REVIEW OF ALGORITHMS FOR ACTIVE NOISE CONTROL

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Abstract. The previous regulations about acoustics in buildings ruled only isolation, forgetting other important subjects. The new code in Spain, specifically the DB-HR document, also include the regulations of excessive noise reverberating that produces and causes discomfort in many cases non-speech intelligibility, this circumstance is crucial in certain areas. The passive control restrictions in these limits of frequencies are well known. The insulating materials, soundwalls, acoustic filters, Helmholtz resonator, expansion chamber, the encapsulation of the noise source, mean large dimensions and/or weight to 500 Hz or less. The active noise control (ANC Active Noise Control) can be used to cancel the noise to high-frequency and the passive techniques can be used to low-frequency. This paper presents algorithms for active noise control and the typical industrial applications.

Keywords: ANC, noise, acoustical, FIR, IIR, X-LMS, U-LMS, genetic algorithms.

1 Introduction

There are two basic classifications of methods used to sound control: active and passive. Some example of passive control include placing a barrier to block sound transmission or resurfacing a room to alter its response. Active noise control (ANC) is based on the principle of superposition, i.e., an unwanted primary noise is attenuated by a secondary noise of equal amplitude and opposite phase (Nelson and Elliot, 1992; Kuo and Morgan, 1996). The design of an active noise control system pursues maximum attenuation of the primary noise (Nelson, Curtis and Elliot, 1987).

The German physicist Lueg, was the first to provide a description of active noise control in a 1936 patent (Lueg, 1936), which gives an example of a one-dimensional duct problem with a wave propagating only in one direction. In 1953 Olson and May (Olson and May, 1953) developed a different system, in which the disturbance noise is detected by a microphone and fed back through a controller to a loudspeaker located close to the microphone. But the real interest for the ANC emerges from the work of Widrow (Widrow et al, 1975) about adaptive filtering and its implementation by DSP's. The power of the adaptive filters lies in its ability to adapt the control system to the variations of the noise. In the 80's practical applications about ANC in ducts (Burgess, 1981) and hearing protector were filed.

Today outstanding results have been achieved for a wide variety of applications which include aircraft engines, automobile interiors, heating, ventilation and air conditioning (HVAC) systems as well as household applications (Emborg, 1994; Hirsch, 1999; Sas, 1998). In general, ANC has proven a viable method for noise suppression in low frequency ranges where traditional passive noise control devices become massive, bulky, or less effective.

In active sound control there are three basic components: the error sensors, the signal processing equipment and the actuators. The error sensors detect the sound field and pass the information to the processing equipment. Commonly, a digital signal processor is employed to analyze the sound field and determine how to drive the actuators to control the sound. The processing determines the ideal amplitude and phase for driving the actuators to cancel the sound in a given situation. To generate the anti noise, two main configurations of ANC systems are often used, feedforward and feedback control, which using adaptive filters (Elliot and Nelson, 1993; Kuo and Morgan, 1999). Both feedforward and feedback configurations, as well as adaptive filters and their new implementations by genetic algorithm will be evaluated in this work.

2 ANC systems

Modern active sound control systems consist of one or more control sources used to introduce a secondary (or controlling) disturbance into the structural/acoustic system. This disturbance suppresses the unwanted noise originating from one or more primary sources. The control signals that drive the control actuators are generated by an electronic controller, which uses as inputs, measurements of the residual field (remaining after introduction of the control disturbance) and in the case of feedforward adaptive systems, a measure of the incoming primary disturbance.

An important property of many modern active sound control systems (particularly feedforward systems) is that they are self-tuning (adaptive) so that they can adapt to small changes in the system being controlled. Changes only need to be small changes to cause a non-adaptive feedforward control system to become ineffective. Non-adaptive controllers are generally confined to the feedback type in cases where slight changes in the environmental conditions will not be reflected in significant degradation in controller performance. An interesting aside is that an adaptive feedfordward controller is effectively a closed loop implementation of a non-adaptive feedforward controller.

One of the problems concerned with ANC is the existence of acoustical feedback between the control value and the reference signal. In this way, Bismor (Bismor, 2008) present new method, namely, virtual unidirectional sound source to acoustic feedback cancellation.

Other work using genetic algorithm to optimize ANC system or using recurrent neural networks for nonlinear ANC can be found in (Jinn-Tsong et al, 2009; Chen et al, 2008).

A new frame of future works could be established by use of controller PID to ANC and genetic algorithms to determine the constants of the PID in industrial machines.

2.1 Feedforward ANC system

Depending on kind of noise in the environment, broadband and narrowband, the configuration of the feedforward ANC system will be different. Broadband feedforward ANC is exemplified by the control of an acoustic noise in long, narrow ducts, such as exhaust pipes and ventilation systems. By contrast, narrowband ANC is related to noise caused by rotating, repetitive machines or nearly periodic. The general implementation of this system is shown in the Figure 1a. First a reference sensor is used to get a reference signal and second an error sensor is utilized to update the adaptive filter by measuring the residual of the anti noise and primary noise. This system was proposed by Paul Lueg to cancel the noise in ducts.

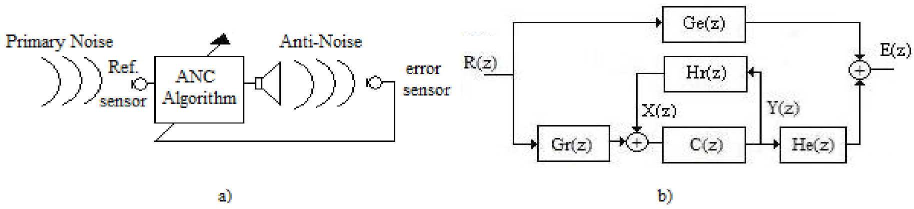

Fig. 1. a) An ANC feedforward system and b) A block diagram ANC feedforward system.

This system can be depict by a block system with all electro/acoustics transfer functions, see Figure 1b.

The controller will evaluate the transfer function C(z) to obtain a error signal equals to zero.

$$E(z)=R(z)\left[G_e(z)+G_r(z)\frac{C(z)}{1-C(z)H_r(z)}H_e(z)\right]=0\,. \tag{1}$$

$$C(z)=\frac{-G_e(z)}{G_r(z)H_e(z)}\left[\frac{1}{1-\dfrac{G_e(z)}{G_r(z)H_e(z)}H_r(z)}\right]. \tag{2}$$

where R(z), E(z) are, respectively, the noise and error signals; X(z), Y(z) are the input and output signals of the controller; G_e (z), G_r(z) are the transfer functions between the noise source and the error or reference microphones, respectively, H_e (z), H_r(z) are the transfer functions between the loudspeaker and the error or reference microphones, respectively.

2.2 Feedback ANC system

The feedback ANC systems was proposed by Olson (Olson and May, 1953). This system uses only one sensor, namely an error sensor. The reference signal and the update of the adaptive filter are made by this sensor, see Figure 2a.

This type of feedback system generally is very problematic. For example, error in the controller phase response will generally result in oscillations because the phase error can change the desired negative feedback into unstable positive feedback.

This kind of system was proposed to reduce the acoustic pressure around the headrest of passenger in the airplane by Olson (Olson, 1956) also this system of control has been explored and improved by a number of researchers (Eghtesadi et al, 1983).

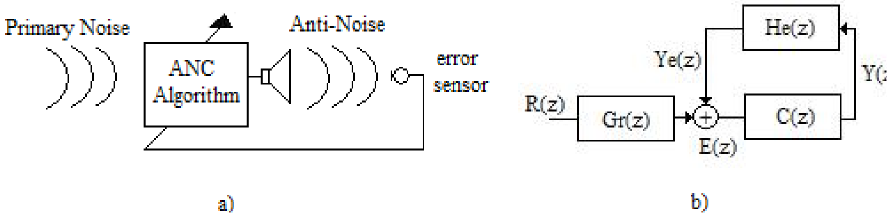

Fig. 2. a) An ANC feedback system and b) Block diagram an ANC feedback system.

From the block diagram, see Figure 2b, the steady-state transfer function can be expressed as follows. The z-transform of the error signal is

$$E(z) = \frac{G_r(z)}{1 - C(z)H_e(z)} R(z). \tag{3}$$

where R(z), E(z) are, respectively, the noise and error signals; Y(z) is the output signal of the controller; $G_r(z)$ is the transfer function between the noise source and the reference microphone, H_e (z) is the transfer function between the loudspeaker and the error microphone. This system can present instabilities and the feedback signal can oscillate from fixed frequency (Sievers and Flotow, 1992), for this reason a compensation filters are necessary in the system to prevent the positive feedback. An application of this system is the cancellation of noise by ANC in headphones (Bartles, 1992).

2.3 Multiple-Channel ANC system

Many applications involve complex modal behavior, such as acoustic ANC in large ducts or enclosures and vibration ANC on rigid bodies or structures with multiple degrees of freedom. Sometimes the primary-noise source is more complicated, it is no longer sufficient to use a single error sensor to cancel it. These problems require the use of a multiple-reference/multiple output adaptive algorithm. The general multiple-channel ANC system consist of an array of sensors and secondary sources. A block diagram of a multiple channel ANC system can be described by the Figure 3.

The number of secondary sources to achieve perfect primary source cancellation is the same as the number of acoustic modes being excited (Elliott, Boucher and Nelson, 1992). In fact, it is very difficult to obtain the perfect cancellation because of the acoustic modal density in enclosures increases rapidly with the frequency. In this cases, passive sound control methods tend to work best at higher frequencies, and thus complement ANC, which is more effective at lower frequencies.

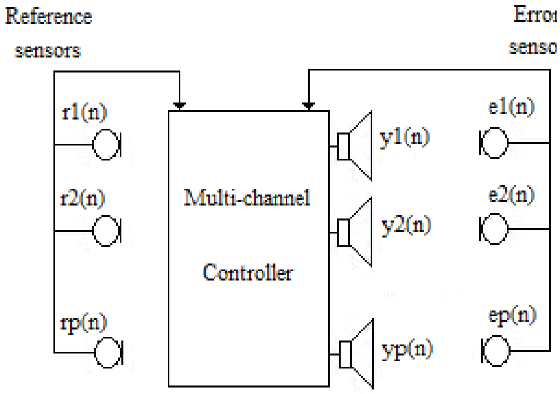

Fig. 3. Multi-channel ANC system.

3 Control Algorithms

The controller have to be able to follow the variations that can be generated in the acoustic field as change of the phase, amplitude or transfer functions. An adaptive digital filter consists of two parts: one is a digital filter which processes the expected output signal, the other one is an algorithm to adjust weighting coefficients of the digital filter.

The analog signals of the sensors, error and reference microphones are sample to 500 Hz and the sample frequency have to be 10 times this value, that it, fs=5000 Hz (Allie, Bremigan and Ericksson, 1988). The “anti-aliasing” filter has a cut frequency lesser than the sampling frequency.

Two digital filters are usually applied to ANC, i.e. IIR or FIR. Any transfer function can be modeled by a FIR filter. Moreover, there are the more coefficients mean the better approximation is reached (Oppenheim and Shafer, 1971). The number of coefficients, establishes the maximum delay that can be imposed by the filter to the input data. If the number of coefficients is large because of the delay, a IIR filter can be used.

The only difference is the store of output data in other table. In addition, they are multiplied by other coefficients in the case of the IIR filter. The transfer function should follow the acoustic changes of the environment, thus the coefficients c(k) of the filter have to be update.

The selection of the filter in the controller, FIR or IIR, depend on the application of the ANC system and on the characteristics of the filter.

The main objective of adaptive algorithms is the calculation of the coefficients to minimize the error signal. Many adaptive algorithms are based on steepest descent algorithm that employ instantaneous estimate of gradient of the mean squared error.When this area correspond to the quadratic instant error and a FIR filter is used to minimize errors between output of the filters and the desired response, the adaptive algorithm is called Least Mean Squares (LMS) (Widrow et al, 1975). This algorithm is the commonest due to its simplicity. The adaptive controllers can be configured either in feedback or in feedforward fashion. When IIR filter based on LMS algorithm is employed in ANC, the resulting structure/algorithm is referred to as U-Filtered LMS (Bambang, 2000). To account the secondary path effect, a filtered version of LMS, called filtered-XLMS, is commonly used in ANC systems (Burgess, 1981). The applications of filtered-X LMS require modeling the secondary path in term of FIR filters, and utilizes this model to adapt the control FIR filter coefficients. Filtered-X LMS has been widely used because of its simplicity and its relatively lower computational load. However, this algorithm presents a well-known drawback since it is limited to linear control/filtering problem (Kuo and Morgan, 1996; Bambang, 2000). Fuzzy logic and neural networks could be non-linear controller and suitable for modeling and control of non-linear system (Baruch et al, 2001).

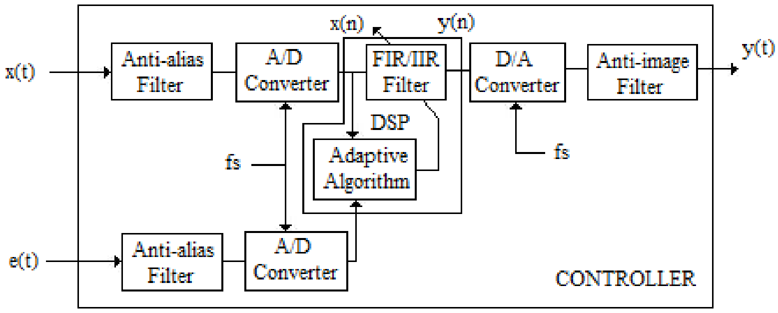

Fig. 4. Elements of a digital controller of ANC.

Genetic algorithms present two problems: a slow convergence velocity and higher cost of computing. The number of operation that this algorithms need depends on the number of filter coefficients and the number of chromosome from each generation.

3.1 Adaptive genetic IIR filtering

$$y(n) = \sum_{k=0}^{M} c(k)x(n-k) + \sum_{k=1}^{N} b(k)y(n-k). \tag{4}$$

1.Aleatory generation of the initial chromosome population.

$$S_i = [c_i(0),..., c_i(M), b_i(0),..., b_i(N)] \quad 1 \le i \le S. \tag{5}$$

2.Selection of chromosomes: to evaluate the mean quadratic error from each chromosome and to select the most optimal one.

$$\sigma_i^2 = \frac{1}{L}\sum_{n=1}^{L} e_i^2(n). \tag{6}$$

3.The coefficients obtained should be used on the adaptive algorithm based on the steepest gradient method.

In the process of daughter chromosome generation, the stability of the IIR filter should be checked for each chromosome. This verification consists of to convert the IIR filter coefficients b(k) in the reflection of a equivalent structure (Oppenheimand Schafer, 1971). IIR filter is stable if the absolute value of the reflection coefficients is lower than one. If some coefficient is larger than this limit, it will be equal to one.

3.2 Adaptive genetic multi channel algorithm

Design of adaptive algorithm of control multi-channel system with P output and P error input, see Figure 3, can be executed by genetic algorithms (Tang et al, 1995). The main advantage of those algorithms is that the electro-acoustic transfer functions PxP are not necessary to estimate them between each input and error signal. Other characteristic is that the output signal is generated by only a FIR/IIR filter. This way, the architecture of the controller is simplified.

$$y(n) = \sum_{k=0}^{M} c(k)x(n-k) + \sum_{k=1}^{N} b(k)y(n-k). \tag{7}$$

1.Aleatory generation of the initial chromosome population.

$$S_i = [c_i(0),...,c_i(M), b_i(0),...,b_i(N)] \quad 1 \le i \le S. \tag{8}$$
$$[S] = \text{matrix of S x P elements.}$$

2.Selection of chromosomes: to evaluate the mean quadratic error from each P group chromosome and to select the most optimal one.

$$J_{S1i,S2j,...,Spt}(n) = \sum_{n=1}^{p-1} e_i^2(n) \quad 1 \le i, j,..., t \le S. \tag{9}$$

3.The coefficients obtained should be used on the adaptive algorithm based on the steepest gradient method.

4 Conclusions

The recurrent neural networks along with DSP implementation provide effective method for controlling acoustic noise under the presence of unknown nonlinear phenomena. There is no systematic way of selecting suitable network topology for a particular ANC problem. However, it is advisable to start with small enough hidden neurons in both Model and Control Neural Networks, then try to increase the number of neurons until no further improvement occurred in the resulting noise attenuation level.

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