International Journal of Applied Mathematics in Control Engineering 3 (2020) 42-48

Contents lists available at YXpublications

International Journal of Applied Mathematics in Control Engineering

Journal homepage: http://www.ijamce.com

The Least Mean Square Algorithm for Finite Impulse Response Identification in Active Noise Control System

Tongrui Peng[a], Quanmin Zhu[a,*], M.Osman Tokhi[b], Yufeng Yao[a]

[a] *Department of Engineering, Design and Mathematics, University of the West of England, Bristol, UK*

[b] *Head of Electrical and Electronic Engineering Division, London South Bank University, London, UK*

ARTICLE INFO

Article history:
Received 9 February 2020
Accepted 12 April 2020
Available online 17 April 2020

Keywords:
Adaptive Noise Control
System Identification
Least mean square

ABSTRACT

This paper presents a feedforward active noise control scheme with a pre-identified adaptive finite impulse response (FIR) filter for point source cancellation in three-dimensional free field acoustical environment. In the author's previous works, parameters of the FIR filter are initialized randomly and it causes heavy time-consuming and degrades the cancellation performance for both narrowband noise and broadband noise. To solve this problem, in this paper, the parameters of the FIR filter are identified based on theoretical information via the least mean square (LMS) algorithm and then the identified parameters are used as the initial values for the adaptive process. Simulation results demonstrate that the employment of pre-identified parameters contributes to reduce the simulation time and increase the cancellation performance for both narrowband and broadband noise.

1. Introduction

The acoustic noise is a challenging problem in the field of industry and the industrial equipment is the main source of noise such as engines and compressors (Kajikawa et al., 2012). The effect of noise on humans is significant and depends on the pressure level and the situation in which people are exposed. For example, in heavy industry or similar situations, noise can cause hearing loss and in daily life, noise can interfere with people's normal speech, make human annoyance and severely disturbing sleep quality. Therefore, to attenuate the negative effects of noise, noise control is becoming an important research field worldwide. Traditional acoustic noise cancellation mainly relies on absorb/isolation materials depends on the type of sound, e.g. air-borne sound or structure-borne sound, and this is called passive noise control (PNC). Based on results from previous experiments and published articles, the PNC technology performs better for high-frequency noise cancellation (Leitch and Tokhi, 1987) and for low-frequency noise, due to the increasing wavelength, the increasing requirement of the material makes the PNC technology costly and inconvenient (Kuo and Morgan, 1999; Nithin, and Ganapati, 2013; Jiang and Li, 2018). To deal with low-frequency noise cancellation, the active noise control (ANC) technique is first proposed by Lueg in 1936 to attenuate the noise pressure level at low frequencies (Lueg, 1936). Following Lueg's work, lots of works regarding from sophisticated algorithm design to implementation have been completed by different researchers and a summary of the history of the ANC development can be found in several review papers (Leitch and Tokhi, 1987; Kuo and Morgan, 1999; Kajikawa et al., 2012; Nithin and Ganapati, 2013). In spite of the rapid development of ANC systems, there are still several problems while designing and implementing an ANC system, e.g. physical constraints for the ANC system design and implementation, nonlinearities, and economical considerations (Kajikawa et al., 2012).

For physical constraints, take point source in the free-field acoustical environment as an example. According to the inverse square law, the sound intensity and the sound pressure are inversely proportional to the transmitting distance (Martin, and Roure, 1997; Duke et al, 2009; Wrona et al., 2018; Peter, 2011). Besides, the transmitting distance and the property of the propagation medium determine the sound velocity. In order to describe the physical process of ANC, in 1987, Leitch and Tokhi completed a milestone work presenting the geometric description of the process of cancellation for a compact (point) source in three-dimensional linear propagation medium (Leitch and Tokhi, 1987). For noise control, there are three ways to attenuate the noise level, i.e. at the source, on a propagation path and at the receiver point. For noise sources, the physical separation between the primary noise source, and the secondary noise source determines the range of cancellation at the receiver point. During the process of noise propagation, traveling distance, the effect of sound absorption through the

* Corresponding author.
E-mail addresses: Quan.Zhu@uwe.ac.uk (Q. Zhu)

medium and the sound insulation directly cause noise attenuation. Among these factors, travelling distance is an important component and based on the inverse square law, the sound intensity and the sound pressure is inversely proportional to the square of the distance and the distance respectively. Besides, the property of the propagation medium determines the value of sound velocity. As for the receiver point, its position determines the acoustic delay, from the primary source to the receiver point, which should be bigger than the electrical delay, from the detected transducer to the receiver point. Therefore, the geometrical arrangement of system components such as actuators and sensors have a significant effect on the degree of cancellation of the ANC system (Raja Ahmad, and Tokhi, 2008; 2009; 2010). For an accurate description of the process of cancellation, Leitch and Tokhi proposed geometrical factors based ANC structure, a transfer function of the controller for complete noise cancellation and the critical distance ratio for an infinite gain controller. They also provided a quantitative analysis of the degree of cancellation in relation to parameters of acoustic waves for a point source in three-dimensional linear propagation medium. However, they did not refer the effects of different distance ratios and parameter adjustment mechanism on the degree of cancellation, which can provide useful insight for a specified degree of cancellation in real life applications and procedures of obtaining the desired controller, which is complicated and strongly depends on characteristics of acoustic paths. In summary, Leitch and Tokhi's work forms a solid foundation for the proposed feedforward ANC structure in this paper.

Apart from the geometrical consideration of noise sources, time variation and nonlinearity are other two challenging issues in the design and implementation of the ANC system (Kuo et al., 2004; Kuo and Wu, 2005; Sahib, and Kamil, 2011). In practice, both noise sources and the surrounding environment are changing with time, and this can directly cause frequency, amplitude, phase and sound velocity of noise sources nonstationary. However, the accuracy of amplitude and phase of the anti-noise generated by a signal processing algorithm determines the extent of the degree of cancellation. Therefore, the concept of adaptive control is introduced into the ANC system. The ANC scheme is thus required to be adaptive. An adaptive filter, defined as the controller with adjustable parameters and related adaptive algorithms, is thus used for tracking and coping with such variations in real time. The structure of the adaptive filter can be in different forms and the most common form is (non-recursive) finite impulse response (FIR) filter due to its advantages of simplicity and low computational load. As for the adaptive algorithm, filtered-x least mean square (FxLMS) algorithm is commonly used and several variants are proposed to solve multidimensional problems, to improve the cancellation performance and speed up the convergence process. However, in the ANC system, the presence of nonlinearities severely degrades the degree of cancellation of the standard FxLMS algorithm. Nonlinearities arise from three main sources. The first source is transducers like loudspeaker(s), microphone(s) and actuator(s), usually employed in the secondary path. The second source is the reference noise and the third source is the propagation path, including the primary path, from the reference microphone to the error microphone, and the secondary path, from the loudspeaker to the error microphone. In order to improve cancellation performance in the presence of nonlinearities, several nonlinear models and different types of nonlinear adaptive algorithms have been proposed. Related summary about these can be found in several review papers (Tan, and Jiang, 1997; 2001; Alberto, and Giovanni, 2004).

In the author's previous work (Peng et al., 2019), a geometrical-configuration based feedforward ANC scheme with an adaptive FIR filter was proposed to solve the problem of physical constraints and nonlinearities. However, the FIR filter is initialized randomly without using the prior information and it causes the running time of simulation experiments too long and the cancellation performance is not good as expected. Therefore, in order to accelerate the simulation process and improve the cancellation performance, in this paper we use the least mean square (LMS) algorithm to identify the parameters of the FIR filter based on known information prior to the simulation experiments. The main contribution to knowledge in this paper is that using the pre-identified parameters based on theoretical information greatly contributes to save time and improve the cancellation performance.

The rest of paper is organized as follows. Section 2 states the problem and presents the process of applying the LMS algorithm for identifying the parameters of the FIR filter. Section 3 presents several simulation results to verify the cancellation capability of the proposed adaptive ANC system. Section 4 concludes the paper.

2. System identification

2.1 Problem definition

Consider a feedforward physical configuration-based ANC scheme with an FIR filter for point source cancellation in free-field acoustic environment (see Fig.1).

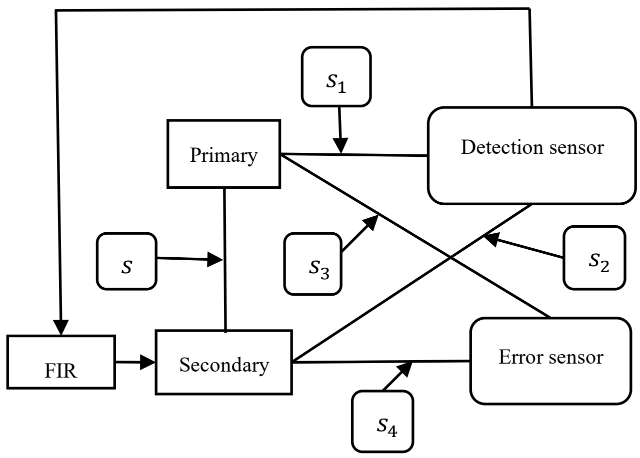


Fig. 1. Structure of feedforward ANC system with an adaptive FIR filter

The symbol s, s_1, s_2, s_3, and s_4 represents physical separation and physical distances between sources and actuators respectively. Mathematical expressions of physical distance based on sound pressure have been provided in the author's previous publications (Peng et al., 2019). Here, the FIR filter acts as the role of adjusting amplitude and phase of the input signal, detected from the detection sensor. Normally, the microphone is selected as the detection sensor (Leitch and Tokhi, 1987). The output of the FIR filter is transmitted to the secondary loudspeaker and used for driving the loudspeaker to generate the secondary source, which will superimpose the primary source at the error sensor to achieve the aim of cancellation. The error sensor here is used for monitoring the cancellation performance of the ANC system in terms of the amplitude of the error signal.

In the author's previous works, the initialization of parameters of the FIR filter is random without using known information, therefore, it degrades the cancellation performance and increases the simulation time. To solve this problem, in this paper, inspired by the inertial particle swarm optimization algorithm (Meng, 2018; Gao et al., 2019; Chen and Yang, 2019), we will use the LMS algorithm to identify the parameters of the FIR filter based on theoretical ideal conditions prior to the adaptive control process, aimed at saving simulation time and improving cancellation performance.

2.2 System identification via least mean square (LMS) algorithm

System identification is the fundamental field of modern control and the least square algorithm and the LMS algorithm are two widely used techniques. The LMS has the advantage of simplicity, low computational load and robustness when compared to the least square algorithm. The following section presents the process of applying the LMS algorithm on the identification of the FIR filter.

Consider a time-invariant FIR system, it is given as:

$$y(n) = \sum_{i=0}^{m-1} w^T(i)x(n-i) + v(n) \tag{1}$$

Where $x(t)$ and $y(t)$ are input signal and output signal of the system, $w(t)$ represents the coefficient and $v(t)$ is a zero mean Gaussian white noise with a variance of σ.

To express conveniently, we define the input vector as:

$$p(n) = [x(n), x(n-1), \dots, x(n-m+1)]^T \epsilon R^m \tag{2}$$

Define the coefficient vector as:

$$c(n) = [w(0), w(1), \dots, w(m-1)]^T \epsilon R^m \tag{3}$$

Where m represents the order of the system.

Applying equation (2-3) in equation (1), the output of the FIR system can be expressed in the form as follows:

$$y(n) = c^T(n)p(n) + v(n) \tag{4}$$

According to the theory of active noise and control, the relationship between the input signal and the output signal is known. Therefore, in order to implement the LMS algorithm for identification, define a cost function in terms of square of error signal, it is given as:

$$J(c) = E[(y(n) - c^T(n)p(n))^2] \tag{5}$$

The updating equation of the coefficient is:

$$c(n+1) = c(n) - \frac{\mu}{2} grad[J(c(n))] \tag{6}$$

Where μ denotes the step size and it is related to the convergence speed and cancellation performance.

$grad[J(c(n))]$ is expressed as:

$$grad[J(c(n))] = -2c^T(n)[y(n) - c^T(n)p(n)] \tag{7}$$

Apply equation (7) in equation (6), it follows that:

$$c(n+1) = c(n) - \mu c^T(n)[y(n) - c^T(n)p(n)] \tag{8}$$

3. Results and analysis

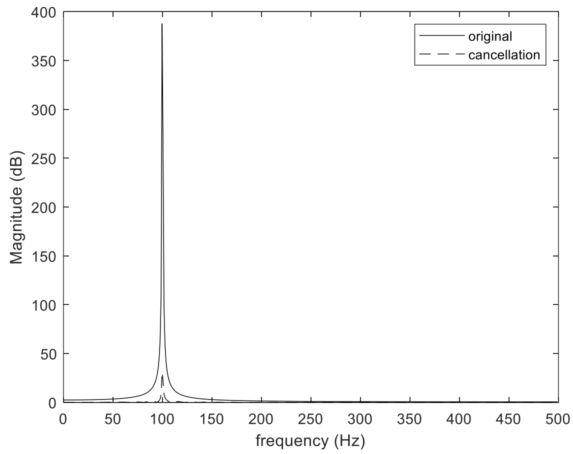
3.1 Results

All simulations are developed in a free-field acoustic environment and several different types of signals are used as the primary source to compare the cancellation performance under two different conditions. A 2000 Hz is used as the sampling frequency in all simulations. In this case, it is assumed that the microphone and the loudspeaker are the sources of nonlinearity and they are modelled by a second-order Butterworth high-pass filter with a cut-off frequency 80 Hz (Zhang and Gan, 2004).

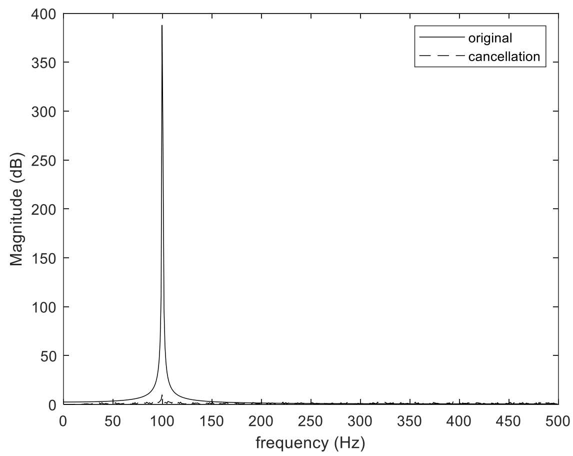
To reflect the degree of cancellation precisely, we adopt different criteria for narrowband and broadband noise. For narrowband noise, the difference between the magnitude in decibels (dB) is used as the comparison criteria and for broadband noise, the average amount of cancellation in decibels (dB) is adopted as the evaluation criteria. In the graphical results, the x label represents frequency in Hertz (*Hz*) and the y label denotes magnitude in decibels (dB).

There are five case studies in this section and simulation results are presented as follows.

Case 1: A sine wave of 200 *Hz*



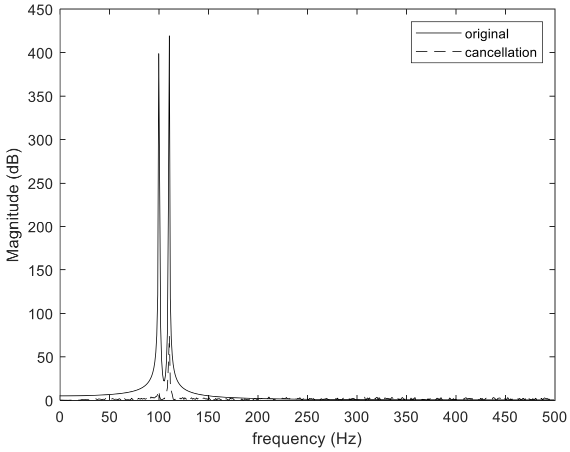
(a)



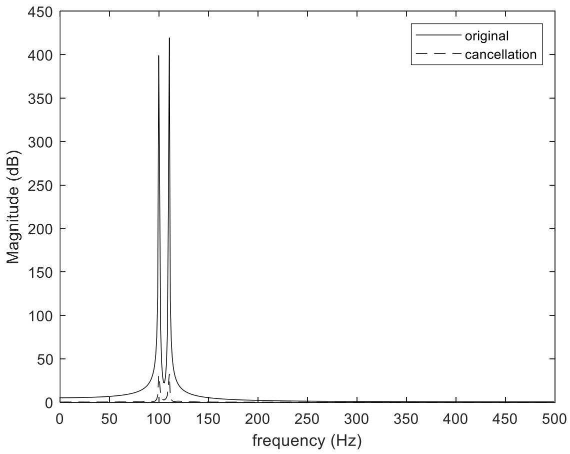
(b)

Fig. 2. Comparison results for the first case

Case 2: A combination wave (a sine wave of 200 *Hz* +a sine wave of 220 *Hz*)



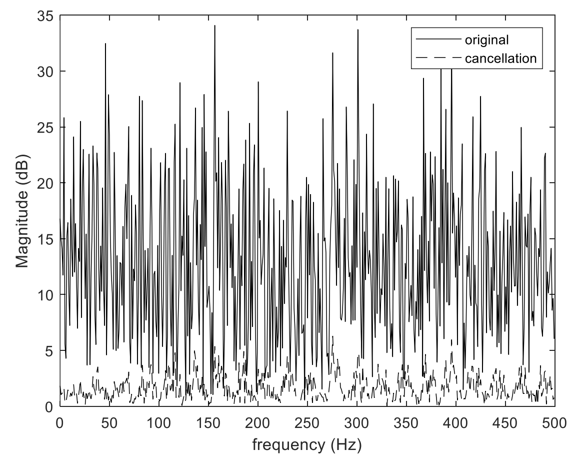
(a)



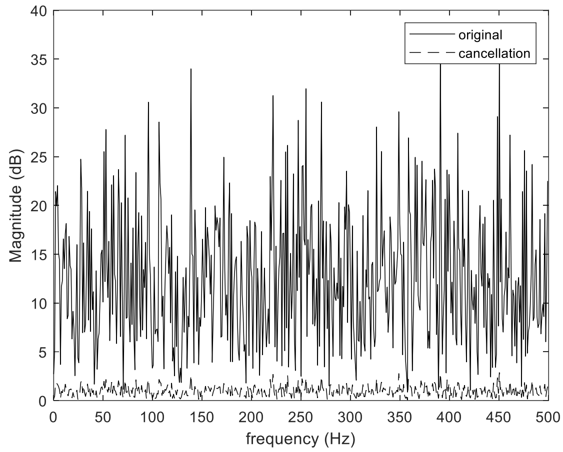
(b)

Fig. 3. Comparison results for the second case

Case 3: Gaussian white noise (μ=0, σ=0.2)



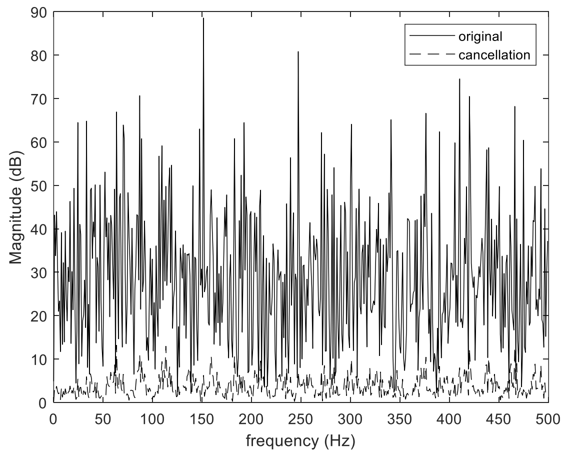
(a)



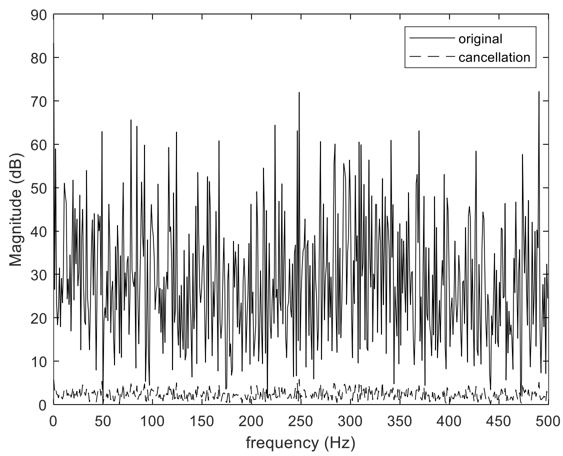
(b)

Fig. 4. Comparison results for the third case

Case 4: Gaussian white noise (μ=0, σ=1)



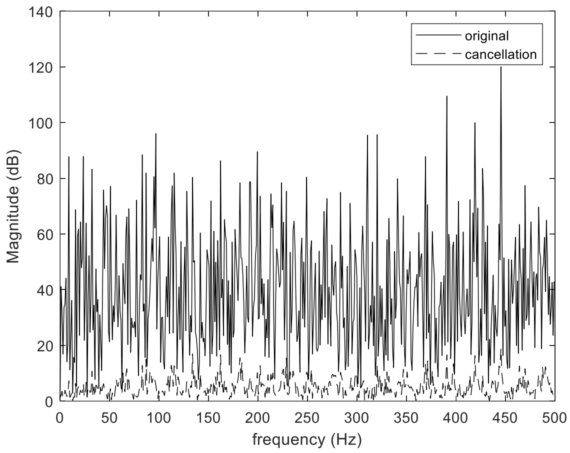
(a)



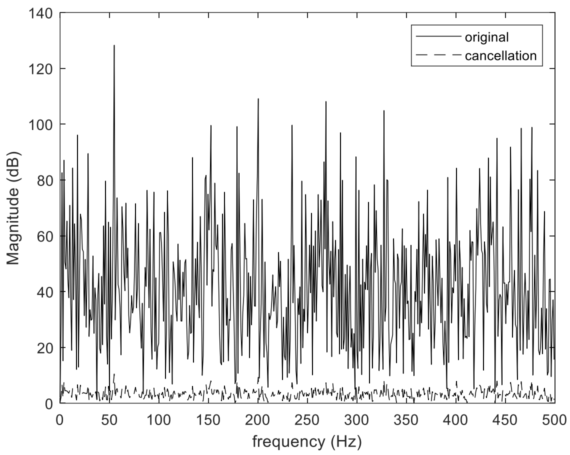
(b)

Fig. 5. Comparison results for the fourth case

Case 5: Gaussian white noise (μ=0, σ=2)



(a)



(b)

Fig. 6. Comparison results for the fifth case

3.2 Analysis

Simulation results from Fig. 2 to Fig. 6 demonstrates the cancellation capability of the adaptive ANC system with pre-identified parameters and reveal the difference in cancellation performance of two conditions. Table 1 summarizes the cancellation performance in decibel (dB) of five different cases.

Tab. 1. Comparison of two conditions in terms of cancellation performance

Case	Random initialization	Pre-identified
Single frequency	356.8 dB	377.8 dB
Two frequencies	345.6 dB	387 dB
Gaussian white noise (μ=0, σ=0.2)	11.2 dB	11.5 dB
Gaussian white noise (μ=0, σ=1)	24 dB	26.2 dB
Gaussian white noise (μ=0, σ=2)	34.3 dB	38.4 dB

For narrowband noise, simulation results from the first two cases reveal that the cancellation performance of pre-identified is better than the cancellation performance of random initialization. For single frequency, the increment of cancellation is 21 dB and for two frequencies, the value increases to approximately 42 dB.

For broadband noise, simulation results from the later three cases demonstrate that cancellation performance is still better when the parameters of the FIR filter are identified prior to the adaptive control process. Meanwhile, the cancelation performance varies from the value of the variance for the Gaussian white noise and the value of difference is increasing with the increment of variance value.

Table 2 presents the comparison results of simulation time for five different cases.

Tab. 2.

Case	Random initialization	Pre-identified
Single frequency	757.6 (s)	651 (s)
Two frequencies	537.6 (s)	391.7 (s)
Gaussian white noise (μ=0, σ=0.2)	481.2 (s)	370 (s)
Gaussian white noise (μ=0, σ=1)	487.8 (s)	375.5 (s)
Gaussian white noise (μ=0, σ=2)	448.1 (s)	404.6 (s)

From table 2, we can find that generally the reduction of the simulation time is significant. For narrowband noise, the reduction of simulation time in seconds can up to approximately 200 and for broadband noise, the reduction of simulation time in seconds varies from the value of variance. The amount of reduction in simulation time for the third and the fourth cases are approximately 120 seconds and the value decreases to 50 seconds for the fifth case.

4. Conclusion

A study about using the pre-identified parameters at the beginning of the adaptive process for the adaptive feedforward ANC system of point source cancellation in free field acoustic environment has been completed. The LMS algorithm is used for identifying the ideal parameters of the FIR filter based on theoretical information. Several different types of signals are used as the primary source for comparing the cancellation performance of pre-identified and random initial parameters. Simulation results reveal that both simulation time and cancellation performance are better when using the pre-identified parameters prior to the adaptive process. For narrowband noise, the improvement of cancellation varies from the number of frequency content and the reduction of simulation time is about 120 seconds. For broadband noise, the average amount of cancellation varies from the value of the variance of the Gaussian white noise and the larger variance, the better cancellation performance. For simulation time, the amount of reduction in seconds decreases with the increasing value of variance. In summary, using pre-identified parameters are better than random initialized and save time and improve performance cancellation.

Acknowledgements

The first author would like acknowledge the support from Engineering Modelling and Simulation Research Group of the University of the West of England, Bristol, UK.

References

Kajikawa, Y., Gan, W.S., and Kuo, S.M., 2012. Recent advances on active noise control: open issues and innovative applications. APSIPA Transactions on Signal and Information Processing. 1(3), 1-21.

Leitch, R.R., Tokhi, M.O., 1987. Active noise control systems. IEE Proceedings. 134(6), 525-546.

Kuo, S.M., Morgan, D.R., 1999. Active noise control: a tutorial review. Proceedings of the IEEE. 87(6), 943-973.

Nithin, V.G., Ganapati, P. 2013. Advances in active noise control: A survey, with emphasis on recent nonlinear techniques. Signal Processing. 93(2), 363-377.

Jiang, J.G., Li, Y., 2018. Review of active noise control techniques with emphasis on sound quality enhancement. Applied Acoustics. 136, 139-148.

Lueg, P. Process of Silencing Sound Oscillations, Patent 2043416, US June 9, 1936.

Peters, R.J., Smith, B.J., Hollins, M. Acoustics and Noise Control. 3rd ed., Pearsons Education Limited. London, UK, 2011: 34-53.

Tokhi, M.O., 1994. Design of Active Noise Control Systems with Compact and Distributed Sources. Research Report. ACSE Research Report 533. Department of Automatic Control and Systems Engineering.

Raja Ahmad, R.K., Tokhi, M.O., 2008. Theoretical Development of Minimum Effort Active Noise Control with Feedback Inclusion Architecture, Journal of Low Frequency Noise, Vibration and Active Control. 27(1), 75-81.

Raja Ahmad, R.K., Tokhi, M.O., 2009. Design of Self-tuning Minimum Effort Active Noise Control with Feedback Inclusion Architecture, Journal of Low Frequency Noise, Vibration and Active Control. 28(3), 205-215.

Raja Ahmad, R.K., Tokhi, M.O., 2010. Analysis of Geometry Related Constraints of Minimum Effort Active Noise Control System, Journal of Low Frequency Noise, Vibration and Active Control. 29(2), 111-128.

Martin, T., Roure, A., 1997. Optimization of an active noise control system using spherical harmonics expansion of the primary field. Journal of Sound and Vibration. 201(5), 577-593.

Duke C.R., Sommerfeldt, S.D., Gee, K.L., et al. 2009. Optimization of control source locations in free-field active noise control using a genetic algorithm. Noise Control Engineering Journal. 57(3), 221-231.

Wrona, S., Diego, M.de., Pawelczyk, M., 2018. Shaping zones of quiet in a large enclosure generated by an active noise control system. Control Engineering Practice. 80, 1-16.

Johan, A.K. Adaptive Control. 2nd ed., Addison Wesley. USA, 1995: 1-33.

Kuo, S.M., Wu, H.T., Chen, F.K., et al. 2004. Saturation effects in active noise control systems. IEEE Transactions on Circuits and Systems I: Regular Papers. 51(6), 1163-1171.

Kuo, S.M., Wu, H.T., 2005. Nonlinear adaptive bilinear filters for active noise control systems. IEEE Transactions on Circuits and Systems. 52(3), 617-624.

Sahib, M.A., Kamil, R., 2011. Comparison of Performance and Computational Complexity of Nonlinear Active Noise Control Algorithms. ISRN Mechanical Engineering. 2011, 1-9.

Tan, L.Z., Jiang, J., 1997. Filtered-X second-order Volterra adaptive algorithms. Electronics Letters. 33(8), 671-672.

Tan, L., Jiang, J., 2001. Adaptive Volterra filters for active control of nonlinear noise processes. IEEE Transactions on Signal Processing. 49(8), 1667–1676.

Alberto, C., Giovanni, L.S., 2004. Filtered-X Affine Projection Algorithms for Active Noise Control Using Volterra Filters. EURASIP Journal on Advances in Signal Processing. 12, 1841-1848.

Peng, T.R., Zhu, Q.M., Tokhi, M.O, et al. 2019. Fuzzy logic feedforward active noise control with distance ratio and acoustic feedback using Takagi–Sugeon–Kang inference. Journal of Low Frequency Noise, Vibration and Active Control. 0(0), 1-16.

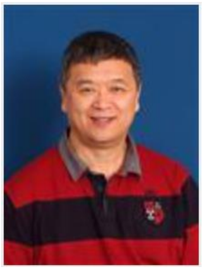
Zhang, Q.Z., Gan, W.S., 2004. Active noise control using a simplified fuzzy neural network. Journal of Sound and Vibration. 272, 437-449.

Meng, R., 2018. Adaptive Parameter Estimation for Multivariable Nonlinear CARMA Systems. International Journal of Applied Mathematics in Control Engineering. 1(1), 96-102.

Gao, X., et al., 2019. Adaptive High Order Neural Network Identification and Control for Hysteresis Nonlinear System with Bouc-Wen Model. International Journal of Applied Mathematics in Control Engineering. 2(1), 17-24.

Chen, X., Yang, J., 2019. An Optimal Compression Algorithm for Ship Trajectory. International Journal of Applied Mathematics in Control Engineering. 2(1), 74-80

Tongrui Peng received the M.S. degree in advanced control and engineering from University of Sheffield, in 2017. He is currently pursuing the Ph.D. degree at the Department of Engineering Design and Mathematics, University of the West of England, Bristol, UK. His research interest includes slat noise prediction, geometry-related active noise control, and adaptive neuro fuzzy inference system (ANFIS) and particle swarm optimization (PSO) algorithm. He has published several papers over these topics. Mr. Tongrui Peng's awards and honors include the member of the International Program Committees for the 11th International Conference on Modelling, Identification and Control (ICMIC 2019), the best student paper for ICMIC 2019, and peer-review for three journals.



Quanmin Zhu is professor in control systems at the Department of Engineering Design and Mathematics, University of the West of England, Bristol, UK. He obtained his MSc in Harbin Institute of Technology, China in 1983 and PhD in Faculty of Engineering, University of Warwick, UK in 1989. His main research interest is in the area of nonlinear system modelling, identification, and control. He has published over 200 papers on these topics, edited five Springer books and one book for the other publisher, and provided consultancy to various industries. Currently Professor Zhu is acting as Editor of International Journal of Modelling, Identification and Control, Editor of International Journal of Computer Applications in Technology, Academic Editor of Complex, Hindawi, and Editor of Elsevier book series of Emerging Methodologies and Applications in Modelling, Identification and Control.

Prof. M. Osman Tokhi, in London South Bank University, is world authority in active control of noise and vibration and has specialist knowledge and expertise in robotics, control and systems engineering. He has extensive research experience in assistive robotics tailored to addressing rehabilitation and mobility needs of elderly and the disabled, control of acoustic noise and vibration, computational intelligence with specific focus on development of bio- and nature-inspired optimisation algorithms for solving complex science and engineering problems, adaptive/intelligent control and high-performance real-time computing. He has authored/co-authored in excess of 750 publications, including research monographs, text books, and journal and conference research articles in these areas, and has supervised more than 55 PhD projects to successful completion.

Yufeng Yao is a professor in Aerospace Engineering and Head of Engineering Modelling and Simulation (EMS) research group at the Department of Engineering Design and Mathematics, University of the West of England, Bristol, UK. His research explores fundamental flow physics by using high-fidelity simulation code (DNS and LES), as well as engineering turbulent flow problems by using industry standard computer code (RANS and URANS). His research covers various inter-connected research themes, including turbulent wake dynamics, turbulent boundary-layers, and laminar transition to turbulence in the shock-induced separation bubbles, among others.