A NEW APPROACH FOR MODELLING THE DYNAMIC FEEDBACK PATH OF DIGITAL HEARING AIDS

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ABSTRACT

This paper proposes a reflection model for the dynamic feedback path of digital hearing aids and compares it with two existing models: a direct model and an initialization model, based on the measured dynamic feedback paths. The comparison shows that the proposed model is superior to the existing two models in terms of maximum stable gain (MSG). For hearing aids with dual microphones, the possibility of relating the two dynamic feedback paths is also investigated. It is shown that in a complicated acoustic environment, the relation between the two feedback paths can be very intricate and difficult to exploit in modelling the dynamic feedback paths.

Index Terms— Feedback cancellation, hearing aids, dynamic feedback path modelling, delay estimation.

1. INTRODUCTION

Feedback is one of the major problems with hearing aids. It limits the maximum gain that can be achieved. A widely adopted approach to feedback suppression is feedback cancellation, where an adaptive filter is used to model the feedback path. The output of the filter is regarded as the instantaneous estimation of the feedback signal and is subtracted from the input signal to remove the feedback.

The maximum stable gain (MSG) obtained by using a feedback canceller depends on how accurately the feedback path can be estimated. A perfect match between modelled and real feedback path will cancel the feedback signal completely, and the system will be stable for any amount of amplification [1]. In practice, however, the feedback path may be subject to dramatic changes, e.g., when the user picks up the phone. In these adverse situations, the feedback canceller usually has problems in obtaining an accurate estimate of the feedback path due to its slow convergence and/or biased adaptation. A whistle is therefore easily triggered. This has become the major concern of hearing aid users with feedback problems today.

In order to improve the performance of a feedback canceller in dynamic situations, the model of dynamic feedback path should be investigated. However, to our best knowledge, very little research has been carried out in analyzing the dynamic change of feedback path in real life. This paper proposes a reflection model for the dynamic feedback path and compares it with two existing models using data from measurements of dynamic feedback paths. The comparison shows that the proposed model is superior to the existing two models in terms of MSG. For hearing aids with dual microphones, the possibility of relating the two feedback paths is also investigated. It is shown that in a complicated acoustic environment, the relation between the two feedback paths can be very intricate and difficult to exploit in modelling the dynamic feedback paths.

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The outline of the paper is as follows: in section 2 two traditional models are explained and a new reflection model is proposed. In section 3 the measurement is described and the results are given based on the measured data. Concluding remarks and directions for future work are given in section 4.

2. MODELS FOR THE DYNAMIC FEEDBACK PATH

The general diagram of feedback cancellation is depicted in Fig. 1. The idea of feedback cancellation is to adjust the parameters θ in the feedback model so that the modelled feedback path $\hat{b}(n,\theta)$ approximates the true feedback $b(n)$ as close as possible. The output $v(n)$ is the instantaneous estimation of the feedback signal $f(n)$ and is subtracted from the input signal $s(n)$ to remove the feedback.

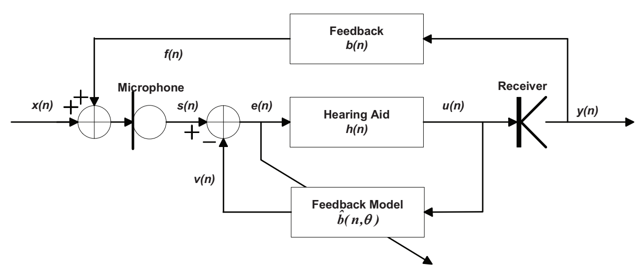

Fig. 1. General diagram of feedback cancellation. The input to the hearing-aid processing is $s(n)$, which is the sum of desired input signal $x(n)$ and the feedback signal $f(n)$. The processed hearing-aid signal is $u(n)$. The signal output into the ear canal is $y(n)$. The impulse response of the feedback path is $b(n)$, and $v(n)$ is the estimation of $f(n)$ from the modelled feedback path $\hat{b}(n,\theta)$.

In real life, the impulse response of the feedback path $b(n)$ is time-varing and can change dramatically. An example is shown in Fig. 2, where the impulse response of the feedback path is measured without any enclosure and with a palm wrapping around the hearing aid, which mimics the situation when the user picks up the phone. As seen from the figure, both the impulse response and the frequency response change remarkably when the hearing aid is enclosed.

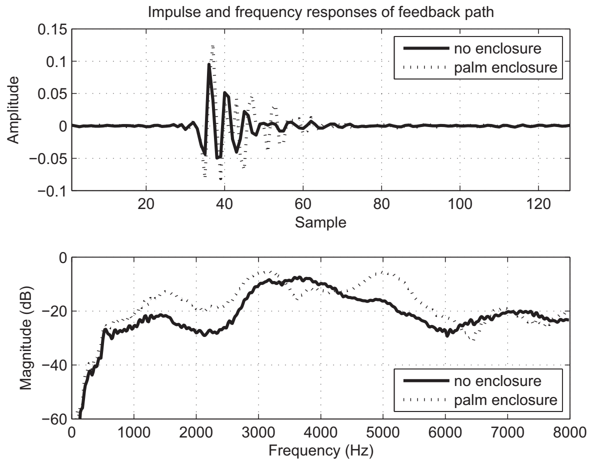

Fig. 2. Impulse responses and frequency responses of feedback paths with (dotted lines) and without (solid lines) palm enclosure.

2.1. Measure of the feedback models

In principle, the impulse response $b(n)$ has an infinite duration. However, as shown in Fig. 2, the amplitude of $b(n)$ decays very fast. Assume that the truncated impulse responses of $b(n)$ and $\hat{b}(n,\theta)$ with length L are sufficient to represent the true feedback path and the feedback model respectively. One natural way of obtaining the optimal parameters θ_{opt} for the feedback model is to minimize the difference between the truncated feedback model and the actual feedback path. This, formulated in the frequency domain, is given by

$$\begin{aligned} \theta_{opt} &= \arg\min_{\theta} \|\mathbf{F}^H(\hat{\mathbf{b}}(\theta) - \mathbf{b})\|_2^2, && (1)\\ \mathbf{b} &= (\ b(0), \ \ \ldots \ \ , b(L-1)\ )^T, && (2)\\ \hat{\mathbf{b}}(\theta) &= (\ \hat{b}(0,\theta), \ \ \ldots \ \ , \hat{b}(L-1,\theta)\ )^T, && (3)\\ \mathbf{F} &= (\ \mathbf{f}_0, \ \ \mathbf{f}_1, \ \ \ldots \ \ \mathbf{f}_{L-1}\ ) && (4)\\ \mathbf{f}_k &= (\ 1, \ \ e^{j\omega_k}, \ \ \ldots \ \ , e^{j\omega_k(L-1)}\ )^T, && (5) \end{aligned}$$

where $\omega_k = 2\pi l/L, l = 0, 1, \ldots, L-1$, $\mathbf{F}$ is the Fourier matrix, and $(\cdot)^T$ denotes the transpose of $(\cdot)$.

To evaluate the performance of a feedback model, MSG is often used, which is determined by the frequency at which the mismatch between the feedback model and the actual feedback path is the largest [2]. We assume that in all the circumstances, the parameters in the feedback model θ can converge to the optimal solution θ_{opt} fast and accurately enough[1]. The MSG of the model is therefore the MSG with converged parameters, denoted as MSG_c,

$$\text{MSG}_c = 20\log_{10}\left(\min_k \frac{1}{|\mathbf{f}_k^H(\hat{\mathbf{b}}(\theta_{opt}) - \mathbf{b})|}\right). \qquad (6)$$

With a specific model and parameters θ, MSG_c is the highest achievable MSG, which is in fact limited by the amount of under-modelled feedback path, the residual feedback path that cannot be modelled due to the limited degrees of freedom in the parameter θ and/or the lack of flexibility in the model form. A more descriptive model with larger degrees of freedom in the parameters θ will yield less under-modelling and larger MSG_c.

In the following text, three models will be described and MSG_c will be computed to evaluate and compare these models.

[1]The feedback canceller usually suffers from the problem of slow convergence and biased adaptation. These two topics, however, are irrelevant with the model of feedback path. Therefore they are not considered in this paper to simplify the model comparison.

2.2. Direct model

One typical form of feedback model is composed of a pre-filtering and an adaptive filter, which is usually FIR (Finite Impulse Response) since IIR (Infinite Impulse Response) adaptive filtering suffers from the problem of instability and local minima [3]. Let $b_0(n)$ and $w(n)$ denote the impulse response of the pre-filtering and the adaptive filter respectively. The feedback model is the convolution of $b_0(n)$ and $w(n)$,

$$\begin{aligned} \hat{b}(n,\theta) &= w(n) \odot b_0(n) = \sum_{l=0}^{M-1} w(l) b_0(n-l), && (7)\\ \theta &= \{w(n), b_0(n)\}, && (8) \end{aligned}$$

where M is the order of $w(n)$, and $\odot$ is the convolution operator.

In the "direct model", the pre-filtering is simply a delay of D samples:

$$b_0(n) = \{ \begin{array}{l} 1, n = D+1 \\ 0, otherwise \end{array}. \qquad (9)$$

Since $b(n)$ usually starts with a certain physical delay (see Fig. 2), the introduction of a corresponding delay D renders a better use of the limited number of taps in the adaptive filter $w(n)$. To calculate MSG_c, the optimal parameters, i.e., $w_{opt}(n)$ and D_{opt} should be obtained first by solving equations (1)-(5), (7)-(8) and (9).

This is a nonlinear optimization problem. However, it can be solved easily in numerical ways. As a special case, if the delay D is fixed, it reduces to a simple optimization problem with the following solution

$$\mathbf{w}_{opt} = (\ b(D+1), \ \ \ldots \ \ , b(D+M)\ )^T. \qquad (10)$$

With the optimal parameters, MSG_c can be calculated from equation (6).

2.3. Initialization model

To model the feedback path accurately, the direct model in 2.2 usually needs a very high-order adaptive FIR filter $w(n)$ to cover the "active" range in Fig. 2. One way to reduce the number of orders needed for modelling the dynamic feedback path is to use an initialization as proposed in [4], which is a measurement of feedback path in a static situation without any reflectors or enclosures near the hearing aid. When the hearing aid is put into use in daily life, to capture the time-varying dynamic feedback path, the adaptive filter $w(n)$ only needs to model the part that is different from the static initialization. Since the impulse responses of microphone, receiver, etc. will not change from the static initialization to the dynamic situation, this different part can be modelled by an adaptive filter with a lower order.

Let $b_0(n)$ denote the impulse response of the static feedback path obtained in the initialization. The modelled feedback model is the same as in equation (7) with

$$\theta = \{w(n)\}, \tag{11}$$

The impulse response $b_0(n)$ is truncated to $L - M + 1$ samples here so that the length of the convolution between $w(n)$ and $b_0(n)$ equals L. In practice $b_0(n)$ can be implemented by an IIR filter [4].

When $w(n)$ is real-valued, the optimal parameter for the initialization model $w_{opt}(n)$ can be found by solving a linear least square problem with equation (1)-(5), (7) and (11):

$$\begin{aligned}
\mathbf{w}_{opt} &= (diag(\mathbf{F}^H\tilde{\mathbf{b}}_0)\tilde{\mathbf{F}}^H)^+(\mathbf{F}^H\mathbf{b}), && (12)\\
\tilde{\mathbf{b}}_0 &= (\ \mathbf{b}_0^T, \quad \mathbf{0}_{1\times(M-1)}\ )^T, && (13)\\
\mathbf{b}_0 &= (\ b_0(0), \quad \dots \quad , b_0(L-M)\ )^T, && (14)\\
\tilde{\mathbf{F}} &= \begin{pmatrix} f_0(0) & \dots & f_{L-1}(0) \\ \cdots & \cdots & \cdots \\ f_0(M-1) & \dots & f_{L-1}(M-1) \end{pmatrix} && (15)
\end{aligned}$$

where $diag(\cdot)$ is a diagonal matrix with diagonal elements $(\cdot)$, $(\cdot)^+$ is a pseudo-inverse defined as $(\cdot)^+ = ((\cdot)^T(\cdot))^{-1}(\cdot)^T$, and $\mathbf{0}_{1\times(M-1)}$ represents a zero vector of length $M-1$.

The optimal solution represents the adaptive filter $w(n)$ of length M that produces MSG$_c$ when being concatenated with the initialization filter $b_0(n)$ to model the dynamic feedback path $b(n)$.

2.4. Reflection model

In section (2.3), the initialization model formulated in equation (7), can also be regarded as a weighted sum of the initialization $b_0(n)$ and its delayed replicas with integer delays. We generalize it to a new model with fractional delays, i.e.,

$$\begin{aligned}
\hat{b}(n,\theta) &= \sum_{l=0}^{M-1} w(l)b_0(n-d_l), && (16)\\
\theta &= \{w(l), d_l\}, && (17)
\end{aligned}$$

where d_l is the delay of the l-th replica, $d_l > d_{l-1} \geq 0, l = 1, \cdots, M-1$.

These delayed replicas can be interpreted as physical reflections with delay d_l and gain $w(l)$. This model is thus named "reflection model". Compared with the initialization model, the reflection model is more precise because it mimics what happens in the physical world. For example, when the user picks up the phone, the feedback path consists of a direct path and multiple reflections with possibly fractional delays. The direct path can be approximated by the initialization since it is done in the static situation without any reflectors or enclosures near the hearing aid. In fact, when $d_l = l$, the reflection model is identical to the initialization model. Therefore, the reflection model is more general and expected to capture the dynamic feedback path better than the initialization model.

The optimal delays $d_{l,opt}$ and weights $w_{opt}(l)$ for the reflection model can be found by solving the optimization problem (1)-(5), (16) and (17), which is a nonlinear optimization problem. However, efficient time delay estimation techniques exist to address the problem. An iterative search of $w_{opt}(l)$ and $d_{l,opt}$ proposed in [5] is found to be very robust. We first cross-correlate $b(n)$ and $b_0(n)$ in the frequency domain to find the coarse delays and gains of the replicas by identifying the peaks of the cross-correlation. Later an iterative search is performed by keeping one replica of $b_0(n)$ at a time (removing the other identified replicas from $b(n)$), repeating the cross correlation and locating the peak to find a better delay and gain estimation for that replica. This process is iterated until the relative change of the cost function in equation (1) is below the threshold.

2.5. Models for dual-microphone hearing aids

For hearing aids with dual microphones, the feedback problem involves two feedback paths, denoted as $b_1(n)$ and $b_2(n)$. One way to deal with the two paths is to model them individually by using one of the three models described above. An alternative approach is to fit one feedback path with the other path. There are two ways of fitting, similar to the initialization model and reflection model respectively.

The first approach for the fitting is:

$$\hat{b}_1(n) = \sum_{l=0}^{M-1} w(l)b_2(n-l), \tag{18}$$

The second is:

$$\hat{b}_1(n) = \sum_{l=0}^{M-1} w(l)b_2(n-d_l), \tag{19}$$

The optimal weights $w_{opt}(n)$ and/or delays $d_{l,opt}$ can be found in similar ways described in section 2.3 and 2.4.

3. MEASUREMENT AND RESULTS

The static and dynamic feedback paths are measured using a commercial open-fitting behind-the-ear (BTE) device from GN ReSound A/S. For each feedback path, MSG$_c$ of the three models and the models for dual-microphone hearing aids is calculated by optimizing the parameters in the model.

3.1. Measurements

The hearing aid is mounted on the head of Kemar Manikin Type 45BA made by G.R.A.S Sound & Vibration A/S. The impulse response of the feedback path is measured by sending out a maximum-length sequence (MLS) with a period of 255 samples through the receiver. One thousand periods are repeated to obtain a high SNR for the feedback path response relative to random room noise. The sampling frequency is 16 kHz. The detailed procedure of the impulse response measurement can be found in [2].

The measurement included two steps: First an initialization was carried out to measure the static feedback path without any reflectors or enclosures. Then dynamic feedback paths were created to mimic the most adverse situations for feedback cancellation in real life by a special setup: A rigid surface facing the hearing aid was moved along the lateral side gradually towards the hearing aid and outwards later. The perpendicular distance between the rigid surface and the hearing aid was kept at around three centimetres during the movement. The impulse responses were measured and five representative snapshots were selected for analysis. Two additional dynamic feedback paths were measured with a open palm facing the hearing aid on its lateral side at a distance of three centimetres and with a palm wrapping around the hearing aid. Altogether eight impulse responses were measured including one initialization (static feedback) and seven dynamic feedback paths.

3.2. Results

For each measured dynamic feedback path, the parameters in the models were first optimized to calculate the MSG_c. The filter length M was varied from 1 to 50. In the direct model, the delay D is not fixed to achieve the best performance.

It is found that for all the seven dynamic paths and all the values M, the reflection model outperforms the initialization model and the direct model in terms of MSG_c. The direct model performs the worst in almost all the cases. To demonstrate the performance of each model in dynamic situations, MSG_c is averaged over the seven dynamic paths. The results are illustrated in Fig. 3 and Fig. 4. The results for the dual-microphone models, denoted as ”2 channel”, are also included.

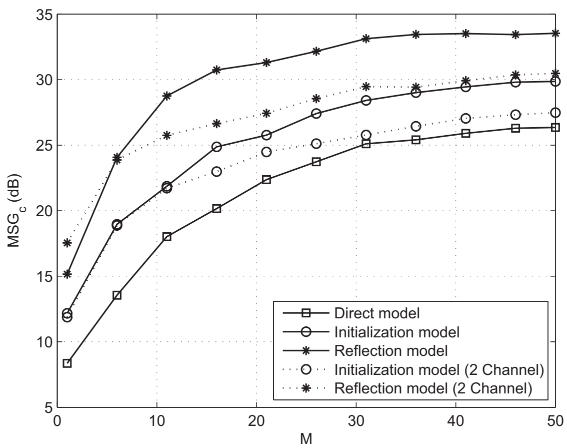

Fig. 3. Comparison of the models for dynamic feedback path modelling.

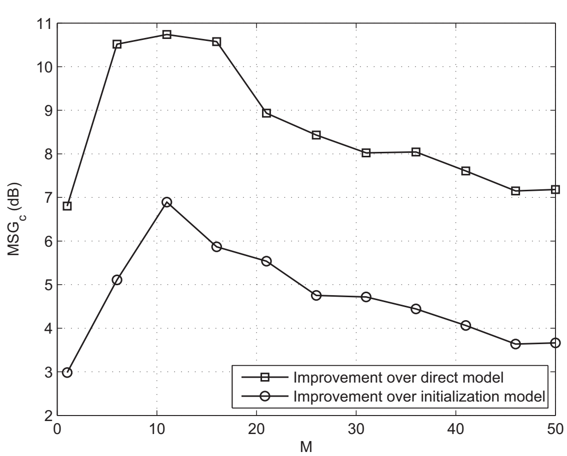

Fig. 4. The MSG_c improvement of the reflection model over direct model and initialization mode for dynamic feedback path modelling.

As seen from the figures, the reflection model is superior to the other two models especially when M is around 11. In practice, M is usually chosen between 10 to 20 to assure a fast convergence. In this region, the reflection model yields 5-7 dB higher MSG_c than the initialization model and 9-11 dB higher MSG_c than the direct model. To achieve a 25dB MSG_c, the direct model needs 31 orders and the initialization model needs 16 orders, whereas, the reflection model only needs 7 replicas of the initialized impulse response.

It is also noted that the dual-microphone models by relating the two feedback paths do not give any benefit. This is because in a complex acoustic environment, the relation between the two feedback paths can be very complicated and even more difficult to model than the feedback paths themselves.

4. CONCLUSIONS AND FUTURE WORK

This paper proposes a novel reflection model for the dynamic feedback path in digital hearing aids. The results based on the measurement of a commercial hearing aid show that the proposed model has better ability in capturing the dynamic feedback path and is superior to the existing two models in terms of MSG.

The results also give the minimum order of the adaptive filter in the two existing models to achieve a certain MSG in the dynamic situations, which could serve as a useful indication in practice for choosing the order of the adaptive filter in the feedback canceller.

Moreover, this paper investigates the possibility of relating the two feedback paths of a dual-microphone hearing aid for modelling the dynamic feedback paths. It is shown that in a complex acoustic environment, the relation between the two feedback paths can be very complicated and difficult to exploit to yield better models.

The drawback of the proposed method is the complexity in estimating the fractional delays. The future work is to find an efficient way of estimating the delays and investigate how to use this reflection model in an on-line adaptation to improve the performance of feedback cancellation in dynamic situations.

5. REFERENCES

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