PEFs and FS to provide good results. We see that NPVSS 2 (with PEFs and FS) performs nearly as good as OSS (with PEFs and FS) and slightly better than NPVSS 1 (without PEFs and FS), and, contrary to the other two, NPVSS 2 uses only accessible signals. Furthermore, the simulation proved that all configurations perform as we expected due to our theoretical consideration in Sec. 2. Another critical aspect of an AFC algorithm in hearing aids is the ability to react to feedback changes. We simulated a feed-

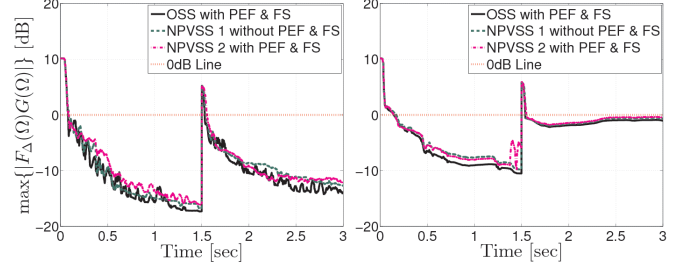


Fig. 6. The graphs show the maximum effective closed loop gain, $\max\{|F_{\Delta}(\Omega)G(\Omega)|\}$, in dB over time for a feedback path change and two different music signals: piano (left), flute (right). Only the three configurations able to handle music signals are shown. All behave very similarly, no entrainment is created and they show good adaptation speed.

back change by switching between our two recorded feedback paths after half of the simulation time. Fig. 6 shows the results for the three configurations that are able to handle music signals (OSS with PEFs and FS, NPVSS 1 and NPVSS 2 with PEFs and FS). As test signals, the piano signal and the flute signal are chosen. All configurations behave very similarly, and no entrainment occurs. Furthermore, all configurations show a good adaptation speed, as they need approximately 0.05 seconds (bell) and 0.08 seconds (flute) or even less to adapt to the new feedback path. Also important to mention is that the NPVSS 2 performs nearly as well as the other two methods, which use inaccessible signals.

4. CONCLUSION

In this paper, we proposed a sub-band feedback cancellation system with variable step size for music signals. Therefore, we analyzed and compared two approaches for adaptive filter control for an AFC application and verified our assumptions with simulation results. Contrary to the NPVSS, the OSS suffers from a assumption which do not hold for AFC. With the integration of PEFs and FS, one can overcome this problem. However, both methods use signals that are inaccessible in real systems. For OSS, this is the power of the undisturbed error $e_u(n)$ and for NPVSS this is the power of the feedback-free input signal $x(n)$. Huang and Lee [11] offer an approach to estimate the power of $x(n)$. Since the approach uses several assumptions, which were not valid in the case of AFC, we modified their method. Additionally, we integrated PEFs and FS to obtain a system which is able to deal with music signals. We showed that our system allows the cancellation of feedback for several critical music signals, and even if the feedback changes. In addition, the approach allows an application for real systems since it only uses signals that are accessible and has a low computational complexity.

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