# An Efficient Active Noise Control System with Online Secondary Path Estimation for Snoring Reduction

1st Stefano Nobili
*Department of Information Engineering*
*Università Politecnica delle Marche*
Ancona, Italy
0000-0002-5529-1891

2nd Valeria Bruschi
*Department of Information Engineering*
*Università Politecnica delle Marche*
Ancona, Italy
0000-0002-1367-5301

3rd Ferruccio Bettarelli
*Leaff Engineering*
Osimo, Italy
info@leaff.it

4th Stefania Cecchi
*Department of Information Engineering*
*Università Politecnica delle Marche*
Ancona, Italy
0000-0002-9625-814X

***Abstract*—This paper presents a new active noise control (ANC) technique with online secondary path estimation and subband adaptive filtering (SAF) for snoring reduction. In particular, the combination with the SAF structure allows to obtain a better estimation of the primary path and also has an impact on the algorithm performance, especially in terms of convergence rate. Although the SAF technique is applied only in the primary path estimation, it improves also the performance of the secondary path estimation guaranteeing a better convergence rate. The proposed algorithm has been first validated using white noise and then tested considering snoring signals. The experimental results have confirmed its effectiveness in comparison with the state of the art.**

***Index Terms*—active noise control, subband adaptive filtering, filters bank, snoring reduction**

## I. Introduction

The noise produced by snoring activity is a significant problem in our society. This type of noise can reach a volume of 90 dB and can cause several problems, such as loss of productivity, reduction of attention and unsafely drive [1], [2]. Recently, several studies have highlighted the strong similarity between the snoring activity and the vocal signal [3], [4]. In fact, the snoring signal is characterized by a fundamental frequency followed by high order harmonics [4], like the vocal signal. The snoring activity could be divided into two phases: inspiration and expiration. Considering the snoring spectrum, the most of the power is located at lower frequencies. In particular, between 100 Hz and 200 Hz during the inspiration and between 200 Hz and 300 Hz during the expiration. Hence, the fundamental frequency to be eliminated resides between 100 Hz and 300 Hz. The literature offers several solutions for snoring attenuation. Passive systems involves the use of devices such as earplugs or special pillow [5]. However, these techniques could be very annoying for the user and they have no effect at low frequencies. Instead, active noise control (ANC) systems are capable of attenuating the low frequency noise where passive techniques are too expensive and, in most case, ineffective. ANC systems must be adaptive in order to follow the variations of the acoustic path. For this reason, adaptive filters are used for ANC algorithms and can be designed in different ways and, in case of ANC, one of the most used is the least mean square (LMS) algorithm. The secondary source, that reproduces the "antinoise" signal, introduces a secondary path between the control source and the error microphone which has to be evaluated. In particular, the ANC system is usually built on filtered-x least mean square (FxLMS) [6] algorithm. In particular, an ANC system based on FxLMS is applied for snoring reduction in [7], [8]. Figure 1 shows a block diagram of a simple ANC system based on FxLMS algorithm, in which $x(n)$ represents the primary noise, $\mathbf{s}(n)$ is the impulse response of the secondary path and $\mathbf{w}(n)$ is the filter to be adapted with an LMS algorithm, controlling the residual noise $e(n)$ captured by the error microphone. In most cases, the secondary path could change due to environmental conditions or loudspeakers and microphones damage, so it too is time varying. Hence, the FxLMS algorithm can be improved with the introduction of online estimation of $\mathbf{s}(n)$. In the literature, two different approaches for online secondary path modeling can be found. The first approach consists of the injection of additional random noise $v(n)$ into the ANC system [9], while the second method avoids the noise injection by modeling $\mathbf{s}(n)$ from the output $y(n)$ [10]. A comparison of these two approaches is analyzed in [11], concluding that the first method is better than the second in terms of convergence rate, speed of response to variations of the primary noise, updating duration and computational cost. For this reason, only systems based on additional random noise injection are considered below. The first who proposed an online estimation of the secondary path with random noise injection is Eriksson

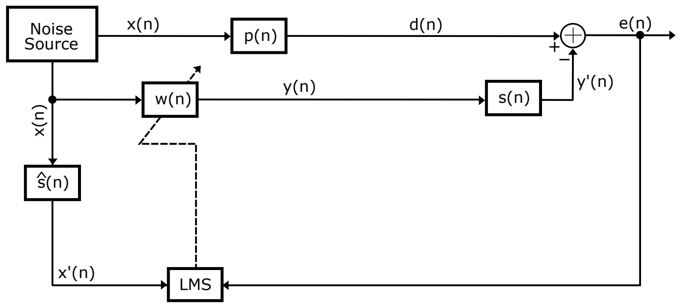



Fig. 1. Scheme of a simple ANC system based on FxLMS.

in [9]. This method introduces another adaptive filter to model $s(n)$ at the same time of ANC system using a white noise uncorrelated with the primary noise $x(n)$. The additional noise introduces a perturbation on the secondary path update that could degrade the convergence rate. In order to reduce this undesirable interference, two methods are proposed by Bao *et al.* in [12] and Kuo *et al.* in [13]. The method proposed in [12] uses another adaptive filter to cancel the interference caused by the additional noise, improving the convergence rate of the second path modeling. However, the additional noise $v(n)$ affects the convergence on the adaptation of the added filter. Differently, in [13] an adaptive prediction error filter is involved to attenuate the interference introduced by the additional noise. However, both in [12] and in [13] the effect of perturbation introduced by the additional noise $v(n)$ on the filter $\mathbf{w}(n)$ is not investigated. This problem has been analyzed and solved in [14], using three cross-updated adaptive filters.

In this paper, the algorithm presented in [14] has been modified in order to improve the performance of a snoring cancellation system. In particular, the adaptive system of the primary path has been enhanced introducing the delayless subband algorithm proposed by [15] in order to improve the performance of primary estimation in terms of convergence rate and error of the adaptive filters. In fact, the algorithm of [14] is called cross-update adaptive filter due to the dependence of each filter and an improvement of the primary adaptive filter enhances the whole algorithm.

The paper is organized as follows. Section II describes the proposed algorithm. Section III shows the experimental results. Finally, in Section IV conclusions and future works are discussed.

## II. Proposed Algorithm

The scheme of the proposed algorithm is shown in Figure 2. The proposed system is based on the approach presented in [14] for the primary path estimation, modifying it with the introduction of a delayless subband approach [15], that allows to improve the performances of the entire ANC system.

### A. ANC with online secondary path estimation

The secondary path estimation aims at improving the performance of previous state-of-the-art algorithms eliminating the perturbation introduced by the additional noise used to adapt the secondary path. The scheme of algorithm is based on FxNLMS where the input signal $x(n)$ is filtered by the estimation of secondary path $\hat{s}(n)$ to delete the contribute of secondary path and the weights adaptation is normalized against the power of input signal. As said above, the secondary path estimation is based on the injection of additional uncorrelated noise to the output of ANC controller and this noise represents a perturbation for the estimation of the primary path. To solve this problem, the approach of [14] calculates the signal error for the primary path estimation $e'(n)$ as follows:

$$e'(n) = e(n) - \hat{s}(n) * v(n), \tag{1}$$

where $v(n)$ is the injected uncorrelated noise, $\hat{s}(n)$ is the estimation of secondary path and $e(n)$ is calculated as:

$$e(n) = d(n) - s(n) * y(n) + s(n) * v(n), \tag{2}$$

where $d(n)$ is the desired signal, $y(n)$ is the output of the ANC controller and $s(n)$ is the real secondary path. In the ideal case, when $\hat{s}(n) = s(n)$, the error becomes $e'(n) = d(n) - s(n) * y(n)$ and the perturbation caused by the additional noise is removed. The error $e'(n)$ is used in the main adaptive filter as error signal for $w(n)$ and as desired signal for the additional adaptive filter $h(n)$. In fact, these filters have the following updating equations:

$$w(n+1) = w(n) + \mu_w x'(n) e'(n), \tag{3}$$

$$h(n+1) = h(n) + \mu_h x(n)[e'(n) - z(n)], \tag{4}$$

where $z(n) = h(n) * x(n)$ is the output of filter $h(n)$, $x(n)$ is the noise signal, $x'(n)$ is the noise signal filtered with secondary path and $\mu_w$ and $\mu_h$ are the step size of the filters $w(n)$ and $h(n)$, respectively. The update equation of the secondary path estimation uses $v(n)$ as input signal and $e_s(n)$ as error signal, as follows:

$$\hat{s}(n+1) = \hat{s}(n) + \mu_s v(n) e_s(n), \tag{5}$$

where $\mu_s$ is the step size of the filter $\hat{s}(n)$ and $e_s(n)$ is computed as follows:

$$e_s(n) = g(n) - \hat{u}(n), \tag{6}$$

where $g(n) = e(n) - z(n)$ and $\hat{u}(n)$ is noise injected filtered by $\hat{s}(n)$.

### B. Subband adaptive filtering

The proposed system introduces a subband adaptive filtering (SAF) structure in the primary path estimation. Due to the dependence of each adaptive filter to other filters, the application of a delayless subband algorithm improves the convergence rate not only of the ANC controller but improves the whole system. In fact, the updates of the three adaptive filters are dependent on each other. The delayless subband adaptive filter algorithm is implemented as proposed in [15], as shown in Figure 2. The signal $x'(n)$, that is the input $x(n)$ filtered by $\hat{s}(n)$, and the error $e'(n)$, obtained by the Equation (1),

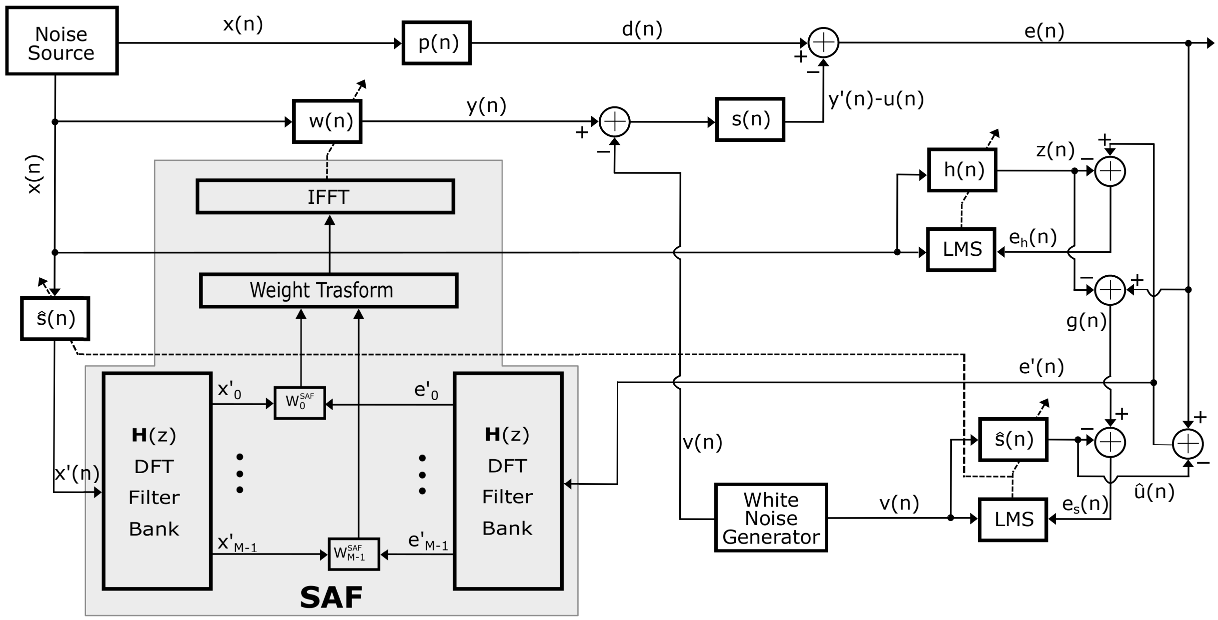



Fig. 2. Scheme of the proposed ANC system with secondary path modelling and delayless subband algorithm.

are decomposed in subband by the analysis filter-bank $\mathbf{H}(z)$, described as follows:

$$\mathbf{H}(z) = [H_0(z), H_1(z), ..., H_{M-1}(z)]^T, \tag{7}$$

where $H_k(z)$ is the transfer function of the $k$-th analysis bandpass filter of length $L = 512$, with $k = 0, ..., M-1$ and $M$ the number of subbands. The weights of the $k$-th subband $\mathbf{w}_k^{SAF}(n)$ are calculated using the following adaptive algorithm:

$$\mathbf{w}_k^{SAF}(n+1) = \mathbf{w}_k^{SAF}(n) + \mu_w \frac{\mathbf{x}_k'^*(n) e_k'(n)}{\alpha + ||\mathbf{x}_k'(n)||^2}, \tag{8}$$

where $*$ denotes the complex conjugation, $\mu_w$ the step size, $\alpha$ is a small number to avoid division by zero, $x_k'(n)$ is the input signal for the $k$-th subband and $e_k'(n)$ is the error of the $k$-th subband. To calculate the fullband filter $W(z)$, all the subband weights have to be stacked by executing the following steps:

- the subband weights are transformed by $(N/D)$-point FFT, where $N$ is the length of the fullband filter and $D = M/2$ the decimation factor;
- the complex samples of FFT are stacked to form the first half of the array of the fullband filter;
- to complete the array, the central point is set to zero and the first half is complex conjugate and reverse in order to fill the second half of array;
- the fullband filter is calculated by a $N$-point IFFT of the array.

The application of subband adaptive filtering (SAF) improves the performance of the whole algorithm as shown in the next section.

## III. Experimental Results

Some experiments have been carried out to evaluate the performance of the proposed algorithm. MATLAB has been

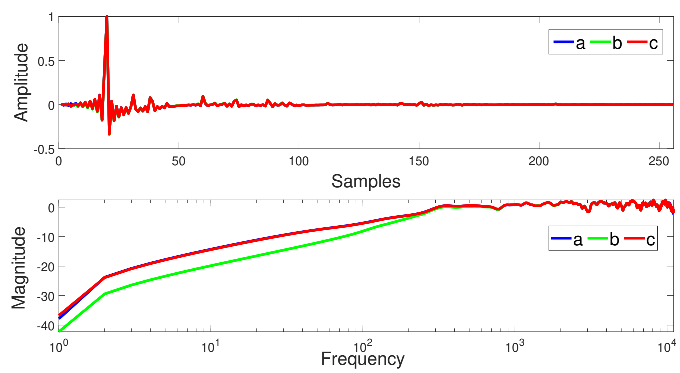



Fig. 3. Comparison between (a) primary path measured, (b) the weights of adaptive filter of reference and (c) the weights of the proposed adaptive filter for the primary path estimation. In time above and frequency below, considering white noise as input.

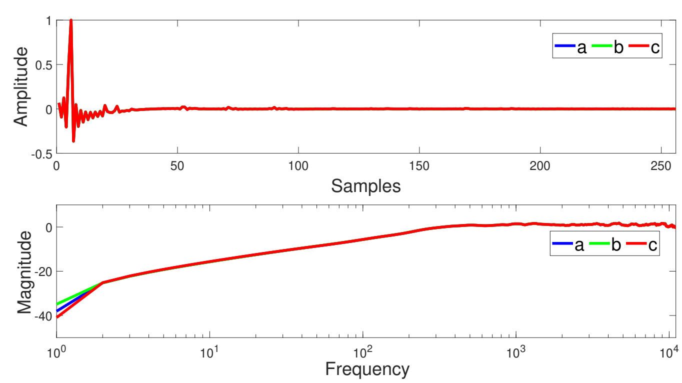



Fig. 4. Comparison between (a) secondary path measured, (b) the weights of adaptive filter of reference and (c) the weights of the proposed adaptive filter for the secondary path estimation. In time above and frequency below, considering white noise as input.

used to implement the algorithm and to compare it with the reference approach of [14]. The simulations have been conducted with broadband noise to evaluate the proposed method in the worst scenario. The primary path and the secondary path are measured from the setup of [8] inside a semi anechoic chamber and they are modeled as FIR filters of length N = 256 taps. The experimental tests have been carried out first with white noise and then considering a snoring signal as input, evaluating:

- the estimation of primary path;
- the estimation of secondary path;
- the convergence rate of the primary path;
- the convergence rate of the secondary path;
- the residual error after cancellation.

In particular, the convergence rate of the primary path has been evaluated the error calculated as follows:

$$\Delta w_e(n) = \frac{||w(n) - p(n)||}{||p(n)||}, \tag{9}$$

where $w(n)$ represents the weights of the adaptive algorithm and $p(n)$ is the impulse response of the primary path. For both algorithms the length of the filters are 512 taps for $w(n)$ and 256 taps for the adaptive filter of secondary path $\hat{s}(n)$ and for $h(n)$. For the delayless algorithm, a prototype filter length of $L = 512$ has been considered for white noise and a length of $L = 256$ for snoring noise.

### A. Results on white noise

The proposed algorithm has been first validated considering white noise as input. A large number of simulations have been realized to find the optimal values of step size for adaptive algorithms. In particular, for the reference algorithm the optimal values for the step size are the following: $\mu_w = 0.002$, $\mu_s = 0.002$, $\mu_h = 0.001$ and for the proposed algorithm are: $\mu_w = 0.008$, $\mu_s = 0.004$, $\mu_h = 0.001$. For the SAF structure, a number of subband of $M = 128$ has been chosen. In Figure 3, the time and frequency responses of the primary path compared to the weights of the adaptive filters of the proposed and of the reference algorithms are shown. The proposed approach fits perfectly the impulse response, while the reference approach has some difference in low frequency range, in particular below 200 Hz. At high frequency both approaches do not have problems to adapt the primary path. The better response of the proposed approach is due to the usage of subband decomposition. In fact, in each subband the signal has a narrower bandwidth than the original fullband signal and this algorithm improves the performance of the adaptive filter. Also the convergence rate is improved, as shown in Figure 7(i), where the displayed error $\Delta w_e(n)$ is calculated following the Equation (9). The comparison between the measured secondary path and the weights of the adaptive filter of the proposed and reference algorithms is shown in Figure 4. In this case, the reference and the proposed algorithms have a frequency response that fits perfectly with the secondary path. In fact, both the algorithms have a good

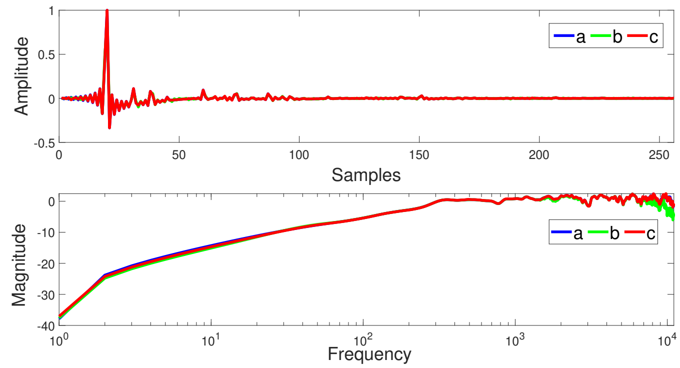



Fig. 5. Comparison between (a) primary path measured, (b) the weights of adaptive filter of reference and (c) the weights of the proposed adaptive filter for the primary path estimation. In time above and frequency below, considering snoring noise as input.

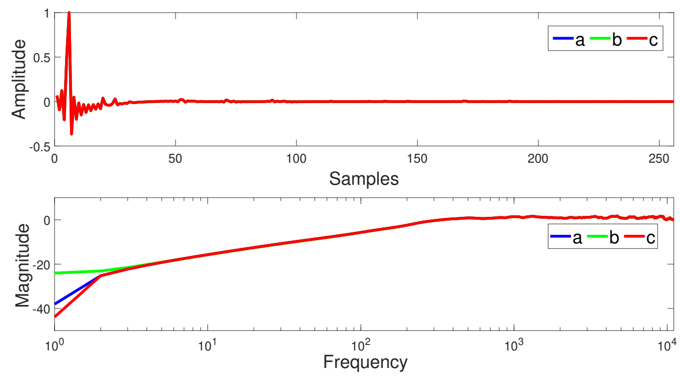
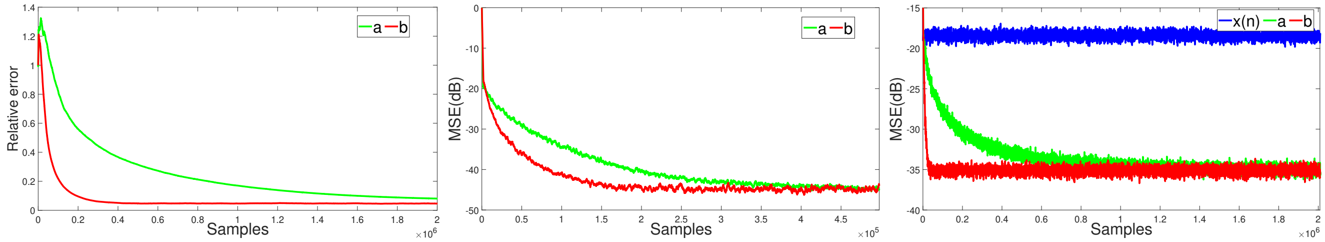



Fig. 6. Comparison between (a) secondary path measured, (b) the weights of adaptive filter of reference and (c) the weights of the proposed adaptive filter for the secondary path estimation. In time above and frequency below, considering snoring noise as input.

performance in terms of adaptation. Considering the convergence rate, the proposed algorithm has better performances, as shown in Figure 7(ii), where the signal error $e_s(n)$, defined by Equation (6), is reported. In this case, the better convergence is a side effect of the application of SAF in the primary path due to the dependence of secondary estimation with the main part of the algorithm. In the Figure 7(iii), the noise cancelling performance is compared reporting the residual noise $e(n)$. The residual noise of both algorithms are the same and this is due to the injection noise, however the proposed approach has a better performance in terms of convergence rate as result of the application of SAF technique.

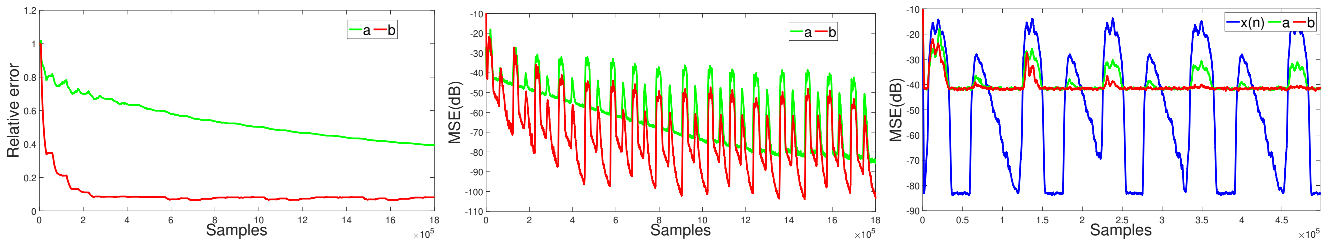
### B. Results on snoring noise

After the validation with white noise, the proposed algorithm has been tested considering the snoring noise as input. The snoring signal has been downloaded from [16]. Also in this case, several simulations have been achieved to find the optimal values of step size. For the reference algorithm the found values are the following: $\mu_w = 0.003$, $\mu_s = 0.0013$, $\mu_h = 0.001$ and for the proposed algorithm are: $\mu_w = 0.014$, $\mu_s = 0.001$, $\mu_h = 0.001$. For the SAF structure, a number of subband of $M = 64$ has been selected. Considering the




(i) (ii) (iii)

Fig. 7. Comparison between (a) the reference algorithm of [14] and (b) the proposed algorithm, evaluating (i) the relative error of the primary path estimation, (ii) the error of the secondary path estimation and (iii) the MSE in relation to the input signal $x(n)$, considering white noise as input.




(i) (ii) (iii)

Fig. 8. Comparison between (a) the reference algorithm of [14] and (b) the proposed algorithm, evaluating (i) the relative error of the primary path estimation, (ii) the error of the secondary path estimation and (iii) the MSE in relation to the input signal $x(n)$, considering snoring signal as input.

primary path estimation, both algorithms reconstruct perfectly the time and frequency responses, as shown in Figure 5. However, evaluating the convergence rate of the primary path, the proposed algorithm exhibits a significant improvement, as shown in Figure 8(i), where the error $\Delta w_e(n)$, calculated by Equation (9) is reported. Regarding the secondary path estimation, the proposed algorithm fits better the time and frequency responses, as shown in Figure 6. Also the convergence rate of the secondary path is greatly improved with the proposed algorithm, as reported on Figure 8(ii), where the error $e_s(n)$, defined by Equation (6), is displayed. Finally, Figure 8(iii) shows the residual noise $e(n)$, compared with the input snoring noise. The proposed algorithm reaches a residual noise about 10 dB lower than the reference approach, with a better convergence rate.

## IV. Conclusion

In this paper, an innovative active noise control algorithm with online secondary path modeling that includes a subband adaptive filtering method is presented and applied for snoring noise reduction. The proposed technique has been compared with an existing state-of-the-art approach through experimental tests. The experimental results have shown better performances of the proposed system in terms of convergence rate and path estimation, especially at the low frequencies and when snoring noise is considered. Future works will be focused on real-time implementation and testing of the proposed algorithm exploiting a DSP platform.

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