

Comparative Study of Adaptive Algorithms for Vehicle Powertrain Noise Control

Ji Xu, Guohua Sun, Tao Feng, Mingfeng Li, and Teik Lim
University of Cincinnati

ABSTRACT

Active noise control systems have been gaining popularity in the last couple of decades, due to the deficiencies in passive noise abatement techniques. In the future, a novel combination of passive and active noise control techniques may be applied more widely, to better control the interior sound quality of vehicles. In order to maximize the effectiveness of this combined approach, smarter algorithms will be needed for active noise control systems. These algorithms will have to be computationally efficient, with high stability and convergence rates. This will be necessary in order to accurately predict and control the interior noise response of a vehicle. In this study, a critical review of the filtered-x least mean square (FXLMS) algorithm and several other newly proposed algorithms for the active control of vehicle powertrain noise, is performed. The analysis examines the salient features of each algorithm, and compares their system performance. Numerical simulations utilizing synthesized data, are conducted to study the convergence rates of these algorithms. These convergence rates are critical for the noise control outcome. Furthermore, measured powertrain noise response is employed, to verify the system's performance under more realistic conditions. The individual engine orders are targeted for attenuation or enhancement, to achieve the desired vehicle interior sound quality.

CITATION: Xu, J., Sun, G., Feng, T., Li, M. et al., "Comparative Study of Adaptive Algorithms for Vehicle Powertrain Noise Control," *SAE Int. J. Passeng. Cars - Mech. Syst.* 9(1):2016, doi:10.4271/2016-01-9108.

INTRODUCTION

Vehicle noise, vibration, and harshness (NVH) characteristic is one of the most important factors in the design of modern vehicles, as it contributes significantly to the perceived product quality, driving pleasure, and overall customer satisfaction [1,2,3]. Over the past decade, new challenges have been presented to vehicle NVH engineers - namely, the demand for more fuel efficient vehicles. This challenge has driven manufacturers to pursue lighter weight vehicle designs. Unfortunately, light weight design often leads to more noise being transmitted into the vehicle cabin. In order to compensate for this undesirable effect, engineers have to enhance the application of noise control in these vehicles. Generally there are two categories of noise control techniques that are utilized in a vehicle cabin, namely passive and active control. Passive control techniques reduce interior noise by modifying the vehicle structure, such as adding mass, tuning stiffness, and/or increasing damping. These methods of passive noise control can be detrimental to the goal of a lighter weight vehicle. Also, passive control is less effective in the lower frequency range. Overall, the pursuit of lighter weight vehicle design limits the ability to apply passive noise control effectively. Therefore, an alternative solution, namely active noise control (ANC), has been developed to make up for the limitation of passive approaches [4,5,6,7]. The fundamental ANC concept is based on the superposition of destructive sound waves, which reduces the undesired noise, by superposing an out-of-phase secondary source on the undesired sound field. While the concept of ANC was proposed in the 1930s [8], it has only drawn the attention of the automotive industry in the last several

decades [9,10,11]. This is mainly due to the evolution of digital signal processors, which have made ANC technology more feasible and affordable for automotive applications.

Most of current ANC systems utilize the traditional filtered-x least mean square (FXLMS) algorithm or its modified versions. Despite its recent successes, the FXLMS algorithm suffers from a low convergence rate and heavy computational burden [12]. The root cause of the low convergence rate is the existence of a secondary path, which is also known as the electro-acoustic path, from the control speaker to the error microphone. To ensure the convergence of the system, the input reference signal is usually filtered by the estimated secondary path model, and the convergence rate is proportional to the power of the filtered input reference signal. Therefore, fast convergence can only be achieved near the resonance of the secondary path dynamics.

A considerable amount of research work has been conducted recently to improve the performance of the FXLMS algorithm. This algorithm was independently derived by Widrow in the context of adaptive control, and Burgess, for ANC applications in 1980 [13, 14]. The Modified-FXLMS (MFXLMS) algorithm was proposed by Bao in 1993 [15]. The MFXLMS algorithm takes advantage of a modification in the structure of the controller, such that, the gradient descent method behaves like the standard LMS algorithm. The MFXLMS algorithm was further improved by Oliveira in 2010. This was done by adding a normalization filter before the controller. This

new algorithm is known as the NX-LMS algorithm [16]. In the NXLMS algorithm, the effect of the secondary path amplitude variation is nullified, by employing a normalization filter. In 2008, Thomas developed a relatively simpler structure to improve the convergence behavior of the FXLMS algorithm. This algorithm is known as the eigenvalue equalization filtered-x least mean square (EE-FXLMS) algorithm [17, 18]. The overall convergence behavior is greatly improved by flattening the magnitude response of the estimated secondary path, while leaving the phase unchanged. In 2009, Duan proposed the time-frequency-domain FXLMS (TF-FXLMS) algorithm, which greatly reduces the computational cost, while still maintaining relatively good performance. He has successfully applied it to control the powertrain disturbance [12, 19].

Very recently, Li proposed the inverse model least mean square (IMLMS) algorithm for harmonic noise control. In his algorithm, the inverse model of the secondary path is placed in series with the actual secondary path to counteract its effect and further improve the convergence [20, 21]. The IMLMS algorithm has been implemented, to control the vehicle powertrain response successfully by Sun [22, 23]. However, one limitation of the IMLMS algorithm is the high computational cost. Therefore, the adaptive notch filter with the inverse model least mean square (ANF-IMLMS) algorithm, was proposed in our previous study [24]. Compared to the conventional adaptive notch filter with filtered-x least mean square (ANF-FXLMS) algorithm, the ANF-IMLMS algorithm can effectively reduce the noise level in a broader frequency range. However, the comparison between the ANF-IMLMS algorithm and other algorithms which have been mentioned before, remains unknown. Therefore, the objective of this study is to conduct a comparative study of the ANFIMLMS algorithm and various algorithms. The performance of the different algorithms is studied, and the results are analyzed.

This article is organized as follows. First, the background information about ANC system for vehicle powertrain response is presented. Then, several newly developed adaptive algorithms, such as the EFXLMS algorithm, the NX-LMS algorithm, the TF-FXLMS algorithm, and the ANF-IMLMS algorithm, are introduced. Furthermore, the result section compares the salient features of the aforementioned algorithms, in terms of the convergence rate and computational complexity. Several numerical simulations are conducted to verify the analysis. The algorithms are applied numerically to control synthesized harmonic responses, and to examine the convergence rate. Then, the ANC systems configured with different algorithms, are implemented to control the vehicle powertrain response. Additionally, the concept of ANC is extended to the active sound quality control (ASQC). The individual engine orders, are targeted for attenuation or enhancement selectively, to meet a certain predefined sound quality matrix. Finally, the conclusions of the study and the suitable recommendations are made.

BACKGROUND

Reference Signal

In general, the noise inside a vehicle cabin can be divided into two categories. The first category is powertrain noise. This noise is synchronized with the engine's rotation and is the noise that is usually

noticeable during vehicle's idle condition and during rapid acceleration. Good control of this noise is necessary in order to ensure an enjoyable operating experience. The other noise category is the noise caused by random sources, such as road surface irregularities and turbulent airflow.

Figure 1 shows the flow diagram of the ANC system for powertrain noise. Powertrain noise is dominated by the harmonics of the engine's rotational speed. The dominant harmonic components depend on the number of cylinders and the firing order of the cylinders. Coherent reference signals can be synthesized using the estimated engine rotational speed, which is measured by a tachometer. Reference signals can then be created by a harmonic wave generator, which can be expressed as:

$$x_0(n) = a_i \cos(\omega_i n / f_s) = a_i \cos(\omega_i' n) \quad (1)$$

$$x_1(n) = a_i \sin(\omega_i n / f_s) = a_i \sin(\omega_i' n) \quad (2)$$

where a_i is the amplitude of the i^{th} order reference signal, n is the time index, ω_i is the i^{th} disturbance frequency, and f_s is the sampling frequency. ω_i is usually the submultiples, or multiples of the engine rotating speed (i.e., $\omega_i = 2\pi v / 60$, v is the engine speed in rpm (revolution per minute)), and ω_i' is the generalized frequency. The objective of the ANC system is to minimize the square of residual noise at the target frequency.

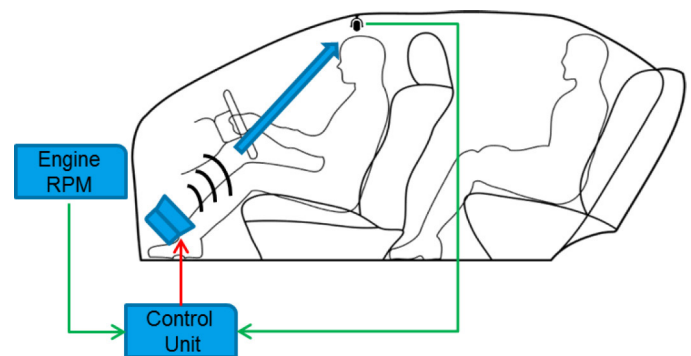


Figure 1. Illustration of the powertrain ANC system

FXLMS algorithm

Figure 2 shows the configuration of the basic FXLMS algorithm, which is applied to control the powertrain response. Detailed analysis of the FXLMS algorithm can be found in the reference [5]. From Figure 2, it can be derived that the residual noise $e(n)$ can be expressed as,

$$e(n) = d(n) - y(n) \quad (3)$$

$$y(n) = S(n) * [W^T(n)X(n)] \quad (4)$$

where n is the time index, $d(n)$ is the primary undesired noise which is the powertrain noise in this case. $S(n)$ is the impulse response of the secondary path $S(z)$, and $*$ denotes linear convolution.

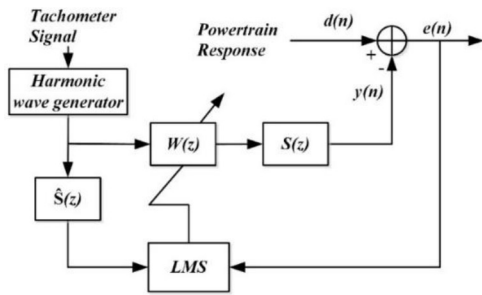


Figure 2. Block diagram of the vehicle powertrain ANC system using the FXLMS algorithm

The adaptive filter weight and the reference signal are

$$W(n) = [w_0(n) \ w_1(n) \ \cdots \ w_{L-1}(n)]^T \quad (5)$$

$$X(n) = [x(n) \ x(n-1) \ \cdots \ x(n-L+1)]^T \quad (6)$$

The objective is to minimize the mean square error (MSE), which can be estimated as follows:

$$\xi(n) = E[e^2(n)] \quad (7)$$

where $E[\cdot]$ represents the mathematical expectation. The MSE $\xi(n)$ can be minimized using the steepest descend method, which updates the adaptive weight vector in the negative gradient direction:

$$W(n+1) = W(n) + \mu X'(n)e(n) \quad (8)$$

where $X'(n) = S(n) * X(n)$. It can be seen that the adaptive filter weight is updated by the filtered reference signal $X'(n)$. Therefore, it's named filtered-x LMS algorithm.

Frequency dependent convergence behavior

Feintuch developed a frequency-domain FXLMS algorithm in 1993, for which the convergence behavior can be analyzed more intuitively [25]. It is reported that the step size of adaption, (μ), needs to meet the following stability condition:

$$\mu P_x(\omega) < \frac{2}{|S(\omega)|^2} \quad (9)$$

where $P_x(\omega)$ is the power of the original reference signal at frequency ω . $|S(\omega)|$ is the amplitude of the secondary path at frequency ω . In general, the upper bound on μ is inversely proportional to the power of the filtered reference signal. Therefore, even if the power of the original reference signal is made uniform across different frequencies, the secondary path model will still affect the upper bound

of the step size, causing certain discrepancies at various frequencies. If a fixed step size is used, components at different frequencies will exhibit various convergence behavior.

$$\tau_{mse} \leq \frac{\lambda_{max}}{\lambda_{min}} T \leq \frac{\max_{\omega} |X(e^{j\omega})|^2}{\min_{\omega} |X(e^{j\omega})|^2} T \quad (10)$$

Similar results can be obtained from making a time domain analysis. It is reported that the overall convergence rate is determined by the dynamic range of the autocorrelation matrix of the filtered reference signal [26]. Equation 10 shows the relationship between the convergence time and the dynamic range of the eigenvalue. λ_{max} and λ_{min} are the maximum and the minimum eigenvalues of the autocorrelation matrix. T is the sampling period, and τ is the time constant, which is the time that is required for any signal to decay to $1/e$ ($\approx 37\%$) of its initial value. Due to the fact that MSE is a squared value, τ_{mse} is the time required for the MSE to be reduced by a factor of e^2 . Therefore, the larger the dynamic range, the longer it takes for the ANC system to converge.

Both the time domain and the frequency domain analysis come to the same conclusion, that the overall convergence is limited by the frequency component, which possesses a smaller secondary path amplitude. If the FXLMS algorithm is directly applied to control the powertrain response, the engine orders with larger secondary path amplitudes can be reduced in a more effective manner. However, the system will have minimal effect on the orders with smaller secondary path amplitudes. As a result, unbalance performance is expected. Recently, many researchers and engineers have developed modified algorithms to improve ANC system performance. Several advanced algorithms are selected and introduced in the following section.

MODIFIED ALGORITHMS

EE-FXLMS Algorithm

Thomas et al. developed the EE-FXLMS algorithm in 2008 [17, 18]. The basic configuration of the EE-FXLMS algorithm for vehicle powertrain response is shown in Figure 3. Compared to other modified algorithms, the major advantage of the EE-FXLMS algorithm is the simplicity of the structure. This algorithm is essentially a FXLMS algorithm, with minor modifications. The effectiveness of EE-FXLMS algorithm comes from reducing the dynamic range of the eigenvalue of the auto-correlation matrix. The convergence time is proportional to the dynamic range of the eigenvalue spread, as indicated in Equation 10. Therefore, reducing the dynamic range can effectively reduce the convergence time. The eigenvalue-equalization process, which is highlighted in Figure 3, can be used to reduce the dynamic range. It is implemented in the following steps:

1. Get the time-domain response $S(n)$ of the secondary path through system identification.
2. Perform Fast Fourier Transform (FFT) on $S(n)$ to obtain the frequency response.
3. Divide each frequency response value by its magnitude.
4. Perform Inverse Fast Fourier Transform (IFFT) to get a new $S(n)$ and use it as normal.

