9

Functional Link Adaptive Filters for NAEC

Contents

In this chapter we apply the nonlinear model of FLAF, described in the previous chapter, to nonlinear acoustic echo cancellation (NAEC), which is the correspondent acoustic application of the nonlinear system identification. As said in Sections 3.2 and 7.1, when nonlinearities occur in the echo path it is necessary to employ a nonlinear echo canceller in order to reduce the quality loss and preserve the intelligibility of a speech communication. In particular, in this chapter we introduce a novel type of FLAF designed *ad hoc* to tackle nonlinearities in an NAEC application. Some experimental results show that FLAFs are an effective alternative to VFs in NAEC applications[1].

9.1 FLAFs FOR ACOUSTIC APPLICATIONS

Flexibility is one of the stronger points of FLAF. However, the FLAF structure may turn out to be not always optimal depending on applications and on the nonlinearity degree engendered by an unknown system. This issue is mainly due to the fact that the FEB expands the whole input buffer. Thereby the expanded buffer may contain more nonlinear elements than necessary and an overfitting case may occur, thus resulting in non-optimal filtering performance. Moreover, a control over the expanded buffer seems to be problematic, as the choice of the input buffer length is bound to an accurate estimate of the acoustic impulse response. Additionally, the choice of optimal parameters of the adaptive filter, such as the step size, is the same for both linear and nonlinear elements of the expanded buffer. This is the reason why also this choice results critical in many situations, in particular when the nonlinearity degree in the echo path varies in time, as it is often the rule in acoustic echo cancellation. Due to these changes of the nonlinearity degree, it could be desirable to have a control over the nonlinearity degree in order to achieve always the best possible fitting. In that sense, improvements can be achieved modifying the FLAF structure up to yield the robust filtering architectures, some of which will be described in this chapter.

9.2 THE SPLIT FUNCTIONAL LINK ADAPTIVE FILTER

A significant improvement can be achieved separating the adaptation of linear and nonlinear elements of the expanded buffer. In particular, it is

[1]The work in this chapter has been partly performed while the author was a visiting Ph.D. student at the Department of “Teoría de la Señal y Comunicaciones”, at “Universidad Carlos III de Madrid”.

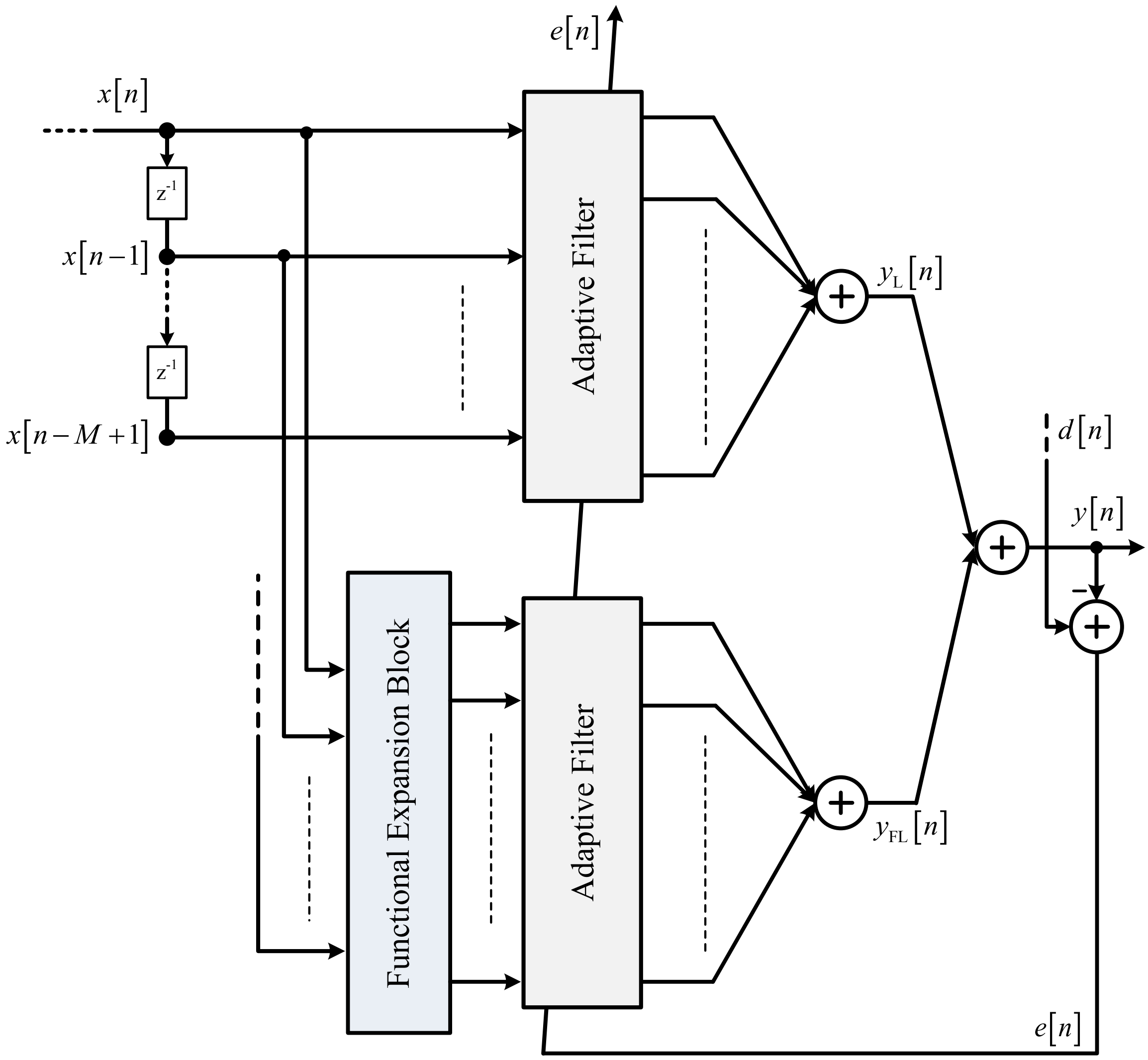

Fig. 9.1: *The split functional link adaptive filter.*

possible to consider two different adaptive filters in parallel, one completely linear and the other purely nonlinear. The linear filter receives the whole input buffer and aims only at estimating the echo path. On the other hand, the nonlinear filter is an FLAF in which the set of functional link does not include the replica of the linear element, as described in Chapter 8, thus the expanded buffer is only composed of nonlinear elements.

Therefore, the nonlinear FLAF only aims at modelling the nonlinearity affecting the echo signal. In this way it is possible to distinguish two different filterings with two different settings of the parameters, such that each filter can accomplish its task at best. Moreover, using this structure, the FEB can receive the whole input buffer or just a portion of it. This yields a further degree of freedom compared to the FLAF described in Chapter 8.

We call this filtering architecture *Split Functional Link Adaptive Filter* (SFLAF), thus remarking the separation between linear and nonlinear elements of the expanded buffer compared to the FLAF. The SFLAF structure is depicted in Fig. 9.1, where it is possible to notice that the SFLAF output signal results from the sum of the output of the linear filter and the output of the nonlinear FLAF:

$$y[n] = y_{\mathrm{L}}[n] + y_{\mathrm{FL}}[n] \tag{9.1}$$

in which $y_{\mathrm{L}}[n] = \mathbf{x}_n^T \mathbf{w}_{\mathrm{L},n}$, and where $\mathbf{w}_{\mathrm{L},n} \in \mathbb{R}^M = \begin{bmatrix} w_0[n] & w_1[n] & \ldots & w_{M-1}[n] \end{bmatrix}^T$ is the coefficient vector of the linear filter, and $y_{\mathrm{FL}}[n] = \mathbf{g}_n^T \mathbf{w}_{\mathrm{FL},n}$, where $\mathbf{w}_{\mathrm{FL},n} \in \mathbb{R}^{M_e} = \begin{bmatrix} w_0[n] & w_1[n] & \ldots & w_{M_e-1}[n] \end{bmatrix}^T$ is coefficient vector of the nonlinear FLAF.

From Fig. 9.1 it is possible to gather that both linear and nonlinear filters are adapted using the overall error signal $e[n] = d[n] - y[n]$. However, each filter can be adapted using a different adaptation rule and different parameter settings. This "splitting" feature of FLAFs opens new interesting scenarios in acoustic applications since it is even more possible to exploit at best the capabilities of linear adaptive algorithms and the effectiveness of functional links for acoustic applications. In fact, the flexibility of the FEB and the possibility to choice the proper adaptive filter, for both the nonlinear and the linear paths of SFLAF, make the SFLAF a versatile and effective tool for the modelling of the AIR affected by nonlinearities.

9.3 EXPERIMENTAL RESULTS

In this section we investigate the performance of the proposed SFLAF architecture in an echo cancellation scenarios. The scenario is a simulated teleconferencing environment in which the AIR is the one depicted in Fig. 6.1 (b), corresponding to a reverberation time of $T_{60} \approx 130$ ms, and truncated after $M = 512$ samples. In order to introduce a nonlinearity in the echo path which can simulate a loudspeaker distortion, we apply a *symmetrical soft-clipping* to the echo signal before that it activates the echo path according to the scheme in Fig. 9.2. The soft-clipping distortion is described by the following expression [165]:

$$f\left(x\left[n\right]\right) = \begin{cases} 2x\left[n\right] & \text{for} \quad 0 \leq x\left[n\right] \leq \zeta \\ \text{sign}\left(x\left[n\right]\right)\frac{3-\left(2-3x\left[n\right]\right)^2}{3} & \text{for} \quad \zeta \leq x\left[n\right] \leq 2\zeta \\ 1 & \text{for} \quad 2\zeta \leq x\left[n\right] \leq 1 \end{cases} \tag{9.2}$$

where ζ is a threshold chosen in the range $(0\ ,\ 0.5]$. We obviously suppose that the input signal is normalized at 1.

Two kinds of input signal are used for this scenarios: a white Gaussian noise input with zero mean and unitary variance and a female speech input. Additive Gaussian noise is added at the output of the echo path in order to provide 20 dB of signal to noise ratio (SNR). The length of the experiments is $t = 10$ seconds. In Fig. 9.3 it is possible to see the effect of the nonlinear

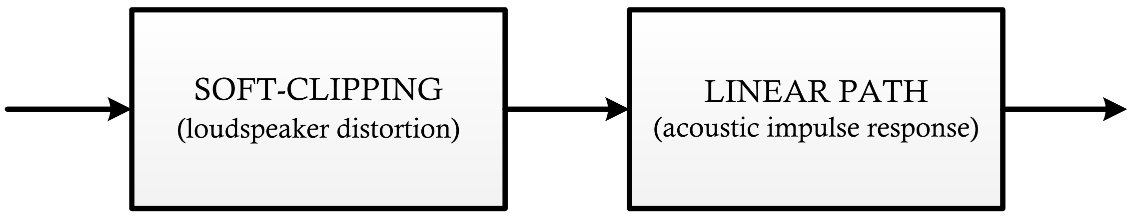

Fig. 9.2: *Scheme of the nonlinearity introduced in the input signal.*

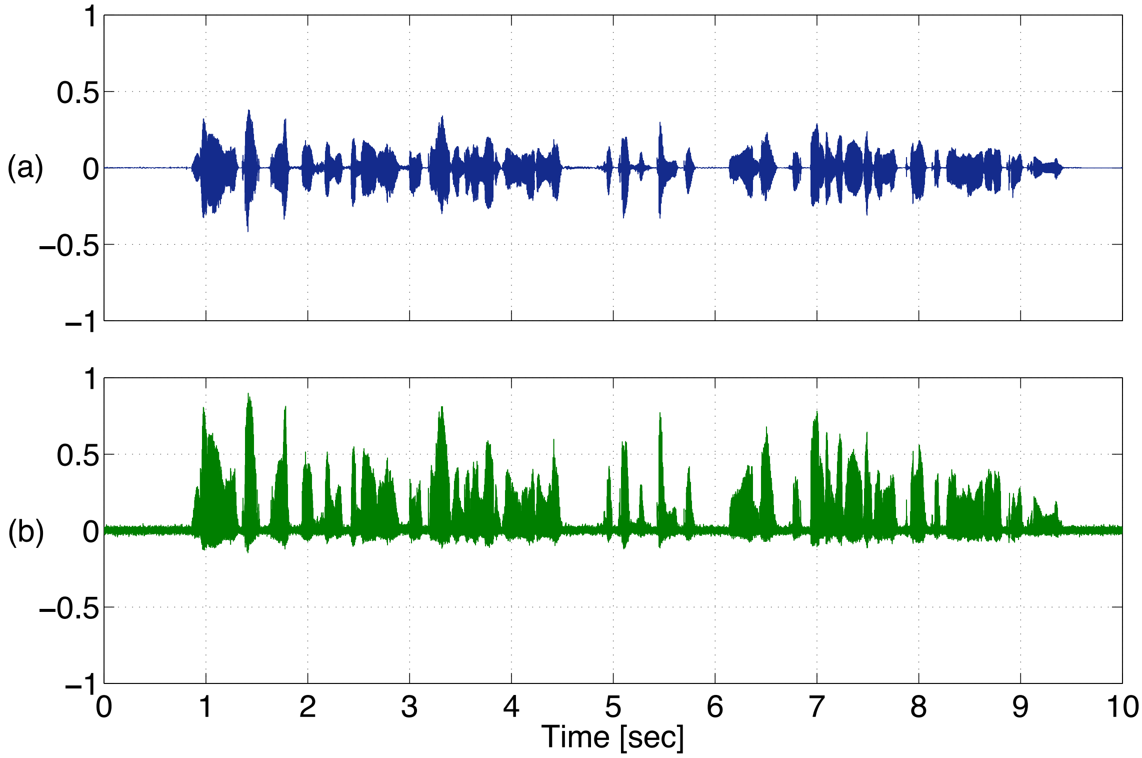

Fig. 9.3: *(a) Far-end female speech input signal. (b) Signal acquired by the microphone after being distorted and reverberated.*

distortion on the speech input signal using a clipping threshold of $\zeta = 1/8$.

9.3.1 Performance improvement of SFLAFs

First of all it is important to show the performance improvement brought by SFLAF compared to FLAF. We use the same parameter setting for both the FLAF and the SFLAF. The input buffer length is set to $M_e = M$, i.e. for the FLAF we use a filter length which is the same of the AIR length and for the SFAF we use the same length for both the linear and nonlinear filters. We choose an expansion order of $P = 5$ and a step size parameter of $\mu = 0.2$ for the FLAF and for both the filters of the SFLAF. Both FLAF and SFLAF are memoryless. All the adaptive filters are updated using an NLMS algorithm. We compare the performance of FLAF and SFLAF in terms of ERLE, both for the white Gaussian noise input and for the female speech input. Results

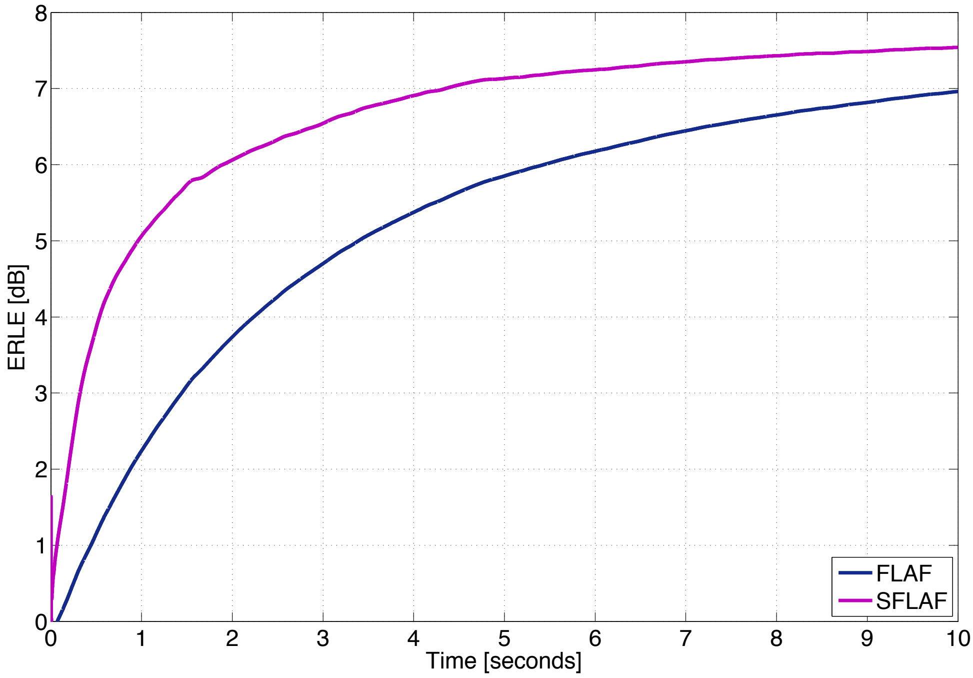

Fig. 9.4: *Performance comparison in terms of ERLE between an FLAF and an SFLAF in case of white Gaussian input.*

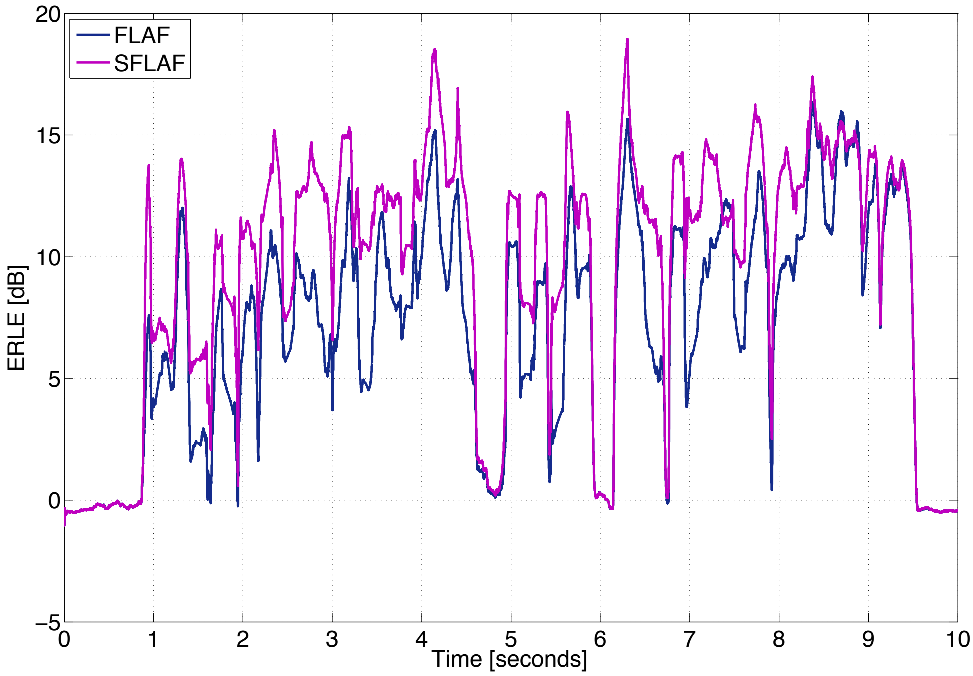

Fig. 9.5: *Performance comparison in terms of ERLE between an FLAF and an SFLAF in case of female speech input.*

are respectively depicted in Fig. 9.4 and Fig. 9.5 in which is evident the performance improvement brought by the SFLAF due to the separation of linear and nonlinear elements. Moreover, it has to be considered that it is also possible to change some parameters values of the SFLAF, such as the step size parameter and the input buffer length of the nonlinear path. A proper choice of such parameters may bring a further improvement of the performance of the SFLAF in terms of ERLE.

9.3.2 An effective alternative to Volterra filters

In the following set of experiments we compare the overall performance of an SFLAF with that of a VF, which, as previously said, remains the most popular NAEC in literature (see Section 7.1). We adopt the parameter setting

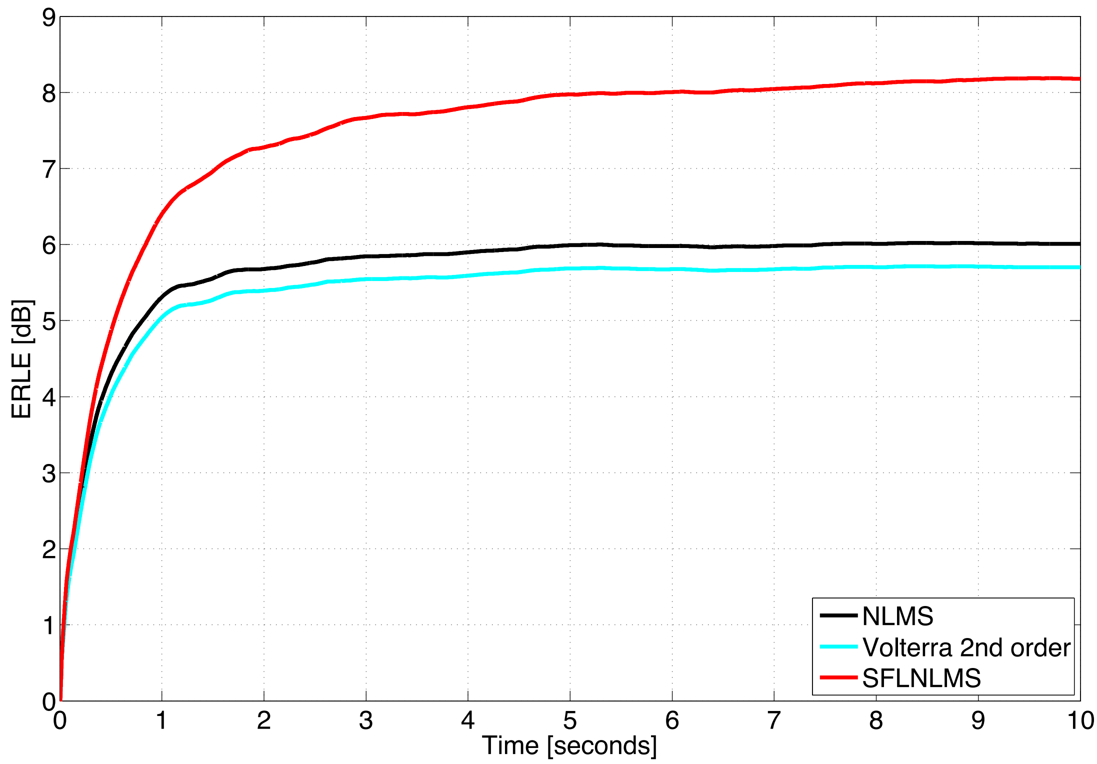

Fig. 9.6: *Performance comparison in terms of ERLE between the SFLAF and a 2nd order VF in case of white Gaussian input.*

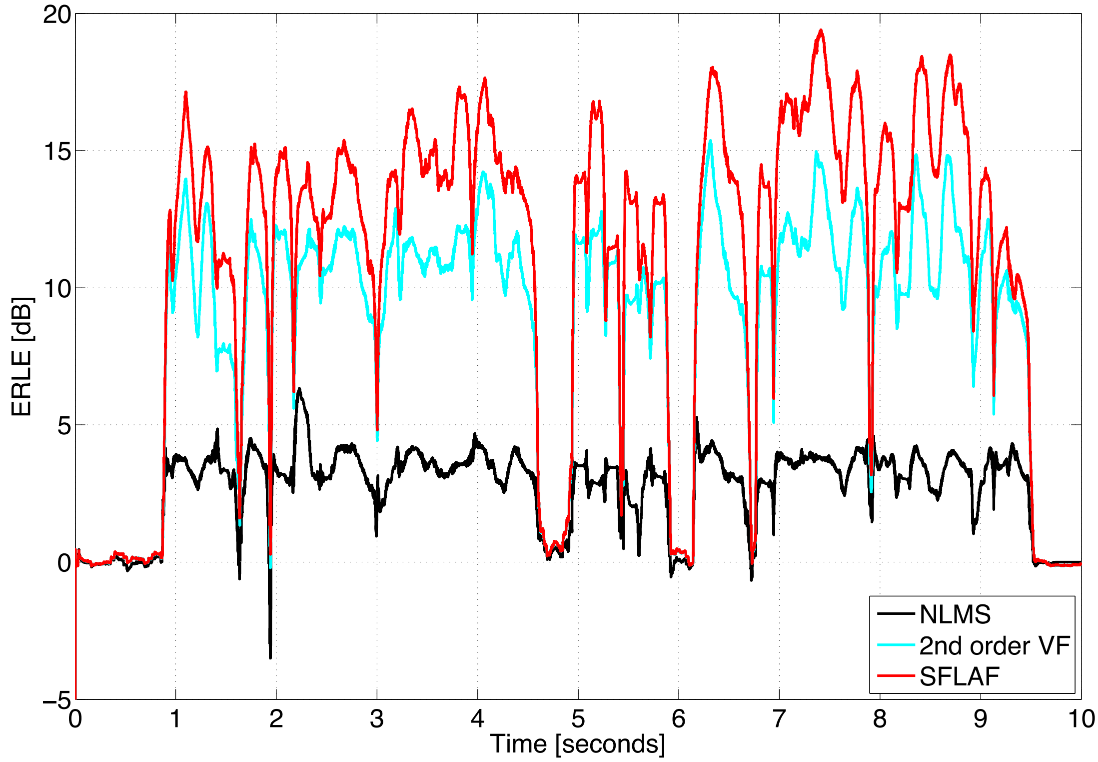

Fig. 9.7: *Performance comparison in terms of ERLE between the SFLAF and a 2nd order VF in case of female speech input.*

of the previous subsection for the SFLAF, but an expansion order of $P = 3$. The same buffer length, step size value and updating algorithm are also used for the adaptive Volterra filter, which is of the second order. Performance are evaluated in terms of ERLE for both the white Gaussian input and for the speech input, and results are respectively depicted in Fig. 9.6 and Fig. 9.7, where also the performance of an NLMS is taken into account as standard reference. Results show that SFLAF overcomes VF in terms of ERLE performance, thus resulting an effective alternative to VF for NAEC.

In terms of computational load, an SFLAF results more advantageous compared with a VF, especially when the SFLAF is memoryless. In a case like the one investigated, it is more convenient to use a memoryless SFLAF since the difference with an SFLAF with memory is quite small as it is possible to see from the comparison in Fig. 9.8. However, when the system may

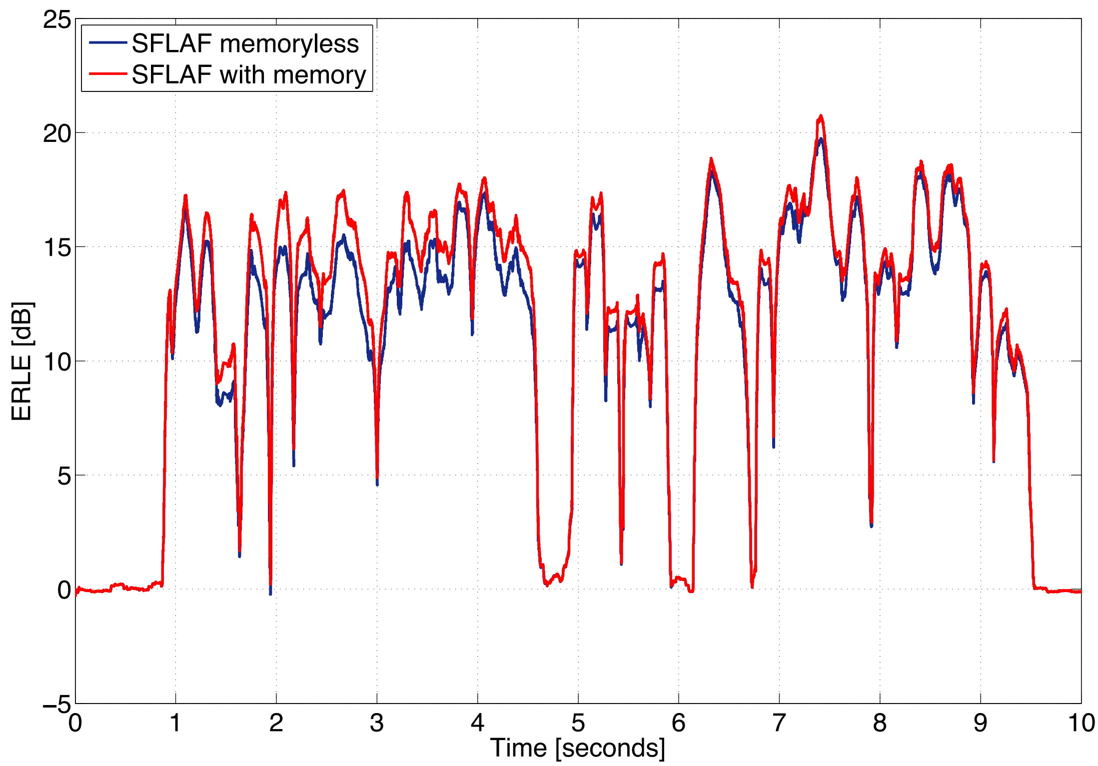

Fig. 9.8: *Performance comparison in terms of ERLE between an SFLAF with memory and a memoryless SFLAF.*

introduce a more dynamic nonlinearity than the used soft-clipping an SFLAF with memory may result definitely the best choice. It has to be taken into account that for speech input the use of an APA instead of the NLMS for the linear path of the SFLAF may bring further improvements in terms of ERLE. Further experiments on FLAFs for NAEC can be found in [29, 27].

9.4 CONCLUSIONS

In this chapter we have introduced a new class of nonlinear adaptive algorithms based on the FLAF model, described in Chapter 8, for acoustic applications. In particular, we have investigated the performance of the *splitting functional link adaptive filters* for NAEC, thus resulting an effective alternative to adaptive Volterra filters. The nonlinear model of SFLAFs has a great worthiness in this research project since it opens new research scenarios in the nonlinear acoustic echo cancellation due to the fact that SFLAFs allow future developments. In fact, using proper adaptive algorithms and nonlinear expansion it is possible to achieve further improvements in terms of ERLE. Moreover, it is possible to apply the proportionate techniques, introduced in the chapters of Part II, thus achieving a better modelling of nonlinearities, especially when they are highly time-variant.