Fast Adaptive Active Noise Control Based on Modified Model-Agnostic Meta-Learning Algorithm

Article *in* Signal Processing Letters, IEEE · March 2021

DOI: 10.1109/LSP.2021.3064756

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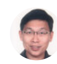

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***Abstract*—With the advent of efficient low-cost processors and electroacoustic components, there is renewed interest in the practical implementation of active noise control (ANC). However, the slow convergence of conventional adaptive algorithms deployed in ANC restricts its handling of typical amplitude-varying noise. Hence, we proposed a modified model-agnostic, meta-learning (MAML) strategy to obtain an initial control filter, which accelerates an adaptive algorithm's convergence when dealing with different types of amplitude-varying low-frequency noise. Numerical simulations with measured paths and real noise sources demonstrate its convergence acceleration efficacy in practical scenarios.**

***Index Terms*—Active noise control, control filter initialization, fast adaptation, FxLMS , model-agnostic meta-learning.**

I. Introduction

ACTIVE noise control (ANC) utilizes a secondary source to generate anti-noise waves to cancel acoustic noise and is an effective solution to mitigate environmental noise [1]–[8]. With advancements in adaptive filter theory [9], adaptive algorithms are widely adopted in ANC applications [10], such as in headphones [11]–[14], air ducts [15], and windows [16]–[19]. Among these algorithms, the filtered-x least mean square (FxLMS) algorithm [20], [21] plays a primary role in the practical implementation of ANC due to its computational efficiency and performance. However, its high sensitivity towards the eigenvalue spread of the input signal's auto-correlation matrix will result in convergence degradation with increased variance in input signal amplitude over time.

Hence, many modified algorithms have been proposed to improve the convergence speed during adaptation [22]–[24]. Among these modified algorithms, the normalized FxLMS (NFxLMS) algorithm makes the convergence speed independent of input power by normalizing the filtered reference signal [25]. However, its linear convergence behavior still weakens its performance in coping with amplitude variation. The subband FxLMS algorithm divides the input signal into different frequency bands, which reduces the influence of the auto-correlation matrix's condition number on the convergence behavior [26]–[29]. By recursively obtaining the inverse auto-correlation matrix, recursive least squares (RLS) filtering [9] can achieve fast convergence to deal with real noise. In statistics and control theory, the Kalman filter [30]–[33] utilizes measurements observed over time and keeps track of the estimated state of the system. It has a good convergence performance in attenuating non-stationary noise at the risk of occasional instability. Nevertheless, these algorithms incur a high computational load that undermines their implementation in real-time ANC systems.

A more efficient solution is to find suitable initial values for the control filter, thus leading the adaptive algorithm to quickly reach its optimal solution without increasing the computational complexity. One popular normalized initialization technique was proposed by Xavier [34], which samples the initial coefficients from a uniform distribution. However, this method was designed for deep neural networks and does not depend on the input signal's information. Another method is sample matrix inversion (SMI), which directly derives the optimal control filter from the first block of the reference signal and disturbance and sets this optimal solution as the initial control filter [35]. Although SMI can accelerate the adaptive algorithm's convergence, it still encounters high computational complexity in matrix inversion and needs to be recomputed when applied to different noises. Some other initialization strategies show effectiveness but largely increase complexity [36]–[38].

Therefore, this letter proposes a modified model-agnostic meta-learning (MAML)[1] algorithm [39]–[41] to get the best initial control filter from a noise sample set. The algorithm eliminates the problem of slow initial convergence due to the initial zeroed input vector passing through the tap delay line of the finite impulse response filter and significantly accelerates the convergence of the FxLMS algorithm. The proposed modified MAML method can achieve a satisfactory initial control for the ANC system to deal with different primary noise sources. Additionally, this technique can also be used to derive a suitable initial control filter for different ANC system configurations (such as different sensor and actuator positions).

II. Problem Statement

This letter considers a feedforward ANC system using a finite-impulse adaptive filter, as shown in Fig. 1, whose reference sensor is placed close to the primary noise source for simplicity. However, the analysis is also applicable to the case where the reference sensor is placed further from the primary noise source. The reference signal $x(n)$ propagates through the primary path $p(n)$ to form the disturbance $d(n)$, while the control filter $w(n)$ processes the reference signal to generate the control signal

Manuscript received January 31, 2021; revised March 1, 2021; accepted March 3, 2021. Date of publication March 11, 2021; date of current version April 1, 2021. The associate editor coordinating the review of this manuscript and approving it for publication was Prof. Z. Jane Wang. *(Corresponding author: Dongyuan Shi.)*

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Digital Object Identifier 10.1109/LSP.2021.3064756

[1]The code of the proposed MAML algorithm has been shared on https://github.com/ShiDongyuan/Meta.git

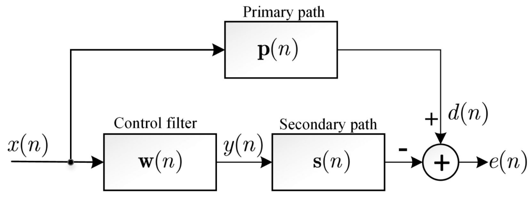

Fig. 1. Block diagram of a feedforward active noise control system [42].

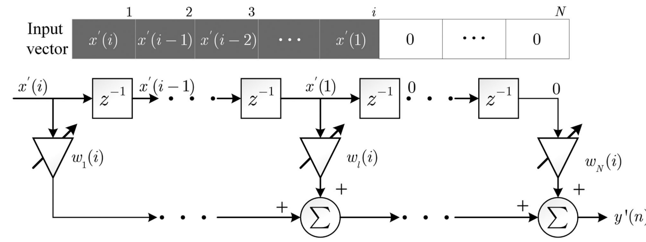

Fig. 2. Block diagram of the equivalent FxLMS algorithm at the end of the first i iterations.

$y(n)$, which goes through the secondary path $s(n)$ to cancel this disturbance at the error sensor. The error signal is expressed as

$$e(n) = d(n) - \left[\mathbf{w}^{\mathrm{T}}(n)\mathbf{x}(n)\right] * s(n) \tag{1}$$

where $*$ denotes linear convolution. The control filter, with N taps, and the reference vector are given by

$$\begin{aligned} \mathbf{w}(n) &= \left[w_1(n) \quad \cdots \quad w_i(n) \quad \cdots \quad w_N(n)\right]^{\mathrm{T}}, \\ \mathbf{x}(n) &= \left[x(n) \quad \cdots \quad x(n-N+1)\right]^{\mathrm{T}}. \end{aligned} \tag{2}$$

To minimize the mean square of terms in (1), we can utilize the filtered-x least mean square algorithm (FxLMS) to update the new control filter as

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu e(n)\mathbf{x}'(n), \tag{3}$$

where μ represents the step size, and the filtered reference vector is obtained from $\mathbf{x}'(n) = \mathbf{x}(n) * s(n)$. The step size bound can be derived as [43]

$$0 < \mu < \frac{2}{LP_{x'}}. \tag{4}$$

L and $P_{x'}$ denote the length of the secondary path and the power of the filtered reference signal, respectively. Therefore, to deal with real noise whose amplitude changes with time, we usually use a small step size to guarantee the FxLMS algorithm's stability at the expense of the convergence speed. Especially when the noise is varying quickly, its slow convergence always influences the user's perception of the noise reduction.

III. Modified Model-Agnostic Meta-Learning Method

Model-Agnostic Meta-learning (MAML) is an elegant yet game-changing solution in meta-learning (or learning to learn). This section introduces a modified MAML method to find the control filter's initial weights, which can accelerate the convergence of the FxLMS algorithm when dealing with quickly-varying noise amplitudes.

Since the aim of ANC is to mitigate the disturbance at the error sensor, its cost function can be defined as the square of the error signal at iteration n as

$$J(n) = e^2(n) = \left\{d(n) - \left[\mathbf{w}^{\mathrm{T}}(n)\mathbf{x}(n)\right] * s(n)\right\}^2. \tag{5}$$

Under the assumption that the control filter is slowly varying during the weight update [43], (5) can be rewritten as

$$J(n) = e^2(n) = \left[d(n) - \mathbf{w}^{\mathrm{T}}(n)\mathbf{x}'(n)\right]^2, \tag{6}$$

where the filtered reference vector is $\mathbf{x}'(n) = \mathbf{x}(n) * s(n)$.

Conventionally, in a practical adaptive system, the initial value of the input vector $\mathbf{x}'(n)$ is usually set to $\mathbf{0}$. For instance, Fig. 2 illustrates the first i iterations of the equivalent FxLMS algorithm, which has $N-i$ zeros in its input vector. It is obvious that these initialized zeros have no contribution to minimizing the cost function.

We assume that there always exists the best initial value $\mathbf{\Phi}$ of the control filter, which can minimize the sum of squared errors in the first N iterations. To mitigate the influence of the zero initial value of the filtered reference, we introduce a forgetting factor $\lambda \in (0, 1]$, and the loss function can be defined as

$$\mathbb{L}(k) = \sum_{i=0}^{N-1} \lambda^i J(k-i). \tag{7}$$

It is worth noting that $J(k)$ is obtained from

$$J(k) = e^2(k) = \left[d(k) - \mathbf{w}^{\mathrm{T}}(n)\mathbf{x}'(k)\right]^2, \tag{8}$$

where $d(k)$ and $\mathbf{x}'(k)$ are randomly sampled from the set of pre-measured disturbance tracks $\{d_1(n), d_2(n), \cdots\}$ and set of filter reference signals $\{\mathbf{x}'_1(n), \mathbf{x}'_2(n), \cdots\}$ under different configuration settings of ANC. A database of these pre-measured samples is obtained from different ANC system configurations and different noise sources. While the filtered vector $\mathbf{x}'(k-i)$, as shown in Fig. 2, is obtained from

$$\mathbf{x}'(k-i) = \left[x'(k-i) \quad x'(k-i-1) \quad \cdots \quad \mathbf{0}_{1\times i}\right]^{\mathrm{T}}, \tag{9}$$

where $\mathbf{0}_{1\times i}$ represents the zero vector with a dimension of i.

Since the best initial value should minimize the cost function (7) at an arbitrary iteration k, we can use the gradient descent method to obtain the recursive formula of the initial value as

$$\mathbf{\Phi}(n+1) = \mathbf{\Phi}(n) - \frac{1}{2}\varepsilon\frac{\partial \mathbb{L}(k)}{\partial \mathbf{\Phi}(n)}, \tag{10}$$

where $\varepsilon \in (0, 1)$ represents the learning rate, and the initial vector is given by

$$\mathbf{\Phi}(n) = \left[\Phi_1(n) \quad \cdots \quad \Phi_i(n) \quad \cdots \quad \Phi_N(n)\right]^{\mathrm{T}}. \tag{11}$$

Furthermore, if it is assumed that the best initial value uses one step to reach the optimal solution based on the FxLMS algorithm [44], we obtain

$$\mathbf{w}(n) = \mathbf{\Phi}(n) - \frac{1}{2}\mu\frac{\partial J^{\dagger}(k)}{\partial \mathbf{\Phi}(n)}, \tag{12}$$

where the cost function $J^{\dagger}(k)$ of the initial control filter can be expressed as

$$J^{\dagger}(k) = {e^{\dagger}}^2(k) = \left[d(k) - \mathbf{\Phi}^{\mathrm{T}}(n)\mathbf{x}'(k)\right]^2. \tag{13}$$

TABLE I
PSEUDOCODE OF THE PROPOSED MODIFIED MODEL-AGNOSTIC META-LEARNING

Algorithm: Modified Model-Agnostic Meta-Learning

1: Randomly initialize $\mathbf{\Phi}(0)$, and set $n=0$
2: **for** n to M **do**
3: Randomly sample the filtered reference vector $\mathbf{x}'(k)$ and the disturbance $\mathbf{d}(k)$ from the recorded sample set: $\{(\mathbf{x}'_1(n), \mathbf{d}_1(n)), (\mathbf{x}'_2(n), \mathbf{d}_2(n)), \cdots\}$
4: Get the error signal based on the initial control filter: $e^{\dagger}(k) = d(k) - \mathbf{\Phi}^{\mathrm{T}}(n)\mathbf{x}'(k)$
5: Obtain the control filter: $\mathbf{w}(n) = \mathbf{\Phi}(n) + \mu e^{\dagger}(k)\mathbf{x}'(k)$
6: Get the error signal based on the new control filter:
  for i = 0 to N-1 **do**
    $e(k-i) = d(k-i) - \mathbf{w}^{\mathrm{T}}(n)\mathbf{x}'(k-i)$
  end for
7: Update the initial value : $\mathbf{\Phi}(n+1) = \mathbf{\Phi}(n) + \varepsilon\sum_{i=0}^{N-1}\lambda^i e(k-i)\mathbf{x}'(k-i)$
8: **end for**

Substituting (13) into (12) yields

$$\mathbf{w}(n) = \mathbf{\Phi}(n) + \mu e^{\dagger}(k)\mathbf{x}'(k). \tag{14}$$

According to the chain rule [45], the gradient of the cost function (7) in term of $\mathbf{\Phi}(n)$ is derived as [46]

$$\frac{\partial \mathbb{L}(k)}{\partial \mathbf{\Phi}(n)} = \frac{\partial \mathbf{w}(n)}{\partial \mathbf{\Phi}(n)}\frac{\partial \mathbb{L}(k)}{\partial \mathbf{w}(n)} = -2 \begin{bmatrix} 1-\frac{\mu\partial^2 J^{\dagger}(k)}{2\partial\phi_1^2(n)} & \cdots & -\frac{\mu\partial^2 J^{\dagger}(k)}{2\partial\phi_N(n)\partial\phi_1(n)} \\ \vdots & 1-\frac{\mu\partial^2 J^{\dagger}(k)}{2\partial\phi_i^2(n)} & \vdots \\ -\frac{\mu\partial^2 J^{\dagger}(k)}{2\partial\phi_1(n)\partial\phi_N(n)} & \cdots & 1-\frac{\mu\partial^2 J^{\dagger}(k)}{2\partial\phi_N^2(n)} \end{bmatrix} \sum_{i=0}^{N-1}\lambda^i e(k-i)\mathbf{x}'(k-i) \tag{15}$$

where

$$\begin{cases} \frac{\partial^2 J^{\dagger}(k)}{\partial\phi_i^2(n)} & = x'^2_i(k), \\ \frac{\partial^2 J^{\dagger}(k)}{\partial\phi_i(n)\partial\phi_j(n)} & = x'_i(k)x'_j(k). \end{cases} \tag{16}$$

For simplicity [39], we can ignore the second derivative of (16), and (15) can be rewritten as

$$\frac{\partial \mathbb{L}(k)}{\partial \mathbf{\Phi}(n)} = -2\sum_{i=0}^{N-1}\lambda^i e(k-i)\mathbf{x}'(k-i). \tag{17}$$

Substituting (17) into (10) yields the recursive formula of $\mathbf{\Phi}$ as

$$\mathbf{\Phi}(n+1) = \mathbf{\Phi}(n) + \varepsilon\sum_{i=0}^{N-1}\lambda^i e(k-i)\mathbf{x}'(k-i), \tag{18}$$

where the error signal based on the new control filter is obtained form

$$e(k-i) = d(k-i) - \mathbf{w}^{\mathrm{T}}(n)\mathbf{x}'(k-i). \tag{19}$$

Therefore, through (14) and (18), we can recursively derive the best initial value of the control filter from the sample sets composed of the reference signals and disturbances. The detailed procedure of the proposed method is shown in Table I.

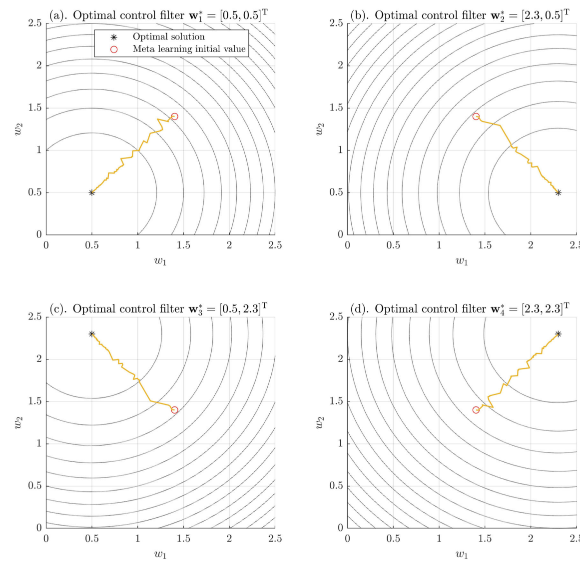

Fig. 3. The convergence paths of the FxLMS algorithm with the same Meta learning initial value for different primary paths. ($*$: optimal control filter; o: initial value.)

IV. SIMULATION RESULT

This section exhibits the comparative simulation results of the proposed MAML and other algorithms for different experimental conditions. The noise data in all simulations are divided into (70%) training set and (30%) test set.

A. Initial Control Filters for Different ANC Systems

In the first simulation, we constructed four different primary path as $\mathbf{p}_1 = [0.2125, 0.2125]^{\mathrm{T}}$, $\mathbf{p}_2 = [1.955, 0.2125]^{\mathrm{T}}$, $\mathbf{p}_3 = [0.2125, 1.955]^{\mathrm{T}}$, and $\mathbf{p}_4 = [1.955, 1.955]^{\mathrm{T}}$. The reference signal $x(n)$ is a Gaussian white noise $N(0,1)$. The secondary path and the sampling rate are set as $\mathbf{s} = [0.85, 0.0001]^{\mathrm{T}}$ and 16 kHz, respectively. The reference signals and disturbances database is obtained from the primary noise modeled by the secondary path and different primary paths.

According to the proposed modified meta-learning method, we can obtain the initial control filter for these four primary paths as $\hat{\mathbf{w}}_0 = [1.40, 1.41]^{\mathrm{T}}$ from the training set, where the forgetting factor is set to 0.95. Subsequently, this value is used to initiate the control filter of the FxLMS algorithm. The convergence paths of the FxLMS algorithm for different primary paths in the test set shown in Fig. 3. In this figure, the control filters from the same initial value finally arrives at their respective optimal solutions as $\mathbf{w}_1^* = [0.25, 0.25]^{\mathrm{T}}$, $\mathbf{w}_2^* = [2.3, 0.25]^{\mathrm{T}}$, $\mathbf{w}_3^* = [0.25, 2.3]^{\mathrm{T}}$, and $\mathbf{w}_4^* = [0.23, 2.3]^{\mathrm{T}}$, which can be obtained from [43] as

$$\mathbf{w}^* = \mathbf{R}_{x'x'}^{-1}\mathbf{P}_{dx'}, \tag{20}$$

where the auto-correlation matrix $\mathbf{R}_{x'x'}^{-1} = \mathbb{E}[\mathbf{x}'(n)\mathbf{x}'^{\mathrm{T}}(n)]$, and the cross-correlation vector $\mathbf{P}_{dx'} = \mathbb{E}[d(n)\mathbf{x}'(n)]$.

It is worth noting that the initial control filter $\hat{\mathbf{w}}_0$ is close to the geometric center of $\mathbf{w}_1^*$, $\mathbf{w}_2^*$, $\mathbf{w}_3^*$, and $\mathbf{w}_4^*$, as shown in Fig. 3. Hence,

$$\hat{\mathbf{w}}_0 \approx \arg\min_{\mathbf{w}_0}\sum_{i=1}^{4}\|\mathbf{w}_0 - \mathbf{w}_i^*\|^2, \tag{21}$$

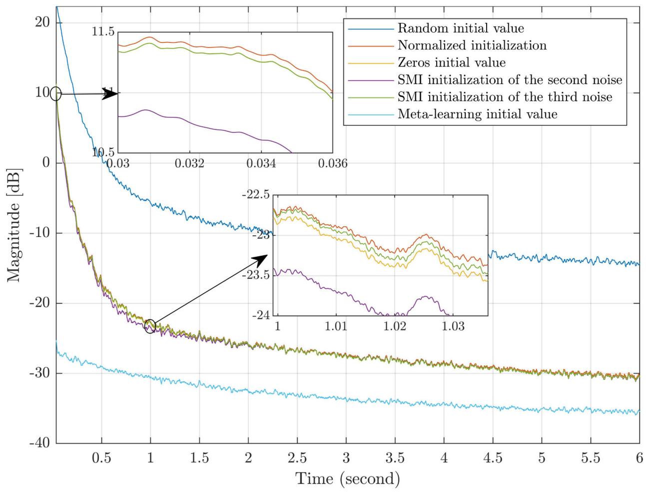

Fig. 4. The mean squared error of FxLMS with different initial control filters. The curves of the zeros initialization and SMI initialization of the third noise overlap at the beginning.

which confirms that the proposed method can accelerate the FxLMS algorithm's convergence for different primary paths by obtaining the nearest initial control filter.

B. The Initial Control Filter for Different Primary Noises

In this simulation, the primary path and secondary path are measured from an air duct. The control filter and the secondary path estimate have 512 and 256 taps. The step size of the FxLMS algorithm and the sampling rate are chosen as 0.0003 and 16 kHz. Furthermore, three different broadband noises are utilized as primary noise. Their frequency bands are from 800 Hz to 2 kHz, from 1.6 kHz to 4.4 kHz, and from 4 kHz to 6 kHz. They form the sample data set.

To compare with the meta-learning method whose forgetting factor is 0.95, we tested four different initialization strategies: 1). zeros initial value; 2) random initial value; 3) initial value obtained by the Sample Matrix Inversion (SMI) method; and 4) Normalized initialization. In these methods, the SMI algorithm obtains the initial control filter through [35]

$$\mathbf{w}(0) = \mathbf{R}_{x'x'}^{-1}(0)\mathbf{P}_{dx'}(0), \tag{22}$$

where $\mathbf{R}_{x'x'}(0)$ and $\mathbf{P}_{dx'}(0)$ represent the auto-correlation matrix and cross-correlation vector at the first block of filtered reference signal, respectively. Normalized initialization [34] obtains the initial control filter by sampling from a uniform distribution

$$w \sim \text{Uniform}\left[-\frac{\sqrt{6}}{n_j + n_{j+1}}, \frac{\sqrt{6}}{n_j + n_{j+1}}\right], \tag{23}$$

where n_j and n_{j+1} denote the number of weights of the input layer and output layer in the control filter. Figure 4 exhibits the mean squared error of the FxLMS algorithms with these initial control filters in canceling the first broadband noise in the test set. We can observe from Fig. 4 that the initial control filter calculated from the meta-learning has the best convergence performance over the other methods tested.

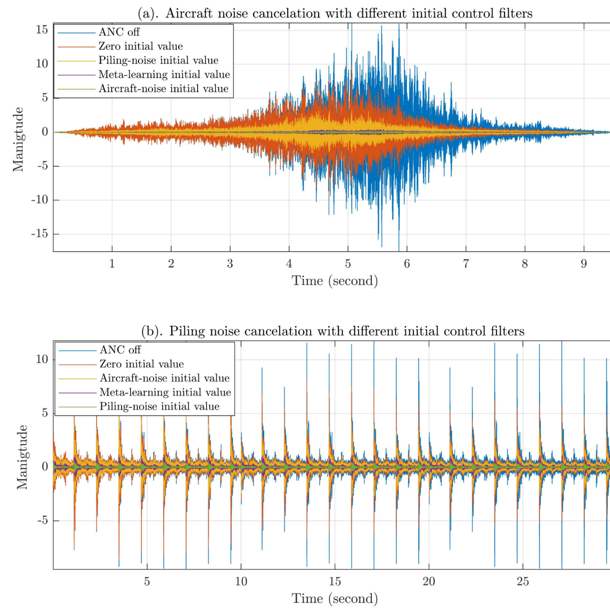

Fig. 5. The FxLMS algorithm with different initial control filters dealing with (a the aircraft noise and (b the piling noise.

C. Real Amplitude-Varying Noise Cancellation

This simulation adapted the FxLMS algorithm with different initial values to cancel recorded aircraft and piling noise in the measured paths. The recorded aircraft and piling noises are divided into the training set (70%) and test set (30%). The other simulation conditions are the same as Simulation B.

For the SMI method, two separate optimal control filters are trained from the aircraft and piling noise in the training set, respectively. These trained controlled filters are used as the initial control filter to test on the unseen segment of the aircraft and piling noise. From Fig. 5, it is evident that these pre-trained control filters performed much better than the zero-initialized control filters. However, the SMI is formulated to train on the targeted noise source and requires different initial control filters for different noise sources. This is unlike the proposed MAML method that has the ability to train one control filter to cancel different noises of similar distribution with the training set.

V. Conclusion

The FxLMS algorithm is widely applied in ANC systems due to its low computational complexity and easy implementation. However, its slow convergence deteriorates its performance in dealing with amplitude-varying noise. Many modified algorithms have been developed to improve the convergence speed, but their heavy computational load usually impedes their application in real-time systems. Therefore, we proposed a modified model-agnostic meta-learning method, which can derive a satisfactory initial control filter from the primary noises and disturbances. This initial control filter can significantly accelerate the adaptation of the FxLMS algorithm in dealing with real noise. Even for different ANC systems, the proposed method obtains an initial value with the shortest distance on average to the optimal solutions. The simulation result demonstrated the convergence acceleration efficacy of the proposed FxLMS initialization with real noise.

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