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[N485] Active Noise Control Experimental Results with FxGAL Algorithm

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ABSTRACT

The filtered reference (or filtered-x) gradient adaptive lattice (FxGAL) algorithm is presented as an alternative to the FxLMS algorithm, widely used in active control of sound and vibration. Due to the orthogonalising properties of the adaptive lattice predictor, convergence obtained with the FxGAL algorithm can be faster and much less signal dependent, while maintaining the numerical stability of stochastic gradient algorithms. Also, better tracking capabilities are obtained in non-stationary environments. In this paper, we present and compare real-time experimental results obtained in a laboratory active noise control application, for both, FxLMS and FxGAL, algorithms. The active noise control system is an active headrest inside an enclosure and local control of engine-like noises is aimed with a feedforward configuration of the controller.

KEYWORDS: Active control, least-mean-square, adaptive lattice algorithms.

INTRODUCTION

When considering adaptive feedforward active control, the main difference with electrical noise cancelling is the presence of a transfer function in the auxiliary path following the adaptive filter. This so-called secondary transfer function accounts for the response of the digital-to-analog converter, the actuator, the physical path from the actuator to the sensor, the sensor and the analog-to-digital converter. Due to the presence of this transfer function, the least-mean-square (LMS) algorithm cannot be directly used, and has to be modified, yielding the Filtered-x LMS (FxLMS) algorithm [1]. The reference signal is filtered by the adaptive filter but it is not also used for the adaptation of the filter weights. Instead, a model of the secondary transfer function is needed to get a filtered reference signal (or filtered-x) to be used in the adaptation process of the filter weights.

The FxLMS algorithm is the most widely used in active control, in the same way as the LMS is used in generic adaptive applications. The reason for this popularity is its simplicity and robustness. Also, its main drawback is its slow and signal dependent convergence. Moreover, the presence of the secondary transfer function has been shown to degrade performance with respect to the classical LMS algorithm: convergence rate is lowered, residual power is increased, and more restrictive stability conditions apply for the adaptation step size, which are dependent on the reference signal bandwidth [2, 3, 4].

An alternative to FxLMS is the FxGAL algorithm [5], which can be seen as a version of the gradient adaptive lattice (GAL) algorithm [6, 7] modified to be used in the context of active control. The aim of FxGAL algorithm is to obtain faster and much less signal dependent convergence than FxLMS, at the expense of an increase in computational cost. In this paper we present experimental results of an active noise control (ANC) application with both algorithms which allow us to compare them.

FXGAL ALGORITHM

In the GAL algorithm, also known as the Griffiths' algorithm, the tapped delay line (TDL) of an FIR filter is substituted by an adaptive lattice predictor (ALP). Thus, approximate selforthogonalization of the input data is performed in the time domain, since the correlated sequence of delayed samples of the input signal,

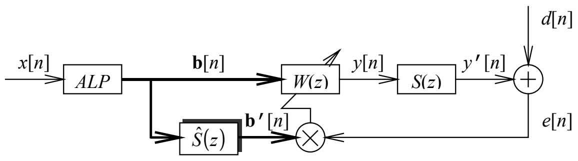
$$\{x[n], x[n-1], \ldots, x[n-M+1]\} \tag{1}$$

is transformed by the ALP in the uncorrelated sequence of backward prediction errors,

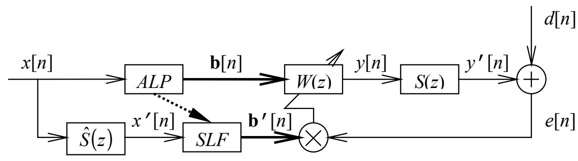
$$\{b_0[n], b_1[n], \ldots, b_{M-1}[n]\} \tag{2}$$

without loss of information. This uncorrelated sequence is the input to an adaptive linear combiner, which finally provides the output of the system. The linear combiner is adapted following the LMS algorithm. Due to the orthogonality property of the backward prediction errors, convergence modes are uncoupled. Thus, using the same normalised step size for all of the modes, it is possible to make them converge at the same rate, speeding up convergence of the whole system with respect to LMS. So, in the GAL algorithm faster convergence can be achieved at the expense of an increase in the computational complexity.

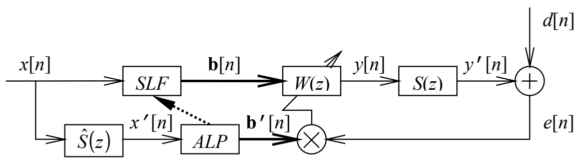
The ALP structure is modular, in such a way that the predictor of order M consists of M–1 identical cascaded stages. The inputs to the stage m are the forward and backward prediction



(a) ALP as preprocessing stage for FxLMS system.



(b) Variation of (a) to reduce computational complexity.



(c) FxGAL system.

Figure 1. Lattice-based active control systems.

errors of the (m–1)-th order predictor, and the outputs are the forward and backward prediction errors of the m-th order predictor. The ALP system itself is an adaptive filter, where a stochastic gradient method is used to adjust the filter coefficients, also named PARCOR, independently at each stage, so as to minimise the mean square of the sum of forward and backward predictor errors at the output of that stage.

When trying to transfer the GAL method to the context of active control, two possibilities arise. This is due to the fact that in the FxLMS system the reference signal, $x[n]$, is the input to the adaptive filter, but the adaptation occurs with the filtered reference signal, $x'[n]$, that is, the result of filtering the reference signal by the secondary model. So, the question is what of this two signals should be the input to the ALP stage.

In [8] a lattice ANC system is proposed which uses the reference signal $x[n]$ as the input to the ALP system (Figure 1.a). An almost equivalent system, which greatly reduces the computational complexity and memory requirements, is also proposed: the secondary model filtering and ALP blocks, needed to get the filtered backward prediction errors, are swapped, reducing the M filterings to only one (Figure 1.b). So, the reference signal is filtered by the secondary model and the filtered reference signal is the input to a slaved lattice filter, whose coefficients are simply a copy of the PARCOR coefficients of the ALP system.

However, the FxGAL system [5] uses the filtered reference signal as input for the ALP system, and a slaved lattice filter is applied to the reference signal prior to the adaptive linear combiner (Figure 1.c). This is due to the fact that the convergence properties of the FxLMS system are determined by the autocorrelation matrix of the filtered reference signal, $x'[n]$: its eigenvalues give rise to the various convergence modes. Therefore, this is the signal that should be decorrelated/orthogonalised in order to decouple convergence modes and speed up convergence with respect to FxLMS. On the other hand, when any of the two lattice ANC

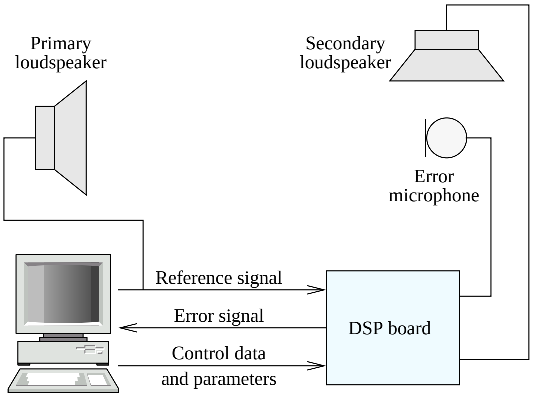


Figure 2. ANC monochannel system.

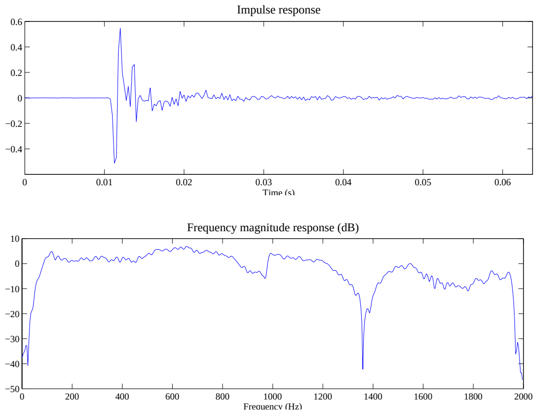


Figure 3. Secondary transfer function model.

systems proposed in [8] is used, the secondary model filtering of the backward prediction errors can re-correlate the signals, and the convergence acceleration might not happen.

EXPERIMENTAL RESULTS

Experimental Setup

In order to test the FxLMS and FxGAL algorithms, a feedforward monochannel (1 reference, 1 actuator and 1 error sensor) active noise control system has been developed. The experimental setup is shown in figure 2. Both algorithms have been implemented in a system based on the Texas Instruments' TMS320C6701 DSP. A computer has also been used to provide a visual interface for the ANC application, record the error signals and generate the noise signal which drives the primary loudspeaker and serves as reference for the algorithms. Thus, with this configuration there are no problems of feedback in the reference. The distance between the secondary loudspeaker and the error microphone is 17 cm. The distance from the primary loudspeaker to the error microphone is 205 cm for all of the experiments except when stated. The sampling frequency is 4 kHz.

Previously to the operation of the algorithms, the secondary transfer function has been modelled as a 256-tap FIR filter making use of the LMS algorithm. In figure 3 are shown the impulse and frequency responses of the secondary model obtained.

Narrowband Experiments

Due to the causality constraint of the controller, most of the ANC applications that try to reduce the acoustical noise inside an enclosure, such as a vehicle interior, aim to cancel only the tonal disturbances. Thus, in this section we inspect the behaviour of FxLMS and FxGAL systems when the reference is a periodic signal.

Figure 4 shows the learning curves obtained with sinusoidal reference for the FxLMS and FxGAL systems in three distinct situations according to the frequency of the sinusoidal signal and the distance between primary loudspeaker and error sensor: (a) 250 Hz and 2.05 m, (b) 200 Hz and 2.05 m, (c) 250 Hz and 2.50 m. Each curve has been estimated by averaging 25 realizations. The number of filter coefficients is 2. The adaptation step size for the FxLMS algorithm is $\mu_{FxLMS} = \dfrac{0.001235}{P_{x'}}$, where $P_{x'}$ is the power estimation of the filtered reference $x'[n]$. The normalised step size for the ALP stages in the FxGAL is $\tilde{\mu}_{ALP} = 0.01$, and the step size of each weight of the linear combiner is $\mu_{FxGAL} = \dfrac{0.001235}{P_{b'_m}}$, where $P_{b'_m}$ is the power estimation of the backward prediction errors $b'_m[n]$. So, the normalised step size of the linear combiner in both algorithms is the same.

As we have already mentioned, one of the main drawbacks of the FxLMS algorithm is that its convergence is much signal dependent. For instance, when trying to cancel a sinusoidal signal with only two filter weights, convergence rate of the FxLMS system exhibits a great variation as a function of the frequency of the signal, as can be seen comparing FxLMS curves (a) and (b). Also, FxLMS convergence rate varies greatly depending on the relative phase between the reference signal and the primary noise. This is also evident when we compare FxLMS curves (a) and (c): a change in the distance from the primary loudspeaker to the error microphone modifies the phase of the primary sinusoid, while keeping the same reference signal.

On the contrary, the FxGAL system exhibits much less signal dependency, due to the orthogonalization performed by the ALP. That is the reason why the three FxGAL curves in figure 4 look much more similar than the three FxLMS ones. Nevertheless, some degree of variation is still appreciated, due to the fact that the ALP system is also adaptive.

In some occasions, as in figure 4.c, FxLMS is fast enough, and the FxGAL system cannot improve convergence. In fact, it can be slightly slower as in this case. However, in general, FxGAL convergence is rather fast and faster than FxLMS.

Non-stationary Environment

In order to test the tracking capability of FxLMS and FxGAL algorithms, a variant noise signal has been generated. The reference signal is initially composed of two harmonically related tones of frequencies 150 and 450 Hz. After approximately 7.5 s the frequencies of the

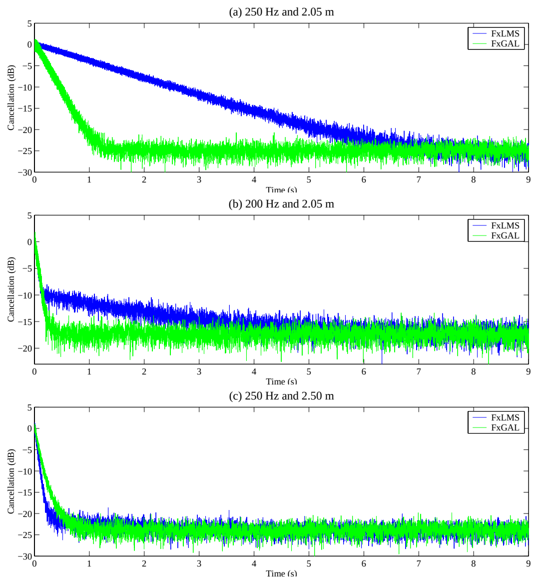


Figure 4. Convergence of FxLMS and FxGAL for sinusoidal reference.

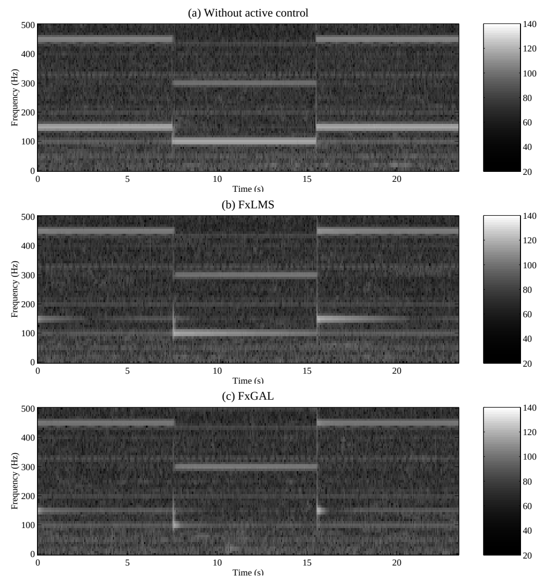


Figure 5. Spectrograms of non-stationary scenario.

two sinusoidal components change suddenly to 100 and 300 Hz. And after another 8 s they change again to their initial values. The power level of the lower frequency tone is 21 dB higher than the higher frequency one. The number of filter coefficients is 4 in this experiment. The adaptation step sizes are $\mu_{FxLMS} = \dfrac{0.0006173}{P_{x'}}$, $\tilde{\mu}_{ALP} = 0.01$ and $\mu_{FxGAL} = \dfrac{0.0006173}{P_{b'_m}}$. So, again the normalised step sizes of the linear combiners of both algorithms are the same.

In figure 5 are plotted the spectrograms of the error signals obtained with the FxLMS and the FxGAL systems. It is also displayed, for comparison purposes, the spectrogram of the signal present in the error microphone when there is no active control. The spectrogram of the signal without control shows clearly that the sudden frequency changes occur at around t = 7.5 s and t = 15.5 s. It can be seen on the FxLMS and FxGAL graphics that both adaptive algorithms invert all of their efforts in cancelling the high amplitude (lower frequency) sinusoid, whereas the low amplitude one remains almost unchanged. The higher amplitude sinusoid is much better cancelled in the FxGAL case after the two sudden changes at t = 7.5 s and t = 15.5 s, since the FxLMS system cannot completely cancel the 100 Hz tone between 7.5 and 15.5 s, and needs also more time to cancel the 150 Hz tone after t = 15.5 s. Therefore, better tracking capabilities are observed in the FxGAL system as compared to FxLMS. Again, this is mainly due to the orthogonalisation performed by the ALP system on the reference signal.

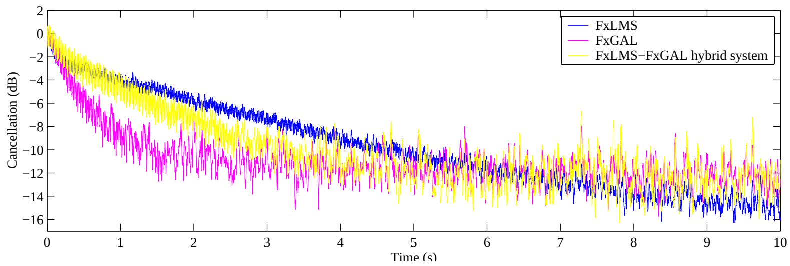


Figure 6. Convergence with broadband signal.

Broadband Experiment

The FxGAL algorithm is also valid for cancelling broadband disturbances: in [5] can be found some simulation results. However, the main disadvantage of the FxGAL system is the increase in computational complexity, due to the ALP system and the slaved lattice filter. Sometimes this can be partly avoided by combining the lattice and transversal filter structures in a hybrid structure [9]. The idea is to use as many ALP stages as necessary to completely decorrelate the signal, but no more. After the decorrelation is complete, there is no need to continue with ALP stages, and they can be substituted by delay elements, as in a transversal structure.

In figure 6 can be seen the convergence obtained with the FxLMS, FxGAL and hybrid FxGAL-FxLMS systems. The reference signal is composed of two sinusoids of frequencies 250 Hz and 300 Hz, and a background white noise. The noise power is 20 dB below the sinusoids, and the power level of the 250 Hz tone is 5 dB higher than the 300 Hz tone. The number of filter coefficients is 20, and the adaptation step sizes are $\mu_{FxLMS} = \dfrac{0.0001235}{P_{x'}}$, $\tilde{\mu}_{ALP} = 0.01$ and $\mu_{FxGAL} = \dfrac{0.0001235}{P_{b'_m}}$ (the same normalised step size is used for the linear combiner in the three systems). In the hybrid system there are 10 lattice stages, which yield 11 backward prediction errors, and the last prediction error is then delayed in a transversal structure with 9 delay elements, to obtain the rest of the inputs to the linear combiner. The curves have been obtained averaging 25 runs, and also, for viewing purposes, they have been smoothed by moving average filtering of 60 coefficients.

Figure 6 shows again that the FxGAL system can be faster than FxLMS. But, also, it shows that sometimes FxLMS cancels more in the end than FxGAL. This is due mainly to the misadjustment of the ALP system, that can be considered as an additional noise in the reference. Additionally, it is clear from figure 6 that the hybrid FxLMS-FxGAL system behaviour is in the middle between FxLMS and FxGAL. So, it can be seen as a way of trading computational complexity and convergence improvement.

CONCLUSIONS

Experimental results in an active noise control application of FxLMS and FxGAL systems have been presented. According to them, the FxGAL algorithm can obtain most of the times faster and much less signal dependent convergence than FxLMS. Additionally, in a non-stationary environment, the faster FxGAL convergence translates into better tracking capabilities and better cancellation. On the other hand, the main drawback is the increase in computational complexity. An alternative hybrid system has also been presented, which is less computationally demanding while still being able to speed up convergence with respect to FxLMS.

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