VARIABLE STEP SIZE IN MULTICHANNEL ACTIVE NOISE CONTROL SYSTEM

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Abstract

The aim of multichannel system is to reduce the sound pressure levels in an area around the error sensors. The multichannel version of the Filtered x Least Mean Square (FxLMS) algorithm has been the most widely used adaptive filtering strategy applied to multichannel active noise control systems, the so-called Multiple Error filtered x LMS algorithm (MeFxLMS). A MeFxLMS algorithm is used in order to cancel out different types of primary noise. As an alternative to the MeFxLMS algorithm, the Least Maximum Mean Squares (LMMS) algorithm is developed in order to reduce computational complexity and achieve a more uniform residual field. Variable Step Size Least Mean Square (VSS LMS) algorithm is used for updating secondary path modeling filter.

Keywords

Filtered x Least Mean Square algorithm (FxLMS), Multichannel active noise control systems, Least maximum mean square, Variable Step Size Least Mean Square (VSS LMS) algorithm.

1. Introduction

A local active noise control system uses a secondary source to cancel the acoustic pressure at the location of an error microphone and thus generates a zone of quiet around this point. Increasing the number of secondary sources and error sensors the extent of the zone of quiet created could be large. The aim of multi channel system is to reduce the sound pressure levels in an area around the error sensors, following a local control strategy [1].

The multichannel version of the Filtered x Least Mean Square (FxLMS) algorithm has been the most widely used adaptive filtering strategy applied to multichannel active noise control systems, the so called Multiple Error Filtered x Least Mean Square (MeFxLMS) algorithm [2]. MeFxLMS algorithm is used in order to cancel out different types of primary noises. As an alternative to the MeFxLMS algorithm Least Maximum Mean Squares (LMMS) algorithm have been developed in order to reduce computational complexity and achieve a more uniform residual field. LMMS is the steepest descent algorithm; it is robust and has good tracking capabilities. LMMS algorithm minimizes the sum of the squares of the measured signals, and produces a residual acoustic field in the enclosure that can have large differences between the values of its maximum and minimum levels. In application such as to control noise around the headrest of a seat, a more uniform acoustic field is desired.

The organization of this paper is as follows. Section 2 describes the Multiple Error Filtered x Least Mean Square Algorithm. Section 3 represents Least Maximum Mean Square Algorithm, Section 4 describes the Variable Step Size Least Mean Square Algorithm, Section 5 describes the Simulation Results, and Section 6 gives Conclusion.

2. Multiple Error Filtered X Least Mean Square Algorithm

The multichannel version of the filtered-X LMS algorithm is called the MeFxLMS algorithm. A system with K reference signals, M secondary sources and L error sensors is considered as shown in Figure 1. Block C represents a matrix of L x M error paths and block W is a matrix of K x M control filters that are designed to minimize the sum of the squares of L error sensor outputs [3]. Primary noise is actively cancelled out by using the M secondary signals which are fed by the K x M adaptive filters. The output of the l^{th} error sensor can then be written as

$$e_l[n] = d_l[n] + \sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{j=0}^{J-1} c_{imj} \sum_{i=0}^{I-1} w_{mki} x_k[n-i-j] \quad (1)$$

Where $d_l[n]$ is the primary noise at the l^{th} error sensor, C_{imj} is the j^{th} coefficient of the impulse response from the m^{th} secondary source to the l^{th} error sensor. The last summation represents the k^{th} reference signal filtered through the corresponding adaptive finite impulse response filter of I coefficients.

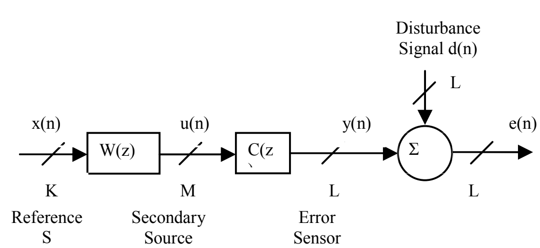

Fig 1-Multichannel Active Noise Control System

Equation (1) illustrates the linear relationship between the error signal and the controller coefficients and is expressed in matrix form as

$$e[n] = d[n] + R[n]w \quad (2)$$

Where R[n] is the filtered reference signals matrix. Parameters involved in equation (1) is defined as

$$e[n] = [e_1[n], e_2[n],\ldots, e_L[n]]^T \quad (3)$$

$$d[n] = [d_1[n], d_2[n],\ldots, d_L[n]]^T \quad (4)$$

$$w = [w_0^T, w_1^T,\ldots,w_{I-1}^T]^T \quad (5)$$

with,

$$w_i = [w_{11i},w_{12i},\ldots,w_{MKi}]^T \quad (6)$$

The optimum value of the coefficient vector w minimizes the cost function

$$J = E\left[\sum_{l=1}^{L} |e_l[n]|^2\right] \quad (7)$$

Where 'J' denotes an expected value. If the reference signal $x_k[n]$ is correlated with d[n], it is possible to reduce the value of J by driving the secondary sources by a filtered version of the reference signal. Equation (7) is evaluated iteratively by using the steepest descent algorithm which uses a stochastic estimation of the cost function gradient vector

$$w[n+1] = w[n] - \alpha \sum_{l=1}^{L} R_l^T[n] e_l[n] \quad (8)$$

Where α the convergence parameter and $R_l[n]$ corresponds to the l^{th} row of the filtered reference signals matrix R[n].

3. Least Maximum Mean Square Algorithm

The cost function is the p-norm of a vector composed of the following signals.

$$J_p = E\left[\sum_{l=1}^{L} |e_l[n]|^p\right] \quad (9)$$

Different values of the parameter p lead one from the minimization of the sum of the squares, p=2, to the minimization of the maximum measured signal at each n, in the limiting case with p tending to infinity. A more uniform residual field is obtained for larger values of p. Only one of the error signals is used in the algorithm's calculations at each n. Therefore, the computational load is reduced. An iterative expression to minimize Jp based on a steepest descent method is used to reach the optimum [3]. The true gradient vector of the cost function is approximated by a stochastic estimation. The stochastic gradient vector is then given by

$$\frac{\partial J_p[n]}{\partial w} = \sum_{l=1}^{L} |e_l[n]|^{p-2} R_l^T[n] e_l[n] \quad (10)$$

An iterative algorithm to minimize equation (9) is built by using the stochastic gradient as in equation (10),

$$w[n+1] = w[n] - \alpha \sum_{l=1}^{L} |e_l[n]|^{p-1} R_l^T[n] \quad (11)$$

When p=2,

$$w[n+1] = w[n] - \alpha \sum_{l=1}^{L} R_l^T[n] e_l[n] \quad (12)$$

Equation (12) is same as used in (8). The minimax type algorithm balances the acoustic field after control by applying a minimax strategy of minimization. The instantaneous value of cost function is

$$J_\infty[n, q] = \max_{1 \le l \le L} \left\{ |e_l[n]|^q \right\} = |e_b[n]|^q$$

(13)

Subscript b selects between the error signals, 1<l<L, the one with larger q order moment. The value of subscript b depends on the current value of the coefficients vector w. A change of this vector could imply a change of the value of b.

Therefore, upon using the stochastic gradient the update weights equation is given by

$$w[n+1] = w[n] - \alpha R_b^T[n] e_b[n] \quad (14)$$

Where the subscript b denotes the error signal with maximum squared value for a given value of the control vector. Equation (14) is quite similar to equation (8); however, summation over all the error sensors in equation (8) has disappeared in equation (14), and consequently a significant computational savings is obtained. The fact means that the Least Maximum Mean Square (LMMS) algorithm has to find out which of the error signals have the maximum estimated mean power. Mean power of the error signals is calculated by means of an IIR (Infinite Impulse Response) filtering of the error powers as follows,

$$\hat{P}_e[n+1] = \lambda \hat{P}_e[n] + (1-\lambda) e^2[n] \quad (15)$$

Where the parameter α is called the forgetting factor and it is typically chosen as 0.91<α<0.94. Even though the algorithm update equations are similar, MeFxLMS and LMMS do not minimize the same cost function. Therefore, different residual acoustic field after cancellation is expected.

4. Variable Step Size Least Mean Square Algorithm

Secondary path from the j^{th} canceling signal $y_j(n)$ to the k^{th} microphone $e_k(n)$ is represented by $S_{kj}(z)$. Modeling filters $\hat{S}_{kj}(z)$ is used to identify the secondary paths $S_{kj}(z)$. Internally generated random noise $v_1(n)$ is uncorrelated with $d_1(n)$, $d_2(n)$, $y_1(n)$, and $y_2(n)$. Inter channel decoupling delay unit $z^{-\Delta}$ is used to generate the uncorrelated excitation signal $v_2(n)$ [4]. The error signal at the k^{th} microphone is given as

$$e_k(n) = d_k(n) - [y'_{k1}(n) + y'_{k2}(n)] + [v'_{k1}(n) + v'_{k2}(n)] \quad (16)$$

Where,

$$v'_{kj}(n) = s_{kj}(n) * v_j(n) \quad (17)$$

$$f_k(n) = e_k(n) - [\hat{v}'_{k1}(n) + \hat{v}'_{k2}(n)] \quad (18)$$

$$= d_k(n) - [y'_{k1}(n) + y'_{k2}(n)] + [v'_{k1}(n) + v'_{k2}(n)] - [\hat{v}'_{k1}(n) + \hat{v}'_{k2}(n)] \quad (19)$$

Where $\hat{v}'_{kj}(n) = \hat{s}_{kj}(n) * v_k(n)$ is an estimate of $v'_{kj}(n)$. The impulse response of the secondary path $S_{kj}(z)$ from the j^{th} control filter to the k^{th} error microphone is $\hat{s}_{kj}(n)$.

Disturbance signal for the online Secondary Path Modeling (SPM) filters is $d_k(n)-[y'_{k1}(n)+y'_{k2}(n)]$. Initially, this disturbance is very large, but as the ANC system converges and the canceling signal approaches the primary noise, this disturbance reduces towards zero. Thus the error signal for the online SPM filter adaptation is corrupted by a disturbance that is decreasing in nature. Hence initially small step size for online SPM modeling is used [5]. When the ANC system starts converging step size is gradually increased.

The procedure to vary the step size is as follows.

The ratio $\rho_k(n)$ is defined as

$$\rho_k(n) = \frac{P_{fk}(n)}{P_{ek}(n)} \quad (20)$$

Where $P_{fk}(n)$ and $P_{ek}(n)$ are respectively, the power of error signals $f_k(n)$ and $e_k(n)$ associated with the k^{th} error microphone.

The powers are estimated by using low pass estimators of the form

$$P_\gamma(n) = \lambda P_\gamma(n-1) + (1-\lambda)\gamma^2(n) \quad (21)$$

Where $\gamma(n)$ is an arbitrary signal and λ is the forgetting factor $(0.9 < \lambda < 1)$.

Using (19), $P_{fk}(n)$ is expressed as

$$P_{fk}(n) = P_{d_k(n)-[y'_{k1}(n)+y'_{k2}(n)]} + P_{[v'_{k1}(n)-\hat{v}'_{k1}(n)]+[v'_{k2}(n)-\hat{v}'_{k2}(n)]} \quad (22)$$

Using (16), $P_{ek}(n)$ is expressed as

$$P_{ek}(n) = P_{d_k(n)-[y'_{k1}(n)+y'_{k2}(n)]} + P_{[v'_{k1}(n)+v'_{k2}(n)]} \quad (23)$$

At n=0, when the ANC system is started, the canceling signals $y'_{k1}(n)$ and $y'_{k2}(n)$ are zero and $\rho_k(n)$ at t = 0 is given as

$$\rho_k(0) = \frac{P_{d_k(n)} + P_{[v'_{k1}(n)-\hat{v}'_{k1}(n)]+[v'_{k2}(n)-\hat{v}'_{k2}(n)]}}{P_{d_k(n)} + P_{[v'_{k1}(n)+v'_{k2}(n)]}} \quad (24)$$

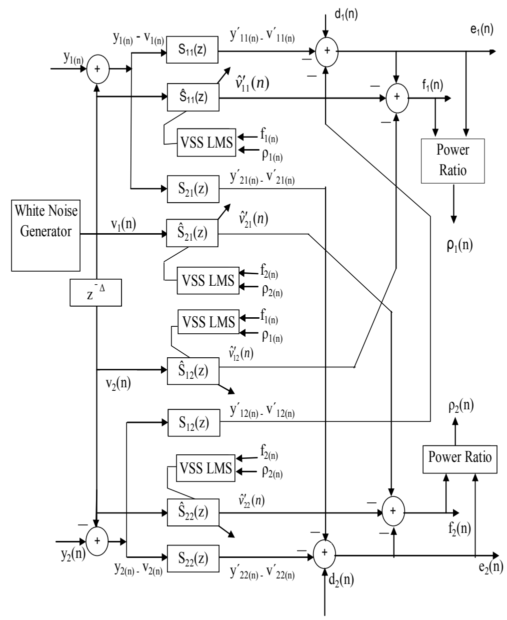

Fig 2 - Online SPM for 1X 2 X 2 ANC System

Since $v'_{kj}(n)$ is generated from a low-level random noise signal, hence $\rho_k(0) \approx 1$. When the ANC system converges, $[y'_{k1}(n) + y'_{k2}(n)] \rightarrow d_k(n)$, and $\hat{v}'_{jk}(n) \rightarrow v'_{kj}(n)$. Hence $P_{fk}(n) \rightarrow 0$. The numerator in (24) converges to 0 and the denominator is non-zero. When the ANC system converges, $\rho_k(n)$ approaches 0.

$\rho_k(n) \approx 1$, indicates that $d_k(n) - [y'_{k1}(n) + y'_{k2}(n)]$ is very large. $\rho_k(n) \approx 0$, indicates that $d_k(n) - [y'_{k1}(n) + y'_{k2}(n)]$ is very small, and the ANC system has converged.

Initially when $\rho_k(n) \approx 1$, small step size is used for the online SPM filters, and subsequently step size is increased for the online SPM filters in accordance with a decrease in $\rho_k(n)$.

Thus the step size for the online SPM filters $\hat{S}_{k1}(z)$ and $\hat{S}_{k2}(z)$ is calculated as

$$\mu_{sk}(n) = \rho_k(n)\mu_{min} + [1 - \rho_k(n)]\mu_{max} \quad (25)$$

Where μ_{min} and μ_{max} are experimentally determined values for lower and upper bounds of the step size. When the online SPM filters converge, $\hat{v}'_{jk}(n) \rightarrow v'_{kj}(n)$., and hence (16) is free of any modeling noise and therefore better suited for adaptation of the control filters. The control filters are updated using Multiple error Filtered x Least mean Square (MeFxLMS) algorithm as

$$w_j(n+1) = w_j(n) + \mu_w \sum_{k=1}^{K} \hat{x}'_{jk}(n) f_k(n) \qquad (26)$$

5. Simulation Results

Simulation waveform for LMMS error curve is shown in figure 3. Simulation waveform for LMMS system output curve is as shown in figure 4.

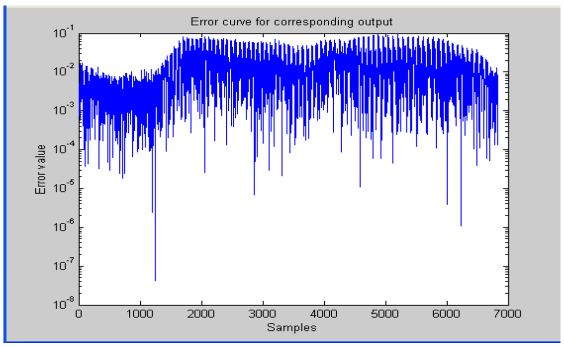

Fig 3 - Simulation Result for Error Curve

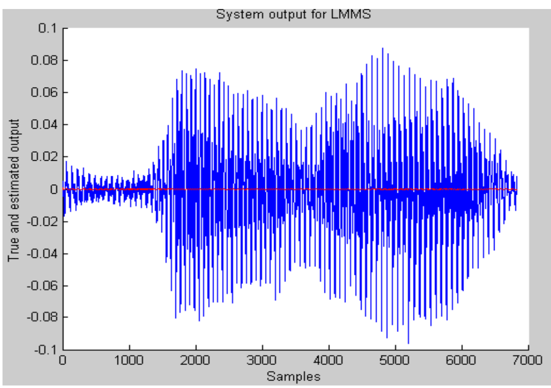

Fig 4 - Simulation Result for LMMS System Output

6. Conclusion

In this paper LMMS algorithm is used to reduce the computational load compared to the MeFxLMS algorithm. Simulation results are shown only for LMMS algorithm. If the number of error sensor increases, the computational complexity of the LMMS is same as that of MeFxLMS. LMMS algorithm provides a more uniform residual field compared with the MeFxLMS.

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