Adaptive Signal Processing for Interference Cancelling Problems in Speech Signal

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***Abstract*—Adaptive signal processing is gaining wide attention for its huge potentials in estimating and tracking the time-varying system dynamics. One of the typical applications of adaptive signal processing is to handle interference cancelling problems in speech data. Here, a few of the well-developed adaptive signal processing techniques are modified and extended to clean online the desired signal (speech plus noise) from the machine noise for denoising. In this project, we propose an adaptive filter system that integrates different adaptive algorithms covering the normalized least mean square (NLMS) and affine projection algorithm (APA) family into an adaptive filter with a goal of minimizing the mean square error (MSE) between the desired response and outputs of the filter. Then we introduce the normalized root mean square error (RMSE), the frequency response from the desired signal to the error, signal to noise ratio (SNR), misadjustment, and convergence to evaluate the interference cancelling performances of the adaptive filter over the noisy speech. Results show that the NLMS algorithm outperforms the APA family in denoising, with lower normalized RMSE, higher SNR, and smaller misadjustment. However, the NLMS algorithm has a slower convergence speed than the APA family, albeit stable. The APAs using Newton's recursion perform better than the APAs using gradient descent in improving SNR, decreasing normalized RMSE, and accelerating convergence speed, but also with a higher misadjustment, implying that the gradient descent is more stable than the Newton's recursion in denoising.**

I. Introduction

Adaptive signal processing is an integration of statistical signal processing techniques and algorithms that deals with a series of challenging problems of estimation and tracks of time-varying systems [1]. A goal of adaptive signal processing is to use adaptive filtering algorithms and structures over time-varying system dynamics to learn the optimal filter or estimator, which can usually achieve better performances than static and fixed filtering techniques [2]. Now adaptive signal processing techniques have been widely used in the fields of acoustics, speech, wireless, and networking applications to improve their performances [3]. In this project, we put a focus on application of adaptive signal processing in interference cancelling problem.

The core of adaptive signal processing is adaptive filtering algorithms and structures that can help filter noise embedded in signals and address interference cancelling. The most common adaptive filtering algorithm is well-known Least Mean Square (LMS) [4, 5], which is a steepest descent algorithm. Its basic features are to estimate the performance surface and identify the steepest gradient over each single data point until convergence. The LMS algorithm takes less computational costs and is faster to converge. However, the dependency of the LMS algorithm on the signal power is bothersome and the filtering performance is closely associated with the step size that determines how much movement along the steepest gradient descent direction. To deal with this, the normalized LMS (NLMS) algorithm is proposed based on the LMS algorithm to find the step size that disturbs the weight updates the least but still converges [5]. As a result, the step size becomes time-varying controlled by the power of the input and the NLMS algorithm also becomes independent of the input power, with a high stability. This property of the NLMS algorithm is very useful in practice that can help achieve better filtering performances. To further accelerate convergence speed of adaptive filtering algorithms, the recursive least square (RLS) algorithm is accordingly put forward to find a recursive solution on each data point [4, 6]. The RLS algorithm can guarantee optimality at each step and use data more effectively [6]. Therefore, the RLS algorithm outperforms the LMS algorithm in non-stationary environments but also requires higher computational costs. Overall, for the LMS-based and RLS-based adaptive filtering algorithms, the estimation of the gradient is based on a single data point and therefore is very noisy, easily affected by outliers in the signals.

To avoid the stochasticity of gradient approximation on each single data point, using more than a sample to estimate the filter weights for each time seems to be a better choice for adaptive signal processing. This is also the essential idea of the affine projection algorithm (APA) family that appear as intermediate complexity/performance algorithms between the LMS and the RLS [7]. The APAs inherit the simplicity and online nature of LMS and RLS while reducing the gradient noise by using multiple samples. In addition to the number of samples for each iteration, the application of some useful tricks constitutes diverse variants in taxonomy of the APAs family, for example, the search method (i.e., gradient descent and Newton's recursion methods) and the regularization item in the cost function for better generalization [7]. Here, we select four types of APAs family: non-regularized APAs by gradient descent (APA1) and Newton's recursion (APA2), regularized APAs by gradient descent (APA3) and Newton's recursion (APA4) [7], to compare their performances in interference cancelling.

The aim of this project is to design and evaluate the filtering performance of a machine learning algorithm using the NLMS and APAs family that can efficiently clean online the desired input (speech plus noise) from the machine noise (input). Also,

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we will further compare the performances of different adaptive filtering algorithms, in terms of computation cost, interference cancelling effects, and algorithm convergence, etc.

The rest of this project report is organized below: Section II presents the implementation of the NLMS and APAs family. Section III describes the experimental design and the findings. Section IV summarizes our main conclusions.

II. Implementation

In this section, we present the major structure of an adaptive filter for interference cancelling problems, as shown in Fig. 1. The proposed adaptive filter system integrates various adaptive algorithms into an adaptive filter to enhance the accuracy and efficiency of interference cancelling so that the adaptive filter can clean online the desired input (speech plus noise) from the machine noise (input). In the adaptive filter system, we use the signal (the machine noise) as the input **u**(j) to the adaptive filter, use the signal (speech plus noise) as the desired response **d**(j), and use the **y**(j) as the output of the adaptive filter system. Two types of adaptive algorithms covering the LMS algorithm and APAs family are applied to update the weights of the adaptive filter.

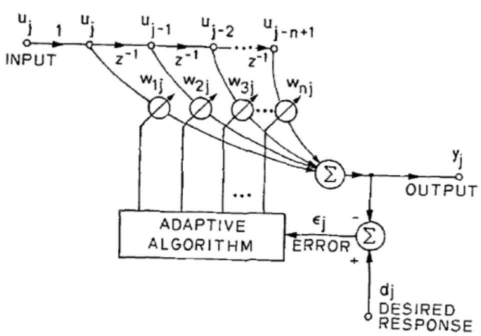


Fig. 1. The structure of an adaptive filter with different adaptive algorithms for interference cancelling [8].

A. Signal Data Sources and Description

In this project, we use time-varying speech data as the signal of the adaptive filter, which is collected by two microphones in a noisy room with a loud vacuum cleaner: one placed on a table that captures speech with the vacuum cleaner noise **d**(j) and the other very close to the vacuum cleaner **u**(j) that basically has no speech. As presented in Fig. 2, the main difference in the power spectral density between **d**(j) and **u**(j) lies in the low frequency domain where the **d**(j) exhibits larger power spectral density (PSD) than the **u**(j). This also implies that the speech is a low frequency signal data to some extent.

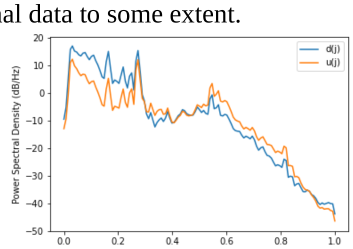


Fig. 2. The power spectral density of the d(j) and u(j).

B. Normalized Least Mean Square (NLMS) Algorithm

The goal of the adaptive filter system is to clean online the desired speech plus noise from the machine noise and to output the expected speech signal. Since we have obtained the input and desired response, the next step is how to acquire the optimal weights of the adaptive filter, as illustrated in Fig. 1. This is also how the adaptive algorithm works in the adaptive filter system. The NLMS algorithm, as one classic online adaptive algorithm, can efficiently filter the noises embedded in the speech signal, with stable convergence property. Its rule of the weight updates is listed below [5]:

$$\boldsymbol{w}(j+1) = \boldsymbol{w}(j) + \frac{\eta}{\delta + \|\boldsymbol{u}(j)\|^2}\boldsymbol{u}(j)\boldsymbol{e}(j) \qquad (1)$$

Where: η is a hyperparameter that determines the step size of the weight updates; δ is used to "regularize" the denominator to avoid instability in low power of the input; $\boldsymbol{e}(j)$ is the error between the desired response **d**(j) and filter output **y**(j), which means $\boldsymbol{e}(j) = \boldsymbol{d}(j) - \boldsymbol{y}(j) = \boldsymbol{d}(j) - \sum_{i=0}^{n-1} w_{ji} u(j-i)$ where n is the order of the adaptive filter.

C. Affine Projection Algorithm (APA) Family

Since the NLMS algorithm online updates the weights of the adaptive filter over each single data point, the performance of the adaptive filter system for interference cancelling problems can be easily damaged by some possible outliers in the speech data signal. The APAs family can use multiple samples to update the weights of the filter once so that it can efficiently deal with the outlier issues. Here, we introduce four types of APAs family to separately investigate their performances on denoising the speech data, in terms of convergence, computational costs, and interference cancelling effects, etc. The four APAs correspond to the APAs family whether regularized or not and using which search method (e.g., gradient descent or Newton's recursion), also labelled as APA1, APA2, APA3, and APA4. Note that the APA1,2 use the least square cost and APA3,4 are regularized; APA1,3 use gradient descent and APA2,4 use Network update [7].

1) **APA1 Adaptive Algorithm**

The APA1 refers to non-regularized APA by gradient descent, and its rule of the weight updates [7] is

$$\boldsymbol{w}(j+1) = \boldsymbol{w}(j) + \eta\boldsymbol{u}(j)\boldsymbol{e}(j) \qquad (2)$$

Where: η refers to the step size.

2) **APA2 Adaptive Algorithm**

The APA2 means non-regularized APA by Newton's recursion, and its rule of the weight updates [7] is

$$\boldsymbol{w}(j+1) = \boldsymbol{w}(j) + \eta\boldsymbol{u}(j)[\boldsymbol{u}(j)^T\boldsymbol{u}(j) + \varepsilon\boldsymbol{I}]^{-1}\boldsymbol{e}(j) \qquad (3)$$

Where: η refers to the step size and $\varepsilon\boldsymbol{I}$ is a regularized item.

3) **APA3 Adaptive Algorithm**

The APA3 refers to regularized APA by gradient descent, and its rule of the weight updates [7] is

$$\boldsymbol{w}(j+1) = (1-\eta\lambda)\boldsymbol{w}(j) + \eta\boldsymbol{u}(j)\boldsymbol{e}(j) \quad (4)$$

Where: η refers to the step size and λ is a hyperparameter that determines how much weight updates from the previous state to the current one.

4) **APA4 Adaptive Algorithm**

The APA4 refers to regularized APA by Newton's recursion, and its rule of the weight updates [7] is

$$\boldsymbol{w}(j+1) = (1-\eta)\boldsymbol{w}(j) + \eta\boldsymbol{u}(j)[\boldsymbol{u}(j)^T\boldsymbol{u}(j) + \varepsilon\boldsymbol{I}]^{-\mathbf{1}}\boldsymbol{d}(j) \quad (5)$$

Where: η refers to the step size and $\varepsilon\boldsymbol{I}$ is a regularized item.

III. Experiments And Results

A. Experimental Design

To evaluate the performance of the adaptive filter system with different adaptive algorithms in interference cancelling, we conducted a series of experiments to clean online the desired input (speech plus noise) from the machine noise and further compare the denoising effects of the NLMS algorithm and APAs family on the noisy speech. The related experimental design is listed as follows:

1) **Clarify a Goal of the Adaptive Filter**
The goal of the adaptive filter is to handle the interference cancelling problem in the noisy speech data and minimize the difference between the desired response and the filter outputs. Here, we introduce the Mean Square Error (MSE) as an evaluation metric to optimize the adaptive filter, as computed below:
$$MSE = E(\boldsymbol{e}^2) \quad (6)$$
2) **Choose the Adaptive Algorithm**
To improve the performance of the adaptive filter, the key step is how to update the weights of the filter. Here, we adopt five adaptive algorithms, the NLMS algorithm and APA1,2,3,4, to reveal their interference cancelling effects on the noisy speech data and further explore the ability to clean online desired speech from the machine noise.
3) **Vary Hyperparameters of the Adaptive Filter**
In the adaptive filter system, different hyperparameters covering the order of the adaptive filter, step size, lambda, regularized item, and the size of samples for each iteration in the APAs family are used and further optimized to study their effects on the performances of the adaptive filter. Here, we separately set the regularized item in the NLMS and APA2,4 as 1e-5 and 1e-3***I** (identity matrix), vary the order of the filter from 2 to 11, and set the default step size as 0.005 and the size of samples for each iteration as 50.
4) **Evaluate the Performance of the Adaptive Filter**
Since we have set the structure and parameters of adaptive filter system, the next step is to use the above five adaptive algorithms to update the weights of the adaptive filter until optimum and clean online the noisy speech data. Then we select the following eight evaluation metrics to assess the performance of the adaptive filter system in interference cancelling problems.

a. *Normalized Root MSE (RMSE)*: To better illustrate the difference (error) between the desired response and filter output, we use the normalized RMSE by the power of the input to evaluate the performances of the adaptive filter so that the magnitude of the error will not significantly increase by the size of data points but still works.
$$Normalized\ RMSE = \left(E(\boldsymbol{e}^2)/E(\boldsymbol{u}^2)\right)^{1/2} \quad (7)$$
b. *Weight tracks*: We plot the weight tracks to describe how the filter weights are updated for each iteration.
c. *Learning curve*: We plot the learning curve to present how the error between the desired response and filter output changes for each iteration.
d. *Frequency response*: The frequency response from the desired signal to the error can be estimated by using the learned weights of the adaptive filter [9]. The frequency response between the d(j) and e(j) can help check whether the adaptive filter is a valid filter that cancels out the frequency of certain harmonics.
e. *Signal to noise ratio (SNR)*: The SNR improvement in dB after denoising is a good indicator to evaluate the interference cancelling effects of the adaptive filter [10], as computed below:
$$SNR = 10log\left(E(\boldsymbol{d}^2)/E(\boldsymbol{e}^2)\right) \quad (8)$$
f. *Misadjustment*: The concept of misadjustment refers to the unavoidable error of the adaptive filter due to the variance of adapting parameters and the setting of initialization conditions [11]. Here, we set different weight initialization conditions and estimate the mean and variance of the misadjustment as indicators to assess the performance of the adaptive filter.
g. *Convergence*: The convergence of the five adaptive algorithms and filter can be evaluated by whether the weight updates converge by iterations or not, as well as the convergence speed to characterize the effects of the adaptive filter system on denoising.
h. *Effects of hyperparameters (filter order, step size)*: In addition to the above seven indicators, it is vital to explore the interference cancelling effects of some important hyperparameters, for instance, the order of the filter and step size, on the adaptive filter system. In this project, we estimate the filter performance as a function of the filter order and step size to determine the optimal order of the filter and investigate how the step size affects the denoising performances of the adaptive filter, respectively.

B. Experimental Results and Analysis

In this project, we illustrate the experimental results of the adaptive filter as follows: (1) plotting the performance surface contour for the two-weight filter case, (2) the filter performance with the NLMS algorithm when the filter order is equal to 2, (3) determining the optimal filter order, (4) the filter performance with the NLMS algorithm and APAs family when the filter order is the optimum, (5) exploring the effects of step size and sample size on the denoising effect of the adaptive filter.

1) **Plot of the Performance Surface Contours for the Two Weights Filter Case**
Here, we vary the two weights of the adaptive filter from 0 to 2 with an interval of 0.04 and compute the normalized RMSE between the desired response and filter output, and the performance surface contour [12] is shown in Fig. 3. The optimal weights of the filter lie in the domain labelled as yellow.

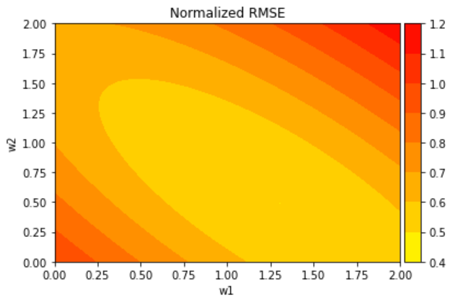


Fig. 3. The performance surface contour for the two-weight filter case.

2) **Filter Order = 2: Filter Performance with the NLMS Algorithm**
We set the step size of the adaptive filter as 0.003 where the filter achieves better denoising performances: SNR = 5.92, the mean and standard deviation of RMSEs between the desired response and filter output of each data point are equal to 0.81 and 0.64, respectively. As shown in Fig. 4-5, the weights of the adaptive filter gradually converge to [0.42, 1.50] that lead to lower error between the desired response and filter output. Fig. 6 shows that the adaptive filter is a low pass filter that surpasses the high frequency in the noisy speech data.

a. Weight tracks

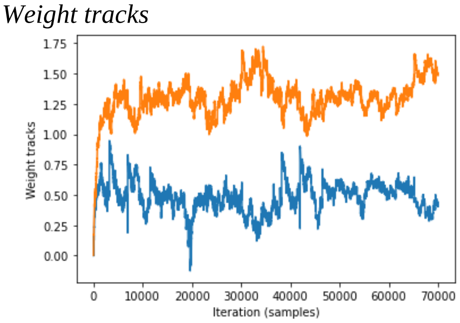


Fig. 4. The weight tracks for the two-weight filter case.

b. Learning curve

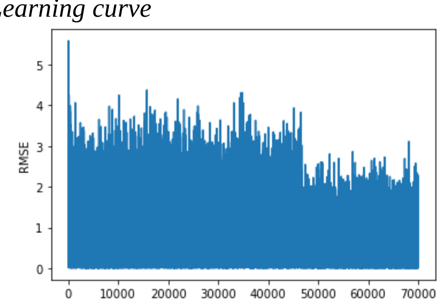


Fig. 5. The learning curve for the two-weight filter case.

c. Frequency response

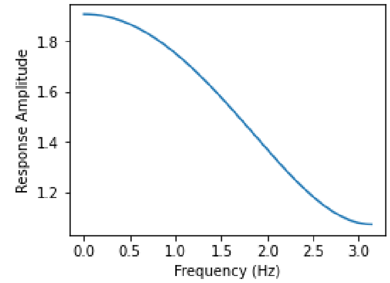
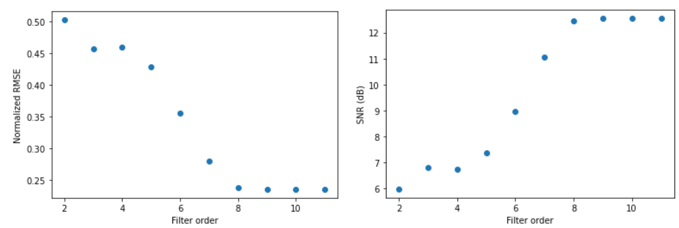


Fig. 6. The frequency response for the two-weight filter case.

3) **Vary the Order of Filter to Determine the Optimum**
Here, we vary the order of filter from 2 to 11 to determine the optimal order that corresponds to a lowest normalized RMSE and highest SNR of the adaptive filter with the LMS algorithm. Fig. 7 shows how the filter performance varies by the filter order and that the optimal filter order is equal to 10, as the final order of the adaptive filter.



(a) Normalized RMSE (b) SNR

Fig. 7. The variations of the filter performance by filter order

4) **Filter Order = 10: Filter Performance with the NLMS Algorithm and APA1,2,3,4**
With the optimal filter order, the structure of the adaptive filter system can be easily determined and the next step is to choose suitable adaptive algorithms for weight updates. Here, we propose five adaptive algorithms: the NLMS and APA1,2,3,4 family to update the weights of the adaptive filter, and the results of filter performances with different adaptive algorithms are shown in TABLE I and Fig. 8-11.

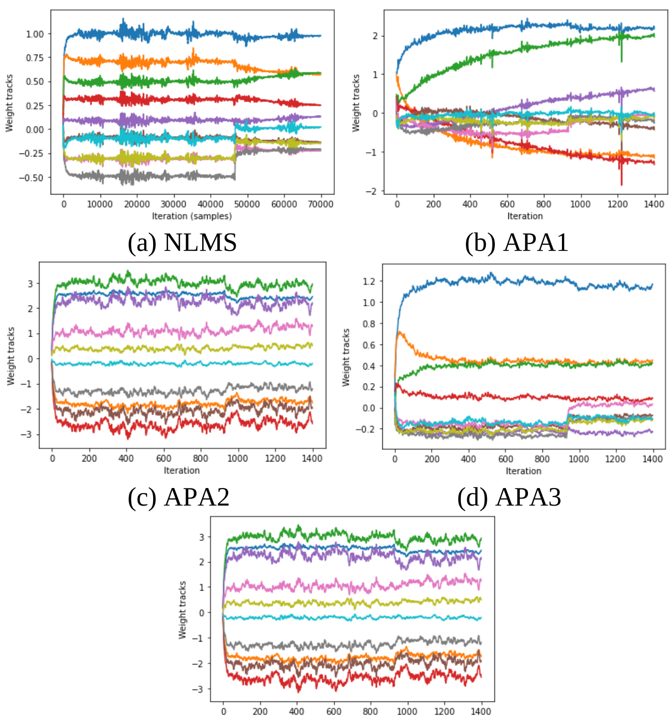
TABLE I
SUMMARY OF SNR, RMSE AND MISADJUSTMENT OF THE ADAPTIVE FILTER WITH THE NLMS AND APAS FAMILY

Algorithm	SNR	RMSE		Misadjustment	
		Mean	Variance	Mean	Variance
NLMS	18.95	0.15	0.18	0.24	4.0e-6
APA1	11.03	0.38	0.43	0.40	1.3e-3
APA2	13.81	0.32	0.27	0.47	4.3e-8
APA3	10.29	0.49	0.38	0.41	8.3e-5
APA4	13.76	0.32	0.27	0.46	4.1e-5

As presented in TABLE I, the NLMS algorithm has a higher SNR improvement, lower misadjustment, and smaller mean and variance of RMSEs between the desired response and filter output of each sample. This can be partly explained by the fact that the NLMS algorithm updates the filter weights over each data point for one iteration, while the APAs family updates the weights on a batch of 50 data points for one iteration. It is worth noting that higher SNR, smaller RMSE and misadjustment can only reveal the efficiency and stability of the adaptive filter in minimizing the difference between the noisy speech and the machine noise but cannot directly suggest better interference cancelling performances of the adaptive filter. TABLE I also indicates that the APAs with Newton's recursion (APA2,4) outperform the APAs with gradient descent (APA1,3) in rising the SNR and reducing the RMSE. However, the APAs using Newton's recursion show higher misadjustment than the APAs using gradient descent, meaning that the gradient descent is more stable than the Newton's recursion in cleaning online the noisy speech data.

a. Weight tracks

As shown in Fig. 8, the NLMS algorithm and APAs family all update the filter weights until convergence, but the learned weights vary greatly for different adaptive algorithms. Totally, the APAs with Newton's recursion (APA2,4) show smoother weight tracks than the NLMS algorithm and the APAs with gradient descent (APA1,3), almost with no abrupt fluctuations in the weight tracking curve. Also, the APAs with Newton's recursion converge faster to the optimal weights than other adaptive algorithms, but they are also accompanied by a larger changing range of weights (-3,3), followed by the APA1 (-1,2), NLMS (-0.5,1), and APA3 (-0.2,1.2).



(a) NLMS (b) APA1

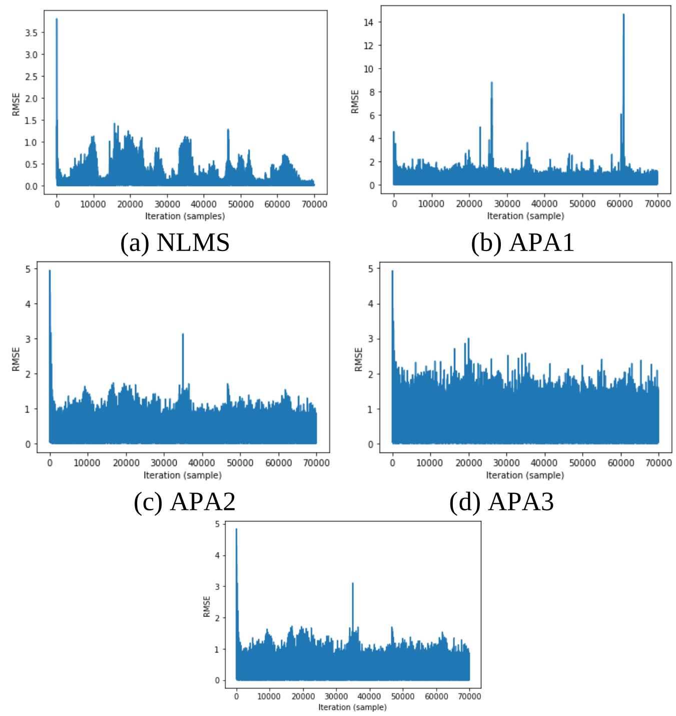
(c) APA2 (d) APA3

(e) APA4

Fig. 8. The weight tracks of the filter with the NLMS algorithm and APAs family

b. Learning curve

Fig. 9 illustrates that the NLMS algorithm has lower RMSEs (0,1) on each data point between the desired response and filter output than the APAs family (0,2), and the RMSEs by the APAs using Newton's recursion are slightly smaller than those by the APAs using gradient descent. This is reasonable because the NLMS updates the filter weights with the goal of minimizing the error on each data point, rather than on a batch of samples that the APAs family does.



(a) NLMS (b) APA1

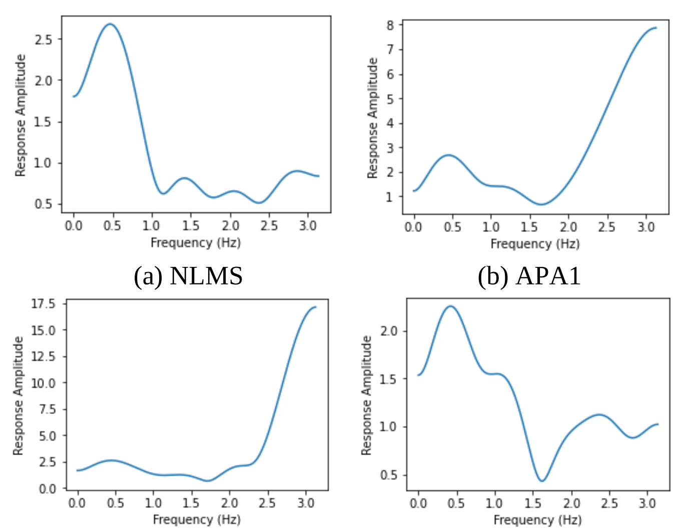
(c) APA2 (d) APA3

(e) APA4

Fig. 9. The learning curve of the filter with the NLMS algorithm and APAs family

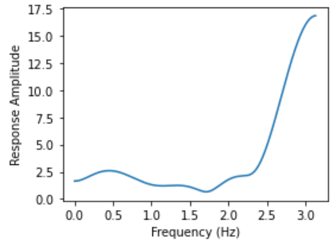
c. Frequency response

Fig. 10 shows that the usage of the NLMS and APA3 makes the adaptive filter become a low pass filter, particularly for the NLMS that surpasses the high frequency in the noisy speech data. By contrast, the APA1,2,4 make the adaptive filter be a high pass filter, especially for APAs using Newton's recursion that surpass the low frequency in the noisy speech data.



(a) NLMS (b) APA1

(c) APA2 (d) APA3



(e) APA4

Fig. 10. The frequency response of the filter with the NLMS algorithm and APAs family

d. Power spectrum density

Here, we plot and compare the power spectrum density of the noisy speech d(j), the machine noise u(j), and different filter output y(j) derived by the NLMS algorithm and APA1,2,3,4. We can see from Fig. 11 that in the low frequency domain, the PSD of filter outputs by the five adaptive algorithms all presents almost the same changing trend as that of the desired response, indicating the efficiency of the adaptive filter in denoising. In the high frequency domain, the filter only with NLMS outputs the similar changing trend of PSD to the desired response, while the filters with other adaptive algorithms all output higher PSD than the desired response, especially for APAs using Newton's recursion, followed by the APAs using gradient descent (APA1 and APA3). It is worth mentioning that in the high frequency domain, the adaptive filter with the APA3 outputs almost the same changing trend of PSD as the machine noise. In summary, the NLMS algorithm outperforms other adaptive algorithms whether in the low or high frequency domain, in terms of fitting the trend of PSD of the desired response, however, the NLMS and APAs family all perform well in the low frequency domain.

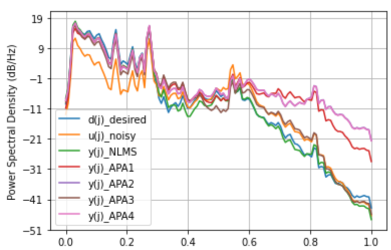
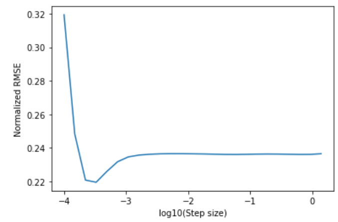


Fig. 11. Comparison of power spectrum density among the desired response d(j), the noisy input u(j) and filter output y(j) by different adaptive algorithms

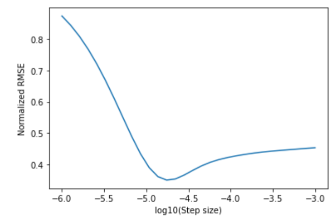
5) **Effect of Step Size on the Filter Performance with the NLMS Algorithm and APAs Family**

Here, we use two evaluation metrics: normalized RMSE and SNR improvement to characterize the performance of the adaptive filter as a function of step size, separately as shown in Fig. 12 and 13. It can be easily found that various adaptive algorithms all have the optimal step size that can minimize the normalized RMSE and maximize the SNR. When the step size is less than the optimum, as the step size rises, the filter performances are greatly improved towards lower normalized RMSE and higher SNR. When the step size is larger than the optimum, as the step size increases, the filter performances are first maintained at a demonstrated level of low normalized RMSE and high SNR and then gradually diverge and do not converge (not shown in Fig. 12-13 due to extremely high magnitudes).

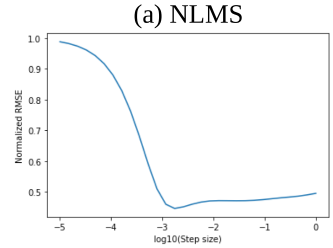
a. Normalized RMSE



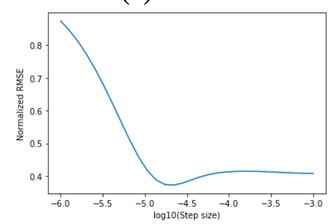
(a) NLMS



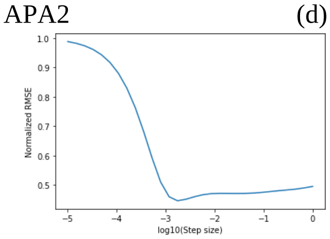
(b) APA1



(c) APA2



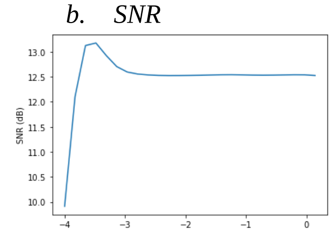
(d) APA3



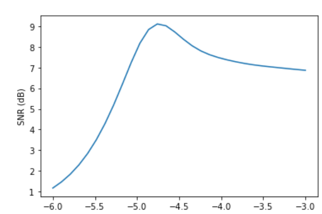
(e) APA4

Fig. 12. Effects of step size on the normalized RMSE of the filter with the NLMS algorithm and APAs family

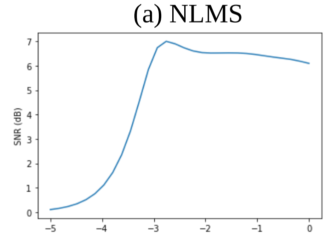
b. SNR



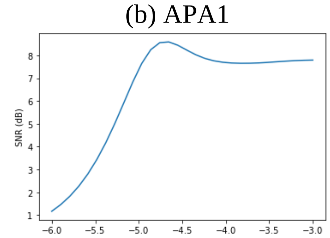
(a) NLMS



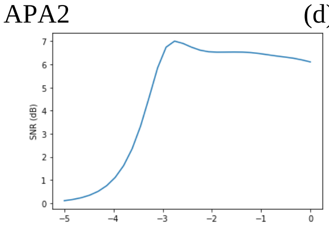
(b) APA1



(c) APA2



(d) APA3



(e) APA4

Fig. 13. Effects of step size on the normalized RMSE of the filter with the NLMS algorithm and APAs family

6) **Effect of Sample Size on the Filter Performance with APAs Family**

In addition to the step size, it is necessary to study another hyperparameter: the size of samples for each iteration, that may affect the performance of the filter with APAs family. Here, we vary the sample size from 10 to 100 to explore how the normalized RMSE and SNR change, as presented in TABLE II. Generally, the APAs using gradient descent outperform those using Newton's recursion whether the size of samples for each iteration, both presenting a lower normalized RMSE and higher SNR. Additionally, we can see from the variances of the normalized RMSE and SNR that the sample size only presented the limited effects on the filter performances, especially for APA1, followed by APA2, APA4, and APA3. This also implies that the size of samples may more easily affect the regularized APAs than non-regularized APAs to some extent, albeit weakly.

TABLE II
FILTER PERFORMANCE WITH APAS FAMILY WHEN SAMPLE SIZE VARIES FROM 10 TO 100

Algorithm	Normalized RMSE		SNR	
	Mean	Variance	Mean	Variance
APA1	0.40	6.5e-5	7.94	1.4e-3
APA2	0.47	4.2e-3	6.57	0.08
APA3	0.42	0.02	7.62	0.37
APA4	0.46	7.8e-3	6.73	0.15

IV. CONCLUSIONS

The objective of the project is to develop an adaptive filter system with different adaptive algorithms covering normalized least mean square (NLMS) and regularized or non-regularized affine project algorithms using gradient descent or Newton's recursion (APAs family) that can clean online the noisy speech from the machine noise. Then we propose several evaluation metrics to assess the performances of the adaptive filter system in interference cancelling and denoising, i.e., normalized root mean square error (RMSE), frequency response from the desired speech signal to the error, signal to noise ratio (SNR), and misadjustment, etc.

Results show that the NLMS algorithm demonstrates lower normalized RMSE, higher SNR, and smaller misadjustment, and outperforms the APAs family in denoising, albeit with a slower convergence speed but stable. Additionally, the APAs using Newton's recursion exhibit better denoising effects than the APAs using gradient descent, in terms of SNR, normalized RMSE and convergence speed, except for misadjustment. This indicates that the Newton's recursion is more efficient but less stable than the gradient descent.

The five adaptive algorithms all work well in denoising low frequency domain, but the NLMS exhibits better interference cancelling effects in the high frequency domain than the regularized APAs using the Newton's recursion, followed by the APAs using the gradient descent. It is worth mentioning that regularization of APAs family hardly brings any positive effects on improving the performances of the adaptive filter system for denoising. It can also be found that the step size has remarkable impacts on the filter performances, while the size of samples for each iteration in the APAs family only presents limited effects on the performance of the adaptive filter system.

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