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BROADBAND ACTIVE SOUND CONTROL SYSTEM WITH SELECTIVE VIRTUAL SENSING

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ABSTRACT

The convergence speed of broadband multichannel adaptive active noise algorithms can be improved if the updating of the time domain control filter is performed in the frequency domain, normalising the power of the reference signals and compensating for the response of the plant. Although the updates are performed one block at a time, no additional delay is then introduced in the processing of the reference signals and the convergence time and the computational load can be reduced compared with time domain adaptation when there are many correlated reference signals, such as in the active control of road noise in vehicles. One method of implementing virtual sensors is to use the auxiliary filter method, which provides targets for the measured error signals to follow, generated from the reference signals. The performance of this virtual sensing algorithm is known to be degraded if the properties of the reference signals change, however. It may still be possible to approximate the properties of the measured reference signals using a limited number of exemplar cases. By classifying the measured reference signals into the closest of these cases, the most appropriate auxiliary filter could then be selected for the adaptive algorithm at any one particular time.

Keywords: *active control, virtual sensing, selective anc.*

1. INTRODUCTION

The convergence rate of multichannel broadband adaptive control systems is limited by the spectral spread of the individual reference signals and by the correlations between them [1]. One way that has been suggested for improving the convergence rate is to precondition the reference signals, $\boldsymbol{x}$, with a matrix of filters $\boldsymbol{P}$, to provide a set of modified reference signals, $\boldsymbol{v}$, that are more white and less correlated than $\boldsymbol{x}$, as shown in Figure 1, in which $\boldsymbol{W}$ is the matrix of adaptive feedforward control filters and $\boldsymbol{G}$ is the matrix of plant responses between the secondary sources and the physical error sensors, with outputs $\boldsymbol{e}$.

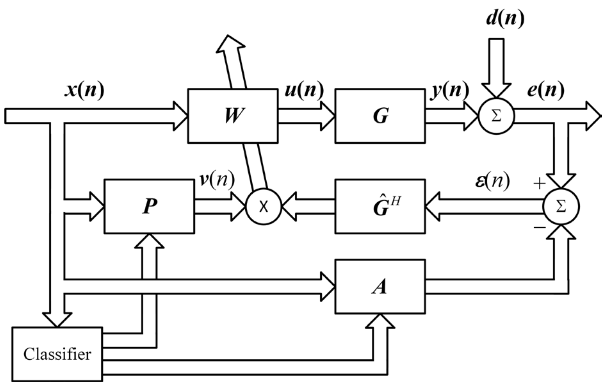

Figure 1. Block diagram of an adaptive feedforward control system having both preconditioning of the references signals, $\boldsymbol{P}$, and using an auxiliary filter, $\boldsymbol{A}$, for virtual sensing, with both of these filters selected according to the properties of the reference signals, as estimated with the classifier.

It is assumed that a filtered-error adaptive algorithm is used, where $\widehat{\boldsymbol{G}}^H$ is the Hermitian transpose of the estimated plant response matrix, although the delays associated with ensuring the causality of this are omitted for clarity. Also shown in Figure 1 is the auxiliary filter, $\boldsymbol{A}$ also called the additional filter, which is used for virtual sensing so that the control filter is adapted to minimise the difference between the measured signals at the physical error sensors and the

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signals at these sensors when the outputs of a number of remote virtual error sensors is minimised [2]. It is known that the auxiliary filter method of virtual sensing is less sensitive to perturbations in the plant response that the remote microphone method, but is more sensitive to changes in the statistical properties of the reference signals [3,4]. The characteristics of both the preconditioning filter, $\boldsymbol{P}$ and the auxiliary virtual sensing filter, $\boldsymbol{A}$ are thus dependent on the statistical properties of the reference signals, which in general may change over time. For this reason, both of these filters could be scheduled on the measured characteristics of the reference signals, as estimated by a classifier, as also shown in Figure 1, in a form of selective active control [5,6]. In the remainder of this paper, simulations of reference signal preconditioning are presented using a database of road noise signals measured on an electric vehicle [7]. It is shown that even under apparently very stationary conditions, preconditioning degrades the performance of the adaptive algorithm if it is based on the long-term properties of the reference signals. A more successful form of preconditioning uses the short-term properties of the reference signals, particularly if this is based on the window size of a frequency domain implementation. Unfortunately, the dataset in [7] does not include virtual error signals, so that the performance of the auxiliary filter method could not be tested using these measurements.

2. SIMULATIONS

An important application of multichannel broadband active noise control is the reduction of road noise in cars [8]. The dataset of road noise signals provided by Yang et al. [7] includes 20 minutes of sampled time histories for the reference signals obtained from 16 accelerometers on an electric car and the disturbance signals measured at 2 error microphones at the ears of a dummy head, sampled at 4 kHz, for 5 different road speeds. Also provided are the drive signals to two headrest loudspeakers and the corresponding response at the error microphones, from which the matrix of plant responses can be estimated.

Figure 2 shows the long-term power spectral density, PSD, of a representative reference signal, recorded at a road speed of 50 kph, and its spectrogram over the 20 seconds of this dataset, indicating that these signals have a large spectral range but appear to be very stationary.

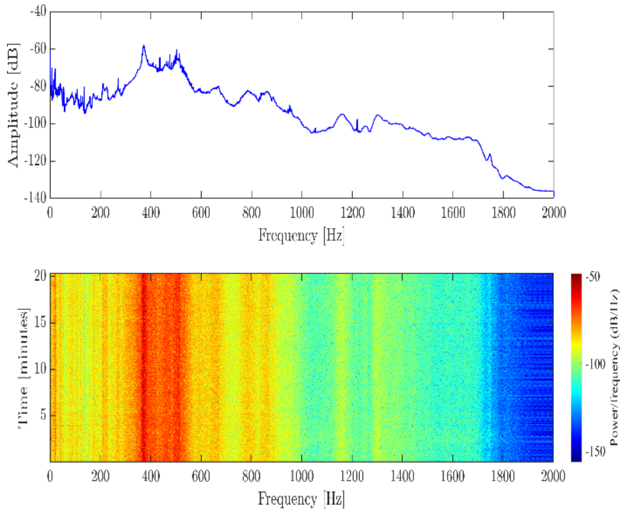

Figure 2 The long-term power spectral density, PSD, of a representative reference signal from [7] and its spectrogram over 20 minutes.

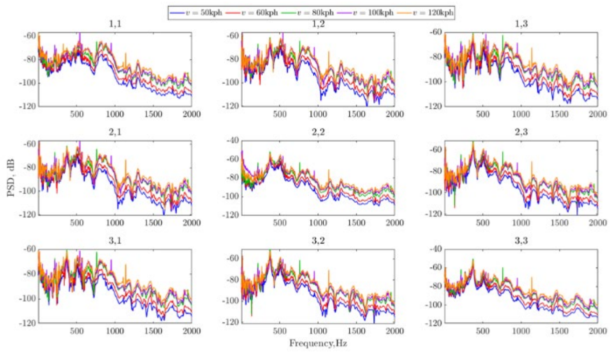

Figure 3 The PSD and CSD of three reference signals from [7], at five different road speeds.

Figure 3 shows the power spectral densities, PSD, diagonal plots, of three representative reference signals in [7] and the cross spectral density, CSD, off-diagonal plots, between these signals, showing that these signals are strongly correlated. Above about 500 Hz their levels rise by about 10dB as the road speed increases from 50 kph to 80 kph, but then remain reasonably constant from 80 kph to 120 kph. The dataset at 50 kph have been used to simulate the convergence characteristics of various adaptive feedforward control algorithms in minimizing the sum of the square outputs at the two microphones using both secondary loudspeakers.

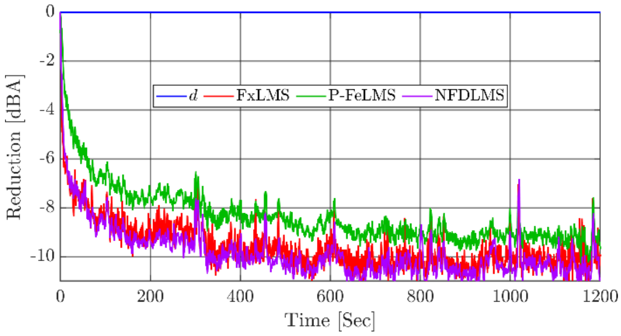

Figure 4. The time histories of the mean square error signals using the FxLMS algorithm, the preconditioned filtered error algorithm, P-FeLMS, and the bin-normalised frequency domain LMS algorithm, NFDLMS

The time histories of the attenuation in the sum of squared, smoothed and A-weighted error signals are shown in Figure 4 when the FxLMS control algorithm is simulated. About 6dB of attenuation is achieved after 10 seconds, but it then takes about 700 seconds to achieve the full 11 dB of attenuation, in agreement with the results presented in [7], demonstrating the slow convergence of some modes in this case [1]. The convergence behaviour is similar if the FxLMS algorithm is simulated in the frequency domain with a window length, *N*, of 512 samples, or if the filtered error algorithm is simulated in the frequency domain.

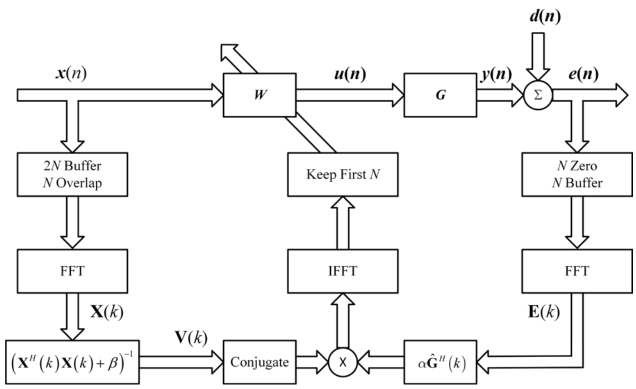

Figure 5. Frequency domain implementation of the bin-normalised filtered error LMS algorithm

Figure 4 also shows the convergence behaviour of the preconditioned algorithm, where the preconditioning filter, ***P*** in Figure 1, was implemented in the frequency domain and calculated from the singular value decomposition of the spectral density matrix of the reference signals [9], calculated over the whole 1200 seconds of the data record. It is clear that the attenuation is less than with the FxLMS algorithm in this case. This degradation was found not to be due to the preconditioning filter calculated in this manner not being strictly causal, but to the fact that the long-term spectral density matrix does not accurately describe the statistical properties of the reference signals over time. The performance of the frequency domain algorithm is more severely degraded, however, if the singular value decomposition is used to approximate, in a non-causal way, the all-pass and minimum phase components of the plant response [9].

Finally, in Figure 4 is shown the attenuation of the frequency domain algorithm shown in Figure 5, in which the convergence coefficient is normalised in each frequency bin by the sum of the magnitude squared reference signals in that bin. In this case, the control filter is implemented in the time domain to limit delays, but the adaptation is implemented in the frequency domain [10,11]. The convergence rate and the final attenuation are slightly improved in this case. The frequency domain implementation is also about a factor of 14 times more computationally efficient than a purely time domain implementation of the control algorithm.

In order to investigate different timescales of averaging in the adaptation, a form of recursive least square, RLS, algorithm was also implemented [12], in which the preconditioning matrix is the iteratively estimated inverse of the reference signal's spectral density matrix. An estimate of this spectral density matrix at each frequency, *k*, and for data block *m*, $\hat{\boldsymbol{S}}_m(k)$, was calculated using:

$$\hat{\boldsymbol{S}}_m(k) = \lambda \hat{\boldsymbol{S}}_{m-1}(k) + \boldsymbol{X}_m(k)\boldsymbol{X}_m^H(k), \tag{1}$$

where λ is a forgetting factor.

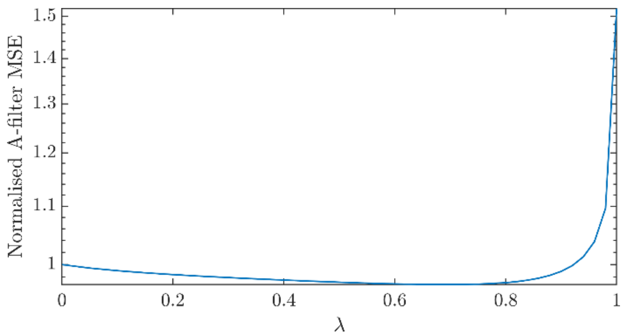

Figure 6. Frequency-averaged mean square error after convergence of the RLS algorithm as a function of the forgetting factor, λ.

The frequency-averaged mean square error after convergence is plotted in Figure 6 as a function of the forgetting factor. Setting λ=1 is very similar to the preconditioned algorithm above, which uses the whole dataset to calculate the spectral density matrix. When $\lambda = 0$, corresponding to no averaging, the algorithm is equivalent to the bin-normalised algorithm whose results are shown in Figure 4. The minimum value of the mean square error is achieved for $\lambda = 0.7$, corresponding to exponentially averaging the spectral density matrix with a time constant of about 1/3 second. The mean square error is, however, then only about 0.2 dB lower than the value when λ=0. Implementing the RLS algorithm is more computationally demanding than the bin-normalised algorithm, so that algorithm appears to be a good trade-off between performance and computational cost.

3. CONCLUSIONS

In principle there are advantages to preconditioning the reference signals in a multichannel feedforward control system, using their long-term spectral properties. In simulations using road noise data, from an electric car travelling at a constant speed on a uniform road, however, the performance of this algorithm is worse than using the instantaneous adaptation of the standard FxLMS algorithm. It would appear that even slight non-stationarity in the reference signals reduces the advantages of preconditioning using the long-term properties. Slightly faster convergence than the FxLMS algorithm is obtained if a bin-normalised frequency domain version of the filtered error LMS algorithm is used, and this also has the advantage of a considerably lower computational cost. Both the long-term preconditioned and the bin normalised filtered error LMS can be viewed as limiting cases in a form of RLS algorithm, by changing the forgetting factor. This provides a systematic method of determining the optimum timescale for averaging the spectral density matrix in a given application.

4. REFERENCES

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