Respuestas, 25 (2) May - August 2020, pp. 42-48, ISSN 0122-820X - E ISSN: 2422-5053

Respuestas
Journal of Engineering Sciences

RESPUESTAS

Original Article

https://doi.org/10.22463/0122820X.2435

Adaptive Noise Cancellation System Using a Recursive Least Squares Filter

Sistema adaptativo de cancelación de ruido usando filtros de mínimos cuadrados

Jorge Gomez-Rojas[1], Rafael Linero-Ramos[2], Yesica Beltran-Gomez[3*]

1PhD in Engineering, jgomez@unimagdalena.edu.co, Orcid: 0000-0002-0840-8743, University of Magdalena, Santa Marta, Colombia.
2Master in Electronic Engineering, rlineror@unimagdalena.edu.co, Orcid: 0000-0003-3361-2719, University of Magdalena, Magdalena, Santa Marta, Colombia.
*3*Master in Electronic Engineering, ybeltranb@unimagdalena.edu.co, Orcid: 0000-0001-8437-4082, University of Magdalena, Magdalena, Santa Marta, Colombia.*

How to cite: J. Gomez-Rojas, R. Linero-Ramos and Y. Beltran-Gomez, "Adaptive Noise Cancellation System Using a Recursive Least Squares Filter". Respuestas, vol. 25, no. 2, pp. 42-48, 2020.

Received on January 27, 2020; Approved on March 19, 2020

ABSTRACT

In this paper, we show an Adaptive Noise Canceller (ANC) that estimates an original audio signal measured with noise. The adaptive system is implemented using a Recursive Least Squares filter (RLS). Its design parameters consider the filter order, forgetting factor, and initial conditions to obtain optimal coefficients through iterations. A medium square error (MSE) around to is reached, and with this, it makes possible a low-cost implementation.

Keywords:

Adaptive filter,
ANC system,
Audio signal,
RLS filter.

RESUMEN

En este artículo, se presenta el diseño de un sistema adaptativo de cancelación de ruido, en el cual se estima una señal medida con ruido. Se implementa este sistema adaptativo utilizando un filtro de mínimos cuadrados (RLS). Este diseño considera parámetros tales como el orden del filtro, factor de olvido y condiciones iniciales para obtener los coeficientes óptimos del filtro a través de iteraciones. Se logró un error cuadrático medio alrededor de 10^{-6} , y con esto es posible hacer una implementación de bajo costo.

Palabras clave:

Filtro adaptativo,
sistema de cancelación de ruido,
señal de audio,
filtros de mínimos cuadrados.

Introduction

Active noise cancellation using adaptive noise canceller (ANC) is one of the most effective techniques to cancel noise. In this system, the objective is to reduce the noise interference that affects the original signal [1]. The main idea of the ANC system is to pass the contaminated signal through a filter that suppresses the noise without modifying the signal [2]. ANC systems work according to the principle of the destructive superposition of acoustic waves [3]. This technique establishes that if two or more waves travel in the same medium, the total displacement in the middle is the sum of the individual displacements of the waves who travel in that environment [4]. Thus, a signal is generated and sum with the measured signal with contamination so that the original sound signal can be canceled and the original signal can be made noise-free.

Noise cancellation systems have a reference sensor measuring primary noise in the signal and generating a reference signal that is correlated with the spectral content of the undesirable noise [5]. The reference signal goes to the control system generating signals that control

***Corresponding author.**
E-mail Address:ybeltranb@unimagdalena.edu.co (Yesica Beltran-Gomez)

the noise-canceling speakers. An error microphone measures the residual error and sends signals to the controller to adapt the control system to reduce the noise [2].

The main problem solved by ANC systems is the interference of external noise that affects the signals of interest, a problem presented in multi-sensor networks in new smart cities [6]. This is done using adaptive algorithms that control the generation of the desired signal by adjusting the filter weights to minimize error as much as possible [7].

Recursive Least Squares (RLS) is one of the most widely used adaptive algorithms for noise cancellation [8]. This algorithm changes its coefficients to minimize its cost function, it is robust and has a high speed of convergence. RLS filters have a high rate of convergence that is independent of the dispersion of the eigenvalues of the input correlation matrix. These algorithms are very useful in applications where ambient noise varies slowly [7].

Some research has made comparisons between adaptive algorithms for acoustic noise cancellation [7]. The RLS algorithm was found to have a convergence time for the mean squared error decrease less than the mean least squares algorithm (LMS). RLS presents mean squared error values of the order of 10 ^ (- 6) in 146 samples while LMS presents mean squared error values of the order of 10 ^ (- 5) in 1988 iterations.

Other adaptive algorithms are used for noise cancellation, minimizing error. Within these algorithms are the Normalized Least Mean Square (NLMS) with the major convergence speed, stable and very useful in speakers and, other audio systems. On the other hand, Block Least Mean Square (BLMS) have been developed, with a fast convergence speed and greater robustness than previously related algorithms [2].

LMS and RLS are described in [9]. An analysis is made to implement both algorithms using a microphone, two speakers, and a sound card. The data is processed using free software. The results shown are like the theoretical results and it is verified that the algorithms can solve real-life problems.

The proportional normalized least squares adaptation algorithm (PNLMS) discussed in [10], converges significantly faster than the NLMS. Generally, it is used in echo cancellers nowadays. In PNLMS, the adaptation gain at each bypass position varies from one position to another and is approximately proportional, at each bypass position, to the absolute value of the current estimate of the bypass weight. However, the adaptation of PNLMS implies an increase in the computational cost.

[11] Describes the concept of implementing a neural network for adaptive noise cancellation using LMS. The network has real-time processing capabilities, so you can optimize the adaptive filter coefficients on each new sample received. This is very useful in mobile environments. The time required by the neural network for calculating the coefficients is small compared to the direct LMS-ANC method. It is possible to improve the mean squared error in LMS using a neural network. The results of this simulation show satisfactory performance.

In this paper design of an adaptive noise cancellation system is presented. Its aim is an original audio estimate from an audible signal measured with noise, through the use of an RLS filter taking into account its advantage of its characteristics high-speed convergence and its high error minimization capacity.

The paper is organized as follows: Section I presents an introduction to ANC systems and RLS filters. Section II presents the development of the designed system. Section III provides the results of the work done and Section IV presents the conclusions of this work.

Methodology

ANC system design

ANC system is composed by speakers and two microphones to make measurement of Principal aim of this system is to estimate the original audio signal $\hat{S}(n)$ from a signal measured with contamination $y(n)$, for this once the estimated signal $\hat{\boldsymbol{x}}(\boldsymbol{n})$ is obtained, subtracted with the measured signal, this is how between the original signal $S(n)$ and the estimated signal $\hat{S}(n)$ the error $e(n)$ that will be used to train the filter is obtained. Below is the mathematical explanation of the operation of the filter and the system in general.

Principal aim of this system is to estimate the original audio signal Ŝ(n) from a signal measured with contamination y(n) , for this once the estimated signal $\hat{x}(n)$ is obtained, subtracted with the measured signal, this is how between the original signal S(n) and the estimated signal Ŝ(n) , the error e(n) that will be used to train the filter is obtained. Below is the mathematical explanation of the operation of the filter and the system in general.

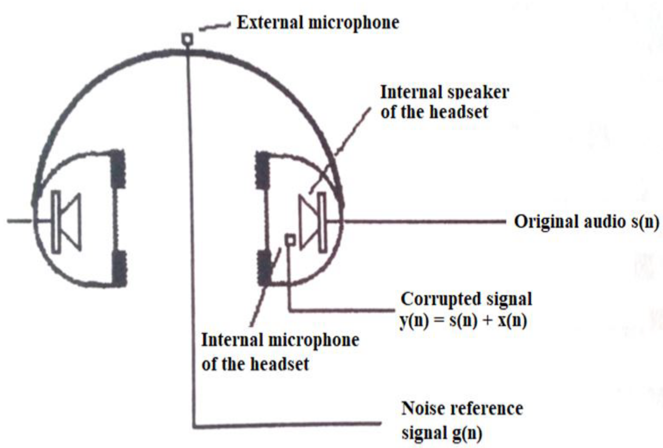

Figure 1. Noise cancellation System.
Source: Own

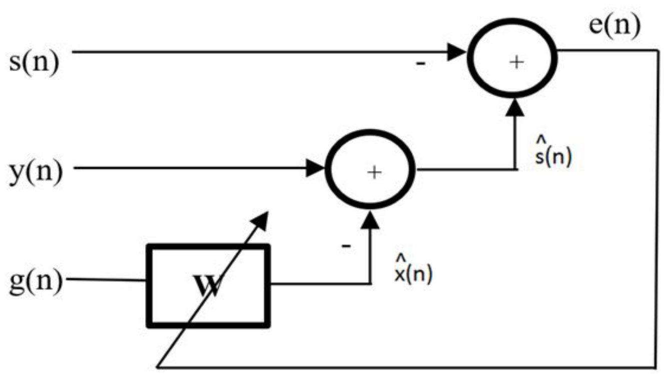

Figure 2. Block diagram designed to cancel system noise.
Source: Own

Recursivity of the filter to calculate the optimal coefficients is defined by (1) [12]. Where *W* are the optimal coefficients, *K* is a profit vector and *Z* is the a priori error.

$$\boldsymbol{W}(n) = \boldsymbol{W}(n+1) + \boldsymbol{K}(n)\, \boldsymbol{Z}(n) \qquad (1)$$

The signals used in the filter design are defined with the following equations:

$$y(n) = s(n) + x(n) \qquad (2)$$

$$\hat{s}(n) = y(n) - \hat{x}(n) \qquad (3)$$

$$e(n) = \hat{s}(n) - s(n) \qquad (4)$$

$$e(n) = y(n) - \hat{x}(n) - s(n) \qquad (5)$$

The a priori error for the calculation of the optimal filter coefficients is given by:

$$\boldsymbol{Z}(n) = y(n) - g^T(n)\boldsymbol{W}(n-1) - s(n) \qquad (6)$$

$$\boldsymbol{Z}(n) = s(n) + x(n) - g^T(n)\boldsymbol{W}(n-1) - s(n) \qquad (7)$$

$$\boldsymbol{Z}(n) = x(n) - g^T(n)\boldsymbol{W}(n-1) \qquad (8)$$

In (8) it is seen that the a priori error results in an expression of the general form, in which the a priori error is calculated to determine the optimal coefficients of an RLS filter, as shown in (9).

$$\boldsymbol{Z}(n) = \boldsymbol{d}(n) - \boldsymbol{X}^T(n)\, \boldsymbol{W}(n-1) \qquad (9)$$

Where is the desired signal, $\boldsymbol{X}^T$ is the vector of input samples and $\boldsymbol{W}(n\text{-}1)$ are the optimal coefficients of the filter, calculated at a previous instant. Because the signal $x(n)$ is not known in the noise cancellation system, it can only be estimated, in the simulation we work (6). In addition to this we have the profit vector $\boldsymbol{K}(n)$ what is defined by the following equation:

$$\boldsymbol{K}(n) = \frac{\lambda^{-1}\varphi(n-1)g(n)}{1 + \lambda^{-1}g^T(n)\varphi(n-1)g(n)} \qquad (10)$$

Being λ the forgetting factor, which allows for reducing the weight of the oldest samples in the filter estimate. This value is contained between [0, 1]. To the development of the project is defined in 0.5, intermediate value to avoid the tendency to a filter of least squares LS and least squares means LMS.

φ(n - 1) is an initial condition in a square matrix of dimensions of the order of the filter, which contains a minimum value in its diagonal. In this case, its value is 0.01, a value that will be updated iteratively through the Riccati equation.

$$\varphi(n) = \lambda^{-1}\varphi(n-1) - \lambda^{-1}K(n)g^{T}(n)\varphi(n-1) \qquad (11)$$

The generation of the signals was used in the audio recorder class of Matlab. Recordings of both the original signal and the noise reference signal are obtained. A sampling frequency of 11025 Hz was used, suitable for acquiring voice signals and musical instruments whose fundamental frequencies do not exceed 5000 Hz. In 5 seconds of recording, vectors of 55125 samples are obtained. The noise signal x (n) was obtained filtering the signal g (n) with an FIR filter Window-Bartlett low-pass with cutter frequency 0.2 and its order 8.

Results

Figure. 3 show spectrum of the original audio signal obtained with the recording in Matlab using audio recorder class.

The spectrum of the noise reference signal is observed in Figure. 4. To choose the order of the filter, measurements of the mean square error for order 4, 6, and 8 were made.

For the case of order 4, an error presents instability in all iterations around of $5x10^4$.

In Figure. 5 the frequency response of the filter applied to the signal $g(n)$ is observed to obtain the signal $x(n)$. In Figure. 6 the spectrum of the obtained signal $x(n)$ is observed after the signal $g(n)$ has passed through the low pass filter.

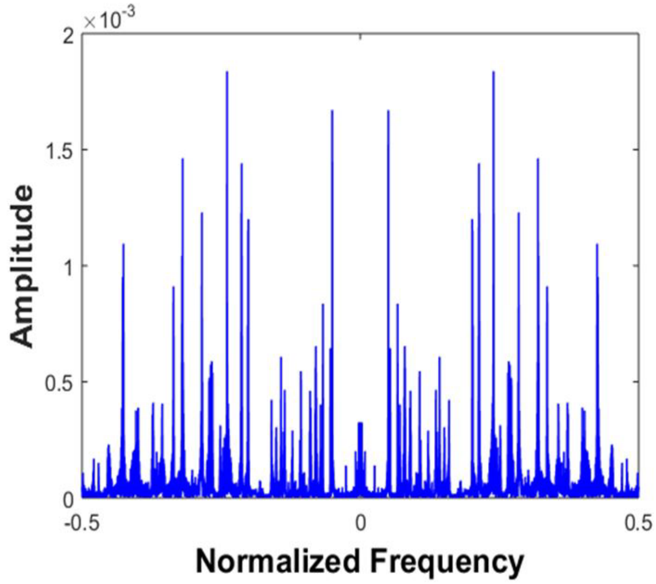

Figure 3. Spectrum of the original audio signal s (n).
Source: Own

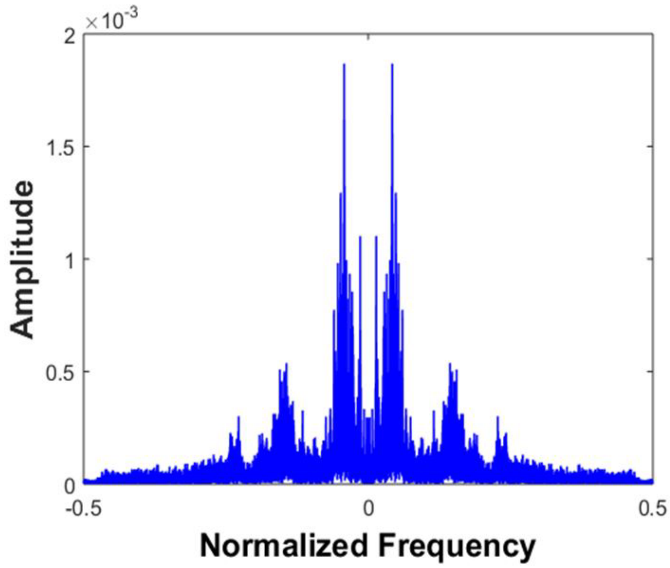

Figure 4. Spectrum of the noise reference signal g (n).
Source: Own

Error measured for the filter with order 6 a considerable decrease is observed in Figure. 8. However, throughout all the iterations, the error value does not converge. Fitting filter to order 8 and the decrease of the error is notorious.

Respuestas, 25 (2), pp. 42-48, 2020, ISSN 0122-820X - E ISSN: 2422-5053

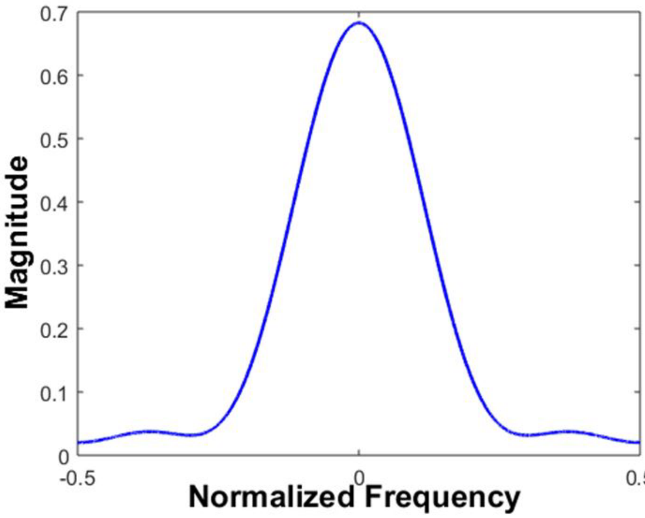

Figure 5. Frequency response with 0.2 low-pass cut parameter
Source: Own

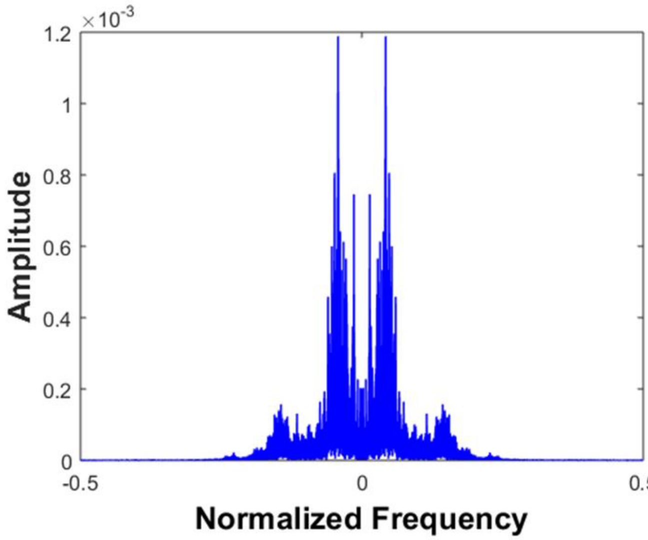

Figure 6. Frequency response to x(n).
Source: Own

In Figure. 7 the comparison between the original audio signal and the signal contaminated with noise is showed.

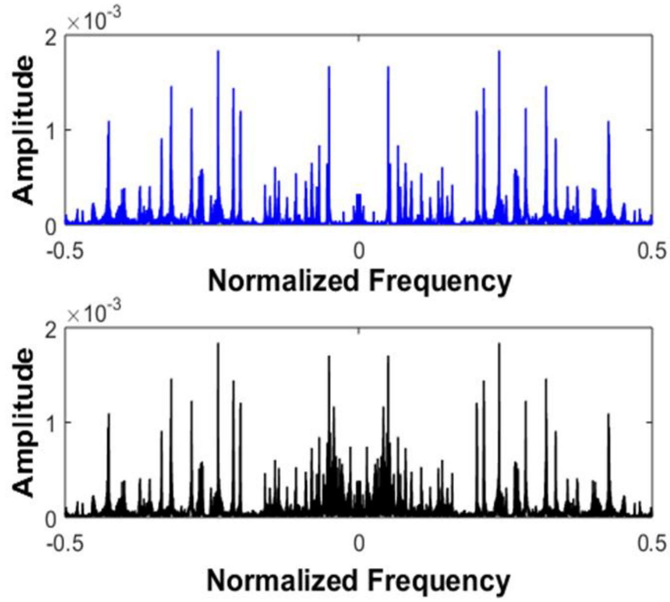

Figure 7. Spectrum of the original audio signal (blue) and spectrum of the signal measured with contamination (black).
Source: Own

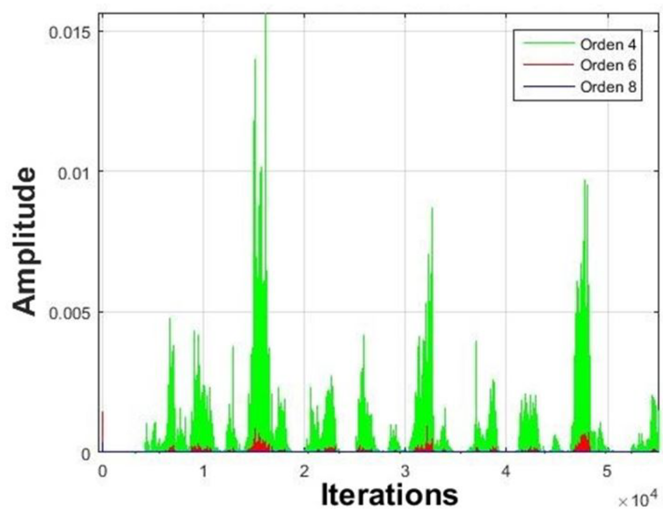

Figure 8. Mean squared error measured for the system with RLS filter order 4, 6 and 8.
Source: Own

Then, new measurements were made for filters with order 8, 9, and 10. It is observed for order 8 there is a value of the initial mean square error higher than that of order 9 and 10, with which the RLS filter is trained. However, the three orders used show that the error value is stabilized towards iteration 35.

However, the three orders used show that the error value is stabilized towards iteration 35. Taking into account that the initial value for order 8 is considerably low, this order is chosen. The results are observed in Figure 9.

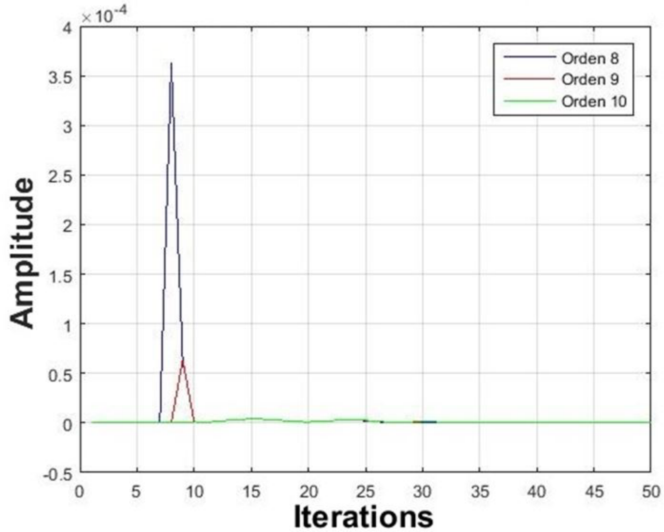

Figure 9. Mean squared error measured for the system with RLS filter order 8, 9 and 10.
Source: Own

A comparison of the spectra obtained from the estimated audio signal for the filters of order 4, 6, and 8 is carried out and showed in Figure 10. It is appreciated that for the lower order filters the spectrum still visibly presents undesired frequency components. Finally, the comparison of the spectrum of the original audio signal with the estimated audio signal is made and it can be shown that they are fitting. Figure 11 shows the spectrum original audio signal and the estimated RLS audio signal.

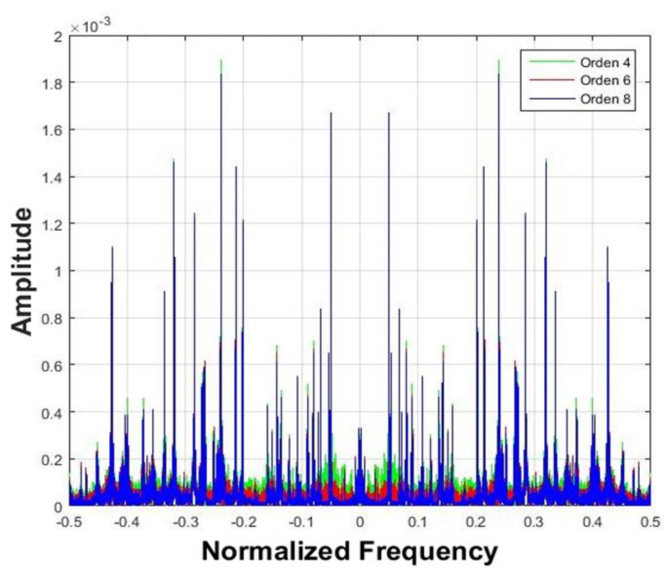

Figure 10. Spectrum of the estimated audio signal with RLS filter of order 4 (green), order 6 (red) and order 8 (blue).
Source: Own

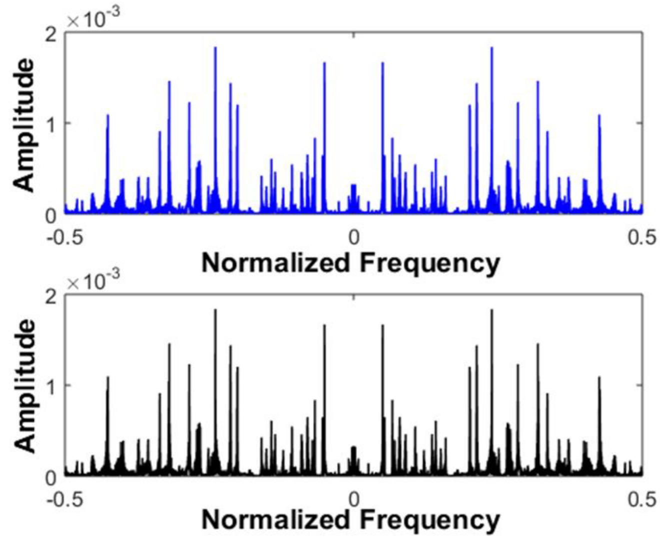

Figure 11. Spectrum of the original audio signal (blue) and spectrum of the estimated audio signal with an RLS filter of order 8 (black).
Source: Own

Conclusions

Adaptive systems allow noise cancellation regardless of the input signal statistic. These systems can be implemented using RLS filters of order ten with a high speed of convergence that allows obtaining a stable system minimizing the values of the root mean square error. This estimates an original audio signal from a measured signal with noise pollution.

Using RLS filters, few iterations are needed to eliminate noise in real problems in audio signal applications. Compared to other investigations, the RLS algorithm has a convergence time for the decrease of the root mean square error less than LMS.

References

[1] J. Gómez-Rojas, R. Linero-Ramos, & Y. Beltrán-Gómez, "Uso del Filtro Kalman extendido para la estimación de las variables de vuelo de un vehículo aéreo no tripulado", *Rev. Espac.*, vol. 41, núm. 10, 2020.

[2] M. Dhal, M. Ghosh, P. Goel, A. Kar, S. Mohapatra, & M. Chandra, "An unique adaptive noise canceller with advanced variable-step BLMS algorithm", *2015 Int. Conf. Adv. Comput. Commun. Informatics, ICACCI 2015*, pp. 178–

183, 2015.

[3] S. Elliot, *Signal Processing for Active Control*, Academic P. Londres, 2001.

[4] S. J. Elliott & P. A. Nelson, "Active Noise Control", *IEEE Signal Process. Mag*., vol. 10, núm. 4, pp. 12–35, 1993.

[5] E. Hansler & G. Schmidt, *Acoustic Echo and Noise Control: A Practical Approach*. 2004.

[6] L. Camargo, J. Gómez-Rojas, & M. Gasca, *La ciudad inteligente y la gestión de las TIC*. 2020.

[7] M. M. Dewasthale, R. D. Kharadkar, & M. Bari, "Comparative performance analysis and hardware implementation of adaptive filter algorithms for acoustic noise cancellation", *2015 Int. Conf. Inf. Process*., pp. 124–129, 2015.

[8] B. Panda, A. Kar, & M. Chandra, "Non-linear Adaptive Echo Suppression Algorithms: A Technical Survey", *en IEEE Sponsored International Conference on Communication and Signal Processing*, 2014, pp. 658–662.

[9] H. Abdullah, M. lkram Yusof, & S. R. M. Baki, "Adaptive Noise Cancellation: A Practical Study of the Least-Mean Square (LMS) Over Recursive Least-Square (RLS) Algorithm", *en Student Conference on Research and Development*, 2002, núm. I, pp. 448–452.

[10] D. L. Duttweiler, "Proportionate normalized least-mean-squares adaptation in echo cancelers", *IEEE Trans. Speech Audio Process*., vol. 8, núm. 5, pp. 508–517, 2000.

[11] S. Dixit & D. Nagaria, "Neural network implementation of least-mean-square adaptive noise cancellation", *Proc. 2014 Int. Conf. Issues Challenges Intell.* Comput. Tech. ICICT 2014, pp. 134–139, 2014.

[12] D. G. Manolakis, V. K. Ingle, & S. M. (Author) Kogon, *Statistical and adaptive signal processing*. 2005.