Implementation of Model-Agnostic Meta-learning Algorithm for Adaptive Filter by Using MATLAB: most computational-efficiency method to accelerate the convergence of the adaptive active noise control

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Accelerating the convergence of the adaptive filter is a long-standing subject in the adaptive signal processing field. Despite some sophisticated methodologies designed to address this challenge, their computational complexity remains a significant obstacle, compromising their viability for implementation in real-world scenarios. Hence, this article implements a Model-Agnostic Meta-Learning (MAML) method, which can seek the best initialization for the adaptive filter to increase its convergence. This study employs this strategy to expedite the convergence of the adaptive active noise control (ANC) system in attenuating aircraft noise. The experimental results demonstrate that the new method achieves significantly better convergence than the standard approach without requiring more computations for the adaptive algorithm. Furthermore, this article offers in-depth guidance on implementing the modified MAML algorithm in Matlab, with potential use in other adaptive signal processing algorithms. The code is available on GitHub.

1 Introduction

Active Noise Control (ANC) is an advanced technique that reduces unwanted noise by using controlled anti-noise signals to cancel out the primary noise through destructive interference, applying the superposition principle in wave physics [1], [2]. ANC's effectiveness in reducing low-frequency noise and its small size have led to its widespread use in different fields, such as headphones [3]–[8], automotive industries, and window ventilation [9]–[17], to address noise issues.

As adaptive filter theory has advanced, numerous adaptive algorithms have been developed for use in active noise cancellation. The derivative algorithms enhance the ANC system's capability to adjust to changes in noise and acoustic surroundings [18]–[37]. Among these algorithms, the filtered reference least mean square (FxLMS) algorithm is of significant importance in the implementation of the real-time ANC system owing to its exceptional computational efficiency. Practical implementations of its derivative algorithms are also prevalent in the resolution of various engineering challenges.

However, these active control algorithms based on the least mean square (LMS) [38], [39] class still encounter an inherent issue: their sluggish convergence impacts the adaptive ANC system's ability to effectively reduce dynamic noise. This slow convergence issue not only influences the ANC system's response time but also impairs the customers' perception. Variable step-size approaches have been developed to enhance convergence speed by dynamically modifying the updating rate of the adaptive algorithm. However, this strategy lacks generalization for different applications. Although some other modified algorithms improve the response speed of the ANC system to rapidly varying noise [40]–[49], they are still slow to cope with some dynamic and nonstationary noises. The Recursive Least Squares filter (RLS) [50] and Kalman filter [51] are recognized for their excellent

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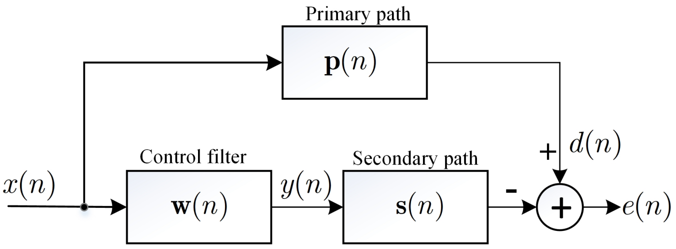

Figure 1: Block diagram of a feedforward active noise control system [58].

capability in tracking dynamic and nonstationary noise as compared to LMS-based approaches in this scenario. However, their high computational demands make them challenging to implement on a real-time processor [52], [53]. Hence, finding a practical approach to accelerate the convergence of the adaptive algorithm becomes more meaningful.

Meanwhile, deep-learning approaches have prevailed across industries since their excellent performance in object detection and classification, natural language processing and generation, etc. With their advanced development, these approaches were also devised for audio and speech applications, such as sound classification, event detection, and localization [54]–[57]. During these methods, meta-learning algorithms have recently been used to determine deep neural work's learning rate, structures, and initialization. Inspired by these algorithms, the previous works proposed a modified Model-Agnostic Meta-learning method dedicated to the adaptive filters [58], [59]. The modified MAML algorithm brings the forgetting factor to alleviate the zero-input issue in practical adaptive filter applications. This article offers a comprehensive overview of how to implement the modified MAML algorithm in MATLAB. This approach is used to help a standard FxLMS algorithm achieve adequate convergence behavior in reducing raw aircraft noise. The numerical simulation results demonstrate its effectiveness.

The following sections are organized as follows: Section 2 and 3 briefly introduce the theoretical foundation of the adaptive active noise control approach and the MAML algorithm. Section 4 provides a detailed explanation of the MAML code and exhibits the experimental results. Finally, Section 5 concludes this article.

2 Adaptive active noise control approach

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 $y(n)$, 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

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

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

$$\mathbf{x}'(n) = \mathbf{x}(n) * s(n). \tag{4}$$

3 Modified Model-Agnostic Meta-learning method

This section presents an enhanced Model-Agnostic Meta-learning (MAML) approach for determining the initial weights of the control filter. This method improves the convergence speed of the FxLMS algorithm for handling dynamic noise.

However, most adaptive algorithms will receive null inputs during the initial iteration, inevitably impacting the algorithm's convergence performance. Hence, the conventional MAML approach is not applicable for directly initializing the adaptive filter. The modified MAML technique incorporates a forgetting factor to address the zero-input problem of the adaptive filter, thereby resolving the issue at hand. Its loss function is defined as

$$\mathbb{L}(k) = \sum_{i=0}^{N-1} \lambda^i J(k-i), \tag{5}$$

where λ and N denote the forgetting factor $\lambda \in (0, 1]$ and the length of the control filter. It is important to mention that k denotes the inner index of the MAML algorithm ($k = 0, 1, \cdots, N-1$). In the equation, the cost function of ANC is expressed as

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

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. n stands for the time index. The filtered vector $\mathbf{x}'(k-i)$ is obtained from

$$\mathbf{x}'(k-i) = \begin{bmatrix} x'(k-i) & x'(k-i-1) & \cdots & \mathbf{0}_{1\times i}\end{bmatrix}^{\mathrm{T}}. \tag{7}$$

According to the gradient descent method, the new initial value of the control filter is derived as

$$\mathbf{\Phi}(n+1) = \mathbf{\Phi}(n) - \frac{1}{2}\varepsilon\frac{\partial \mathbb{L}(k)}{\partial \mathbf{\Phi}(n)}, \tag{8}$$

in which ε represents the learning rate. Here, we assumed that the best initial value **uses one step to reach the optimal solution**:

$$\mathbf{w}(n) = \mathbf{\Phi}(n) + \mu e^{\dagger}(k)\mathbf{x}'(k). \tag{9}$$

The error signal $e^{\dagger}(k)$ is given by

$$e^{\dagger}(k) = d(k) - \mathbf{\Phi}^{\mathrm{T}}(n)\mathbf{x}'(k). \tag{10}$$

By ignoring the second derivative, the gradient in (8) can be derived as

$$\frac{\partial \mathbb{L}(k)}{\partial \mathbf{\Phi}(n)} = -2\sum_{i=0}^{N-1} \lambda^i e(k-i)\mathbf{x}'(k-i). \tag{11}$$

Therefore, the recursive formula of $\mathbf{\Phi}$ can be derived as

$$\mathbf{\Phi}(n+1)=\mathbf{\Phi}(n)+\varepsilon\sum_{i=0}^{N-1}\lambda^{i}e(k-i)\mathbf{x}'(k-i), \tag{12}$$

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

$$e(k-i)=d(k-i)-\mathbf{w}^{\mathrm{T}}(n)\mathbf{x}'(k-i). \tag{13}$$

The recursive formula stated in equation (12) is commonly referred to as the modified MAML algorithm, whose pseudocode is shown in Table 1. **It is important to mention that n in the previous paragraph represents both the time index and the epoch index of the MAML algorithm. Each epoch consists of N iterations.**

The entire progress of the modified MAML algorithm is shown in Figure 2. This MAML algorithm contains the following steps:

Algorithm 3.1: Main steps of Modified MAML algorithm

- *Building the input vectors from the randomly sampled pair:* $\{\mathbf{x}'(n),\mathbf{d}(n)\}$. *Here,* $k=n$

$$\begin{cases}\mathbf{x}'(k-i) & =\begin{bmatrix}x'(n-i) & x'(n-i-1) & \cdots & \mathbf{0}_{1\times i}\end{bmatrix}^{\mathrm{T}}\\ d(k-i) & =d(n-i)\\ i & =0,1,\cdots,N-1\end{cases} \tag{A1}$$

- *Get the error signal based on the initial control:*

$$e^{\dagger}(k)=d(k)-\mathbf{\Phi}^{\mathrm{T}}(n)\mathbf{x}'(k) \tag{A2}$$

- *Obtain the control filter:*

$$\mathbf{w}(n)=\mathbf{\Phi}(n)+\mu e^{\dagger}(k)\mathbf{x}'(k) \tag{A3}$$

- *Get the error signal based on the new control filter:*

$$e(k-i)=d(k-i)-\mathbf{w}^{\mathrm{T}}(n)\mathbf{x}'(k-i) \tag{A4}$$

- *Update the initial value :*

$$\mathbf{\Phi}(n+1)=\mathbf{\Phi}(n)+\varepsilon\sum_{i=0}^{N-1}\lambda^{i}e(k-i)\mathbf{x}'(k-i) \tag{A5}$$

4 Code Explanation

The section provides a concise introduction to all the MATLAB codes used to validate the proposed modified MAML algorithm. The project contains three main programs.

- **MAML_Nstep_forget.m**: the code of the modified MAML algorithm.
- **FxLMS.m**: the code of the conventional single-channel FxLMS algorithm.

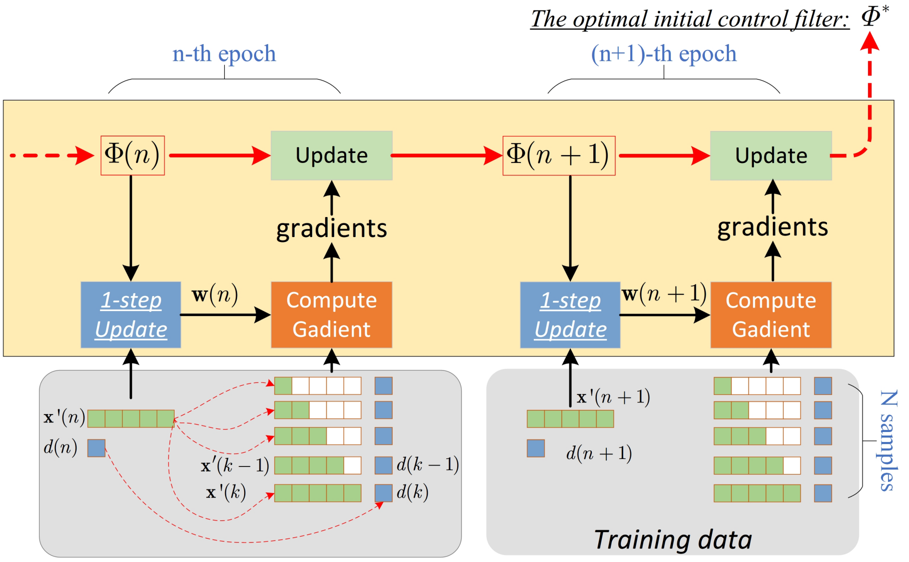

Figure 2: Block diagram of the modified MAML algorithm progress.

- **Main_tst_function.m**: the main program that validates the performance of the modified MAML algorithm.

Additionally, the primary and secondary paths, which have been measured, are used for the main numerical simulation. These paths can be found in the **Path** folder. The main source of noise in the testing program is the sound produced by aircraft, which is stored in the file named **707_Sound_for_Simulation.mat**.

4.1 Modified MAML algorithm

The program of **MAML_Nstep_forget.m** implements the proposed modified MAML algorithm, as outlined in Table 1. Table 1 shows the pseudocode of the proposed approach. It is worth noting that the random sampling method is completed during the preparation of the dataset. However, the code provided fully implements steps 4 to 7, clearly described in the code comments. The definitions of the variables in the program are illustrated in Table 2.

```
%% Modified MAML algorithm
classdef MAML_Nstep_forget
    properties
        Phi % The initial control filter
    end
    methods
        function obj = MAML_Nstep_forget(len_c)
            % len_c : the lenght of control filter
            obj.Phi = zeros(len_c,1);
        end
        function [obj,Er] = MAML_initial(obj,Fx,Di,mu,lamda,epslon)
            % Fx : the filtered reference vector
            % Di : the disturbance vector
            % mu : the step size
```

Table 1: 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
```

Parameters	Definition	Parameters	Definition
Phi	Initial control filter	len_c	Length of control filter
Fx	Filtered reference vector	Di	Disturbance vector
Grad	Gradient accumulator	Er	Error signal
mu	Stepsize of FxLMS	lamda	Forgetting factor
epslon	Learning rate of MAML		
Li	Length of control filter	e	error signal

Table 2: The definitions of the variables used in **MAML_Nstep_forget.m**.

```
        % lamda : the forget factor
        Fx   = flipud(Fx);
        Dis  = flipud(Di);
        Grad = 0; % Temporal gradient accumulator
        Er   = 0; % Training error signal
        Li   = length(obj.Phi) ; % The length of the control filter in the FxLMS algorithm.
                    %<-4-> Get the error signal based on the initial control filter.
                    e    = Dis(1)  - obj.Phi'*Fx;
                    %<-5-> Obtain the control filter
        Wo   = obj.Phi + mu*e*Fx    ; % One-step updation for the assumed optimal control filter.
        for jj = 1:Li
            Fd   = [Fx(jj:end);zeros(jj-1,1)];
                            %<-6-> Get the error signal based on the new control filter.
            e    = Dis(jj) - Wo'*Fd          ;
                            % Get the gradints based on the assumed optimal control filter
            Grad = Grad    + epslon*(mu/Li)*e*Fd*(lamda^(jj-1));
```

```
                if jj == 1
                    Er =  e ;
                end
            end
                        %%<-7-> Upate the initial value
            obj.Phi = obj.Phi + Grad ;
        end
    end

end
```

4.2 Single-channel FxLMS algorithm

The program of **FxLMS.m** implements the conventional FxLMS algorithm. This algorithm can use the initial control filter to realize adaptive active noise control. The definitions of the variables in the program are illustrated in Table 3.

Parameters	Definition	Parameters	Definition
Len_Filter	Length of control filter	Wc_initial	Initial control filter
Dis	Disturbance vector	Rf	Filtered reference vector
muW	Stepsize of FxLMS	Er	Error signal

Table 3: The definitions of the variables used in **FxLMS.m**.

```
%% single-channel FxLMS algorithm
function Er = FxLMS(Len_Filter, Wc_initial, Dis, Rf, muw)
% Len_Filter : the length of the control filter
% Wc_initial : the initial control filter
% Dis        : the disturbance
% Rf         : the filtered reference vector
% muw        : the step size
N    = Len_Filter ;
Wc   = Wc_initial ;
XD   = zeros(N,1) ;
Er   = zeros(length(Rf),1);
    for tt = 1:length(Rf)
        XD    = [Rf(tt);XD(1:end-1)];
        Rf_i = XD'         ;
        Rf_i = Rf_i'       ;
        y_t  = Wc'*Rf_i     ;
        e    = Dis(tt)-y_t ;
        Er(tt) = e           ;
        Wc     = Wc + muw*e*Rf_i;
    end
end
```

4.3 Aircraft noise cancellation on the measured path

The following code snippet offers a concise overview of **Main_tst_function.m**, which serves as the main function for evaluating the effectiveness of the proposed MAML method. For this numerical simulation, three distinct broadband sounds are utilized to train the MAML algorithm and obtain a single initial control filter. Subsequently, the aforementioned initial control is employed within an FxLMS algorithm to effectively eliminate actual aircraft noise. In comparison to zero initialization, the MAML technique can significantly enhance the convergence speed of the conventional FxLMS approach. The entire program comprises the following primary components:

- Cleaning the memory and workspace
- Configure the system simulation condition
- Build the broadband noise for training set
- Radomly sampling the noise tracks to build dataset for the MAML algorithm
- Using Modified MAML algorithm to get the best initial control filter

4.3.1 Cleaning the memory and workspace

This segment of code is utilized to clean the memory and workspace of the MATLAB software.

```
close all ;
clear     ;
clc       ;
```

4.3.2 Configure the system simulation condition

This code snippet provides the system configuration for the numerical simulation. In this program, f_s and T denote the system sampling rate and the simulation duration, respectively. Len_N represents the length of the control filter. The definitions of the variables in the program are illustrated in Table 4.

Parameters	Definition	Parameters	Definition
fs	Sampling rate	T	Simulation duration
Len_N	Length of the control filter		

Table 4: The definitions of the variables used in **Part 1**.

```
%% Configure the system simulation condition
fs   =   16000    ; % The system sampling rate.
T    =   3        ; % The duration of the simulation.
t    =   0:1/fs:T ;
N    =   length(t); % The number of the data.

Len_N = 512       ; % Seting the length of the control filter.
%<<===Progress bar===>>
f = waitbar(0,'Please␣wait...');
pause(.5)
```

Parameters	Definition	Parameters	Definition
Pri_path	Primary path	Track_num	Number of the noise tracks
Pri_n	n-th primary noise	Dis_n	n-th disturbance
Rf_n	n-th filtered reference vector		

Table 5: The definitions of the variables used in **Part 2**.

4.3.3 Build the broadband noise for training set

This section of the program produces filtered references, disturbances, and primary noises. These are then used in the modified MAML algorithm to obtain the initial control filter. The main sounds consist of three distinct broadband noises, as depicted in Figure 3. The definitions of the variables in the program are illustrated in Table 5.

```
%% Build the broad band noise for training set
%<<===Progress bar===>>
waitbar(0.25,f,'Build␣the␣broad␣band␣noise␣for␣training␣set');
pause(1)
%<<===Progress bar===>>
% Loading path
load('path\P1.mat')    ;
load('path\S11.mat')   ;
Pri_path = conv(P1,S11);

Track_num = 3          ; % Seting the number of the track for the trainning noise.
if exist('Primary_noise.mat', 'file') == 2
    disp('Primary_noise␣exists␣in␣the␣current␣path.\n');
    % Loading the primary noise
    load('Primary_noise.mat');
    load('Disturbance.mat')  ;
    load('Reference.mat')    ;
else
Noise     = randn(N,1);
% filter
filter_1 = fir1(512,[0.05 0.25]);
filter_2 = fir1(512,[0.20 0.55]) ;
filter_3 = fir1(512,[0.5,0.75]) ;
% Primary noise
Pri_1 = filter(filter_1,1,Noise) ;
Pri_2 = filter(filter_2,1,Noise) ;
Pri_3 = filter(filter_3,1,Noise) ;
% Drawing fiture
data = [Pri_1,Pri_2,Pri_3];
figure ;
len_fft = length(Pri_1)   ;
len_hal = round(len_fft/2);
title('Frequency␣spectrum␣of␣primary␣noises')
for ii = 1:3
    freq = 20*log(abs(fft(data(:,ii))));
    subplot(3,1,ii);
    plot(0:(fs/len_fft):(len_hal-1)*(fs/len_fft), freq(1:len_hal));
    grid on   ;
    title("The "+num2str(ii)+"th primary noise")
```

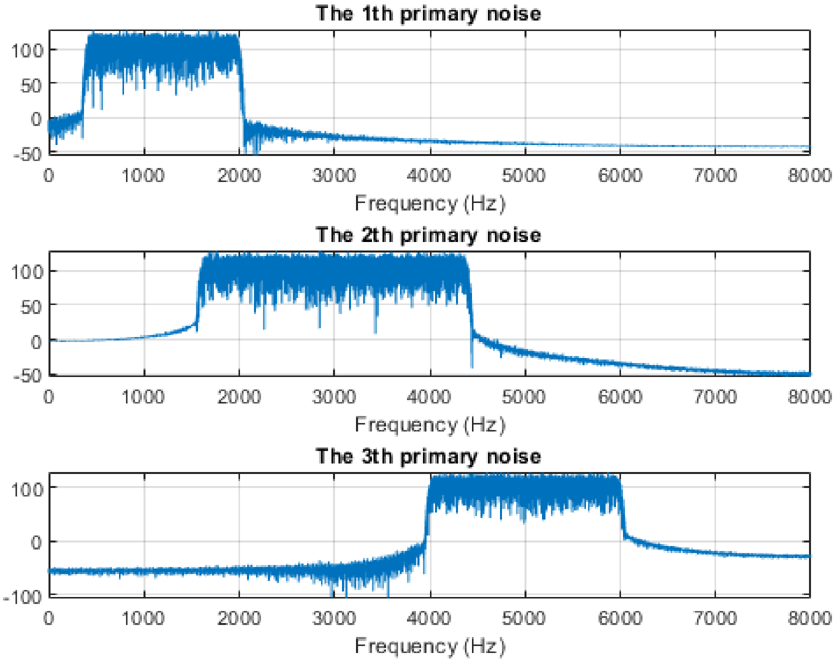

Figure 3: The frequency spectrum of the primary noises for the MAML algorithm.

```
    xlabel('Frequency␣(Hz)')
end
% Save primary noise into workspace
save('Primary_noise.mat','Pri_1','Pri_2','Pri_3');
% Generating Distrubance
Dis_1 = filter(Pri_path,1,Pri_1);
Dis_2 = filter(Pri_path,1,Pri_2);
Dis_3 = filter(Pri_path,1,Pri_3);
% Save distrubancec into workspace
save('Disturbance.mat','Dis_1','Dis_2','Dis_3');
% Genrating Filtered reference signal
Rf_1 = filter(S11,1,Pri_1);
Rf_2 = filter(S11,1,Pri_2);
Rf_3 = filter(S11,1,Pri_3);
% Save filter reference signal into workspace
save('Reference.mat','Rf_1','Rf_2','Rf_3');
end
```

4.3.4 Randomly sampling the noise tracks to build dataset for the MAML algorithm

This part of the program randomly samples the previously generated three types of noise tracks and their corresponding reference signals and disturbances to form the dataset. The length of the sampled vector equals that of the control filter, and these samples will be used in the proposed

MAML algorithm to get the best initial control filter. The definitions of the variables in the program are illustrated in Table 6.

Parameter	Definition	Parameter	Definition
N_epcho	Number of training epoch	Di_data	Disturbance matrix
Fx_data	Reference signal matrix	Trac	Randomly sampling matrix

Table 6: The definitions of the variables used in **Part 3**.

```
%% Radomly sampling the noise tracks to build dataset for the MAML algorithm
%<<===Progress bar===>>
waitbar(0.5,f,'Radomly sampling the noise tracks to build dataset for the MAML algorithm');
pause(1)
%<<===Progress bar===>>
if exist('Sampe_data_N_set.mat', 'file') == 2
    disp('Sampe_data_N_set in the current path.\n');
    load('Sampe_data_N_set.mat');
else
N_epcho  = 4096 * 80                   ; % Setting the number of the epcho
Trac     = randi(Track_num,[N_epcho,1]); % Randomly choosing the different tracks.
Len_data = length(Dis_1)               ;
% Seting the N steps
len   = 2*Len_N -1 ;
Fx_data = zeros(Len_N,N_epcho);
Di_data = zeros(Len_N,N_epcho);
Ref_data = [Rf_1,Rf_2,Rf_3]   ;
Dis_data = [Dis_1,Dis_2,Dis_3];
for jj = 1:N_epcho
    End = randi([len,Len_data]);
    Di_data(:,jj) = Dis_data(End-511:End,Trac(jj));
    Fx_data(:,jj) = Ref_data(End-511:End,Trac(jj));
end
save('Sampe_data_N_set.mat','Di_data','Fx_data');
end
```

4.3.5 Using Modified MAML algorithm to get the best initial control filter

This segment of the program applies the proposed modified MAML algorithm to compute the best initial control filter for the conventional FxLMS algorithm. The step size of the FxLMS algorithm, the learning rate of the MAML algorithm, and the forgetting factor are set to 0.003, 0.5, and 0.99, respectively. Figure 4 illustrates the proposed MAML algorithm's learning curve and demonstrates the proposed algorithm's convergence. The definitions of the variables in the program are illustrated in Table 7.

```
%<<===Progress bar===>>
waitbar(0.75,f,'Using Modified MAML algorithm to get the best initial control filter');
pause(1)
%<<===Progress bar===>>
```

Parameter	Definition	Parameter	Definition
N	Number of samples in Dataset	Er	Residual error vector
mu	Step size	lamda	Forgetting factor
epslon	Learning rate of MAML	Wc	Control filter
Phi	Initial control filter		

Table 7: The definitions of the variables used in **Part 4**.

```
if exist('Weigth_initiate_Nstep_forget.mat', 'file') == 2
    disp('Weigth_initiate_Nstep_forget␣in␣the␣current␣path.\n');
    load('Weigth_initiate_Nstep_forget.mat');
else
% Create a MAML algorithm
a  = MAML_Nstep_forget(Len_N);
N  = size(Di_data,2)         ; % The number of the sample in training set.
Er = zeros(N,1)              ; % Residual error vector
% Seting the step size for the embeded FxLMS algorithm
mu    = 0.0003              ;
% Seting the forget factor
lamda = 0.99                ;
% Seting the learning for MAML
epslon = 0.5 ;
% Runing the MAML algorithm
for jj = 1:N
    [a, Er(jj)] = a.MAML_initial(Fx_data(:,jj),Di_data(:,jj),mu,lamda,
        epslon);
end
% Drawing the residual error of the Modified MAML algorihtm
figure    ;
plot(Er)  ;
grid on   ;
title('Leanring␣curve␣of␣the␣modified␣MAML␣algorithm');
xlabel('Epoch');
ylabel('Residual␣error');
% Getting the optimal intial control filter
Wc = a.Phi  ;
% Saving the best initial control filter into workspace
save('Weigth_initiate_Nstep_forget.mat','Wc');
end
```

4.3.6 Testing aircraft noise cancellation by using MAML initial control filter

The program employs the FxLMS algorithms, utilizing zero initialization and MAML initialization, to reduce the impact of aircraft noise. Figure 5 illustrates the error signal produced by the FxLMS algorithm during both the on and off states. It has been observed that the utilization of MAML initialization significantly enhances the convergence rate of the adaptive algorithm in comparison to the conventional zero initialization approach. The definitions of the variables in the program are illustrated in Table 8.

```
%% Testing aircraft noise cancellation by using MAML initial control filter
%<<===Progress bar===>>
```

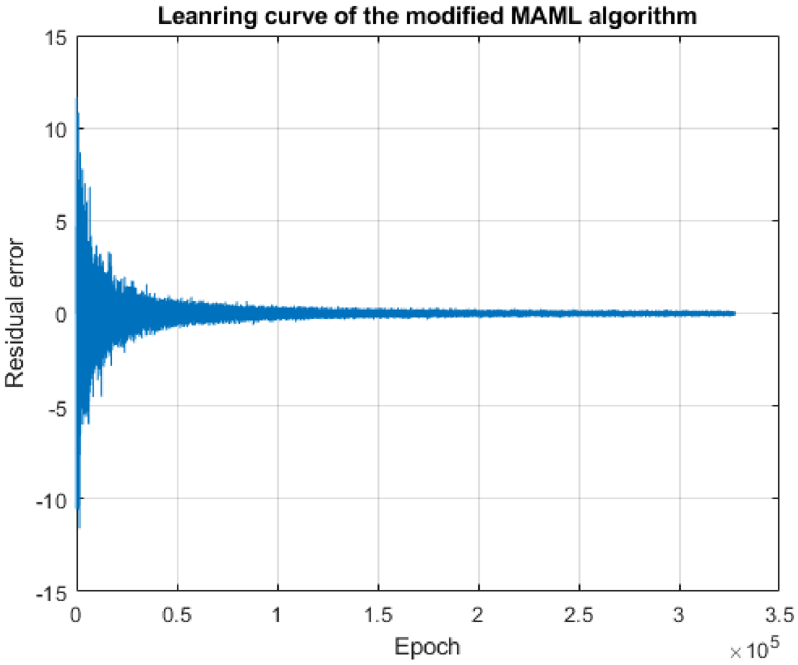

Figure 4: The learning curve of the modified MAML algorithm used to compute the initial control filter for the FxLMS algorithm.

Parameter	Definition	Parameter	Definition
Pri_1	Primary noise	Dis_1	Disturbance
Rf_1	Reference signal	Wc_initial	Initial control filter
muw	Step size	Er	Error signal of FxLMS with zero-initialization
Wc	MAML initial value	Er_1	Error signal of FxLMS with MAML-initialization

Table 8: The definitions of the variables used in **Part 5**.

```
waitbar(0.95,f,’Testing␣aircraft␣noise␣cancellation␣by␣using␣MAML␣initial␣control␣filter’);
pause(1)
%<<===Progress bar===>>
% Loading aricrat noise data
aircrat = load(’707_Sound_for_Simulation.mat’);
% Building primary noise
Pri_1    = aircrat.PilingNoise(1:153945)        ;
% Generating the disturbacne
Dis_1    = filter(Pri_path,1,Pri_1)             ;
% Generating the filter reference
Rf_1     = filter(S11,1,Pri_1)                  ;
% Runging the FxLMS with the zero-initialization control filter
Wc_initial = zeros(Len_N,1);
muw        = 0.00001 ; % Step size of All FxLMS algorithms.
Er         = FxLMS(Len_N, Wc_initial, Dis_1, Rf_1, muw);
% Runging the FxLMS with the MAML-initialization control filter
```

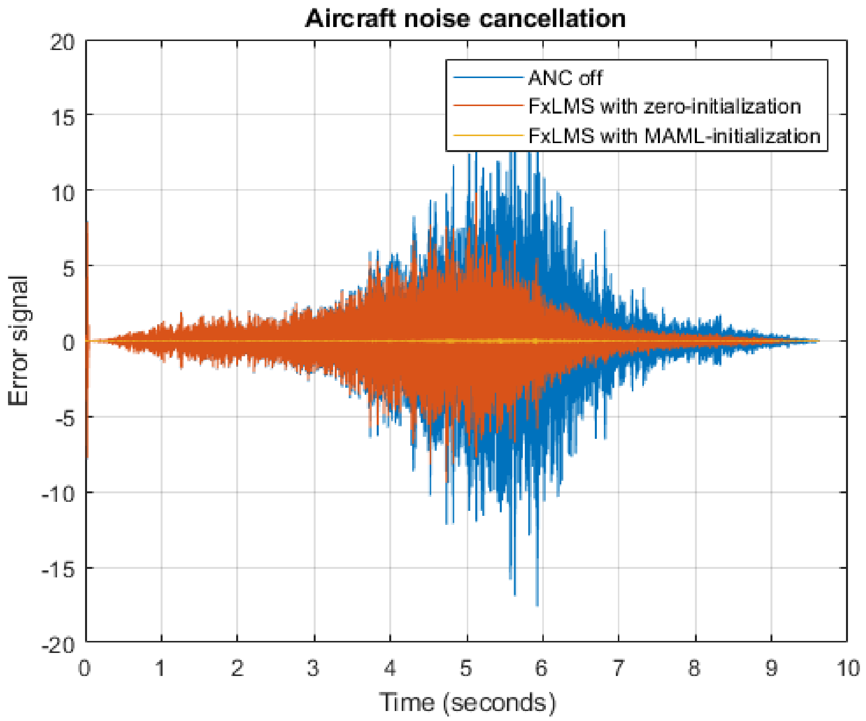

Figure 5: Aircraft noise reduction performance of the FxLMS algorithms with the zero and MAML initializations.

```
Wc_initial  = Wc;
Er1         = FxLMS(Len_N, Wc_initial, Dis_1, Rf_1, muw);
figure
% Drawing the figures of the MAML and FxLMS
plot((0:length(Dis_1)-1)*(1/fs),Dis_1,(0:length(Er)-1)*(1/fs),Er,(0:length(
    Er1)-1)*(1/fs),Er1);
title('Aircraft␣noise␣cancellation')
xlabel('Time␣(seconds)')
ylabel('Error␣signal')
legend({'ANC␣off','FxLMS␣with␣zero-initialization','FxLMS␣with␣MAML-
    initialization'})
grid on;
%<<===Progress bar===>>
waitbar(1,f,'Finishing');
pause(1)
%<<===Progress bar===>>
%------------------------------end--------------------------------------
```

5 Conclusion

The document provides a detailed introduction to implementing a modified Model-Agnostic Meta-learning (MAML) algorithm in Matlab. This modified MAML algorithm takes the forgetting factor to alleviate the initial-zero-input issue of the adaptive filters. This work uses the proposed method to seek the best initial control filter for the adaptive active noise control system based on its noise dataset. With barely additional computations, the modified MAML algorithm can assist the filtered reference square (FxLMS) algorithm in achieving fast convergence. The numerical simulation demonstrates that the FxLMS algorithm with the MAML initialization converges much faster than that with normal zero initialization when dealing with raw aircraft noise.

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