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An improved CLMS algorithm for feedback cancellation in hearing aids

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ABSTRACT

In LMS algorithm-based feedback estimation, the value of the adaptation step size chosen imposes establishes a compromise between the speed at which the algorithm converges to the feedback-path estimate and the misadjustment between the true and estimated feedback paths at steady state. The combined LMS (CLMS) scheme overcomes this issue, but itself suffers from a sluggish adaptation of the mixture parameter during periods of a rapidly-varying or a stationary feedback path, leading to a degradation in the performance of the feedback canceller. In this work, we propose an acoustic feedback canceller with an improved affine combination of two different-step-size LMS filters, for a bias-less estimation of the acoustic feedback. The new filter-combiner parameter controls the filter combination and ensures at least a minimum adaptation of the mixture parameter for a stationary as well as a varying acoustic environment. We analyse the proposed algorithm for feedback reduction and prove that it performs as well as the element filters or even better in some situations, as compared to the CLMS algorithm. A detailed behaviour analysis of the proposed algorithm is also presented for scenarios of a stationary as well as a time-varying acoustic environment of the user. Simulation results verify the validity of the derived expressions.

1. Introduction

The popularity of the least mean square (LMS) algorithm is obvious from its wide usage in different applications due to its simplicity, robustness, ease of implementation and tracking capability. The control-mechanism in the LMS algorithm is governed by the step size, which controls the convergence of the algorithm. Infact, the value chosen for the step size imposes a trade-off between the convergence speed of the algorithm and the steady-state performance [1]. The misadjustment of the LMS algorithm, defined as the ratio of the excess mean square error (EMSE) and the minimum mean square error (MMSE), varies in direct proportion to the adaptation step parameter [1]. The robustness of the LMS algorithm and a low error at steady state are guaranteed for a small value of the adaptation step. However, the cost incurred for the aforementioned benefits is a slow convergence, due to an increase in the time constant of the learning rate, and leading to a reduction in the statistical efficiency of the algorithm [1]. The design compromise that exists for the LMS algorithm, with regard to the step size, also exists for the other adaptive algorithms.

In the recent past, several schemes have been proposed that attempt to overcome this compromise, viz., the least mean fourth (LMF) algorithm [2], algorithms that facilitate the variation of the step size [3] and the algorithms with step size adaptation [4,5]. Each of the aforementioned schemes come with their own set of disadvantages or complexities such as a more rigid upper limit on the value of the step size, susceptibility to the presence of noise and introduction of new parameters that need a priori initialization. A simpler method to circumvent the compromise between the algorithm convergence and its steady-state error compromise is to combine the adaptive filter outputs optimally such that the equivalent output is improved in quality, in that it allows for a faster convergence of the algorithm towards the estimate of the feedback path while at the same time incurring a reduced misadjustment [6,7].

In [6,7], a combined LMS (CLMS) scheme is described in which two LMS filters of different step sizes are combined together to eliminate the steady-state error and convergence speed dilemma. The output of the equivalent CLMS filter is a convex combination of the outputs of the element filters of the combination. The mixture parameter, used for establishing this affine combination by adjusting the filter-combiner parameter, is updated non-linearly. However, the adaptation process of the mixture parameter becomes very sluggish when the filter-combiner parameter is too

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near to its endpoints, leading to a degradation in the performance of the equivalent filter.

In this paper, we propose an improved CLMS (ICLMS) algorithm-based acoustic feedback canceller using linear prediction and probe-based adaptation for hearing aids, to improve upon the performance of the CLMS algorithm. The issue of stagnation in the update of the mixture parameter in the CLMS algorithm is remedied by introducing a new filter-combiner parameter, which prevents the stopping of the mixture parameter adaptation at limit values of the filter-combiner parameter. Also, the said feedback canceller design, with linear prediction and probe noise, facilitates the attenuation of the low as well as the high-frequency bias in the estimate of the acoustic feedback path by circumventing the problem of signal correlations within the closed loop. A detailed mathematical analysis is performed to prove the complete universality of the proposed algorithm at steady state, as compared to the CLMS algorithm. Further, we extensively study the behaviour of the proposed algorithm in the mean-square sense for situations of a stationary as well as a time-varying feedback path to derive conclusions on the improved performance of the equivalent filter as compared to that of the element filters of the proposed combination as well as the CLMS algorithm.

The following notation is adopted throughout the paper; $[.]^T$ for the transpose operation, $\mathrm{Tr}(.)$ for the trace operation, $\mathrm{sgm}(.)$ for the sigmoid function, $\min(.)$ for minimum of the values under consideration, $\|.\|$ for the norm of a vector, $\mathrm{E}[.]$ for the expectation operation, k for discrete-time index, z for discrete-time delay operator such that $z^{-1}g(k) = g(k-1)$, bold-faced upper-case letters for the matrices and bold-faced lower-case letters for the column vectors. A discrete-time filter $F(z)$ of length L is represented as a polynomial in terms of z^{-1} as $F(z) = f_0 + f_1 z^{-1} + \ldots + f_{L-1} z^{-L+1}$ or by its coefficient vector $\mathbf{f} = [f_0, f_1, \ldots, f_{L-1}]^T$. The signal $g(k)$ is filtered by $F(z)$ as $F(z)g(k) = \mathbf{f}^T(k)\mathbf{g}(k)$, with $\mathbf{g}(k) = [g(k), g(k-1), \ldots, g(k-L+1)]^T$.

2. Brief system description

2.1. Adaptive feedback canceller with linear prediction and probe-based estimation

In this section, we summarize the adaptive feedback canceller with linear prediction and probe-based estimation (see Fig. 1), the idea of which was originally proposed in [8]. In place of the single-adaptive-filter configuration [8,9] of the aforementioned feedback canceller, an affine combination of LMS filters is used for more efficient feedback cancellation. Hearing-aid user's acoustic surroundings are depicted via a feedback route between the loudspeaker and the microphone using an FIR filter $M(z)$ of length L_{m} and a coefficient vector $\mathbf{m}(k) = [m_0, m_1, \ldots, m_{L_{\mathrm{m}}-1}]^T$. For adaptively estimating the user's surroundings $M(z)$, an FIR filter $\hat{M}(z)$ of length $L_{\hat{\mathrm{m}}}$ and a coefficient vector $\hat{\mathbf{m}}(k) = [\hat{m}_0, \hat{m}_1, \ldots, \hat{m}_{L_{\hat{\mathrm{m}}}-1}]^T$ is used. Assuming that the incoming signal $x(k)$ is a wide sense stationary process, we can express the output of the microphone as

$$y(k) = x(k) + f(k), \tag{1}$$

where

$$f(k) = M(z)u_{\mathrm{p}}(k) \tag{2}$$

is the signal which is fed back and

$$u_{\mathrm{p}}(k) = u(k) + p(k) \tag{3}$$

is the loudspeaker output signal, $u(k)$ is the input signal to the loudspeaker and $p(k)$ is the probe noise signal, with the respective vector definitions being $\mathbf{u}_{\mathrm{p}}(k) = [u_{\mathrm{p}}(k), u_{\mathrm{p}}(k-1), \ldots, u_{\mathrm{p}}(k - L_{\hat{\mathrm{m}}} + 1)]^T$, $\mathbf{u}(k) = [u(k), u(k-1), \ldots, u(k - L_{\hat{\mathrm{m}}} + 1)]^T$ and $\mathbf{p}(k) = [p(k), p(k-1), \ldots, p(k - L_{\hat{\mathrm{m}}} + 1)]^T$. The loudspeaker input $u(k) = q_{\mathrm{syn\_hp}}(k) + q_{\mathrm{lp}}(k)$ is expressed in vector form as

$$\mathbf{u}(k) = \mathbf{q}_{\mathrm{syn\_hp}}(k) + \mathbf{q}_{\mathrm{lp}}(k), \tag{4}$$

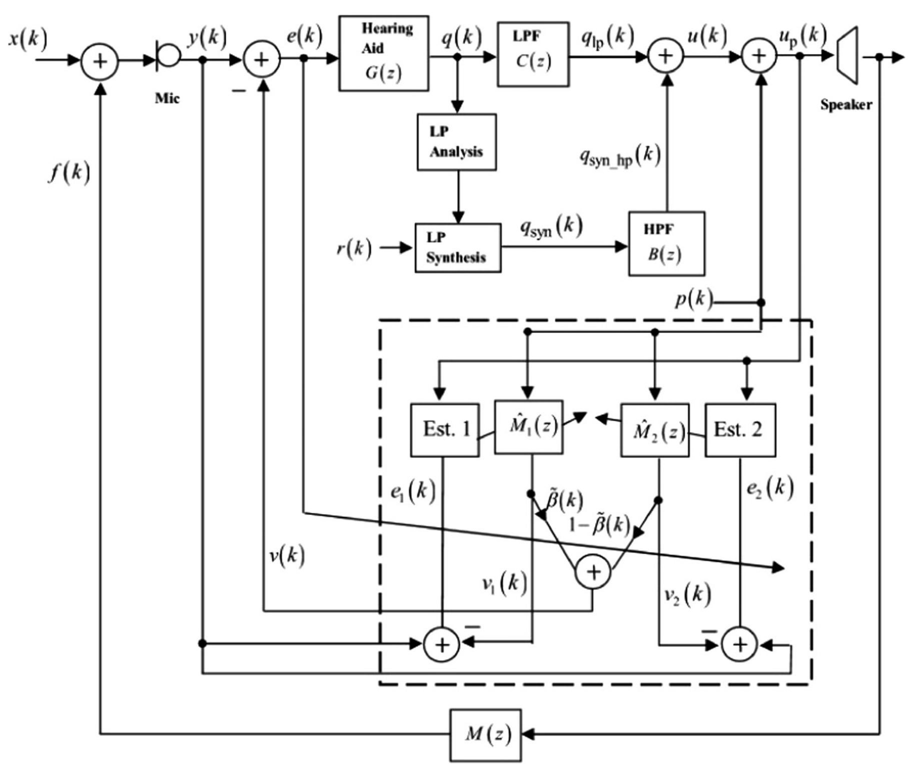

Fig. 1. ICLMS algorithm-based feedback canceller with linear prediction and probe-based adaptation.