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Performance of Adaptive Filters for Real-Time Acoustic Echo Cancellation in Non-Stationary Environment

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Abstract:- Adaptive filtering is at the core of many signal processing applications as phenomenal advances both in research and application have been made during the past three decades. The main objective of an adaptive filter is to minimize error signal at the cost of high convergence rate and reduced computational complexity. This paper presents the performance of adaptive filter algorithms for acoustic echo cancellation by eliminating the echo signal from the original signal. The adaptive filtering process is carried out by using Least Mean Square (LMS), Normalized-Least Mean Square (NLMS) and Kalman filter in a real-time non-stationary environment and its performance is measured in terms of convergence rate, Mean Square Error and Echo Return Loss Enhancement (ERLE). Simulations are carried out by using MatLab and the output results show clearly that Kalman filter converges after about 7000 iterations and outperforms LMS and NLMS algorithms with 42dB ERLE against 12dB ERLE and 20dB ERLE for LMS and NLMS respectively. Therefore, Kalman filter is more suitable for echo cancellation in a non-stationary environment.

Keyword:- *Acoustic Echo Cancellation, Adaptive filtering, LMS, NLMS, Kalman filter.*

I. INTRODUCTION

Echo generation is an ubiquity phenomenon in wireless communication system in which a delayed and distorted version of a signal is reflected back to the source. One of the main challenges faced by network providers in delivering voice services with the same quality as existing landline networks is the existence of acoustic echoes and background noise. The echo components severely degrade the fidelity and intelligibility of the speech signal and decrease the performance of human-to-machine interfaces (i.e automatic speech recognition systems).

Methods for the cancellation of acoustic echoes are of high interest to designers of speech processing systems and key ingredient to improving perceived voice quality of a call and a boost to revenues. Basically, there are two main sources of echo [1]. The Hybrid echo is generated in a Public Switched Telephone Network (PSTN)-originated calls due to impedance mismatch in transmission lines while, the acoustic echo originates from a feedback path set between the speakers and the microphones of a communication device. Acoustic echo is mainly found in mobile phones, hands-free phones, Teleconference or hearing aid systems. The Echo reduction techniques used in telephony to improve voice quality include echo suppressors and echo cancellers. Due to high computational complexity and cost of the existing technique, adaptive filters with associated recursive algorithms present an alternative approach to detect error and automatically update their coefficients quickly in order to achieve an optimal desired output in a changing and unknown environment. The cost function of the adaptive algorithm is reduced until the output of the adaptive filter is equal to desired output and the error signal effectively cancels out. Adaptive filters have found their use in several and diverse fields such as communications, acoustic echo and noise cancellation/suppression, radar signal processing, system identification, signal enhancement, array beamforming, channel equalization, and signal prediction [2]. In the last few years, different adaptive algorithms have been developed for eliminating distortion from signals and these algorithms are measured using parameters like MSE [3], ERLE [4], and Signal-to-Noise-Ratio (SNR) [5]. The objective of the research paper is to present among various existing adaptive filters, an effective adaptive filter for acoustic echo cancellation in a non-stationary environment using a real-time speech signal.

II. LITERATURE REVIEW OF ADAPTIVE ECHO CANCELLATION

An echo formation system is an active loud speaker and a microphone as depicted in figure (1). The echo signal in addition to the near end signal received by the microphone signal is transmitted back to the far end. The far end user will perceive a delay and distorted version of the original voice as an echo.

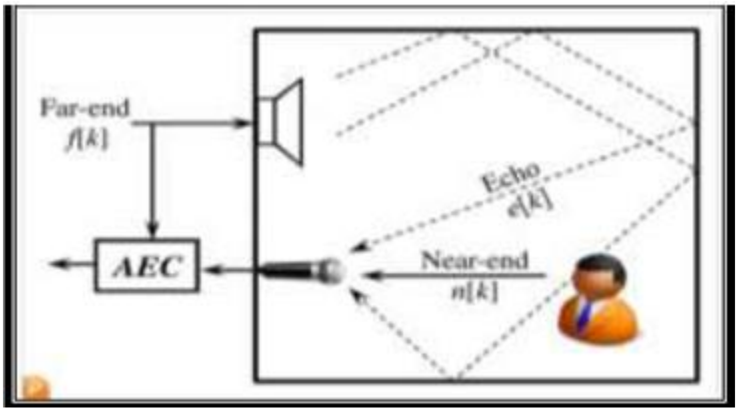

Fig 1:- Acoustic echo Formation [6]

An effective echo cancellation solution uses adaptive filters to manage acoustic echoes by rapidly adjusting its parameters in order to achieve an optimal output. Figure 2 depicts the block diagram of an adaptive filter.

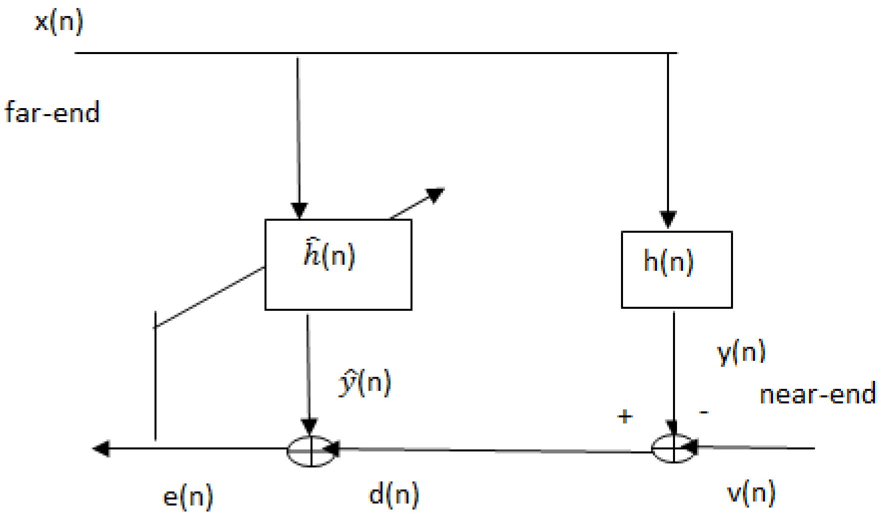

Fig 2:- Block Diagram for an Adaptive Filter for echo cancellation

The voice signal x(n) from the far end is sent in parallel to a DSP path ($\check{h}$) and to an acoustic echo path h(n) which consists of a loudspeaker, an acoustic environment and a microphone. The signal receives from the output of the loudspeaker is the echoed signal d(n) and is fed back as the input to the microphone. The measured signal consists of the echo signal y(n) and the near end signal v(n).

$$d(n) = v(n) + y(n) \quad (1)$$

These echo signals cause the degradation of the quality of the voice signal. The acoustic echo canceller utilizes adaptive FIR filter to automatically adjust its parameters based on the algorithm driven by the error signal,

$$e(n) = d(n) - \dot{y}(n) \quad (2)$$

The error signal is fed back into the adaptive filter in order to minimize a function of this difference. However, in an ideal case when the adaptive filter output $\acute{y}(n)$ is equal to desired output d(n), the error signal will be removed completely and no kind of disturbance will be perceived by the far-end users

A. *Adaptive Filtering Algorithm*

There are numerous adaptive algorithms used for adaptive filtering, out of which LMS, NLMS and Kalman filter are considered and their capacities are compared based on the rate of convergence, computational cost and echo attenuation. These algorithms are simulated using MATLAB.

➢ *Least Mean Square adaptive filter Algorithm (LMS)*

The Least Mean Algorithm (LMS) is a stochastic steepest-gradient descent algorithm proposed by Bernard Widrow and Ted Hoff in 1958 for updating filter weight in order to converge to optimal Wiener solution. The main features that attracted the use of the LMS algorithm adaptive filtering are low computational complexity, proof of convergence in stationary environments and stable behavior when implemented with finite precision arithmetic. The cost function is determined by taking the

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difference between the desired signal and the filtered signal according to the following steps [7]:

The adaptive filter output : $y(n) = \sum_{i=0}^{N-1} w(n)x(n-i) = w(n)^T x(n)$ (3)

The error signal is given as: e (n) =$d(n) - y(n)$ (4)

The update weight factor : $w(n+1) = w(n)$+µ$e(n)x(n)$ (5)

Where w_n is the coefficients vector, x_n is the filter input vector and µ is the step size lying between 0< µ < $\frac{2}{\lambda_{max}}$ which gives good results if correctly chosen.

➢ *Normalized Least Mean Square Adaptive (NLMS)*

The Normalized Least Mean Square algorithm is a useful variant of the LMS algorithm, derived from the conventional LMS algorithm in order to reduce computational complexity or convergence time associated with the LMS adaptive filter. The main shortcoming of LMS algorithm is its weak convergence due to the fixed step-size parameter used in every iteration. The NLMS algorithm overcomes this problem by finding the maximum step size parameter based on the current input values. The algorithm can be implemented using the following steps [7]. The adaptive filter output : $y(n) = \sum_{i=0}^{N-1} w(n)x(n-i) = w(n)^T x(n)$ (6)

The error signal : e(n) =d $(n) - y(n)$ (7)

The step size value for the input vector is given: µ(n) = $\frac{1}{x(n)^T * x(n)}$ (8)

The weight vector update equation: $w(n+1) = w(n) +$ µ$e(n)x(n)$ (9)

➢ *Kalman Filter*

Kalman filter is a powerful computational recursive algorithm that is based on the Bayesian approach [8] and operates through a prediction and correction mechanism. It offers moderate computational complexity and superior convergence features than wiener filtering when derived with appropriate simplification. It combines information about the dynamics of the system, measured data and measuring devices to produce an estimate of the desired variables (i.e., past, present and future states of the system) in such a way to minimize error even with unknown or imprecise modelled system. The Kalman filter projects the true state ahead at any particular time k from the previous time k-1 as [9],

$$X^{\wedge}_{K-1} = A_K X_{K-1} + B_K\, U_K + w_K \quad (10)$$

where A_K is the state transition matrix, B_K is the control input, U_K is the control input vector and w_K is the process noise vector. This process noise is assumed to be normally distributed with zero mean and Q covariance.

The actual measured variable at time k can be modelled in the form,

$$Z_K = HX_K + v_K \quad (11)$$

where v_K is the error associated with the measurement; H is the noiseless connection between the state vector and the measurement vector. The measurement error, v_K is assumed to be normally distributed white noise with zero mean with R covariance. The Kalman gain is a function of relative certainty between the current (predicted) state estimate and the estimated measurement. Therefore, Kalman gain,

$$K = P_K^- H^T (H P_K^- H^T + R)^{-1} \quad (12)$$

where P_K^- is the predicted error covariance matrix. The high value of K will make Kalman filter follow measurement closely while low value of K places more weight on the model prediction as given by,

$$X^{\wedge}_K = X^{\wedge}_{K-1} + K\,(Z_K - H\,X^{\wedge}_{K-1}) \quad (13)$$

The current state estimate $X^{\wedge}_{K-1}$ and its corresponding covariance P_K^- are based on their previous values as given,

$$X^{\wedge}_{K-1} = A_K X_{K-1} + B_K\, U_K + w_K \quad (14)$$

$$P_K^- = AP_{K-1}A^T + Q$$

(15)

where w_K is the process noise and assumed to be normally distributed with zero mean and Q covariance. The first iteration requires initialization values for the two variables. As iteration increases, the Kalman filter converges the state variables to the accurate value, therefore reducing its covariance through the effect of Kalman gain as,

$$P_K = (1 - KH)P_K^-$$

(16)

III. PERFORMANCE EVALUATION PARAMETERS

The performance parameters used for the evaluation of different adaptive error cancellation algorithms are:

A. **Mean Square Error (MSE):** Mean Square Error is an essential tool to quantify the difference between the true values of the quantity being estimated and the values implied by an estimator. It is expressed mathematically as [3],

$$\text{MSE} = \frac{1}{N}\sum_{k=1}^{N} e(k)^2 \quad (17)$$

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where N is the filter length and e(k) is the error signal at the output of the filter.

B. **Echo Return Loss Enhancement (ERLE):** Echo Return Loss Enhancement is an important parameter widely used for measuring how much echo attenuation the echo canceller removes from the microphone signal. It is also, referred to as echo signal attenuation. Mathematically, it can be expressed as [4],

$$\text{ERLE} = 10 log_{10} \frac{P_d(n)}{P_e(n)} \tag{18}$$

IV. RESULTS AND DISCUSSION

The section presents the performance of the acoustic echo cancellation based on LMS, NLMS and Kalman filter. The performances of the three algorithms were evaluated and their source codes were written in MatLab in order to select the most suitable algorithm for echo cancellation in a non-stationary environment based on convergence rate, ERLE and MSE parameters. The algorithms were applied to echo signal combined with the speech signal observed in a teleconference hall at a sampling frequency of 16KHz. Figures 3, 4 and 5 depict the results of application of AEC using LMS, NLMS and Kalman filter respectively. It is observed in figure 5, that Kalman filter cancels out the echo signal to a large extent and brings the error signal close to the original input speech signal. Figures 6, 7 and 8 present the convergence curves of the MSE against the number of iterations. The three algorithms tend to minimize the MSE between the output of the adaptive filters and the desired signal. The convergence curves show that the MSE decreases by increasing the number of iterations. In figure 6, it is observed that the LMS algorithm has a very slow convergence. It does not converge until after 35000 iterations where it converges to a higher error value of 35dB. In figure 7, that NLMS converges after about 10000 iterations to 30dB. In figure 8, Kalman filter converges faster as the power of the error signal drastically reduces and remains stable with changes in the input power. The algorithm exhibits a wonderful result after 7000 iterations, the original speech signal is restored from the distorted echo signal.

Figure 9, presents the comparison between the three algorithms' ERLE. According to [10], for better performance of an echo canceller, the value of ERLE should lie in the range [40dB, 50dB]. It can be seen from the plot that Kalman filter exhibits high rate of echo cancellation compared to the other two algorithms. It achieves approximately 42dB ERLE against 20dB for NLMS algorithm and 12dB for LMS algorithm. Kalman filter achieves the required value and outperforms the other two algorithms. Table 1 shows the overall performance results of the three algorithms.

Algorithm	Mean Square Error (dB)	Echo Return Loss Enhancement (dB)
LMS	**-35**	**-12**
NLMS	**-30**	**-20**
Kalman Filter	**-22**	**-42**

Table 1:- Performance of the Adaptive Algorithm

The Figure 3 is the plot of echo cancellation using LMS algorithm. The plot consists of non-stationary input signal, desired signal and clean signal after the echo has been removed.

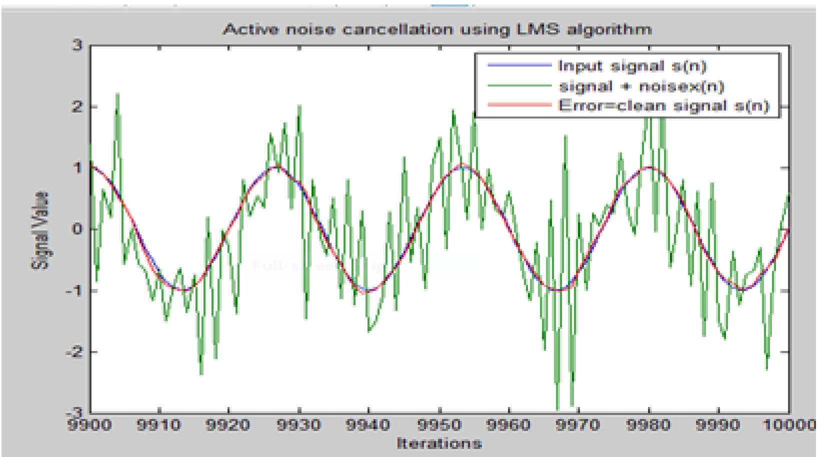

Fig 3:- Echo cancellation using LMS algorithm

Figure 4 shows the echo cancellation experiment in a non-stationary environment using NLMS algorithm.

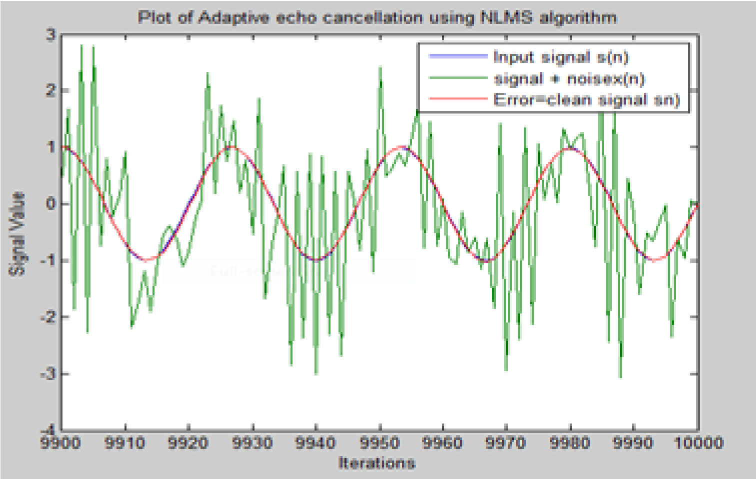

Fig 4:- Echo cancellation using NLMS algorithm

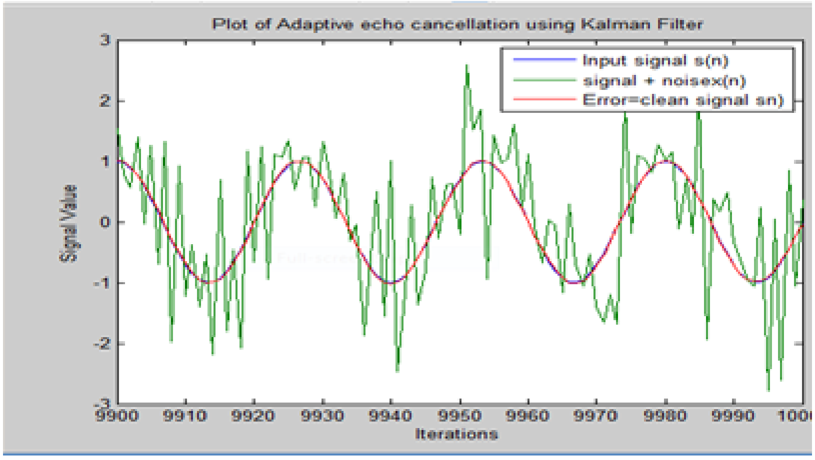

Fig 5:- Echo cancellation using Kalman filter

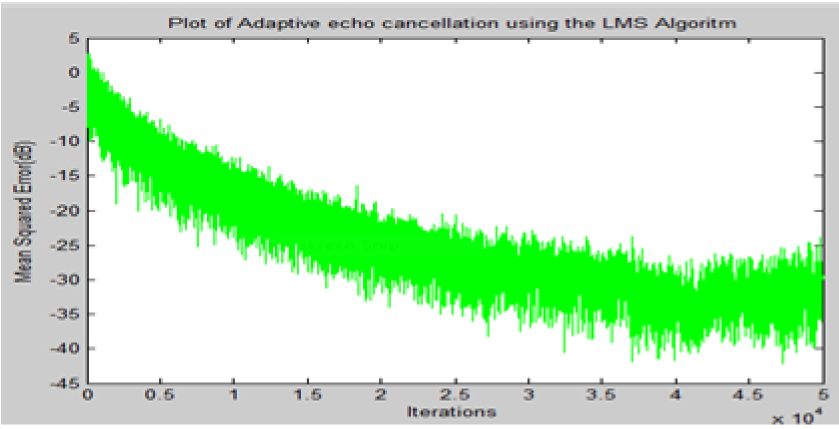

Fig 6:- The plot of MSE for LMS algorithm

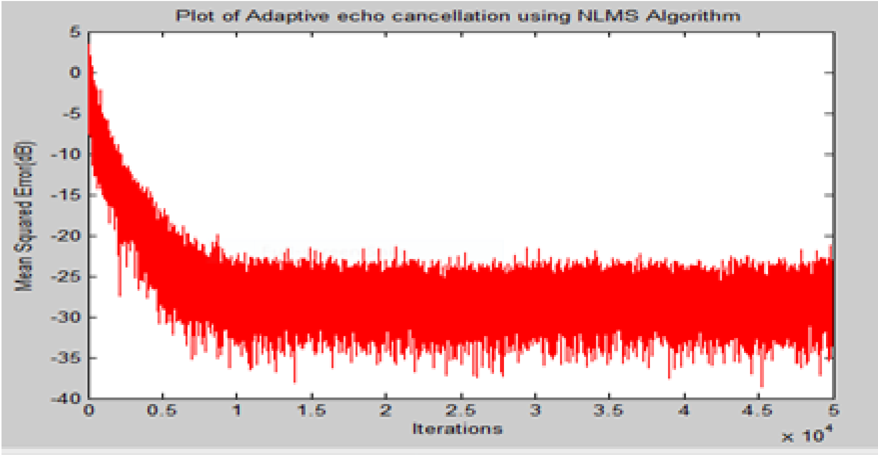

Fig 7:- The plot of MSE for NLMS algorithm

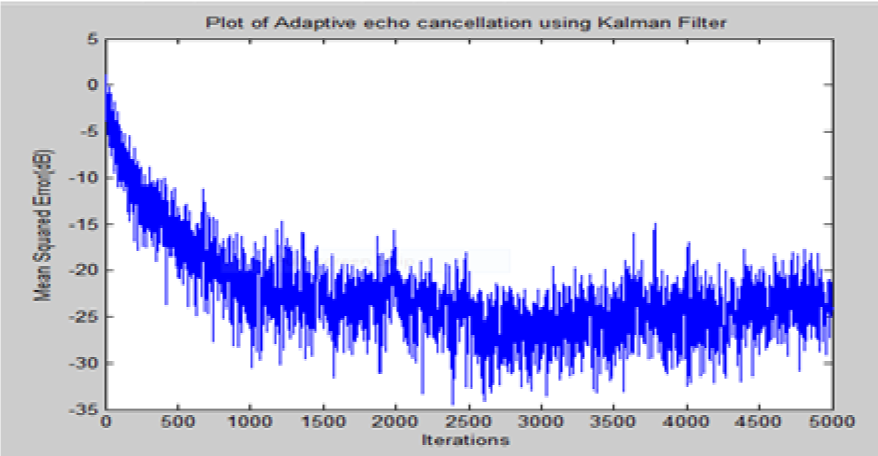

Fig 8:- Plot of MSE for Kalman filter

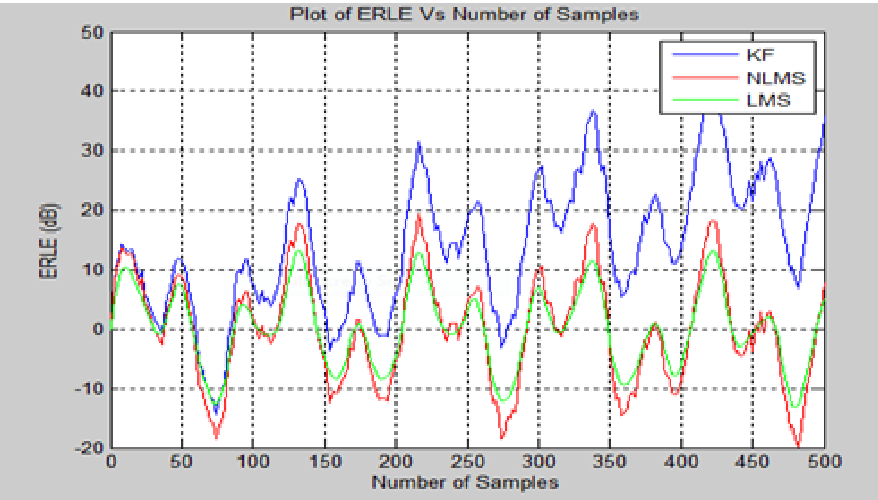

Fig 9:- The plot of ERLE for LMS, NLMS and Kalman filter

V. CONCLUSION AND RECOMMENDATION

This paper presents performance evaluations of LMS, NLMS and Kalman filter for acoustic echo cancellation in a non-stationary environment. The efficiency of each of the algorithms was studied, analyzed and simulated. The simulation results show that with increasing iterations, Kalman filter presents more precise estimate of the speech signal from the distorted signal in an iterative way. The Kalman filter performs with higher convergence rate, better echo signal attenuation and reduced error signal but it comes with more computational complexity unlike LMS algorithm with computational simplicity.

Adequate filter structure selection and parameter adjustment become a challenging task when a prior knowledge about the filtering scenario is imprecise or limited and this can lead to inadequate performance of the filter. A powerful approach to address this challenge, is to rely on combinations of adaptive filter structures.

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