ANNHBPAAs Based Noise Cancellation Employing Adaptive Digital Filters for Mobile Applications

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Abstract The persistent improvement of the hybrid adaptive algorithms and the swift growth of signal processing chip enhanced the performance of signal processing technique exalted mobile transceiver systems. The proposed artificial neural network hybrid back propagation adaptive algorithm for mobile applications used for noise cancellation. Adaptive noise cancellation using ANN has been implemented on audio speech signal is a new and intelligent method for real-time noise cancellation based on neural networks. Networks of this kind are quite often used for error cancellation, speech signal processing and control systems. The proposed hybrid algorithm consists all the significant features of gradient adaptive lattice and least mean square algorithms. The performance analysis of the method is performed by considering convergence complexity and bit error rate parameters along with performance analyzed with varying some parameters such as number of filter coefficients, step size, number of samples along with input noise level. The outcomes suggest the errors are reduced significantly for the number of epochs are increased. Also, incorporation of less hidden layers resulted in negligible computational delay along with effective utilization of memory. All the results have been obtained using hardware implementation and computer simulations built on MATLAB platform.

Keywords Adaptive filter · Noise cancellation · Convergence complexity · Bit error rate · Adaptive noise cancellation

Introduction

In wired or wireless communication systems, noise cancellation has become a prime concern and considered an open research problem in current era of mass communication of data all over the world. The mechanism and technologies are invented in recent past for noise cancellation from the noise-containing desired signal. The existence of noise in the desired signal may distort the received signal in random pattern, which may have several sources. From the researches of Qadri et al. [1] and Riahi Manesh et al. [2] found that some of the sources like (a) nonlinearity exist in RF frontend (b) existence of time-varying thermal noise exist at receiver end and (c) noise interference from adjacent environment. In addition, several other factors are affecting the received signal such as cross talk along with electromagnetic interference. For the past few decades, several denoising techniques are addressed in Qadri et al. [3], Tandra et al. [4] and Zeng et al. [5] and are divided as gradient-descent adaptive filter algorithm (AFA) and non-gradient AFA. The Gradient descent is a steepest descent which is a multivariate optimization approach and is initialized by assigning initial value for a negative gradient to achieve desired local minimum. Earlier various algorithms were provided to identify this desired signal. The LMS algorithm considered as significant with respect to need of computational efficiency and storage ability at low convergence speed. Also normalized LMS algorithm was considered at moderate speed of convergence in turn its response is sluggish for colored input signals.

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Further RLS algorithm was considered an effect with respect to high speed of convergence and tracking ability. However, RLS yields high computational cost. This paper aims to design an artificial neural network (ANN) based on hybrid back propagation algorithm to achieve better noise cancellation through adaptive control. Noise reduction ratio is the ratio of noise power to the error power.

**Related Work**

The prior section involves with the discussion of the most recent researches subjected with the mobile applications with different techniques adopted to offer better performance by considering BER, SNR, noise cancellation, interference cancellation, correlation, computational complexity as performance parameters. Recently the exponential growth of the mobile applications usage is creating huge traffic in wireless broadband technologies. In Alom and Li [6] comparative analysis of beam forming algorithm is performed with respect to correlation values at different angle of signal arrival by using back propagation algorithm. The work towards achieving accurate results for noise cancellation, echo cancellation and equalization is found in Kayode et al. [7] that implement the LMS based adaptive filtering technique for digital audio signals. The simulation result come up with accurate and desired input/output signal by noise signal removal.

Similarly, an experimentation work is observed in Mohammed [8] that adopt the adaptive noise cancellation for health monitoring applications. Here, adaptive filters and modified LMS algorithms were used to eliminate the interference and noise from the mobile phones, respectively. A work considering the mobile traffic issue is found in Yoon et al. [9] and have offered a multicast resource allocation scheme for 4G networks. The experimental analysis of is incorporated with the modulation and coding scheme by considering average PSNR as performance parameter with significant improvement than existing schemes. The implementation of error back propagation (EBP) is found in Roy and Rodrigues [10] for noise cancellation in the echo corrupted signal by building correlation with pure signal. Here, the voice/speech data are trained using ANN and analyzed performance with respect to SNR, echo tracking, error tracking, echo variance from the recovered pure signal. Most of the researches were incorporated with an aim of interference cancellation schemes for the mobile communication and are perform well under synchronous environment which are not handled with GMSK modulation schemes. The solution to this scenario is presented in Ruder et al. [11] with proper modifications in the conventional GSM systems toward the effects of asynchronous co-channel interferences and complexity. The outcome of the modified GSM system gives the robust results against such asynchronous interferences than unmodified GSM systems.

A significant research towards the hardware architectures proposed model designed using Xilinx platform using Verilog-HDL and simulated using ModelSim and implemented on Artix-7 FPGA device is observed in Vijaya et al. [12]. This approach has achieved area optimization as well as power optimization with high data rates. Towards the noise removal for real-time sinusoidal signals in healthcare applications. Kelly et al. [13] have offered an adaptive filter approach which tracks the sinusoidal frequency and achieved narrow bandwidth results. The experimentation was done with Electro-Cortico-Graphic (ECoG) neural data consisting of power line noise and outcomes with enhanced SNR. Similarly, Chilipi et al. [14] worked for distributed power generation system through adaptive filters for noise/harmonics cancellations to achieve power quality enhancement.

Further, Garcia et al. [15] used adaptive filter to have noise suppression for echo cancellation, channel equalization, array beam forming in surveillance, tracking and target localization applications. A review work on noise cancellation using adaptive filter based LMS algorithm is presented in Dixit and Nagaria [16] by considering computational complexity and convergence rate.

The similar direction of research is performed by Zheng et al. [17] and introduced the robust approach by utilizing the adaptive filtering algorithms for acoustic echo cancellations. The approach outcomes with performance improvement with respect to sparsity of impulse response as well as differentiable cost function.

Similarly, Zhang et al. [18] have come up with a robust solution for echo cancellation application by using LMS algorithms. The outcome of the simulation using Monte Carlo suggests that the proposed gives robustness in different environments.

There has been much research by Prasanna Kumar et al. [19] on active noise control (ANC) systems and presented simulated results for transaural sound reproduction systems.

With an intention to suppression of residual self-interference, Ahmed and Tsimenidis [20] have used adaptive mean squared error filter for iterative decoding/detective. Here, both the Rayleigh fading and AWGN channels were considered for modulation and its simulation outcomes high light the system performance with respect to BER, SNR as performance parameters. A novel implementation of adaptive filtering algorithm is found in Menguc for quaternion-valued least-mean kurtosis (QLMK) method.

This [21] method is significant with applicability for wide range of noise signals cancellation and improvement in convergence, steady-state error. On analyzing the
existing researches, it is observed that very rare works are incorporated with adaptive approach for noise cancellation. Among these, most of the works adaptive approaches are implemented only the LMS algorithms.

Most of the researches were used back propagation or feed forward propagation approach for noise cancellation and minimize noise error rate. This paper introduces an artificial neural network based adaptive approach which incorporates hybrid back propagation for noise cancellation by using different algorithms like LMS, gradient adaptive algorithm and hybrid adaptive algorithm. The proposed adaptive filter-based noise cancellation system (AFNCS) considers the convergence error and computational complexity for performance analysis.

**Proposed Solutions**

In voice communication systems, noise cancellation using adaptive digital filter is a renowned technique for extracting desired speech signal by eliminating noise from the speech signal corrupted by noise. For noise cancellation various gradient adaptive lattice (GAL) and LMS algorithms used. Recently, the hybrid adaptive algorithms with neural networks have gained popularity in cancelling the noise available in communication system. The working principle of the proposed intelligent adaptive filter-based noise cancellation system (AFNCS) is the continuation of prior work [22] which is further empirically designed and simulated to enhance the performance of the input synthetic signal with respect to noise cancellation. In this, a hybrid back propagation algorithm is introduced by which learning of multi-layer network is achieved. The noise analysis of the system is performed by using artificial neural network (ANN).

This intelligent hybrid back propagation algorithm involves both GAL and LMS algorithm. The prime objective of the proposed intelligent AFNCS is to acquire signal from reference signal and output noisy signal, among this signal noise is eliminated by subtracting the reference signal and noisy signal with original signal. The use of AFNCS can significantly restore the original signal by eliminating the noise by using adaptive control and adjustment of weights through ANN. The following Fig. 1, indicates the block representation of the AFNCS which intakes the input signal “i(t)” and generates signal at output “O(t)” by using adaptive system and reference signal “R(t)”. Finally, the signal with error e(t) is computed by finding the difference among reference signal and output signal as given in (1).

\[ e(t) = R(t) - O(t) \]  

where ‘t’ represents number of iterations.

The adoption of hybrid algorithm considers this error signal e(t) to generate a function for execution. This function performs the computation of desired filter coefficients. The minimized error rate indicates that output signal is same similar as that of original signal. Here back propagation algorithms are used to evaluate the error rate of each neuron. The following Fig. 2 highlights the structural model of back propagation layer diagram of ANN network. The layer diagram of ANN network is made up of three layers comprising input layer, hidden layer, and output layer. The hidden layer is existing in between input and output layer which couples both the layers. The overall back propagation network is affected by one neuron error. The network allows audio or speech signal to propagate via ANN and provides output signal. As given in Eq. (1), the error results of the output layer are computed and this error is forwarded back to input layer through hidden layer until the desired output is obtained.
Further, to minimize its error signal, adjustment of weight is performed for each neurons. The proposed hybrid algorithm combines both the back propagation algorithm of LMS and GAL which helps to tackle slow convergence.

The proposed AFNCS shown in Fig. 1 adopts adaptive filtering for implementation of ANN and also adopts a control system for adjustment of adaptive filtering parameters. The elements connection is trained with ANN by weight adjustment. The output of ANN can be obtained by using below formula as given in (2).

The following Table 1, indicates the parameters used in design.

Table 1 Parameters used in intelligent AFNCS system

| Parameter | Description |
|-----------|-------------|
| \(i(t)\)  | Signal applied at input |
| \(R(t)\)  | Reference signal |
| \(O(t)\)  | Signal obtained at output |
| \(e(t)\)  | Error signal |
| \(Wg\)    | Weight |
| \(Nr\)    | Neurons |
| \(Bps\)   | Baseband signals |
| \(Th\)    | Threshold (0–1) |
| ANN\(_{out}\) | Output of ANN |

ANN\(_{out}\) = \(\sum i(t) \times Wg\)  \(\ldots (2)\)

Each of the input are accompanied by a weight.

If, \(\sum Wg \geq Th\)

then the output of ANN will be 1 given in \(\ldots (3)\)

ANN\(_{out}\) = 1

However, if \(\sum Wg < Th\), then the output of ANN will be 0, as given in \(\ldots (4)\)

ANN\(_{out}\) = 0

To get the desired output signal ANN needs to be adjusted for the weights with respect to input samples. The formation of the ANN system shown in Fig. 2 is done by considering three layers such as the output layer, hidden layer, and the input layer. The audio signal is fed to the input layers having neurons. The hidden layer features in minimizing the reducing the error rate to achieve the respective output. The output layer does the competition of neuron nodes based on the requirement of output.

In the proposed ANFCS implements the LMS mechanism to compute the instantaneous value of the gradient vector. Then, the minimization of the MSE is performed by varying the filter weights. For each iteration of the adaptive filter, the optimized Weiner solution is obtained which can be referenced with \(\ldots (5)\) where \(n, S, Ws(n), I(n)\) represent the time, step size, adaptive filter coefficient and input vector respectively.

\[
Ws(n + 1) = Ws(n) + (S \times e(n) \times I(n)) \ldots (5)
\]

In order to avoid the instability, output divergence and convergence time, the optimal value of \(S\) is selected. Further, to reduce the error, negative gradient functions are considered. Equations \(\ldots (6)\) and \(\ldots (7)\) gives the computation of \(e(n)\) and \(I(n)\) respectively.

\[
e(n) = R(n) - (Ws(n) \times I(n)) \ldots (6)
\]

\[
I(n) = [(i(n) \times i(n - 1) \ldots x(n - T) - (Ws(n) \times i(n + 1)^T)] \ldots (7)
\]

Then the LMS Algorithm can be described as

\[
O(n) = \sum_{i=0}^{M-1} Wi(n) \times i(n - i) \ldots (8)
\]

\[
e(n) = R(n) - O(n) \ldots (9)
\]

\[
WI(n + 1) = W_i(n) + (Sr(n)^* \times i(n - i)) \ldots (10)
\]

\[
O(n) = W_0(n)^* \times i(n) \ldots (11)
\]

where \(W(n) = [w(n) \times w_1(n) \ldots (W_{M-1}(n)^T\text{ is a coefficient vector.}

In the proposed method, the convergence rate of error signal increases with the value of \(S\). LMS mechanism is adopted in the proposed method because of its easier implementation, simple computational, dynamic usage of memory ability and is performed by adjusting filter coefficient for error minimization.

To evaluate the performance of the proposed adaptive noise cancellation algorithm by simulation, the proposed algorithm is implemented on the experimental board. As shown in Fig. 3, the experimental board includes one main board and one DA/AD data conversion card. The 14-bit D/A data conversion card is used to generate two signals. One signal is the communication signal which is mixed with SaS noise. Another signal is the SaS noise with variable time delay. Then, the two signals are processed by the proposed algorithm after 14-bit A/D conversion against noise.

Firstly, the time delay estimation performance and noise cancellation performance are evaluated in different mixed SNR environments, respectively. Secondly, the noise cancellation performance of proposed algorithm is evaluated when the time delay between the primary input and reference input is changing.
Experimental Method

In order to verify the viability of the proposed algorithm, adaptive noise cancellation system based is built on FPGA, which is shown in Fig. 4. The sinusoidal signal with 10 kHz frequency is generated by the signal generator and is amplified by the amplifier. Then the signal is transmitted by the loop antenna, whose diameter is 20 cm. The transmitted magnetic signal is received by a three-channel tunnelling magnetoresistance (TMR) sensor (TMR2305). The Y channel of TMR sensor is parallel to the axis of the loop antenna. The Y channel and X channel of TMR sensor are parallel to the horizontal plane. The Z channel of TMR sensor is vertical to the horizontal plane. The three channels are perpendicular to each other. After amplifiers, filters and 14-bit A/D converters, the received signals are processed by the FPGA. To generate the impulsive noise, a switched-mode power supply is used as the noise source. The comparison between original signal and filter output is made to show the noise cancellation performance of proposed algorithm.

Algorithm

In a numerical computing environment proposed AFNCS is modeled by means of soft computation-based algorithm design and implementation. The system specifications which are required to know the AFNCS algorithm performance includes a 64-bit operating system, an x 64-based processor supported with 4.00 GB installed memory (RAM), where the processor type is Intel® Core™ i-8250U, CPU@1.60 GHz, 1.80 GHz. The following algorithm exhibits the steps associated with AFNCS design goals to achieve cost-effective adaptive noise cancellation from a sinusoidal (speech signal).

Proposed AFNCS Algorithm

The above algorithm represents the computational steps associated with the proposed AFNCS which combines the strength and significant features of adaptive algorithms such GAL and LMS for the purpose of accomplishing multi-layer perceptron network. The proposed system incorporates a hybrid back propagation learning for the adaptive noise cancellation in mobile applications. The proposed hybrid algorithm consists of all the significant features of LMS and GAL algorithms. The above algorithm clearly shows that how incorporating ANN based adaptive learning AFNCS significantly reduces the error rate of an input speech signal from a soft-computing viewpoint. It also applies weight adjustment in ANN which influences lower convergence performance with less iterative steps driven by non-recursive functions. The algorithm is designed simulated in a numeral computing platform, and the performance of the proposed AFNCS has been justified with respect to two different parameters such as processing time(s) and bit error rate (BER) from both complexity and signal quality viewpoint.

Results

Table 2 is about the experimental outcome attained subsequently simulating the projected AFNCS in a numerical computing environment.

A closer glance into the above Table 2 indicates that the suggested AFNCS accomplishes better outcome as it yields very less output signal error as compared to the predictable baselines. It is also observed that incorporation of less hidden layers resulted in negligible computational delay along with effective utilization of memory. Along with performance evaluation of adaptive noise elimination employing NLMS algorithm is carried out. The operation is analyzed by changing some factors like number of filter coefficients, input noise level, step size and number of
samples. All the results attained using computer simulations built on MATLAB platform.

It is also closely observed during the numerical computation that, number of hidden layers which having a relationship with computational delay. As the number of hidden layer increases delay will increase. i.e., less the amount of hidden layer less will be computational overhead, which will result in the faster response. It will also lead to the effective utilization of system memory. The following Comparison Table 2 shows a comparative performance analysis where the outcome of SNR from simulating the proposed AFNCS has been compared with RLS, FTF and GAL algorithms with respect to error [1].

| At 30 dB       | RLS [1] | FTF [1] | GAL [1] | AFNCS  |
|----------------|---------|---------|---------|--------|
| Chirp          | 13.9296 | 12.0000 | 14.0000 | 9.7591 |
| Sinusoidal     | 14.5297 | 14.9000 | 13.4000 | 7.8592 |
| Saw tooth      | 12.7979 | 12.8500 | 12.1000 | 7.5173 |
| Audio          | 13.0794 | 13.7000 | 12.8000 | 8.2704 |

| At 10 dB       | RLS     | FTF     | GAL     | AFNCS  |
|----------------|---------|---------|---------|--------|
| Chirp          | 24.7287 | 24.9000 | 24.7000 | 8.3550 |
| Sinusoidal     | 14.5130 | 14.6000 | 14.4000 | 7.7007 |
| Saw tooth      | 12.7880 | 12.8000 | 12.7000 | 7.5087 |
| Audio          | 25.5130 | 25.6000 | 25.5000 | 9.3365 |

| At −10 dB      | RLS     | FTF     | GAL     | AFNCS  |
|----------------|---------|---------|---------|--------|
| Chirp          | 68.7400 | 68.8000 | 68.7000 | 19.3497|
| Sinusoidal     | 72.7454 | 72.8000 | 72.7000 | 12.4497|
| Saw tooth      | 71.4740 | 71.5000 | 71.4000 | 20.4481|
| Audio          | 46.6549 | 46.7000 | 46.6000 | 10.0652|

Effects of Number of Filter Coefficients

Nineteen observations are shown in Table 5 [23] to evaluate the variations of the system performance with the number of filter coefficients. The system performance is measured by calculating noise reduction ratio (in dB).

Effects of Step Size

The impact of step size (adaptive algorithm parameter) on the performance of the system are evaluated. The step size is increased from 0.01 to 0.2 and the system performance corresponding to respective step size is measured in terms of noise reduction ratio (NRR). The simulation parameters and the results obtained for 20,000 samples are tabulated in Table 5. [23]. A graphical depiction of tabular data is shown in Fig. 10. It is observed from tabulated values in Table 6. Fig. 9 shows that that above a particular value of step size (0.03), the NRR gradually declines with increasing step size. Below that value, NRR gradually increases with the rise in step size. The optimum step size (at which the best noise reduction is seen) is 0.03 for the given simulation parameters.
Table 3. Six neurons hidden layer, 10,000 iterations

| Signal type | Actual | Predicted | Error | Actual GAL | Predicted | Error | Hybrid algorithm | Predicted | Error |
|-------------|--------|-----------|-------|------------|-----------|-------|------------------|-----------|-------|
| Chirp       | 0.8401 | 0.8591    | 0.0190| 0.9218     | 0.9361    | 0.0143| 0.8657          | 0.0156    |
| Sinusoidal  | 0.9464 | 0.9663    | 0.0199| 0.9403     | 0.9403    | —     | 0.9270          | — 0.0189  |
| Saw Tooth   | 0.8935 | 0.8796    | — 0.0139 | 0.8591    | 0.9021    | — 0.0430| 0.8909          | 0.9473    | 0.0564 |
| Audio       | 0.9798 | 0.9711    | 0.0087| 0.9663     | 0.9989    | — 0.0326| 0.9988          | 0.9473    | — 0.0564|

Total Error: 0.0337

Fig. 5 Comparison of LMS, GAL, and hybrid algorithm correlation coefficient for 10,000 iterations

Table 4. Comparison of convergence time

|            | LMS [22] | GAL [22]  | ANNHBPA |
|------------|----------|-----------|---------|
| Chirp      | 0.0127   | — 0.5759  | 0.0005  |
| Sinusoidal | 0.5801   | 0.0000    | — 0.0006|
| Saw Tooth  | 0.5801   | 0.0000    | 0.0000  |

Fig. 6 Comparison of convergence time

Fig. 7 Evaluation of BER computation after assessing AFNCS
This paper introduces an intelligent adaptive filter-based noise cancellation system (AFNCS) by using LMS and GAL algorithms. The AFNCS is modelled in the numerical computing environment by means of soft computation-based algorithm design and implementation. The performance of the proposed AFNCS is performed by considering convergence complexity and bit error rate (BER) as a performance parameter. From the analysis of the outcomes, it is found that the errors are reduced significantly when the number of epochs is increased. From computational numerical data, it is found that as the number of the hidden layers increases the delay will increase and have a faster response the number of hidden layers should be less. The performance analysis of AFNCS considers (chirp, sinusoidal, saw tooth and audio) signals at an SNR value of 30, 10 and −10 db and are compared with Ferdouse et al. [23]. From the comparative analysis it is found that the AFNCS has achieved better results than Ferdouse et al. [23]. Adaptation capability of the system to any input noise situation as well as the impacts of step size, number of filter coefficients, number of samples and input noise level on the performance of the system are thoroughly studied considering a speech signal as useful signal. Our future work includes making a comparison of the performance of adaptive noise cancelling system employing ANNHBPA with RLS (recursive least square) and LMS (least mean square) algorithms through computer simulations and then

Fig. 9 Noise reduction ratio versus filter coefficient

Table 5 Effects of number of filter coefficients [23]

| Simulation parameters                                      |            |
|-----------------------------------------------------------|------------|
| Total number of samples: 20,000                           |            |
| Noise power: −16.8004 dB                                  |            |
| Step size: 0.15                                           |            |
| Frequency range of colored noise: 1200–2000 Hz            |            |

| Number of filter coefficients | Noise reduction ratio (in dB) |
|------------------------------|------------------------------|
| 3                            | 27.0656                      |
| 4                            | 28.7159                      |
| 5                            | 28.9636                      |
| 6                            | 29.1950                      |
| 7                            | 29.9992                      |
| 10                           | 29.1705                      |
| 12                           | 29.4239                      |
| 14                           | 29.1195                      |
| 16                           | 29.4878                      |
| 18                           | 28.6723                      |

Fig. 10 Variations of noise reduction ratio with step sizes

Table 6 Effects of step size [23]

| Simulation parameters                                      |            |
|-----------------------------------------------------------|------------|
| Total number of samples: 15,000                           |            |
| Noise power: −16.8004 dB                                  |            |
| No. of filter coefficients: 32                           |            |
| Frequency range of colored noise: 1200–2000 Hz            |            |

| Step size | Noise reduction ratio (in dB) |
|-----------|------------------------------|
| 0.01      | 26.2926                      |
| 0.02      | 26.6716                      |
| 0.03      | 27.1593                      |
| 0.04      | 26.9859                      |
| 0.05      | 26.0503                      |
| 0.06      | 25.4877                      |
| 0.07      | 24.9614                      |
| 0.08      | 24.8289                      |
| 0.09      | 23.4080                      |

Conclusion

This paper introduces an intelligent adaptive filter-based noise cancellation system (AFNCS) by using LMS and GAL algorithms. The AFNCS is modelled in the numerical computing environment by means of soft computation-based algorithm design and implementation. The performance of the proposed AFNCS is performed by considering convergence complexity and bit error rate (BER) as a performance parameter. From the analysis of the outcomes, it is found that the errors are reduced significantly when the number of epochs is increased. From computational numerical data, it is found that as the number of the hidden layers increases the delay will increase and have a faster response the number of hidden layers should be less. The performance analysis of AFNCS considers (chirp, sinusoidal, saw tooth and audio) signals at an SNR value of 30, 10 and −10 db and are compared with Ferdouse et al. [23]. From the comparative analysis it is found that the AFNCS has achieved better results than Ferdouse et al. [23]. Adaptation capability of the system to any input noise situation as well as the impacts of step size, number of filter coefficients, number of samples and input noise level on the performance of the system are thoroughly studied considering a speech signal as useful signal. Our future work includes making a comparison of the performance of adaptive noise cancelling system employing ANNHBPA with RLS (recursive least square) and LMS (least mean square) algorithms through computer simulations and then
double check the obtained results by performing the real-time experiments using DSP hardware.

The merit of ANNHBPA algorithms lies in its reduced computational complexity and fast convergence rate as compared to other available solutions. It is evident that individually each of these parameters has an optimum value at which the adaptive noise canceller showed best performance. AFNCS accomplishes very less output signal error as compared to the conventional baselines. Also, incorporation of less hidden layers resulted in negligible computational delay along with effective utilization of memory.

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