Adaptive Feedback Control for Active Noise Cancellation with In-Ear Headphones

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Introduction

This paper presents a method to design adaptive FB controllers for ANC (active noise control) applications with in-ear headphones. The main problem with regard to in-ear headphones are the variances of the transfer function of the secondary path. This problem will be presented in the next chapter. These interpersonal variances can cause an unstable closed loop. Hence an inverse identification of the secondary path will be shown in chapter "Iterative Adaptive Feedback Control". This improves the stability of the closed loop and also speeds up the adaptation. Thereafter measurements show that the adaptive feedback generates a very good noise attenuation because of its self-adjustment to the disturbance.

Problem Statement

Nowadays we are often exposed to noises, for example produced by trains, airplanes or cars. Active headphones are a possible solution to this problem. They use a loudspeaker to generate an out-of-phase antinoise. The aim is to reduce the sound pressure level at the eardrum. There are two main control strategies to calculate the antinoise: feedforward and feedback control [1]. In this paper we will focus on feedback (FB) control. Figure 1 shows that in FB ANC the output of the speaker $u(n)$

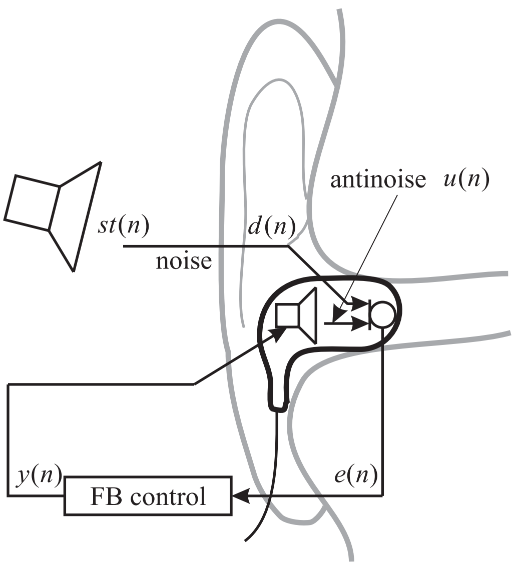

Figure 1: Principle of feedback ANC with in-ear headphones

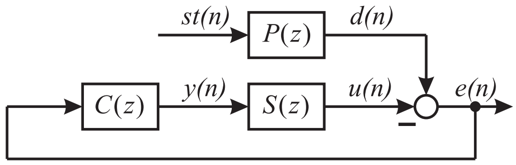

Figure 2: Block diagram of feedback ANC

is calculated based on the signal of the error microphone $e(n)$ and the FB controller wants to minimize the power at the error microphone:

$$e^2(n) = (d(n) - u(n))^2 . \qquad (1)$$

The block diagram in figure 2 describes this effect. $P(z)$ is the primary transfer function and describes the way from the noise source to the digitalized signal $d(n)$ at the error microphone. The presented FB controller is realized on a digital real-time platform, so $C(z)$ is a digital controller. $S(z)$ is the secondary path. It describes the way from the digital output of the controller to its input. It contains the acoustical path from the loudspeaker to the error microphone and all electrical components of the digital platform.

The disturbance transfer function describes the attenuation of the closed loop:

$$F_Z(z) = \frac{E(z)}{D(z)} = \frac{1}{1 + C(z) \cdot S(z)}. \qquad (2)$$

We want to get a good attenuation, so $F_Z(z)$ has to be small. But it is not possible to minimize $F_Z(z)$ in the whole frequency range because of the bodes integral theorem [2]. Hence, we define the goal of FB control to minimize the expected value of (1):

$$E[e^2(n)] = E[(d(n) - u(n))^2]. \qquad (3)$$

And that means that we have to optimize (2). But there are two main problems: $F_Z(z)$ is non-linear in $C(z)$, and, as shown in figure 3, $S(z)$ differs from person to person.

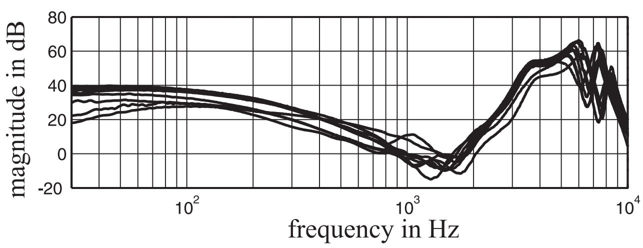

Figure 3: Measured secondary path of different test persons using the same in-ear headphone

Adaptive Feedback Control

In this chapter we will describe the state of the art of adaptive filters and their use in adaptive FB control. The great advantage of adaptive ANC strategies is that they are self-adjusting to the noise and therefor they can lead to a better attenuation than static controllers.

Adaptation

Adaptive filters are used to identify unknown plants, such as $G(z)$ as shown in figure 4. Therefore they calculate the best linear filter between the input $x(n)$ and the output $d(n)$. The aim is to bring the error $e(n)$ to zero or to minimize the squared error $e^2(n)$. If $W(z)$ is a finite impulse response filter (FIR) then the adaptation problem becomes convex and it is possible to use gradient methods to minimize the squared error. Here we are using the least mean square algorithm (LMS) because of its low computational effort [3].

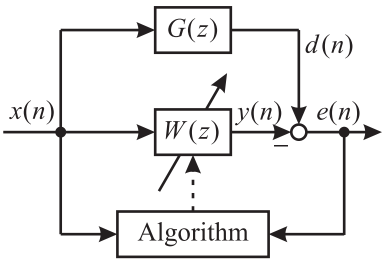

Figure 4: Block diagram of an adaptive filter

As shown in figure 5, there often is an additional plant in the adaptation path in ANC applications. And therefor the output of the adaptive filter $y(n)$ does not interfere directly with the signal $d(n)$. To ensure the convergence of the adaptive algorithm, a model of the path $\hat{S}(z)$ has to be considered in the reference path of the adaptation. This extended LMS is called the "filtered reference" or the "filtered-x" LMS (FXLMS).

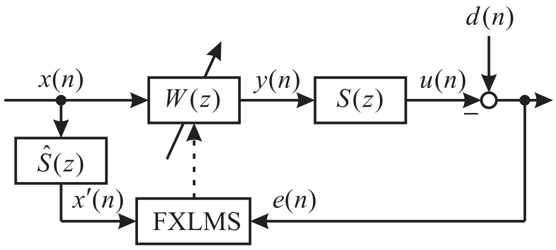

Figure 5: Block diagram of the FXLMS algorithm

Feedback Control

Equation (2) shows that the disturbance transfer function $F_Z(z)$ is non-linear in $C(z)$. To solve this problem it is possible to use the internal model control technique (IMC) [4]. Figure 6 demonstrates the FB loop with a model of the secondary path inside the controller $C(z)$:

$$C(z) = \frac{C_{IMC}(z)}{1 - C_{IMC}(z) \cdot \hat{S}(z)}. \quad (4)$$

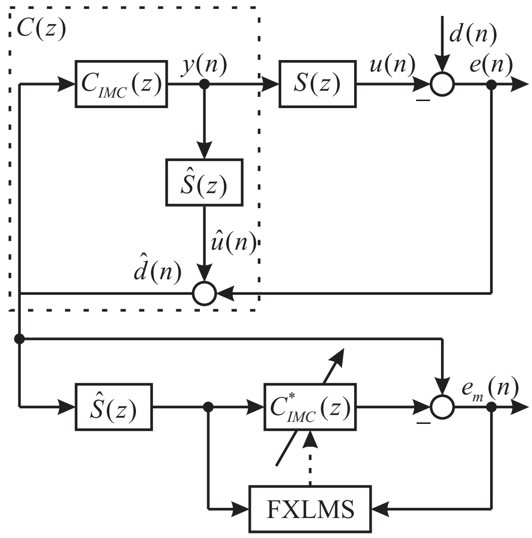

Figure 6: Feedback loop with internal model and adaptive filter

If the model $\hat{S}(z)$ and the secondary path $S(z)$ are equal, then the disturbance transfer function (2) becomes a linear optimization problem in $C_{IMC}(z)$:

$$F_Z(z) = 1 - C_{IMC}(z) \cdot \hat{S}(z). \quad (5)$$

In addition figure 6 shows the adaptation based on the estimated disturbance $\hat{d}(n)$. The FXLMS adapts the filter $C^*_{IMC}(z)$ to optimize the squared modified error $e_m^2(n)$. The coefficients of the static intern controller $C_{IMC}(z)$ gets exchanged by the adaptive filter $C^*_{IMC}(z)$ for example every few samples or if $e_m^2(n)$ is small enough. This design guaranties a possible convergence of the adaptation [5].
But the adaptation wants to identify a transfer function "1" and has the secondary path in the adaptation path. To bring $e_m(n)$ to zero the optimal filter has to be non-causal. That is not realizable. So the algorithm will find the best linear filter for the estimated disturbance.
But that is not the main problem. In figure 3 we show that $S(z)$ differs from person to person. And this interpersonal variances can cause an unstable feedback loop.

Solution

In this chapter we will show a possible solution to the problems with interpersonal variances.
Every linear, time invariant (LTI), digital transfer function $S(z)$ can be separated into its minimum-phase part $S_{mp}(z)$ and its allpass $S_{ap}(z)$ using the complex cepstrum [6]:

$$S(z) = S_{mp}(z) \cdot S_{ap}(z). \quad (6)$$

In [7] we have shown for in-ear headphones that the interpersonal variances only affects the minimum-phase plant and the allpass $S_{ap}(z)$ is approximately constant and looks like a delay (figure 7).

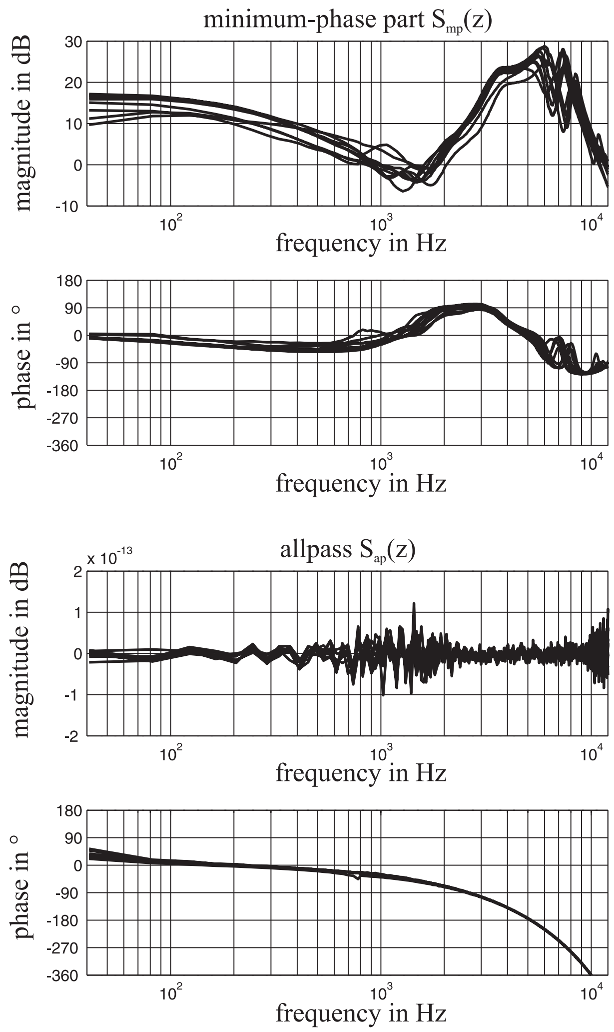

Figure 7: Secondary Path separated using the complex cepstrum

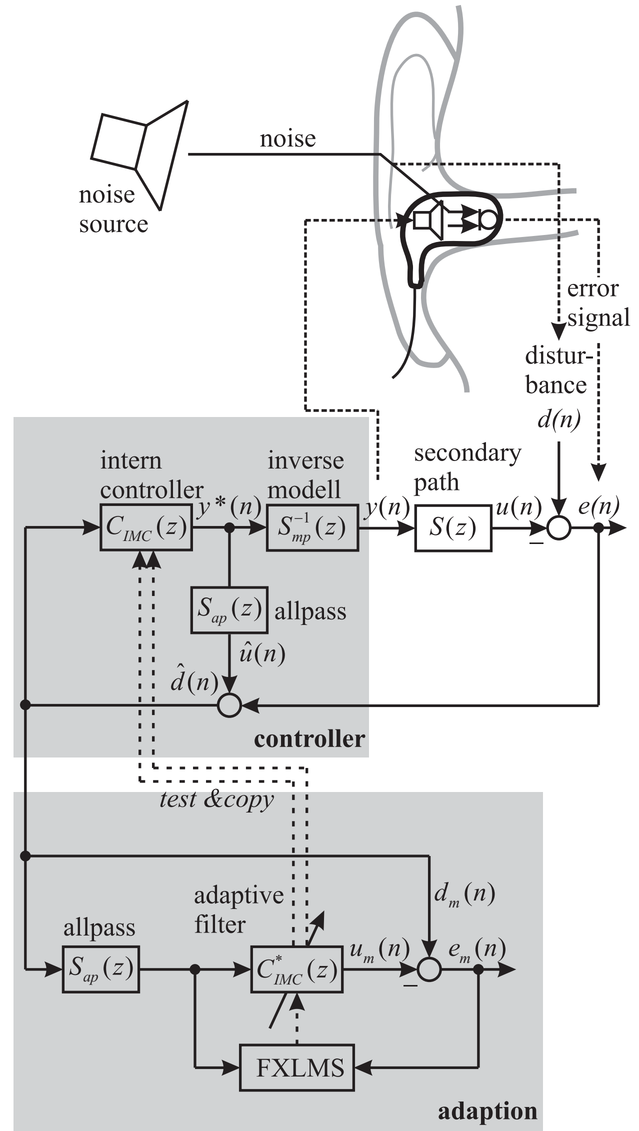

Figure 9: Iterative, adaptive feedback controller in the closed loop

Identification of the Secondary Path

So our approach is making an on-line identification of the inversion of the minimum-phase part of the secondary path $S_{mp}^{-1}(z)$. The block diagram in figure 8 shows the setup. The additional identification noise $v(n)$ is used to equalize the secondary path. After the convergence the adaptive filter times the secondary path is equal to the allpass:

$$S_{ap}(z) = S_{mp}^{-1}(z) \cdot S_{ap}(z). \tag{7}$$

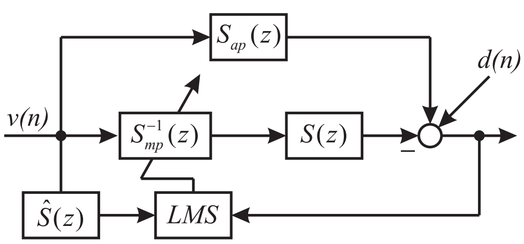

Figure 8: Identification

Iterative Adaptive Feedback Control

After the identification, the inverse minimum-phase model inside the controller times the secondary path is approximately equal to the intern allpass $S_{ap}(z)$ (figure 9). Hence the estimation of the disturbance $\hat{d}(n)$ is very good. Based on this estimation it is possible to adapt the filter $C_{IMC}^{*}(z)$. This adaptation is more efficient than the common one in figure 6 because the allpass is a delay filter. And delay filters needs fewer parameters than a model of the secondary path.

We realized the exchange of the coefficients of the intern controller with the adaptive one by clicking on a button of the digital platform. Before the coefficients get copied the new controller is tested whether it leads to a robust stable closed loop.

Results

We have made the following measurements to benchmark the active attenuation of the adaptive feedback controller: The excitations were made by a surround sound system in an anechoic room. We measured the signal of the error microphone with a spectrum analyzer. The in-ear headphones were in a human ears. We used

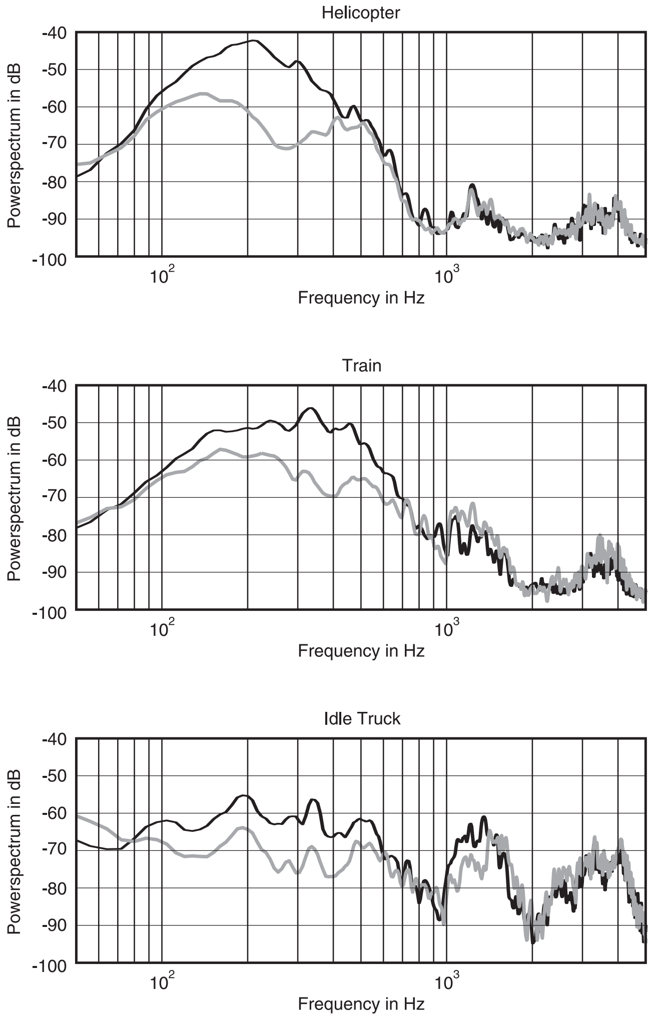

Figure 10: Measured spectrum at the error microphone without (black) and with (grey) the adaptive ANC feedback

different excitations: a helicopter, a train and an idle truck noise.
The black lines in figure 10 show the error signal without the active FB and the grey lines with the adaptive FB. The results show that the adaptive FB generates a very good attenuation especially in the frequency areas where the power of the noises is high. For example the area from 50 to 350 Hz in the helicopter signal has high values in the power spectrum. The FB brings the signals down with a damping of up to 22 dB. And in the signal of the idle truck we can see that in the higher frequency range of about 1300 Hz the FB also damps the signal.

Conclusion

In this paper we presented the first adaptive ANC FB controller for in-ear headphones. We have shown that the interpersonal variances are the main problems in adaptive FB ANC applications because they can cause an unstable closed loop. A possible solution to this problem is the identification of the inverse minimum-phase part to equalize the secondary path. This way also leads to an adaptation with a lower computational effort.
We realized an adaptive controller which is tested for stability before the old controller is replaced.
The measurements of the active attenuation of the FB show the self-adjusting to the noise and as a result a very good noise attenuation.

Acknowledgments

The authors are thankful for the financially support of this project by the European Regional Development Fund and the Federal State of Lower Saxony, Germany.

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