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Technical note

Robust equalizer design for adaptive room impulse response compensation

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ABSTRACT

Adaptive room equalization aims at providing a listener with an audio experience, which is very close to the original audio signal. The equalizer, which is an adaptive filter, compensates for the disturbance in the audio signal contributed by the impulse response of the room. One of the most popular algorithms employed for the design of an adaptive room equalizer is the filtered-x improved proportionate normalized least mean square (Fx-IPNLMS) algorithm. IPNLMS is effective in equalizing sparse as well as non-sparse room impulse responses. However, Fx-IPNLMS is not robust to strong disturbances picked up by the microphone used in the equalization process and the algorithm may even diverge in such scenarios. With an objective to overcome this limitation of IPNLMS based adaptive room equalization schemes, a robust Fx-IPNLMS algorithm has been developed in this paper. The new algorithm has been shown to provide robust room equalization and thus an enhanced audio experience.

1. Introduction

It is a well known fact that the sound perceived by a listener in a closed environment like a room is different from the original sound. This disturbance may be partly attributed to the different paths followed by the original sound in reaching the listener. The listener receives the sound via the direct path as well as from multiple reflections. This feature of an acoustic environment is usually represented using the room impulse response (RIR), which is the impulse response of the acoustic path between two points [1–3]. Adaptive room equalizers, which work on the principle of adaptive signal processing, have been recently developed to compensate for these distortions in order to enhance the quality of the sound perceived by the listener [4–8].

In a basic room equalizer system, an adaptive finite impulse response (FIR) filter is added ahead of the loudspeaker which produces the sound. In addition, a microphone is placed near the listener to measure the quality of the sound received at the listener's end. The adaptive weights of the equalizer are updated using a suitable algorithm, which has the original sound signal and the sound signal measurement obtained from the microphone as inputs [9]. In a traditional linear room equalization system, a filtered-x least mean square (FxLMS) algorithm is employed as the adaptive algorithm [10,11].

RIRs are generally sparse in nature and it has been observed that the steady state impulse response of the equalizers also contain several values which are zeros or very close to zeros [12]. The conventional FxLMS algorithm based room equalization schemes are not designed to utilize the sparse nature of the equalizer. A proportionate normalized least mean square (PNLMS) has been recently employed for sparse system identification [13]. However, PNLMS algorithm fails to converge to optimal values when the system to be identified is non-sparse. An improved PNLMS (IPNLMS) has been reported in [14], which can effectively handle sparse as well as non-sparse scenarios and filtered-x version of IPNLMS (Fx-IPNLMS) has been employed successfully for room equalization in [12].

Both FxLMS and Fx-IPNLMS algorithms fail to provide optimal convergence properties when strong disturbances are picked up by the microphone employed in the equalization process. In worst cases, the algorithms may even diverge. This limitation of conventional room equalization schemes can be overcome by designing robust room equalization mechanisms. In an endeavour to develop a room equalizer system, which is not only robust against strong disturbances at the microphone, but also capable of providing enhanced convergence characteristics for sparse as well as non-sparse scenarios, this paper presents a robust Fx-IPNLMS (RFx-IPNLMS) algorithm based adaptive room equalizer.

The rest of the paper is organized as follows. A brief introduction to the adaptive room impulse response equalization task is made in Section 2. The proposed robust approach towards room equalization is developed in Section 3. The effectiveness of the

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proposed scheme is tested using a simulation study in Section 4 and the concluding remarks are made in Section 5.

2. Adaptive room impulse response equalization

Fig. 1 shows the schematic diagram of a basic adaptive room equalization process, which consists of an equalizer which drives the loudspeaker and a microphone which senses the sound perceived near the listener. In the figure, the source signal $x(n)$ is the filtered through an adaptive equalizer before driving the loudspeaker. The adaptive weights of the equalizer are updated using a suitable algorithm, which has $x(n)$ and the microphone output $g(n)$ as the input.

The block diagram of the filtered-x algorithm based equalization scheme is shown in Fig. 2, where $W(z)$ is the transfer function of the equalizer, $H(z)$ is the transfer function of the electro-acoustic path (path from the input of the loudspeaker to the output of the microphone) and $H_m(z)$ is the transfer function of the model of $H(z)$, which is obtained by modeling the path from the input to the loudspeaker to the output of the microphone. In this study, we have assumed perfect modeling in obtaining $H_m(z)$. Considering $\boldsymbol{w}(n) = [w_1(n), w_2(n), \ldots, w_i(n), \ldots, w_N(n)]^{\mathrm{T}}$ as the adaptive weight vector of the equalizer (of length N), the output of the equalizer is given by

$$y(n) = \boldsymbol{w}^{\mathrm{T}}(n) * \boldsymbol{x}(n), \tag{1}$$

where $\boldsymbol{x}(n) = [x(n), x(n-1), \ldots, x(n-N+1)]^{\mathrm{T}}$ is the tap delayed input signal vector, $*$ represents the linear convolution operator and T denotes the transpose operator. The output of the equalizer, passes through an electro-acoustic path before reaching the listener. The signal perceived at the output of the microphone is given by

$$g(n) = \boldsymbol{h}^{\mathrm{T}}(n) * \boldsymbol{y}(n), \tag{2}$$

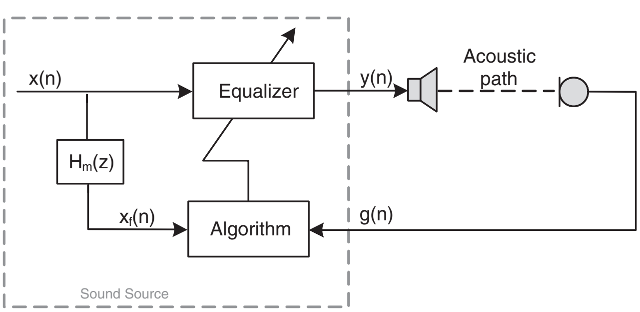

Fig. 1. Schematic diagram of the room equalization process.

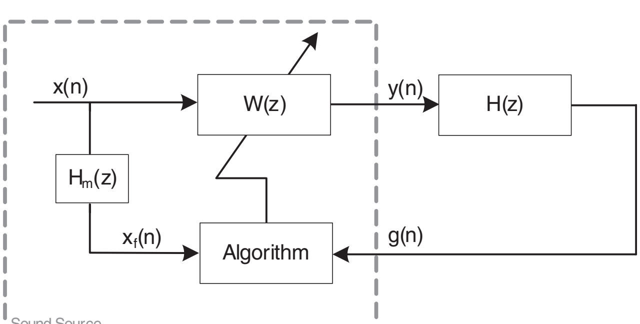

Fig. 2. Block diagram of a filtered-x algorithm based adaptive room equalization system.

where $\boldsymbol{h}(\boldsymbol{n}) = [h_1(n), h_2(n), \ldots, h_M(n)]^{\mathrm{T}}$ is the impulse response of the electro-acoustic path and $\boldsymbol{y}(n) = [y(n), y(n-1), \ldots, y(n-M+1)]^{\mathrm{T}}$ is the tap delayed equalizer output signal vector.

The primary objective of the adaptive equalizer is to minimize the difference between the microphone output and the delayed version of the source signal. Thus the error signal is given by

$$e(n) = x(n-D) - g(n) \tag{3}$$

where D is the delay caused by the equalizer and the electro-acoustic path. In a conventional filtered-x LMS algorithm based adaptive equalizer, the adaptive weight vector $\boldsymbol{w}(n)$ of the equalizer is updated in such a way as to minimize the cost function given by

$$\xi(n) = \mathrm{E}[e^2(n)] \approx e^2(n), \tag{4}$$

where $\mathrm{E}[\cdot]$ is the expectation operator and the weight update rule is given by

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \mu e(n)\boldsymbol{x}_f(n), \tag{5}$$

where μ is the learning rate and $\boldsymbol{x}_f(n)$ is $x(n)$ filtered through a model of the electro-acoustic path (which has a transfer function $H_m(z)$). The normalized version of FxLMS algorithm is written as

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \frac{\mu e(n)\boldsymbol{x}_f(n)}{\boldsymbol{x}_f^{\mathrm{T}}(n)\boldsymbol{x}_f(n) + \delta_L}, \tag{6}$$

where δ_L is a small constant. This algorithm is hereafter referred to as Filtered-x Normalized LMS (FxNLMS).The FxNLMS algorithm given by (6) can divergence in the presence of strong disturbances picked up by the microphone. In addition, the algorithm is not designed to take advantage of the near sparse nature of the equalizer. An attempt has been made in the next section to design a room equalizer, which can overcome both the above mentioned disadvantages of FxLMS algorithm based equalizers.

3. Design of robust room equalizers

In an endeavour to exploit the sparse nature of the steady state impulse response of a system being identified, an improved proportionate normalized LMS (IPNLMS) algorithm has been recently reported in [14]. In an IPNLMS algorithm, each coefficient of the weight vector has a separate step size and the update rule for a system identification task is given by

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \frac{\mu\boldsymbol{K}(n)\boldsymbol{x}(n)e(n)}{\boldsymbol{x}^{\mathrm{T}}(n)\boldsymbol{K}(n)\boldsymbol{x}(n) + \delta_P} \tag{7}$$

where

$$\delta_P = \frac{(1-\zeta) \times \delta_L}{2N} \tag{8}$$

is the regularization factor, with $-1 \leqslant \zeta < 1$ as a small constant and δ_L as the regularization factor of a normalized LMS (NLMS) algorithm [14]. In (7),

$$\boldsymbol{K}(n) = \mathrm{diag}[\kappa_0(n), \kappa_1(n), \ldots, \kappa_{N-1}(n)]. \tag{9}$$

with

$$\kappa_i(n) = \frac{(1-\zeta)}{2N} + \frac{(1+\zeta)|w_i(n)|}{2||w(n)||_1 + \psi}, \tag{10}$$

where ψ is a small positive number. Because of the presence of the $H(z)$ at the output of the equalizer, when applied for updating the weights of a room equalizer, the weight update rule becomes

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \frac{\mu\boldsymbol{K}(n)\boldsymbol{x}_f(n)e(n)}{\boldsymbol{x}_f^{\mathrm{T}}(n)\boldsymbol{K}(n)\boldsymbol{x}_f(n) + \delta_P}, \tag{11}$$

which is referred to as the filtered-x IPNLMS (Fx-IPNLMS) algorithm. The robustness of the above mentioned algorithm may be