Active control of noise and vibration for time-varying transfer paths

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Abstract

Active noise and vibration control has been successful in a limited number of applications. Successful applications often rely on stationary or periodic signals, stationary geometry or small regions of silence. In many potential applications, the signals and or the geometry are to be considered non-stationary. Following a brief review, this paper describes a technique that could be useful in systems for active noise and vibration control to track changes of the primary signal path from noise source to reference sensor, and to track the secondary path from control source to the error sensor.

1 Introduction

Recent overviews of theory and application of active noise control are given by, e.g., Miljkovic [1], Qiu et. al [2] and Kajikawa et. al. [3]. Other texts presenting overviews are from, e.g., Elliott [4], Tokhi and Veres [5], Guicking [6] and Kuo and Morgan [7].

Existing applications for active sound and vibration control are mostly limited to stationary tonal signals, e.g. transformer noise, non-stationary tonal signals, e.g. propeller aircraft and automotive engine, or broadband signals, but the latter mainly in compact and confined spaces, e.g., ANC headphones (Fig. 3) and ventilation systems.

The active noise control system adds a secondary acoustic signal to the primary acoustic signal using secondary sources. The sum of the primary signal and secondary signal is the error signal, which is minimized by a controller. In a feedforward system independent reference signals are used as input to the controller. An active noise reduction system for the cabin of propellor aircraft can take reference signals from the propellor shafts, resulting in stable operation with adaptive harmonic control for each tone (Figs. 1 and 2), using a regularized form of Newton's algorithm [9] for improved tracking.

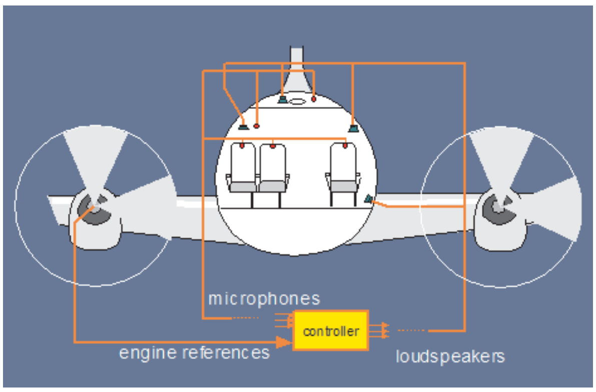

Figure 1: Active noise control in the cabin of propellor aircraft, taking reference signals from the propellor shafts, and using error microphones in the cabin.

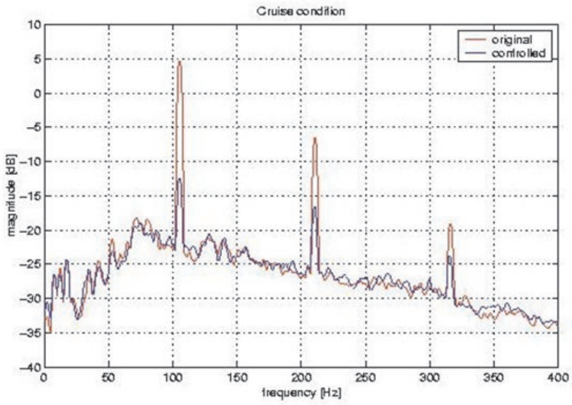

Figure 2: Active control result in the cabin of propellor aircraft, taking reference signals from the propellor shafts, using error microphones and loudspeakers in the cabin.

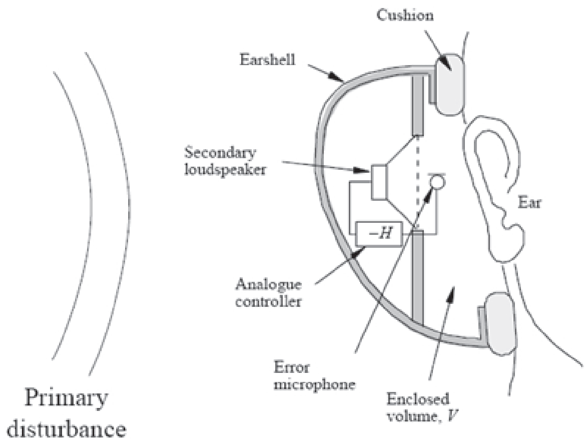

Figure 3: Active noise control headset with error sensor, control source and feedback controller (source: S.J. Elliott).

A result of active control of broadband ventilation noise, in this case using two reference sensors, three error sensors, and three control sources is shown in Fig.4. However, the multiple input multiple output controller makes the system relatively expensive. If the disturbing frequencies are low enough so that single input single output can be used, then implementation often can be cost effective.

Control of broadband noise exciting a resonance often allows a simplified implementation, making it cost effective. The ANC system of Honda also combines the hardware with that of an audio system ([8], Fig. 5). To reduce the complexity of the controller and the cost of the system, the controller is often fixed, such as in many ANC headsets, ANC in cars, or ventilation systems. If the disturb-

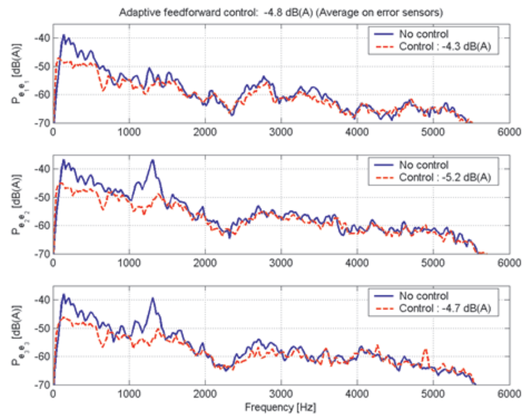

Figure 4: Active noise control result in a ventilation system.

ing sound consists of time-varying tones and the transfer functions between ANC sources and sensors are constant then the controller can be made adaptive at a reasonable cost, such as in propellor aircraft. Adaptive controllers for reduction of broadband noise are often too expensive to allow a cost effective implementation, especially with multiple active sources and multiple sensors. However, it is expected that with increasing computing power adaptive control will eventually become available for a larger number of applications.

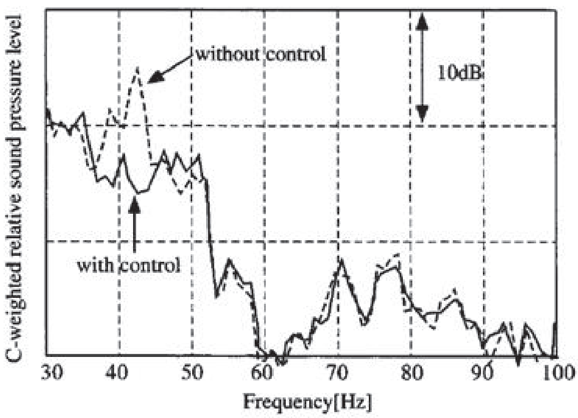

Figure 5: Active noise control in a car interior using combined feedforward and feedback control. [8].

2 Methods for non-stationary signals and geometries

2.1 Control of broadband noise

Controllers for broadband noise often rely on either a small region of silence, low-order transfer functions, only feedback (e.g., many ANC headphones), stationary signals and transfer functions (e.g. ventilation systems), excitation of a resonance (e.g., ANC for the car interior). For slowly changing signals and/or transfer functions, controllers for broadband noise are sometimes made adaptive in order to increase performance. One such technique for slow variations is described.

2.2 Slow variations

Assuming a system representation according to Fig. 6 in which the transfer path G between the secondary source and the error sensor is constant and in which the spectral characteristics of the disturbance signal d change slowly over time, the order of the controller W and the secondary path G can be interchanged, at least for the SISO case, which then provides the so-called filtered reference signal r, obtained by filtering the reference signal x with the secondary path G. An estimated filtered reference signal $\hat{r}$, obtained by filtering x with a model $\hat{G}$ of the secondary path G, can be used together with the error signal e to adapt the controller W (Fig. 7). This method is called the filtered reference least mean squares algorithm, which forms the basis for many adaptive active noise control implementations. For future reference we also define a primary transfer path P which produces the disturbance signal d from the reference signal x. Changes of the primary path are relevant for tracking behavior of the system.

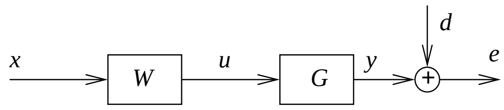

Figure 6: Feedforward active noise control with primary noise signal d, secondary signal y, error signal e, controller W, controller output u, and reference signal x; the transfer function between secondary source and error microphone is denoted by G.

Until now, it has been assumed that the reference signal does not depend on the output of the secondary source. If there is such a dependency, i.e., in case of feedback from the secondary source to the reference sensor, then the contribution of the secondary source on the reference signal can be subtracted if the open-loop transfer path of the control signal u to the reference signal x is known [9]. In fact, this subtraction provides a method to realize an adaptive feedback controller using the design techniques for feedforward control. If the transfer paths from secondary source to the sensors in the system are time-varying, then it may be necessary to apply on-line identification. Usually, such on-line identification is made possible by injecting additional noise in the system. Because the injected noise is produced by the secondary source it will contribute to the error signal. Therefore, the level of the injected identification noise has to be kept as low as possible. In a subsequent section an example is given of an adaptive noise control system with on-line system identification.

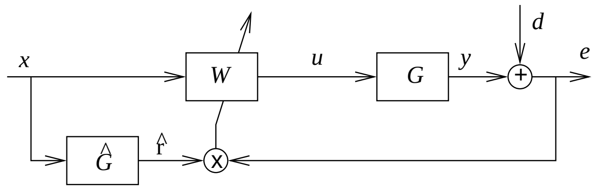

Figure 7: Filtered reference LMS algorithm, assuming secondary path transfer function G, controller W, where an estimate $\hat{r}$ of the filtered reference signal r is obtained by filtering the reference signal x with an estimate $\widehat{G}$ of the secondary path G.

The filtered reference least mean squares algorithm may react slower than desired when the primary path P is rapidly varying. There are many potential applications of active noise control in which signal properties are changing rapidly or in which the geometry is non-stationary. An example is the control of noise in houses near a runway, as depicted in Fig. 8.

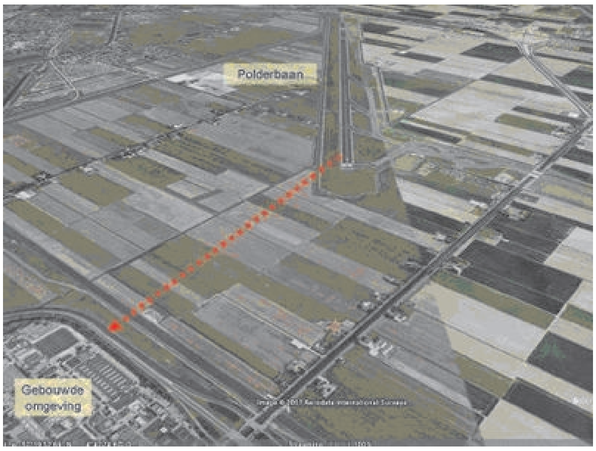

Figure 8: Runway of an airport with nearby houses.

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The next subsection gives an example of a method intended for more rapid variations, with respect to both the primary path and the secondary path.

2.3 More rapid variations

The method described in this section is based on Ref. [10]. It is a particular method to implement a numerically stable controller with rapid tracking. The basis is formed by the recursive least squares filter or the closely related Kalman filter. Since these filters provide a new signal value at every sample which is optimum in the least square sense, they are potentially interesting for applications with rapid time-variations. The fast tracking performance required for rapid variations can be obtained with the introduction of a so-called forgetting factor. Since the recursive least squares- or Kalman filters are computationally complex, efficient implementations are often neccessary. However, some of the more efficient versions of recursive least squares algorithms [11] have been found to be numerically unstable when used in combination with a forgetting factor [12]. Improved numerical behavior is given by the sliding window version [11] but still a numerical breakdown exists.

To achieve numerical stability and rapid tracking, a convex mixing approach was used to emulate the sliding window RLS filter. An example of convex filters in the context of ANC is given by Ferrer [13]. A parallel implementation of filters can be used that are guaranteed to be stable within a limited time period [14]. For the adaption of the filter coefficients a filter is used which behaves like a constant length finite memory RLS algorithm with a linear calculation complexity $O(n_c)$, equivalent to the Chandrasekhar form of the sliding window RLS filter [15], but which does not exhibit the round-off error propagation. Numerical stability is ensured by using a mixing approach [14] which approximates the sliding window RLS filter. A block diagram of this system is shown in Fig. 9. Instead of a single control filter c_i used to minimize ε_i, two sets of control coefficients $c_{1,i}$ and $c_{2,i}$ are used to produce outputs $\tilde{y}_{1,i}$ and $\tilde{y}_{2,i}$ which minimize $\varepsilon_{1,i}$ and $\varepsilon_{2,i}$, respectively. A control filter $c_{mix,i}$ is used to produce the actual control output u_i. The latter filter consists of a convex combination of $c_{1,i}$ and $c_{2,i}$, as described below.

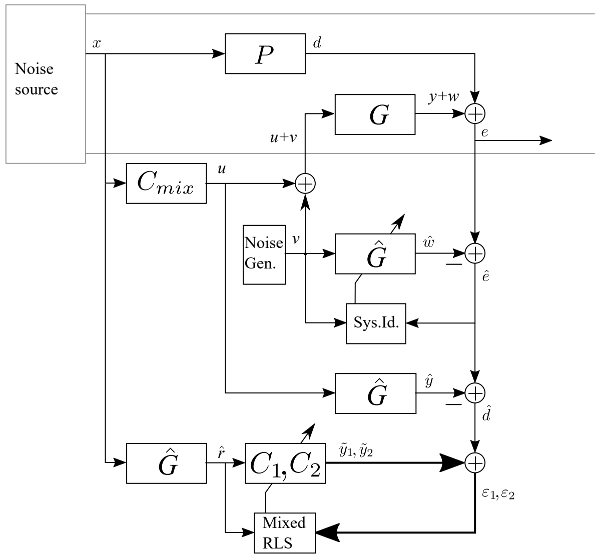

Figure 9: Block diagram of a feedforward active noise control system based on a recursive least squares mixing scheme with on-line system identification [10].

Two parallel growing memory filters are mixed in such a way, that the total available information used for calculating the least squares solution are equal at every time instance. Firstly, the equations for a recursive update of the mixed solution are presented. The mixing parameters α_i and β_i are constrained by $0 \leq \alpha_i \leq 1$, $0 \leq \beta_i \leq 1$, and sum up to unity:

$$\alpha_i + \beta_i = 1, \ \forall i. \tag{1}$$

A possible choice for the mixing parameters can be found in Ref. [14]. The first filter is activated at time instance U and the second filter is activated after $V = U + W/2$ iterations. The filters are defined by the data matrices $\mathsf{R}_{1,i}$, $\mathsf{R}_{2,i}$ and measurement vectors $\mathsf{d}_{1,i}$, $\mathsf{d}_{2,i}$:

$$\mathsf{R}_{1,i} = \begin{bmatrix} \hat{r}^T_{n_c,U} \\ \hat{r}^T_{n_c,U+1} \\ \vdots \\ \hat{r}^T_{n_c,i} \end{bmatrix}, \ \mathsf{R}_{2,i} = \begin{bmatrix} \hat{r}^T_{n_c,V} \\ \hat{r}^T_{n_c,V+1} \\ \vdots \\ \hat{r}^T_{n_c,i} \end{bmatrix}. \tag{2}$$

$$\mathsf{d}_{1,i} = \begin{bmatrix} \hat{d}_U \\ \hat{d}_{U+1} \\ \vdots \\ \hat{d}_i \end{bmatrix}, \ \mathsf{d}_{2,i} = \begin{bmatrix} \hat{d}_V \\ \hat{d}_{V+1} \\ \vdots \\ \hat{d}_i \end{bmatrix}. \tag{3}$$

The cost functions of the parallel RLS filters are:

$$\min_{c_{1,i}} [c^T_{1,i} \Pi c_{1,i} + \|\mathsf{d}_{1,i} + \mathsf{R}_{1,i} c_{1,i}\|^2], \tag{4}$$

$$\min_{c_{2,i}} [c^T_{2,i} \Pi c_{2,i} + \|\mathsf{d}_{2,i} + \mathsf{R}_{2,i} c_{2,i}\|^2], \tag{5}$$

in which the matrix $\Pi \in \mathbb{R}^{n_c \times n_c}$ is a positive definitive regularization matrix. In Ref. [14] it is shown that the

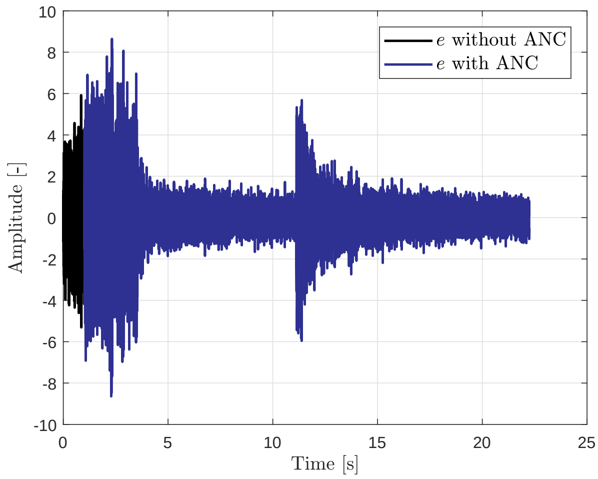

Figure 10: Error signal $e = d + y + w$ with controller switched on at 1 s and modification of the primary path at 11 s. The rms value of the identification noise v is 0.8 from 1 s to 3.5s and 0.1 after 3.5 s [10].

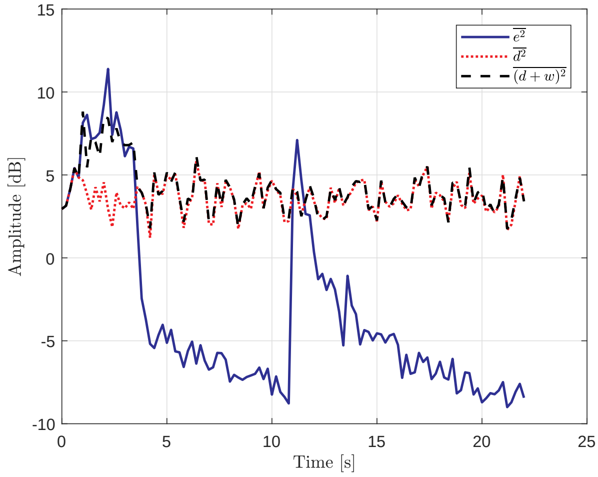

Figure 11: Averaged square error signal, averaged square disturbance signal, and averaged square disturbance + identification signal.

resulting update equations are:

$$c_{mix,i} = \alpha_i(c_{1,i-1} - K_{1,i}R_{1,i}^{-1}\varepsilon_{1,i}) + \beta_i(c_{2,i-1} - K_{2,i}R_{2,i}^{-1}\varepsilon_{2,i}). \tag{6}$$

in which $K_{1,i}$, $K_{2,i}$ are Kalman gains, $\varepsilon_{1,i}$, $\varepsilon_{2,i}$ are the innovations and $R_{1,i}$, $R_{2,i}$ are the expected values of the innovations.

The parameters in Eq. (6) are updated with two parallel growing memory (forgetting factor $\lambda = 1$) fast array RLS algorithms. The complexity of these algorithms grows linearly with n_c. The filter parameters of the two filters are calculated completely in parallel and no interaction takes place between the filters. Both filters are reset every time a window length W has passed. A complete description of the control algorithm can be found in Ref. [14].

2.4 System identification

The system identification procedure updates the estimate $\hat{g}_i$ of the impulse response coefficients of the secondary path. LMS and RLS identification methods were used. The system identification update based on RLS is provided by a parallel, mixed fast-array scheme similar to that of the controller:

$$\hat{g}_i = \alpha_i(g_{1,i-1} + K_{m,1,i}R_{m,1,i}^{-1}\hat{e}_{1,i}) + \beta_i(g_{2,i-1} + K_{m,2,i}R_{m,2,i}^{-1}\hat{e}_{2,i}), \tag{7}$$

in which $K_{m,1,i}$, $K_{m,2,i}$ are Kalman gains, $\hat{e}_{1,i}$, $\hat{e}_{2,i}$ are the innovations and $R_{m,1,i}$, $R_{m,2,i}$ are the expected values of the innovations, and $g_{1,i}$, $g_{2,i}$ the corresponding estimates of the secondary path. For both LMS and RLS, v_i is normally distributed and white.

3 Results

This section presents an update of results of Ref. [10]. The performance of the algorithm was evaluated using a model of a loudspeaker in a duct having a diameter of 0.1 m and a length of 1.37 m, with reflection coefficients $R_0 = 0.95$ and $R_L = -0.9$. The primary/disturbance, the secondary/control speaker and error microphone are located 0.172 m, 0.515 m and 1.201 m, respectively, from R_0. A sample rate of 2 kHz was used with 250 finite impulse response coefficients for the secondary path model and 250 finite impulse response coefficients for the control filters. The initial rms value of the identification noise is at a relatively high level of 0.8 for times between 1 s and 3.5 s, whereas the rms value for times later than 3.5 s equals 0.1. The controller is switched on at time 1 s. The primary path is modified at time 11 s. The modification consists of an additional sample delay added to the primary path. In this paper only the results for identification with a parallel version of RLS is shown. All initial FIR coefficients of the controller and the secondary path model are zero. The resulting error signal is shown in Fig. 10 and the averaged square disturbance and error signals in Fig.11. Using the modified RLS control scheme, the reduction of the error signal obtained between 1 s and 11 s starting from zero, i.e., the behavior defining the convergence rate, and the reduction of the error signal obtained between 11 s and 16 s after the change of the primary path at 11 s, i.e., the behavior defining the tracking rate, were found to be considerably improved as compared to a filtered reference least mean square adaptive control filter. Real-time control results [17] were found to agree with simulations.

4 Conclusions

A brief overview has been presented of systems for active noise control. Examples have been given of controllers for tracking the disturbance signal, the primary path and the secondary path. As compared to the filtered reference based least mean squares methods, improved tracking results for rapidly varying transfer paths have been obtained with an approximate method using parallel recursive least squares filters.

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