Evaluation of Acoustic Feedback Cancellation
Methods with Multiple Feedback Paths

B. C. Bispo and D. R. Freitas
Department of Electrical and Computer Engineering, University of Porto, Porto, Portugal

Keywords: Public Address System, Acoustic Feedback Cancellation, Evaluation, Multiple Feedback Paths.

Abstract: Acoustic feedback limits the maximum stable gain of a public address system and may cause the system to become unstable. Acoustic feedback cancellation methods use an adaptive filter to identify the impulse response of the acoustic feedback path and then remove its influence from the system. However, if the traditional adaptive filtering algorithms are used, a bias is introduced in the estimate of the acoustic feedback path obtained by the adaptive filter. Several methods have been proposed to overcome the bias problem but they are generally evaluated considering a public address system with only one microphone and one loudspeaker. This work evaluates some of the state-of-art methods considering a public address system with one microphone and four loudspeakers that results in multiple feedback paths and corresponds to a more realistic scenario of a typical system. Simulation results demonstrated that, with multiple feedback paths, the acoustic feedback cancellation methods are able to increase in 12 dB the maximum stable gain of the public address system when the source signal is speech.

1 INTRODUCTION

In a typical public address (PA) system, a speaker uses loudspeakers and microphones along with an amplification system to apply a gain on his/her voice signal, aiming to be heard by a large amount of people in the same acoustic environment. The speaker's speech signal $v(n)$, after being picked up by the microphones, amplified and played back by the loudspeakers, may return to the microphones going through several paths. Such a system is illustrated in Fig. 1 with, as usual, only one microphone and one loudspeaker.

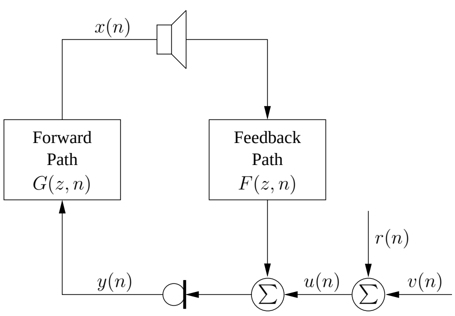

Figure 1: Acoustic feedback in a PA system.

Among these paths are included the direct one, if it exists, as well as the ones given by a large number of reflections. In all cases there is some signal attenuation which becomes more intense with the increase in length and therefore only a finite number of reflections can be considered in the feedback path. For simplicity, the feedback path also includes the characteristics of the D/A converter, loudspeaker, microphone and A/D converter. Although some non-linearities may occur due to saturation of the loudspeaker, almost invariably it is considered that these devices have unit responses and that the feedback path is linear. Hence, the acoustic feedback path is usually defined as a finite impulse response (FIR) filter

$$
\begin{aligned}
F(z,n) &= f_0(n) + f_1(n)z^{-1} + \ldots + f_{L_F-1}(n)z^{-(L_F-1)} \\
&= [f_0(n) \;\; f_1(n) \;\; \ldots \;\; f_{L_F-1}(n)] \begin{bmatrix} 1 \\ z^{-1} \\ \vdots \\ z^{-(L_F-1)} \end{bmatrix} \\
&= \mathbf{f}^T(n)\mathbf{z} \qquad (1)
\end{aligned}
$$

with length L_F.

The forward path includes the characteristics of the amplifier as well as of any other signal processing device inserted in the signal loop, such as an equalizer. Once again, although some non-linearities may exist because of compression, the forward path is usu-

Bispo B. and Freitas D..
Evaluation of Acoustic Feedback Cancellation Methods with Multiple Feedback Paths.
DOI: 10.5220/0005068201270133
In *Proceedings of the 11th International Conference on Signal Processing and Multimedia Applications* (SIGMAP-2014), pages 127-133
ISBN: 978-989-758-046-8

ally assumed to be linear and defined as an FIR filter

$$\begin{aligned} G(z,n) &= g_0(n) + g_1(n)z^{-1} + \ldots + g_{L_G-1}(n)z^{-(L_G-1)} \\ &= \mathbf{g}^T(n)\mathbf{z} \end{aligned} \quad (2)$$

with length L_G and has $g_0(n) = 0$, $\forall n$, for closed-loop analysis.

Let the system input signal $u(n)$ be the source signal $v(n)$ added to the ambient noise signal $r(n)$, i.e., $u(n) = v(n) + r(n)$, and, for simplicity, also include the characteristics of the microphone and A/D converter. The system input signal $u(n)$ and the loudspeaker signal $x(n)$ are related by the system closed-loop transfer function as

$$X(z) = \frac{G(z,n)}{1 - G(z,n)F(z,n)}U(z). \quad (3)$$

According to the Nyquist's stability criterion, the closed-loop system will become unstable if there is at least one frequency ω such that

$$\begin{cases} \left|G(e^{jw},n)F(e^{jw},n)\right| \geq 1 \\ \angle G(e^{jw},n)F(e^{jw},n) = 2k\pi,\ k \in \mathbb{Z}. \end{cases} \quad (4)$$

It means that if at least one frequency component is reinforced after traversing the system open-loop transfer function $G(z,n)F(z,n)$ and is added to the input signal $u(n)$ with no phase shift, this frequency component will never disappear from the system even if there is no more input signal. After each loop through the system, its amplitude will increase causing a howling at that frequency, a phenomenon known as Larsen effect (Rombouts et al., 2006; van Waterschoot and Moonen, 2011). This howling will be very annoying for all listeners present and the system gain generally has to be reduced. As a consequence, the maximum stable gain (MSG) of the PA system is limited by the occurrence of acoustic feedback (Rombouts et al., 2006; van Waterschoot and Moonen, 2011).

In order to eliminate or, at least, to control the Larsen effect, several methods have been developed over the past decades (van Waterschoot and Moonen, 2011). The acoustic feedback cancellation (AFC) methods identify and track the acoustic feedback path $F(z,n)$ using an adaptive filter that is generally defined as an FIR filter

$$\begin{aligned} H(z,n) &= h_0(n) + h_1(n)z^{-1} + \ldots + h_{L_H-1}(n)z^{-(L_H-1)} \\ &= \mathbf{h}^T(n)\mathbf{z} \end{aligned} \quad (5)$$

with length L_H. Then, the feedback signal $\mathbf{f}(n) * x(n)$ is estimated as $\mathbf{h}(n) * x(n)$ and subtracted from the microphone signal $y(n)$ so that, ideally, only the system input signal $u(n)$ is processed by the forward path $G(z,n)$. Such a scheme is shown in Fig. 2.

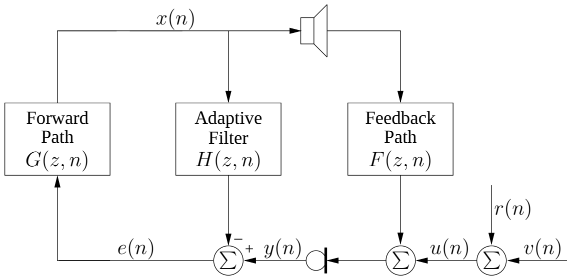

Figure 2: Typical AFC system.

But, because of the presence of the forward path $G(z,n)$, the estimation noise (system input $u(n)$) and input (loudspeaker $x(n)$) signals to the adaptive filter are highly correlated. Then, if the traditional adaptive filtering algorithms based on the Wiener theory or least squares are used, a bias is introduced in the estimate of the acoustic feedback path (Siqueira and Alwan, 2000; Hellgren and Forssell, 2001). As undesired consequences, the adaptive filter $H(z,n)$ will only partially cancel the feedback signal $\mathbf{f}(n) * x(n)$ and will also apply distortions in the system input signal $u(n)$.

Mostly, the solutions existing in the literature to overcome the bias in the estimate of the feedback path try to, somehow, decorrelate the loudspeaker $x(n)$ and system input $u(n)$ signals. Among them, the PEM-AFROW stands out for having the best performance (Rombouts et al., 2006; van Waterschoot and Moonen, 2011). Recently, one method that extracts well-defined information from the cepstrum of the microphone signal to update the adaptive filter was proposed (Bispo et al., 2013). However, until nowadays, only results in PA systems with a single feedback path were presented.

The present work evaluates the performance of some state-of-art AFC methods in a more realistic scenario with multiple feedback paths. The paper is organized as follows: Section 2 presents a typical PA system with multiple feedback paths; Section 3 briefly presents the AFC methods under evaluation; Section 4 describes the configuration of the simulated experiments; in Section 5, the obtained results are presented and discussed. Finally, Section 6 concludes the paper emphasizing its main contributions.

2 AFC SYSTEM WITH MULTIPLE FEEDBACK PATHS

Typically, aiming to be heard by a large audience in the same acoustic environment, a speaker uses a PA system with one microphone, responsible for picking up his/her own voice, one amplification system, responsible for amplifying the voice signal, and several loudspeakers placed in different positions, responsible for playback and distributing the voice signal in the acoustic environment so that everyone in the audience can hear it.

Such typical PA system with 1 microphone and C loudspeakers is showed in Fig.3. The loudspeaker signal $x(n)$, after played back by the kth-loudspeaker, may be picked up by the microphone going through the feedback path $F_k(z,n)$. The C acoustic feedback signals $\mathbf{f}_k(n) * x(n)$ are added to the system input signal $u(n)$, generating the microphone signal

$$y(n) = u(n) + \sum_{k=1}^{C} \mathbf{f}_k(n) * x(n). \tag{6}$$

Then, the feedback signals are estimated as $\mathbf{h}(n) * x(n)$ and subtracted from the microphone signal $y(n)$, generating the error signal

$$\begin{aligned} e(n) &= u(n) + \sum_{k=1}^{C} \mathbf{f}_k(n) * x(n) - \mathbf{h}(n) * x(n) \\ &= u(n) + \left[\sum_{k=1}^{C} \mathbf{f}_k(n) - \mathbf{h}(n) \right] * x(n), \end{aligned} \tag{7}$$

which is effectively the signal to be processed by the forward path $G(z,n)$. The error signal $e(n)$ will contain no acoustic feedback as desired if

$$H(z,n) = \sum_{k=1}^{C} F_k(z,n). \tag{8}$$

In this multiple feedback paths scenario, the adaptive filter has an optimum solution equal to the sum of the single acoustic feedback paths. Indeed, the AFC system with multiple feedback paths in Fig.3 can be simplified to the AFC system with single feedback path in Fig. 2 by considering $F(z,n)$ as the overall acoustic feedback path such that

$$F(z,n) = \sum_{k=1}^{C} F_k(z,n). \tag{9}$$

However, in this case, $F(z,n)$ generally has more prominent peaks and a lower sparseness which have influence on the performance of adaptive filtering algorithms (Das and Chakraborty, 2012). Therefore, the evaluation of AFC methods using multiple feedback paths is essential because it corresponds to a more realistic scenario of a typical PA system.

3 EVALUATED AFC METHODS

In this Section, a brief description of the AFC methods under evaluation is presented.

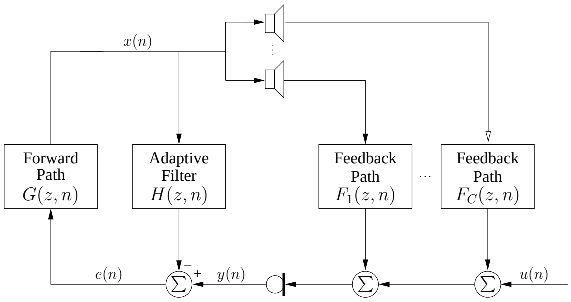

Figure 3: Typical AFC system with multiple feedback paths.

3.1 AFC Based on Whitening Pre-filtering

The PEM-AFROW method considers that the system input signal $u(n)$ can be approximated according to

$$U(z) = M(z,n)W(z), \tag{10}$$

where $w(n)$ is a white noise with zero mean and the inverse source model $M^{-1}(z,n)$ is defined as

$$M^{-1}(z,n) = A(z,n)B(z,n), \tag{11}$$

where $A(z,n)$ is a short-time prediction filter that models the vocal tract and $B(z,n)$ is a long-time prediction filter that models the periodicity.

From each frame of the error signal $e(n)$ which is expected to be close to $u(n)$, the PEM-AFROW method estimates $A(z,n)$ using the well-known Levinson-Durbin algorithm and thereafter $B(z,n)$ using a one-tap filter with lag equal to the pitch period. Then, the method pre-filters the loudspeaker $x(n)$ and microphone $y(n)$ signals with the inverse source model in order to obtain whitened versions of them. Finally, these whitened signals are used to update the adaptive filter according to the NLMS algorithm (Rombouts et al., 2006).

3.2 AFC Based on Cepstrum of the Microphone Signal

In an AFC system as depicted in Fig. 2, if $\left|G(e^{j\omega},n)H(e^{j\omega},n)\right| < 1$ and $\left|G(e^{j\omega},n)\left[F(e^{j\omega},n) - H(e^{j\omega},n)\right]\right| < 1$, the cepstrum of the microphone signal $y(n)$ is defined as (Bispo et al., 2013)

$$\begin{aligned} c_y(\tau) = &c_u(\tau) + \sum_{k=1}^{\infty} \frac{\mathbf{g}^{*k}(n)}{k} \\ &* \left\{ \left[\mathbf{f}(n) - \mathbf{h}(n)\right]^{*k} + (-1)^{k+1} \mathbf{h}^{*k}(n) \right\}, \end{aligned} \tag{12}$$

where $\{\cdot\}^{*k}$ denotes the kth convolution power.

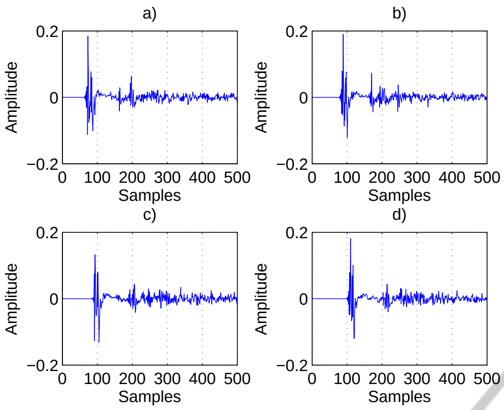

Figure 4: Impulse responses of the acoustic feedback paths (zoom in the first 500 samples).

From (12), the AFC-CM method extracts $\{\mathbf{g}(n) * \mathbf{f}(n)\}^{\frown}$, an instantaneous estimate of the system open-loop impulse response, and thereafter obtains $\hat{\mathbf{f}}(n)$, an instantaneous estimate of the impulse response of the feedback path. Finally, the method updates the adaptive filter according to (Bispo et al., 2013)

$$\mathbf{h}(n) = \lambda \mathbf{h}(n-1) + (1-\lambda)\hat{\mathbf{f}}(n), \tag{13}$$

where $0 \leq \lambda < 1$ is the factor that controls the trade-off between robustness and tracking rate of the adaptive filter.

4 SIMULATION CONFIGURATIONS

To assess the performance of the AFC methods, an experiment was made in a simulated environment to measure its abilities to increase the maximum stable gain of a PA system. For this purpose, the following configuration was used.

4.1 Simulated Environment

In order to simulate a PA environment with multiple feedback paths, 4 measured impulse responses of the same room, from (Jeub et al., 2009), were used as the impulse response $\mathbf{f}_k$ of the acoustic feedback paths. The impulse responses was downsampled to $f_s = 16$ kHz and then truncated to length $L_F = 4000$ samples, and are illustrated in Fig. 4.

The forward path, that is the amplifier of the PA system, was simply defined as an unity delay and a gain according to

$$G(z,n) = g_1(n)z^{-1}, \tag{14}$$

with length $L_G = 2$.

The insertion of a delay filter immediately after the forward path $G(z,n)$ is a common practice in the AFC methods. Then, the forward path $G(z,n)$ was followed by a delay filter

$$D(z) = z^{-(L_D-1)} \tag{15}$$

with length $L_D = 401$ so that generates a time delay of 25 ms.

4.2 Maximum Stable Gain

In order to measure the maximum stable gain of the PA system, a broadband gain $K(n)$ was defined, similarly to (van Waterschoot and Moonen, 2011), as the average magnitude of the frequency response $G(e^{j\omega},n)$ of the forward path

$$K(n) = \frac{1}{2\pi} \sum_{\omega=0}^{2\pi} |G(e^{j\omega},n)|, \tag{16}$$

and is extracted from $G(z,n)$ by

$$G(z,n) = K(n)J(z,n). \tag{17}$$

Considering that $J(z,n)$ is known, the maximum stable gain (MSG) was defined as

$$\begin{aligned} &\mathrm{MSG}(n)(\mathrm{dB}) = 20\log_{10} K(n) \\ &\text{such that } \max_{\omega \in P(n)} \left| G(e^{j\omega},n)D(e^{j\omega})F(e^{j\omega},n) \right| = 1, \end{aligned} \tag{18}$$

resulting in (19), where $P(n)$ denotes the set of frequencies that fulfill the phase condition in (4), also called critical frequencies of the PA system, and is defined as (20).

The MSG of the PA system with no AFC method was defined as $\mathrm{MSG}_0 = 20\log_{10} K_0$. $K(n)$ was initialized to a value K_1 such that $20\log_{10} K_1 < \mathrm{MSG}_0$ in order to allow the AFC method to operate in a stable condition and thus the adaptive filter to converge. As suggested in (van Waterschoot and Moonen, 2011), it was defined that $20\log_{10} K_1 = \mathrm{MSG}_0 - 3$, i.e., a 3 dB initial gain margin.

In a first configuration, $K(n)$ remained at the same value, $K(n) = K_1$, during all the simulation time $T = 20$ s in order to verify the methods' performance for a time-invariant forward path $G(z,n)$. In a more practical configuration, $K(n) = K_1$ until 5 s and then $20\log_{10} K(n)$ was increased at the rate of $^{1\mathrm{dB}}/_{\mathrm{s}}$ up to $20\log_{10} K_2$ such that $20\log_{10} K_2 = 20\log_{10} K_1 + \Delta K$. Finally, $K(n) = K_2$ during 10 s totaling a simulation time $T = 15 + \Delta K$ s.

As the main goal of the AFC methods is to increase the MSG of the PA system, it is necessary to include the frequency response $H(e^{j\omega},n)$ of the adaptive filter in the MSG measurement. Then, the MSG of a

$$\text{MSG}(n)(\text{dB}) = -20\log_{10}\left[\max_{\omega\in P(n)} \left|J(e^{j\omega},n)D(e^{j\omega})F(e^{j\omega},n)\right|\right]. \tag{19}$$

$$P(n) = \left\{\omega | \angle G(e^{j\omega},n)D(e^{j\omega})F(e^{j\omega},n) = 2k\pi, k\in\mathbb{Z}\right\}. \tag{20}$$

$$\text{MSG}(n)(\text{dB}) = -20\log_{10}\left[\max_{\omega\in P_H(n)} \left|J(e^{j\omega},n)D(e^{j\omega})\left[F(e^{j\omega},n)-H(e^{j\omega},n)\right]\right|\right]. \tag{21}$$

$$\Delta\text{MSG}(n)(\text{dB}) = -20\log_{10}\left[\frac{\max_{\omega\in P_H(n)} \left|J(e^{j\omega},n)D(e^{j\omega})\left[F(e^{j\omega},n)-H(e^{j\omega},n)\right]\right|}{\max_{\omega\in P(n)} \left|J(e^{j\omega},n)D(e^{j\omega})F(e^{j\omega},n)\right|}\right]. \tag{22}$$

$$P_H(n) = \left\{\omega | \angle G(e^{j\omega},n)D(e^{j\omega})\left[F(e^{j\omega},n)-H(e^{j\omega},n)\right] = 2k\pi, k\in\mathbb{Z}\right\}. \tag{23}$$

PA system with an AFC method was defined as (21). Moreover, the increase in MSG provided by the AFC method, ΔMSG, was defined as (22). In both equations, P_H denotes the set of frequencies that fulfill the phase condition of the system with the insertion of the adaptive filter, also called critical frequencies of the AFC system, as defined according to (23).

4.3 Frequency-weighted Log-spectral Signal Distortion

The sound quality was measured by the frequency-weighted log-spectral signal distortion defined as (van Waterschoot and Moonen, 2011)

$$\text{SD}(n) = \sqrt{\sum_{\omega=\omega_l}^{\omega_u} w(\omega)\left[10\log_{10}\frac{S_e(e^{j\omega},n)}{S_u(e^{j\omega},n)}\right]^2}, \tag{24}$$

where $S_e(e^{j\omega},n)$ and $S_u(e^{j\omega},n)$ are the short-term power spectrum density of the error signal $e(n)$ and system input signal $u(n)$, respectively, and $w(\omega)$ is a weighting function that gives equal weight to each auditory critical band between $\omega_l = 0.0375\pi$ (equivalent to 300 Hz) and $\omega_u = 0.8\pi$ (equivalent to 6400 Hz) (ANSI, 1997). The short-term power spectrum densities $S_e(e^{j\omega},n)$ and $S_u(e^{j\omega},n)$ are computed using frames of 20 ms.

Indeed, $\text{SD}(n)$ quantifies the distortion inserted in the error signal $e(n)$ in comparison with the system input signal $u(n)$. The $\text{SD}(n)$ value will be as low as the inserted distortion is and has optimum value $\text{SD}(n) = 0$ when $e(n) = u(n)$. In general, $\text{SD}(n) \to 0$ as long as $e(n) \to u(n)$.

4.4 Speech database

The signals database used in the simulations was formed by 10 speech signals. Each speech signal was composed of several basic signals from a speech database. Each basic signal consisted of one 4 s short sentence with original sampling rate of 48 kHz but downsampled to $f_s = 16$ kHz. All basic signals were recorded in the talkers native language, and their nationalities and genders were the following:

- 4 Americans (2 males and 2 females)
- 2 British (1 male and 1 female)
- 2 French (1 male and 1 female)
- 2 Germans (1 male and 1 female)

But since the performance assessment of adaptive filters needs longer signals, several basic signals from the same talker were concatenated and had their silence parts removed by a voice activity detector (VAD), resulting in the mentioned 10 speech signals (1 signal per talker).

5 SIMULATION RESULTS

This Section compares the performance of the AFC methods under evaluation using speech signal as the source signal $v(n)$. The evaluation was done in a situation close to real-world conditions where the source-signal-to-noise ratio (SNR) was 30 dB. With the exception of the adaptive filters' parameters, the parameters of all methods had the same values as originally proposed (adjusted to $f_s = 16$ kHz in the case of PEM-AFROW).

The optimization of the adaptive filter parameters (λ and L_H in the case of the AFC-CM, and stepsize μ, normalization parameter δ and L_H of the PEM-AFROW) was performed for each signal. From a predefined range for each one, the values were chosen empirically in order to optimize the curve $\text{MSG}(n)$, and consequently $\Delta\text{MSG}(n)$, in terms of minimum area of instability and, secondarily, of maximum mean value within the simulation time. The optimal curves for the kth signal were defined as $\text{MSG}_k(n)$ and $\Delta\text{MSG}_k(n)$ while the respective $\text{SD}(n)$ curve as $\text{SD}_k(n)$.

Then, the optimal average curves $\text{MSG}_o(n)$, $\Delta\text{MSG}_o(n)$ and $\text{SD}_o(n)$ were obtained by averaging the optimal curves of each signal according to

$$\text{MSG}_o(n) = \frac{1}{10}\sum_{k=1}^{10} \text{MSG}_k(n), \tag{25}$$

$$\Delta\text{MSG}_o(n) = \frac{1}{10}\sum_{k=1}^{10} \Delta\text{MSG}_k(n), \tag{26}$$

and

$$\text{SD}_o(n) = \frac{1}{10}\sum_{k=1}^{10} \text{SD}_k(n). \tag{27}$$

And their respective mean values were defined as

$$\overline{\text{MSG}_o} = \frac{1}{N_T}\sum_{n=1}^{N_T} \text{MSG}_o(n), \tag{28}$$

$$\overline{\Delta\text{MSG}_o} = \frac{1}{N_T}\sum_{n=1}^{N_T} \Delta\text{MSG}_o(n), \tag{29}$$

and

$$\overline{\text{SD}_o} = \frac{1}{N_T}\sum_{n=1}^{N_T} \text{SD}_o(n), \tag{30}$$

where N_T is the number of samples relating to the simulation time. In addition, the asymptotic value of ΔMSG_o was defined as $\overrightarrow{\Delta\text{MSG}_o}$, which represents the MSG increase provided by the AFC methods, and was estimated only by inspection of the curve.

In the first configuration, the broadband gain $K(n)$ remained constant, i.e., $\Delta K = 0$. Fig. 5 shows the results obtained by the AFC methods under evaluation for $\Delta K = 0$. As can be observed, the AFC-CM method outperformed the PEM-AFROW. The PEM-AFROW obtained $\overline{\Delta\text{MSG}_o} = 5.6$ dB and $\overrightarrow{\Delta\text{MSG}_o} \approx 7.4$ dB while the AFC-CM achieved $\overline{\Delta\text{MSG}_o} = 7.9$ dB and $\overrightarrow{\Delta\text{MSG}_o} \approx 10$ dB.

With respect to sound quality, the same order of performance was obtained but with very similar results. The PEM-AFROW obtained $\overline{\text{SD}_o} = 1.9$ while the AFC-CM achieved $\overline{\text{SD}_o} = 1.8$. These low and similar $\overline{\text{SD}_o}$ values may be explained by the fact that, with such fixed value of $K(n)$ and with the increase in MSG provided by all the AFC methods, the systems were too far from the instability.

In the second configuration, $K(n)$ was increased by $\Delta K = 13$ dB. Fig. 6 shows the results obtained by the AFC methods for $\Delta K = 13$ dB. As can be observed, the AFC-CM outperformed the PEM-AFROW in the first half of the simulation runtime while the opposite occurs in the second half. The AFC-CM obtained $\overline{\Delta\text{MSG}_o} = 8.5$ dB and $\overrightarrow{\Delta\text{MSG}_o} \approx 11.2$ dB while the PEM-AFROW achieved $\overline{\Delta\text{MSG}_o} = 8.2$ dB and $\overrightarrow{\Delta\text{MSG}_o} \approx 12.4$ dB.

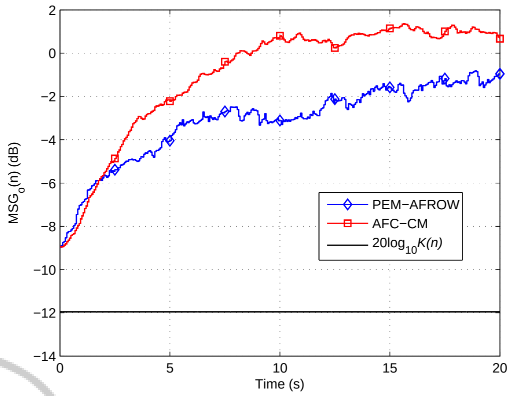

Figure 5: Average results of the methods for speech signal and $\Delta K = 0$.

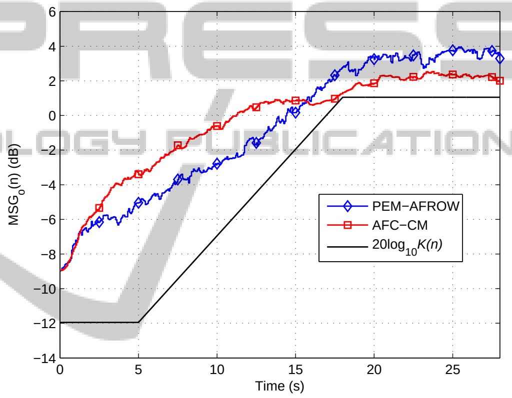

Figure 6: Average results of the methods for speech signal and $\Delta K = 13$.

Table 1: Summary of results obtained by the PEM-AFROW and AFC-CM methods using speech as source signal.

		$\overline{\Delta\text{MSG}_o}$	$\overrightarrow{\Delta\text{MSG}_o}$	$\overline{\text{SD}_o}$
$\Delta K = 0$	PEM-AFROW	5.6	7.4	1.9
	AFC-CM	7.9	10	1.8
$\Delta K = 13$	PEM-AFROW	8.2	12.4	3.1
	AFC-CM	8.5	11.2	3.7

In terms of sound quality, the AFC-CM method presented the worst performance by achieving $\overline{\text{SD}_o} = 3.7$ because it had a low stability margin after $t = 17$ s, as can be observed in Fig. 6, which resulted in an excess reverberation in the error signal $e(n)$. The PEM-AFROW obtained $\overline{\text{SD}_o} = 3.1$.

6 CONCLUSIONS

Acoustic feedback limits the maximum stable gain of a public address system and thus may cause the system to become unstable resulting in a howling at a specific frequency, a phenomenon known as Larsen effect. Acoustic feedback cancellation methods use an adaptive filter to identify the impulse response of the acoustic feedback path and then remove its influence from the system. However, since in such a system the source and loudspeaker signals are correlated, acoustic feedback cancellation methods that use traditional adaptive filtering algorithms based on the Wiener theory or least squares present a bias in the estimate of the acoustic feedback path if no decorrelation algorithm is used.

Several methods have been proposed to overcome the bias problem. However, the methods are generally evaluated considering a public address system with only one microphone and one loudspeaker. This work evaluates some of the state-of-art methods considering a public address system with one microphone and four loudspeakers that results in multiple feedback paths and corresponds to a more realistic scenario of a typical system.

Simulation results demonstrated that, with multiple feedback paths, the AFC methods are able to increase in around 12 dB the maximum stable gain of the public address system when the source signal is speech.

ACKNOWLEDGEMENTS

This work was partially supported by FCT - Fundação para a Ciência e a Tecnologia (SFRH/BD/49038/2008) and by the project AAL4ALL - FCOMP-01-0124-FEDER-13852, co-financed by European Community Fund FEDER through COMPETE - Programa Operacional Factores de Competitividade (POFC).

REFERENCES

ANSI (1997). ANSI S3.5: American national standard methods for calculation of the speech intelligibility index. American National Standard Institute.

Bispo, B. C., Rodrigues, P. M. L., and da S. Freitas, D. R. (2013). Acoustic feedback cancellation based on cepstral analysis. In *Proceedings of 17th IEEE Conference on Signal Processing Algorithms, Architectures, Arrangements and Applications*, pages 205–209, Poznan, Poland.

Das, R. L. and Chakraborty, M. (2012). Sparse adaptive filters - an overview and some new results. In *Proceedings of the 2012 IEEE International Symposium on Circuits and Systems*, pages 2745–2748, Seoul, Soutjh Korea.

Hellgren, J. and Forssell, U. (2001). Bias of feedback cancellation algorithms in hearing aids based on direct closed loop identification. *IEEE Transactions on Speech and Audio Processing*, 9(7):906–913.

Jeub, M., Schäfer, M., and Vary, P. (2009). A binaural room impulse response database for the evaluation of dereverberation algorithms. In *Proc. International Conference on Digital Signal Processing*, Santorini, Greece.

Rombouts, G., van Waterschoot, T., Struyve, K., and Moonen, M. (2006). Acoustic feedback cancellation for long acoustic paths using a nonstationary source model. *IEEE Transactions on Signal Processing*, 54(9):3426–3434.

Siqueira, M. G. and Alwan, A. (2000). Steady-state analysis of continuous adaptation in acoustic feedback reduction systems for hearing-aids. *IEEE Transactions on Speech and Audio Processing*, 8(4):443–453.

van Waterschoot, T. and Moonen, M. (2011). Fifty years of acoustic feedback control: state of the art and future challenges. *Proceedings of the IEEE*, 99(2):288–327.