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## **Review: Noise Reduction Techniques for Enhancing Speech**

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#### Abstract

Speech is a signal produced by humans to interact and communicate. Different information is gained from speech signals, such as the language being spoken, emotion, gender, speaker identification, and other information. Speech signals are exposed to different noises, which can be generated at the beginning of the speech or during the transmission. Due to this problem, noise reduction processes are an interesting field in different communication application systems that cultivate the intelligibility and quality of speech signals. It refers to removing or reducing the background noise in order to obtain an improved quality of the original speech signal without distorting the original (clean) signal. This paper reviews the state-of-the-art research, reviewing different speech enhancement filters and algorithms and comparing their performance to reach a conclusion about which is the best filter or the most effective one based on the kind of noise that was used and the most difficult noise to remove from the signal.

Keywords: Adaptive filtering, Kalman filter, spectral subtraction, wavelet denoising, wiener filter.

مراجعة: تقنيات تحسين الكلام

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#### الخلاصة

الكلام هو إشارة تنتج من الإنسان للتفاعل والتواصل. يتم الحصول على معلومات مختلفة من إشارات الكلام ، مثل اللغة التي يتم التحدث بها والعاطفة والجنس وتحديد المتحدث وغير ذلك من المعلومات. تعرضت إشارات الكلام في الماضي إلى ضوضاء مختلفة يمكن أن تتولد من بداية الكلام أو أثناء الإرسال. بسبب هذه المشكلة ، تعد عمليات الحد من الضوضاء مجالًا مثيرًا للاهتمام في أنظمة تطبيقات الاتصالات المختلفة التي تزرع وضوح وجودة إشارة الكلام. يشير إلى إزالة ضوضاء الخلفية أو نقليلها من أجل الحصول على جودة محسنة لإشارة الكلام الأصلية دون تشويه الإشارة الأصلية (النظيفة). يستعرض هذا البحث أحدث الأبحاث ، حيث يقوم بمراجعة مرشحات وخوارزميات تحسين الكلام المختلفة ، ومقارنة أدائها للوصول إلى استنتاج حول أفضل مرشح أو الأكثر فعالية بناء على نوع الضوضاء التي تم استعمالها وأصعب ضوضاء لإزالتها من الإشارة.

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#### 1. Introduction

Speech is a type of communication used to convey ideas. The mechanism for generating the human voice can be subdivided into three parts, such as those presented in Fig. 1. The lungs, the vocal folds within the larynx (voice box), and the articulators. The vocal tract of a human person is used to produce a variety of sounds, including talking, singing, laughing, sobbing, screaming, shouting, humming, and yelling since the voice can be affected by emotion [1]. The vocal folds (vocal cords), which are the main sound source in human sound production, are a special portion of the human voice frequency [2], where the articulators in the mouth and nose, which are responsible for articulation, will influence the airflow in the lungs [3],

The audible frequency range for human beings is from 20 Hz to 20 KHz. Audio signal processing often suffers from noise.



Figure 1: Human speech production [4]

Nowadays, humans are able to interact with computer hardware and others in many aspects of life. Speech processing is widely used in numerous applications, such as teleconferencing systems, speech coding for communications, speech recognition, mobile speech communication, biomedical signal processing, hearing aids, ATM machines, and others. Such applications exist in areas where there is interfering background noise, such as a motor vehicle passing [5]. These interference noises degrade the quality of the original speech in such a way that it does not remain clear anymore.

Noise reduction is a hot research area in signal processing and remains a challenging issue because, in most cases, only noisy speech is available [6].

The most common type of noise that causes the degradation of speech's quality and intelligibility is background noise, which can be stationary or non-stationary and is assumed to be uncorrelated and additive to the speech signal [7].

Due to the varying characteristics of noise over time, it is hard to enhance speech in a noisy environment. Till now, removing noise from noisy speech has been a grueling issue because spectral parcels of non-stationary noise are veritably delicate to estimate and prognosticate. Noise calculation is a serious issue when noise power is greater than speech power because speech content may be removed when treating it as noise. This survey covers all the work that was implemented. It will be useful to add the statistical and mathematical approaches implemented in noise reduction.

In this paper, we will examine the studies done by other researchers on noise reduction in speech signals and help other researchers make decisions about which filter or method will be used in their work to get the best noise reduction and the fittest filter based on the type of noise.

This paper is structured as follows: The problem is introduced, and a general overview is provided in the introduction in Section 1. Some of the related work of other researchers is explained to the reader, and different researchers' work in different years is compared in the related work and state-of-the-art work in Section 2. A brief definition of noise in our lives is in Section 3. We discuss the most familiar and fundamental strategies for noise reduction in Section 4. Then, in Section 5, the types of filters for noise reduction are classified. Discuss the approaches and filters of other researchers in Section 6, and Section 7 will offer a conclusion.

#### 2. Related Work and State of Art Works

Noise reduction is an attractive field for researchers to explore. Since 1960 until now, many researchers have conducted research and improved noise reduction techniques.

In 2014, the authors proposed [8] (Noise Cancellation in Speech Signal Processing: A Review). They categorize existing noise cancellation schemes and thoroughly investigate various suggestions in each category in order to demonstrate the limitations of existing techniques as well as their effective contributions. Several techniques for filtering noise from a speech waveform have been investigated. They found that the recursive least squares (RLS) algorithm produces the maximum SNR and outperforms the least mean square (LMS) for the lower-order FIR adaptive filter. But for the finite impulse response (FIR) filter Taps, LMS converges more quickly than RLS. By establishing the FIR tap weight, the ideal Mu (LMS) and Lambda (RLS) values have been discovered. Cancellation of acoustic noise: the best method for reducing background noise is adaptive noise cancellation (ANC). The performance of conventional wideband ANC algorithms rapidly declines as the noise's bandwidth and center frequency rise, but they perform better in lower frequency bands.

The authors in 2014 proposed [9] (A Survey on Statistical Based Single Channel Speech Enhancement Techniques). They contrast various estimators (classical and Bayesian estimators). They compare various estimators. The difficulties and possibilities of improving speech are also covered, which facilitates selecting the most effective statistically-based speech enhancement strategy. Techniques based on statistics are described, along with their advantages and disadvantages. It is explained how classical and Bayesian estimators compare. In this work, the fixed window technique's drawbacks are examined. The study of single-channel speech augmentation approaches includes significant and important distinctions between causal and non-causal estimators.

In 2018, the authors proposed [10] (A Review on Various Speech Enhancement Techniques). They reviewed various speech enhancement techniques. They mainly focused on noise removal in speech signals and discussed various single- and multi-sensor speech augmentation techniques. Since it is impossible to totally avoid noise, the authors concentrate on reduction using a variety of criteria. Noise cancellation and echo suppression are also crucial components of speech enhancement. Because the Kalman filter is recursive, it is one of the most effective ways to enhance a signal.

In 2018, authors proposed [11] (A Survey on Techniques for Enhancing Speech). They discuss many such techniques, including the benefits and drawbacks of each. Review the study on alternative machine learning methods, including neural networks, deep networks, convolutional networks, and optimization methods used to improve speech, that was done by other researchers. And neural networks have proven to be the most effective technique. Following simple NN, deep neural networks (DNN) followed, which produced better results but had poor real-world generalization when it came across noise and speech signals that hadn't been visible to it during the training phase. Then came the era of the Convolutional Neural Network (CNN), which has now established itself as a trustworthy instrument for extrapolating real-world noise cancellation issues. During the training phase, it is capable of handling all types of noise signals, whether they are visible to it or not. The effectiveness of neural networks has been demonstrated.

And the authors, in 2022, proposed [12] (Review Paper on Noise Cancellation using Adaptive Filters). The most crucial technique is adaptive noise cancellation (ANC). ANC employs adaptive filters to assess continuously changing real-time data. Numerous algorithms are used in ANC in order to cancel out the noise. The Least Mean Square (LMS) algorithm was the author's main focus. To find the available literature on adaptive filtering in noise reduction using the LMS adaptive algorithm, a thorough review has been conducted. LMS is easy to implement, has a low level of computing complexity, and has a higher rate of a noise cancellation problem.

Table 1 illustrates the state-of-the-art work related to noise reduction techniques published from 1976 until now.

Ref.	Year	Filter Approach	Type of noise	Conclusion	Performance measurement units
[13]	1976	Adaptive Filter Time— Variant digital comb filter	Speakers , Backgro und noise	The authors show how the adaptive system can respond to the test input signal. To demonstrate the degree of intended speaker distortion produced by the systems in this scenario, the filtering system is set up to function as an identity system.	-
[14]	1979	Spectral subtraction , modified spectral subtraction	Broadba nd noise	To sum up, he subtracts an overestimate of the noise spectrum and keeps the resulting spectral components from falling below a spectral floor, which is the key distinction between their implementation and the classic spectral subtraction approach. Their application of the spectral noise removal method allows for a significant reduction in background noise with little impact on speech comprehension.	According to tests, the intelligibility of the improved speech is equal to that of the unprocessed signal at SNR = +5 dB. The enhancement procedure did not result in any loss of understanding.
[15]	1982	Nonlinear multiband envelope filtering, Logarithmi c filtering log—lin filtering	Stationar y white noise	When power signals are not linear It was discovered that preprocessing before adding noise improved significantly when filters with a logarithmic or combination log/lin characteristic and high slow level variation compression were used. Better preprocessing for hearing loss due to sensorineural impairment may result from this as well.	signals (including noise) had their intelligibility assessed and compared, the latter using two different FIR filters: one without expansion (0.05 at 0 Hz, +5 db from 2 to 16 Hz, 1 at > 18 Hz) and one with it (0.05 at 0 Hz, +5 db from 2 to 16 Hz, 1 at > 18 Hz). The results were intelligence scores of 64.5, 87.2, and 95.5, respectively.

**Table 1** State-of-the-art noise reduction publications

[16]	1999	Approach is based on the introductio n of an auditory model in a subtractive -type enhanceme nt process, Power spectral subtraction , modified spectral subtraction	White Gaussian noise, Car noise, Speechli ke noise (long term average Speech spectrum ), Aircraft cockpit, Helicopt er cockpit, Factory	<ul> <li>Background noise is minimized, and residual noise is less organized than with traditional approaches, yet speech distortion remains acceptable. The following are the proposed algorithm's primary benefits: <ol> <li>It is efficient in terms of computing.</li> </ol> </li> <li>A criterion that is much more correlated with speech perception than the SNR is used to alter the subtraction parameters.</li> <li>It provides the option to alter the trade-off between speech distortion, residual noise, and noise reduction.</li> </ul>	N oi sy ty pe 6 db 9 db	py N si S N R 0 d b 0 d b	ioisy ignal S 3 6 2 6	sed alg AI 0.1 7 0.2 1	gorithi Enhar d sign 6.5 db 7.7 db	m nce hal I S 2 2 1 6	A I 0. 3 8 0. 4 1
[17]	2003	Adaptive and Non- adaptive filtering techniques: Beamformi ng, Adaptive noise cancellatio n (ANC), Spectral modificatio n	White Gaussian noise, Direction al noise condition , Stationar y noise	reduction since the noise is stationary. While the NLMS algorithm converges more quickly, the LMS approach takes longer. Both the LMS and NLMS algorithms are outperformed by the RLS algorithm. Spectral modification techniques like spectral subtraction and Wiener filtering are more frequently used to accomplish noise reduction. For comparison, the performance of the ideal Wiener filter is also provided. As can be seen, for most frequencies, the parametric Wiener filter eliminates noise more effectively than the ideal Wiener filter. Compared to a beamformer or an ANC technique, spectral modification can decrease noise more effectively overall.				-			
[18]	2007	Minimum- Mean- Square- Error (MMSE)	White Gaussian Noise (WGN), M109 tank noise, F16 cockpit noise	Results indicate that the proposed algorithm yields better performance than several recently proposed methods.	Me Lap Gar	ethod MMS nMM E	Is SE IS	Ga 5 SNR ) 15.17 14.89	ussian noise (db 721 932	n whi (dB) 10 SNR ) 13.1 12.2	te 0 8(db 893 724
[19]	2010	Adaptive Filter Algorithms : (LMS), (NLMS), (RLS), APA, FEDS, FAPA	Office noise	Compared to the LMS algorithm, the NLMS and AP algorithms converge faster. Both the learning curve and the filtered output make this reality clear. The results show that the convergence rates of the FEDS and FAP algorithms are equivalent to those of the RLS method and are quicker than those of the LMS, NLMS, and AP algorithms. They also show that, compared to the LMS, NLMS, and AP algorithms, the RLS technique converges more quickly. The results show that the FEDS and FAP are on par with the RLS algorithm in terms of performance and exceed the LMS, NLMS, and AP algorithms.		Compa LM NLM AP FEI FAI RL	ariso al <b>ithm</b> IS MS A DS PA S	n of ac lgorith	laptiv ms <b>SNI</b> 13 16 20 22 24 29	e filte <b>EI (dl</b> .5905 .8679 .0307 .2623 .9078 .7355	er ))

[20]	2011	Novel algorithm	White, Pink, Buccane er2, Destroye r engine, Factory noise, Destroye rs noise	The the prov estim app sim
[21]	2012	Perceptual distortion measure. Speech Pre- Processing Algorithm	White, Babble, Factory, F16	Fo ta re: decre t intel
[22]	2014	Adaptive Wiener filtering, Spectral subtraction , Traditional frequency- domain Wiener Filtering method, Wavelet.	Additive White Gaussian Noise (AWGN) as well as colored noise.	Th color m reco (A' su enha b p AW a a imj sugg the a
[23]	2014	Wiener Filter, Adaptive Filter (LMS)	Real time noise, Mixed noise	The c is th s co comp rise mean show appro cost t is th
[24]	2015	LMS, RLS, ANC, FIR - LMS, lattice gradient algorithms	White noise, pink noise, blue noise	Acc produ the ada Impu conv tap w La cano ambi algori (LMS bac dE mal

The reverberation effect characteristic of
the DD approach is diminished by the
provided technique since it enhances the
estimate of the a priori SNR using the DD
approach and has the capacity to follow
changes in the speech signal. The
simulation findings support the analysis
presented above.
For all types of noise, the suggested

all types of noise, the sugge echnique performs better than the ference methods. The SNR may be eased by 3-5 dBs using the suggested technique, according to objective ligibility prediction findings, without sacrificing intelligibility. e simulation results show that both ed and additive white Gaussian noise ay be filtered effectively using the mmended Wiener filtering approach WGN). The outcomes show that the aggested adaptive Wiener filtering approach beats all other speech ncement methods currently in use for oth low and high SNR levels. The roposed filter successfully handles GN and colored noise situations. The daptive characteristics of the filter pulse response account for this. The gested adaptive Wiener filter also has advantage of only requiring the noisy signal as a single input. oldest technique for noise cancellation he Wiener filter; however, it is rather ophisticated. In order to decrease mplexity and computational speed, daptive filters are introduced. The lexity and stability of the systems will e as the authors attempt to lower the n square error. The simulation results *w* that the LMS algorithm is the most opriate due to its simplicity and lower than the Wiener filter. Although LMS e best algorithm, it has a slow rate of convergence. ording to studies, the RLS algorithm ices the highest SNR and outperforms LMS algorithm for lower-order FIR ptive filters. However, for the Finite alse Response (FIR) filter Taps, LMS erges faster than RLS. Fixing the FIR reight yielded the best Mu (LMS) and mbda (RLS) values. Acoustic noise cellation (ANC) is best for removing ent noise. Traditional wideband ANC ithms perform best in lower frequency bands and degrade rapidly as the ndwidth and center frequency of the se increase. The least mean squares S) and lattice gradient (LG) techniques have been demonstrated to lower kground noise strength by at least 20

ackground noise strength by at least 20 dB with little to no speech stuttering, naking them potentially effective noise suppression pre-processors for voice communication in loud environments.

Noise type	Input SNR	Segmental SNR (dB)
		proposed algorithm
White	0 dB	4.9109
	5 dB	6.7544
	10 dB	9.1751

	STOI
SNR	White noise
0	>90
5	100

Results	for	SNR = 5	dB	for	the
		AWON			

Signals	Metric	Adaptive Wiener filtering
Male	SNR	6.8726
	SNRseg	6.8423
Female	SNR	6.8373
	SNRseg	6.8021

Algo rith m	Sp ee d	Conv ergen ce rate	Com plexi ty	M S E
Wie	Lo	-	High	L
ner	W			0
filter				W
LMS	Hi	Low	Low	Hi
	gh			gh

Original	1
unsmoothed noise	
Smoothed white	0.1
noise	
Smoothed pink	0.55
noise	
Smoothed blue	0.01
noise	

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ctra

[7]	2016	Spectral subtraction & Wiener filter technique	White noise, Helicopt er, noise, Babble noise, Car noise	In spectral subtraction. The method is not efficient for corrupting speech with non- stationary noise such as car noise, babble noise, and helicopter noise.	se T y p e W hi te n oi se	<b>p</b> ut S N R (d B ) 0	1 Sub trac tion 11.8 2 13.0 9	<b>pro</b> ach 11. 7 13. 68	R M et ho d 12. 83 14. 35	N R an d H R N R 13 .4 0 45 .2 7
						5	14.7 6	16. 57	16. 26	17 .6 1
[25]	2016	Adaptive Wiener filter	Fan noise	The concept of an adaptive Wiener filter with TSNR and HRNR methods is used to enhance the noisy speech signal. Two-step noise reduction methods are used to enhance the speech signal. Then harmonic regenerated noise reduction is used to regenerate the harmonics that are lost from	me od	th s	Inp ut SN R (dB )	Out put SNR (dB)	Impr men SN (dl	rove t in R B)
		·		the original signal. Experimental results show that the SNR of the input signal is improved by using the TSNR and HRNR methods. The HRNR method gave the best SNR compared to TSNR.	TS R HR R	N N	0.6 49 0.6 49	1.10 9 1.35 97	0.4	46 71
[26]	2016	Deep Neural Networks (DNN)	Stationar y, Non- stationar y, Multiple noises	Results demonstrate the effectiveness of DNN-based voice augmentation techniques in these challenging settings that closely resemble real-world settings. Over all test SNRs, the best model provides an average PESQ increase of 23:97%. This value is about 30% at lower SNRs. In comparison to traditional approaches like log-MMSE, this is substantially better.	10 5 SNR (db)	2.53 2.11 PESO A No.	0.89 0.81 STOI 2.69 PESO 1.62 0.81 0.82 0.82 0.82 0.82 0.82 0.82 0.82 0.82	0.92 0.87 STOI Q S 3.14 2.75 PESO 8 p	STOI <b>C</b> <b>O</b> <b>O</b> <b>O</b> <b>O</b> <b>O</b> <b>O</b> <b>O</b> <b>O</b>	3.14 2.74 PESO =
[27]	2017	Windowin g Technique, windows used: Kaiser, Rectangle, Hamming, Hanning, Welch	power line noise muscle noise EMG noise	Among all the selected performance factors, Kaiser Windows had the best performance. Closely following this came the rectangle window, which similarly performed well across the board with the exception of SNR. Therefore, it can be inferred that Kaiser window has the best denoising performance, followed by rectangle window and, in some instances, Hamming window as well. Both Kaiser and rectangle windows performed adequately in eliminating power line noise from the ECG data.	1. the l and l rese M win 0. sui 2. ham valu	M owes Hami embla SE h rindo dows 069 a table ming ming ming S S S	SE: The t MSE ning w ance in igher th ws. Ha have h and 0.0 for go- den SNR: F windo denois B. Han s, too, h NR ind	e Kaiser of 0.047 indows perform nan that nning an nigh MS 71, whic od perfo oising. Caiser, ra ws have sed SNR ning an ave goo	windo '. Recta have a have a have a have a lance, v of Kais d Welc have r rmance ectangle the high ., i.e., a d Welc bd value thy a construction the high ., i.e., a d Welc bd value thy a construction thy a construction the high ., i.e., a d Welc bd value thy a construction thy a construction the high ., i.e., a d Welc , i.e., a d Welc , i.e., a d Welc	ow has angle close with ser ch es of tot e in e, and ghest bout h es of

[4]	2018	Different linear filtering techniques: LMS, NLMS, Kalman, Wiener	AWGN noise	It was discovered that the Kalman filter provides better results than other adaptive filters like LMS and NLMS. We have also discovered from the results that the performance of the Kalman filter is superior to that of the LMS, NLMS, and Wiener filters for AWGN noise, but performance varies for practical noise. In light of the investigation, it can be said that the Kalman filter performs the best among all of the filters for AWGN noise but not for real-world noise.	Sl         H           N         n           o.         Com           1         P           2         M           3         1           6	Para neter npariso av SNR MSE Max error	LM S ms of th wgn nc 56.2 380 0.15 46 2.16 50	NL MS           ne filter           ise           57.8           854           0.10           58           1.40           57	Kal man 69.6 564 0.00 17 1.35 63
[28]	2018	Wavelet filtering	Additive White Gaussian Noise (AWGN)	Based on wavelet analysis in speech signals, the use of wavelets from different families is compared, including nine- and tenth-order Daubechies wavelets, fourth- order Symlets, and fifth-order Coiflets. The value of the cross-correlation at point 0 for all types is of the order of 0.8, and the outcomes of noise suppression are sufficiently high.	The produ mutual po Daubec ninth o order of order	e wavel uced th correla int 0: 7 hies wa order is symle ler of c	let type the follo tion fu The ten avelets s 0.788 tts is 0. coiflets	es emplo wing ave nction v th order is 0.793 65. The 78883. T is 0.787 ferent sr	yed erage alues at of 82. The fourth The fifth 76.
[29]	2018	LPC based FEM in Wiener filter	Engine noise	<ul> <li>Inc experimental mutuage demonstrate that our suggested approach yields superior results while preserving all of the original voice signal's information. The observed values and results demonstrate that a formant enhancement approach based on linear predictive coding and Wiener filtering yields greater values of PESQ, SNR, NC, and PSNR. Higher PESQ, SNR, NC, and PSNR values indicate higher and enhanced output signal quality when compared to previous speech enhancement strategies</li> </ul>	Noise Wiene FEM	e 1 cer 3 c 1 c 1 c 1 c 1 c 1 c 1 c 1 c 1 c 1 c 1	nt meth IR, NC Dbjecti PES Q 1.80 3.54	since and provide the second s	ed on NR. 1ation PSN R (db) 55 99.18
[30]	2018	Kalman filtering	Non- stationar y noise, White noise, Babble noise, F16 noise, Factory noise	According to experimental findings, it is advantageous to track speech in the log bark power spectral domain while also accounting for the temporal dynamics of each bark subband envelope.	FEM LSA and pMMSE only yield a PE improvement of around 0.4; howeve the BSNT method achieves a PES improvement of 0.62. PESQ improvements for ST, SNT, and OMLSA are all around 0.5, while improvements for BST are about 0.55. In comparison to the LSA are pMMSE baselines, the PESQ improvement for the BSNT methoor greater at about 0.22, 0.12 for OMLSA, 0.1 for ST and SNT, and				a PESQ owever, a PESQ SQ 7, and while about SA and ESQ aethod is 2 for T, and
[31]	2019	Neural network methods 'ADALIN E'	Stationar y noise	The research concluded that the most effective denoising strategy for the majority of speech signals is the adaptive filter employing the LMS algorithm. ADALINE produces the greatest outcomes out of all the neural network techniques. In order to reduce error between network output and the targets, ADALINE employs the adaptive LMS algorithm. The fundamental performance difference between filtering and neural network denoising techniques, however, is that neural networks take longer to execute than filtering techniques. The most complicated technique is the deep learning denoising technique. Deep learning has a very long	Av g. SN R Av g. PS N R	Ada ptiv e Filte r 13.2 977 38.4 618	ADA LIN E 6.722 9 31.85 17	We           ine           r           filte           r           1.0           089           26.           130           9	Kal ma n Filt er - 0.46 6 24.6 559

				execution time, but the outcomes are unsatisfactory. Therefore, deep learning denoising techniques cannot be used for speech applications.					
[32]	2020	Electroenc ephalograp hy (EEG) signals using a Generative adversarial network (GAN) based model, Compare with traditional	Gaussian noise	Utilize cutting-edge deep learning models similar to the ideas of GAN, GRU, TCN regression, and EEG signal processing. This is the first instance where deep learning models have been used to show how to improve spoken pronunciation using EEG characteristics.	Log MMSE GRU Regressi TCN Regressi GRU-TC Reg.	I Con CN	Test         Set           Avg         PESQ           2.4         2.4           2.4         2.4	Enha           Out           A           PE           2           2           2           2	<b>inced</b> <b>put</b> <b>vg</b> <b>SQ</b> 48 59 48 52 52
[33]	2020	log (MMSE) Deep neural network (DNN)- augmented colored noise Kalman filter	Pink, Buccane er2, Destroye r engine, Hf channel, Babble, White, Street, Factory	The suggested method is better equipped to handle color noises seen in real-world settings. Experiments have demonstrated the suggested system's advantage in two areas. First, the enhanced performance of colored-noise Kalman filtering is significantly enhanced by the use of DNN for parameter estimation and post- subtraction for residual noise suppression. Second, because our suggested approach benefits from both supervised and unsupervised techniques, it is more generalizable. In fact, it gives much superior results on unseen noise, even though it achieves equivalent performance to contemporary DNN-based techniques on visible noise.	GAN Metho d Noisy FNN- MAG FNN- CKFS LSTM -CKFS	See PE 3d B 1.6 8 2.3 4 2.3 2 2.3 8	2.4 en noise SQ 6d B 1.8 6 2.5 5 2.5 1 2.5 8	2.: ST 3d B 0.7 8 0.8 6 0.8 5 0.8 5	50 OI 6d B 0.8 3 0.8 8 0.8 8 0.8 8 0.8 8 8
[34]	2020	Long short-term memory (LSTM) And (CNN)	Factory2, Buccane er1, Destroye r engine, HF channel	According to the experimental findings, the proposed time-frequency smoothing neural network greatly enhances the voice quality and understandability of improved speech and performs speech enhancement more effectively than previous networks.	Filter size PESQ STOI (%) Parame ters (M)	<b>5</b> 2.4 2 74. 83 0.6 4	<b>7</b> 2.4 5 75. 57 0.6 8	<b>9</b> 2.5 1 77. 05 0.7 2	<b>13</b> 2.5 1 77. 32 0.8

					SN R	Meth od	PES Q	ST OI	SN RI
				They proposed a brand-new, two-stage	10	CED -cSA-	2.96	0.9 5	23. 40
[35]	mask- based long short-term memory 2020 (LSTM), convolutio nal encoder- decoder (CED)		strategy for improving speaking. An LSTM network estimates T-F masks for both actual and fictitious portions of the noisy speech spectrum in the first stage, and a convolutional encoder-decoder (CED) network conducts spectral mapping in the		LST M- cMS A + DNN -cSA	3.03	0.9 5	25. 88	
		memory (LSTM), convolutio nal encoder- decoder (CED)	Office, Pub, Traffic noise.	ice, second stage. They notice a tremendous b, improvement of more than 5 dB in SNR ffic over the baselines, but little to no improvement in overall quality (PESQ). When using both stages, it is possible to achieve average PESQ gains of roughly 0.1 MOS points in undetected, highly non-		LST M- cMS A + CED -cSA- du	3.12	0.9 6	25. 11
				speech. In comparison to the baselines, our method also enhances STOI in low-SNR situations.			3.15	0.9 6	26. 06
					S. No ·	Nois e Typ e	Param eters	N L 5 d B	oise evel 10 dB
[26]	Modified 2021 LMS algorithm	Modified LMS	Airport, Babble, Restaura	This experiment showed that the proposed method did a better job than the LMS algorithm of improving the quality of the	1	AW	Noisy SNR De- noised	1. 17 0. 11	0.4 4 1.7 7
[00]		nt, AWGN	objective measures of dbsnr, LLR, and ISD.		GN	SNR dB SNR LLR	4. 99	8.1 0	
						-	ISD	21 76 .6	5 11 7.6
[37]	2021	Filter bank	Acoustic noise, Impulsiv e noise, Transient noise	While MFCC and other feature extraction algorithms aren't as good at ignoring noise when getting information, band-pass filtering gets the characteristics of the transmitted signal more accurately and with more reliability. In noisy situations, the voice signal may be accurately extracted using the filter bank analysis approach. The suggested method has demonstrated the ability to extract features from speech signal properties at a substantial pace. When the signal's detailed	Noise Fea Z Cro Pi Lou Cep P	Suppres tures ero ssing tch dness ostral eak	sion with Speecl Activit 0.54 0.41 0.71 0.84	n Filter n C y ( ( (	Bank. <b>ther</b> 0.75 0.69 0.31 0.79
			Babbling Cars	performance of the suggested system hasn't degraded much. To estimate clean speech from noisy speech, the implicit Wiener filter with a	Nois	Inp ut	LL R	CD	WS S
[38]	2021	Wiener filter	Street, Trains, Restaura nts,	recursive noise estimation algorithm is suggested and contrasted with the traditional spectral subtraction approach. Compared to spectral subtraction. the	Typ e	SN R (db		W F	2
			Airport noise.	results reveal that the envelop of the predicted noise using the implicit Wiener		5	0.9 33	5.5 84	75.0 49

[39]	2021	Recursive Least Squares (RLS) algorithms and Least Mean Square (LMS).	white, colored noises	<ul> <li>filter is pretty similar to the envelop of the noisy speech spectrum. The suggested approach produces an improved speech signal that is spectrally comparable to the clean speech signal and perceptually similar to the clean speech signal. While the voice distortion is still tolerable, the musical noise is less organized than the spectral subtraction.</li> <li>This technique reduces the noise levels in a specific signal and makes it simple to analyze the signal's properties. Without lowering the signal's quality, the voice signal's comprehensibility and quality are improved. In comparison to all other algorithms, the system now performs better. The MSE and SNR were computed. We concluded from the findings that the suggested strategy is successful in reducing noise. The suggested technique has successfully been applied in the real-time speech de-noising test, which shows a considerable improvement in speech intelligibility.</li> </ul>	
[40]	2021	Recursive EM (REM) algorithm and Kalman filter.	air- condition er (AC) noise, pseudo- diffused babble noise,	The three issues are all being addressed at once by the suggested statistical approach. Each STFT timeframe employs the E-step and M-step. The Kalman filter is used to implement the E-step. In the M-step, the model parameters are estimated. The echo signal at each channel is assessed using the estimated acoustic route of the far-end signal. The method has convergence capabilities even in time-varying double- talk circumstances. We demonstrate that our approach outperforms rival NLMS- based approaches in terms of speech quality, comprehension, and echo cancellation performance.	
[41]	2021	LBLG and NBLG	White noise and babble noise.	LBLE performed well in terms of speech component regeneration. On the other hand, the suggested SEA is a hybrid estimator made up of two stages in a cascade. It is based on a high-characteristic orthogonal transform that improves noisy signals. The suggested SEA's comparative assessment reveals its efficacy and ability to reduce noise in terms of LLR, SIG, OVL, BAK, PESG, and segSNR measures. Simulations of several noisy situations demonstrate that the proposed SEA suppresses unwanted noise more effectively than existing techniques.	() () () () () () () () () () () () () (
[42]	2021	(MMSE), linear bilateral Laplacian gain estimator (LBLG), and nonlinear,	White noise, F- 16 noise, speech shaped noise, pink noise.	In terms of several objective metrics, the suggested estimators outperformed existing approaches such as the standard MMSE approach, the perceptually driven Bayesian estimator, the dual-gain Wiener estimator, and the dual MMSE estimator. The suggested estimators' results demonstrate their usefulness and capability in decreasing unwanted noise in terms of	

Car	5	0.8	5.1 22	65.6 74
Airp	5	0.8	5.1	70.2
ort		22	95	6

	LS	SR	ST	_S
	D	MR	ΟΙ	ER
Propo	3.5	7.40	95.	23.
sed	4		57	16

The findings were presented in terms of SegSNR, PESQ, LLR, SIG, BAK, and OVL. The comparison values

presented are the averages of ten input signals. The suggested SEA (DKTT-Two stage) provided superior output signals compared to the DCT-NBLE, DCT-LBLE, and DCT-Two stage, yielding the best values. In the

instance of babble noise, the suggested SEA produces the greatest results across most testing parameters and settings. It can be shown that for LLR, PESQ, and OVL, the suggested SEA delivers a comparable result to the other estimators for specific levels of SNR only, but for all other levels of SNR, it provides the best results in most circumstances.

SNR results

SINK ICSUITS.								
Nois	SN	Propos	Propos					
у	R	ed	ed					
type	(db)	LBLG	NLBL					
			G					
Whit	5	4.86	5.17					
e								
F-16	5	4.75	4.71					
speec	5	4.39	4.41					

		bilateral Laplacian gain estimator (NBLG),		segSNR and PESQ measures. Furthermore, the suggested estimators outperform the competition since residual noise and speech signal distortion are lower.	h shape d pink	5	4.46	4.49
[43]	2022	Modified wiener filter	Exhibitio n, Airport, Car, Restaura nt, Street, Babble noise	The performance of the Wiener filter is contrasted with that of the modified noise reduction method (MNRM). Based on a comparison of these two filters, our suggested model of the MNST filter boosted the SNR ratio for those various sounds. By utilizing the suggested model, the SNR ratio rose by about 14 to 15%. Modern subband domain DHA can use the MNST for noise reduction. This will result in a better and more relaxing listening experience for the hearing aid user	Vari Amb nois Airport Car n Street Babble	ous ient ses noise noise Noise Noise	<b>SNI</b> <b>proj</b> <b>MNR</b> 23. 25. 24. 23.	<b>R by</b> posed <u>M (db)</u> 456 345 456 456
[44]	2022	Adaptive LMS filtering	stationar y white Gaussian , engine noise.	The suggested strategy can enhance the performance and quality of noisy audio signals, according to simulation findings. They have shown through computer simulations that the suggested strategy is highly efficient in reducing noise, particularly in the case of stationary white Gaussian noise.	For cas power i NLM a becon statisti algorith qualified that using produce cl higher qu	es where is very un pproach ines more ically exa m after u balance. the adap lear voice ality than	the filter apredictal is approp challeng mine the pdating t The resu tive LMS e signals	's input ble, the riate. It ing to NLM he fully ults show 5 filter can that are of produced
[45]	2022	implicit Wiener filter	Exhibitio n, Station, Drone, Helicopt er, Airplane, White Gaussian stationar y noise	The implementation findings demonstrate that the suggested speech enhancement algorithm outperforms the spectral subtraction technique for the various types of noise degradations examined. Additionally, the estimated or enhanced speech signal's envelope is quite similar to the clean speech spectrum's envelope. It is demonstrated that the perceived quality of the augmented speech signal and the clean speech signal are comparable. The clean speech spectrogram and the enhanced speech spectrogram share similarities. Additionally, when compared to the spectral subtraction algorithm, the enhanced speech signal produced by the proposed speech enhancement algorithm has a clearer sound.	Type of noise AWGN	Input SNR (dB) 0 2.5 5	PI SS 1.563 1.908 1.656	ESQ IWF 1.657 1.932 2.008

#### **3.** Noise Definition

In a communication system, noise is essentially undesired or undesirable signals that are added at random to the signal that is really carrying the information or combined with a voice signal at the time of speech signal production or transmission. As a result, the original signal that is being transmitted from one end to another is disturbed. Even when they are not interfering with other signals or may have been purposely created as comfort noise, the term can also be used to describe signals that are random (unpredictable) and provide no meaningful information [46], such as noises in the sonar images [47], or seismic data [48].

To put it another way, noise is a signal that transmits information about its sources and the environment in which it spreads. For instance, background voice dialogues in a busy place might create interference with the hearing of a desired conversation or speech, and the noise from a car engine conveys information about the condition of the engine and how efficiently it is working. There are two different types of noises here:

1- According to life

In our life there is different face of noised in general the noise classified into 4 known types [49]:

• Continuous noise: a noise that is continually created, for example, by machinery that runs continuously.

• Intermittent noise: a noise volume that rapidly rises and falls. This might be caused by a passing train.

• Impulsive noise: most often linked to the building and demolition industries. These loud blasts of sound. Explosions and construction equipment frequently produce impulsive sounds.

• Low-frequency noise: Low-frequency noise is woven into the fabric of our everyday soundscape. We are frequently exposed to low-frequency noise, whether it is the low background hum of a neighboring power plant or the roaring of massive diesel engines.

2- According to signal processing (colored noise):

There are many types of noises that signals carry when generated or transmitted, such as additive noise (white noise, additive white Gaussian noise, black noise, Gaussian noise, pink noise or flicker noise, brownian noise, contaminated Gaussian noise, power-law noise, Cauchy noise, and multiplicative noise), quantization noise, poisson noise, shot noise, transient noise, burst noise, phase noise, background noise, comfort noise, and electromagnetically induced noise [46].

# 4. Classification of Noise Reduction Strategies

A broad classification of noise reduction methods can be given as spectral processing and temporal processing methods. The degraded speech goes through processing in the frequency domain in the spectral processing methods, whereas processing will be in the time domain for the temporal processing methods [46].

Several methods were proposed for noise reduction, such as:

The noise in the surroundings corrupts the information signal as it travels in a free environment. Eliminating this noise turns out to be one of everyone's top concerns. There are numerous traditional methods for reducing the noise in the information signal.

## 4.1. Spectral subtraction

The simplest and most familiar method to remove stationary background noise is spectral subtraction. In this technique, the average magnitude of the noise spectrum is subtracted from the noisy speech spectrum. The average magnitude of the noise spectrum is estimated from the frames of speech absence. The main disadvantage of the spectral subtraction method is that it produces residual noise with irritating and noticeable tonal characteristics known as "musical noise" [7]. Additionally, spectral subtraction does not sufficiently reduce noise during the silent period [22].

## 4.2. Wiener filtering

The second most familiar method is the Wiener filter, which is a substitute method of spectral subtraction for increasing the quality of the speech signal. A wiener filter is a kind of optimum filter that uses statistical assumptions and previous information to estimate the desired signal from a noisy observation. The main aim is to develop a filter that minimizes the squared difference between the output and the real signal. The drawback of this filter is that it requires previous knowledge of the power spectra of the input, noise, and real signals. In many circumstances, this can be difficult or impracticable to acquire, especially if the signal and noise are non-stationary or non-Gaussian. [50]

# 4.3. Kalman filter

It is broadly used in speech improvement. The Kalman filter is a model-based system that models a speech signal as an autoregressive (AR) process and also recovers the speech signal. The Kalman filtering system for speech improvement has no supposition of stationary speech signals; it is designed to work with finite data sets; it makes use of models; and it can be made to work with non-stationary signals. The Kalman filter has two major limitations: It assumes that the equations for the system and observation models are both linear, which is unrealistic in many real-world situations. It is assumed that the state belief distribution is Gaussian [4].

# 4.4. Subspace

Another technique for improving speech is used when speech estimation is seen as a constrained optimization issue. A signal subspace and a noise subspace are formed from the noisy speech signal vector universe. A signal-subspace speech improvement approach was put forward by Surendran et al. [51] employing a perceptual feature and the human auditory system's frequency masking or frequency disguising properties. [52] In comparison to various benchmark speech enhancement techniques, the results of their studies demonstrated the effectiveness of their algorithm. It was demonstrated that their method performed better with white noise compared to colored noise. SNR greater than 10 dB had poor performance.

# 4.5. Adaptive Filters

Several techniques for filtering noise from a speech waveform have been investigated. The majority of these techniques are based on the concept of adaptive filtering [8]. A system having a linear filter and a transfer function controlled by adjustable parameters and a way to change those parameters in accordance with an optimization technique is called an adaptive filter [53]. Modern digital signal processing (DSP) uses adaptive filters extensively in applications such as active noise control (ANC), adaptive control systems, telephone echo cancellation, noise cancellation, communications channel equalization, and biomedical signal amplification. One of the most frequently suggested ways to reduce the signal corruption brought on by predictable and unpredictable noise is the use of adaptive filters. For almost 50 years, adaptive filters have been employed in a variety of fields. Adaptive filtering configurations include inverse modeling, adaptive equalization, adaptive noise cancellation, and more [12].

# 4.6. Least-Mean-Square (LMS)

There are a number of noise reduction algorithms that may be used and implemented using MATLAB. An adaptive algorithm is one that modifies its features during execution according to the available data and prior techniques. The LMS algorithm, or least mean squares algorithm, is a well-known algorithm for adaptive systems that functions as a self-adjusting algorithm. In 1959, Widrow and Hoff produced the LMS (Least Mean Square) algorithm [54], a fairly simple method for noise cancellation. Due to its durability and dependability, the LMS algorithm's simplicity, cheap computing complexity, and quick convergence rate have led many academics to embrace it for hardware implementation. In a noise cancellation problem, the LMS algorithm has demonstrated good performance [12]. Furthermore, with colored interference signals, the LMS suffers from significant performance degradation [24].

## 5. Types of Filters

In signal processing, a filter is a device or system that removes some undesirable additives or features from a signal. Filters are commonly utilized in electronic and telecommunications applications such as radio, television, audio recording, radar, control systems, music synthesis, image processing, and computer graphics. There are numerous classifications of filter bases that overlap in a variety of ways; there is no simple hierarchical classification. Filters include [55]:

- Non-linear or linear.
- Time-variant or time-invariant.
- Analog or digital.
- Discrete-time (sampled) or continuous-time
- Passive or active type of continuous-time filter.
- Infinite impulse response (IIR) or finite impulse response (FIR) types of discrete-time or digital filters.

Table 2 illustrates the different speech enhancement techniques and their sub-methods.

Optimal Filters in the Time Domain	Optimal Filters in the Frequency Domain	Statistical Based Approaches	Adaptive Filters	Filter Bank
1. Wiener	1. Wiener Filter	1. Wiener	1. Finite	1. Discrete
Filter	2. Parametric	Filtering	Impulse	Cosine Transform
<b>2.</b> Tradeoff	Wiener Filter	<b>2.</b> Maximum	Response (FIR)	(DCT) Filter Banks
Filter	<b>3.</b> Tradeoff Filter	Likelihood (ML)	Adaptive filters	2. Polyphase
<b>3.</b> Subspace	4. Fourier-	Estimators	2. Infinite	Filter Banks
Approach	transform	<b>3.</b> Bayesian	Impulse	3. Gabor
<b>4.</b> Mean.	<b>1.</b> Low-Pass	Estimators	Response (IIR)	Filter Banks
5. Median.	Filter (LPF).	4. MMSE	Adaptive filters	4. Mel Filter
<b>6.</b> Gaussian.	2. High-Pass	Estimators	3. Kalman	Banks
7. Bilateral.	Filter (HPF)	• MMSE	Filtering,	5. Filter
8. Comb	5. Wavelet	Magnitude	4. H	Bank Multicarrier
Filtering	transforms.	Estimator	algorithm	(FBMC)
9. Linear	• Low-	• MMSE	5. Adaptive	6. Discrete
predictive coding	Pass Filter (LPF).	Complex	wiener filter	Fourier Transform
(LPC)based	• High-	Exponential	6. Adaptive	(DFT) Filter Banks
Filtering	Pass Filter (HPF).	Estimator	Kalman filter	7. Uniform
<b>10.</b> Adaptive	~ /	5. LogMMSE	7. Least	DFT Filter Bank
Filtering		Estimators	Mean Square	
• Kalman		6. Maximum	(LMS) algorithm	
Filtering,		A Posteriori (MAP)		
• H		Estimators		
algorithm		7. Perceptually		
11. Hidden		Motivated Bayesian		
Markov Model		Estimators.		
HMM Filtering				
12. Neural				
Networks				
13. Tradeoff				
Filters				
14. Subspace				
Approach				

 Table 1:Speech enhancement techniques

## 6. Discussion

People have become more dependent on communication technology in recent years as it has grown on a huge scale [56], and speech communication is increasingly significant in everyday applications, especially with the invention of mobile phones and Internet services, which enabled the transmission of voice through networks in digital format [57]. For that, we need filters to eliminate the noise of transmitted speech. A noise-reduction filter is used to generate the clean speech estimate during the noise reduction process, which is conceptualized as a filtering issue. With such a formulation, the fundamental challenge of noise reduction is how to create an ideal filter that can fully use the speech and noise statistics to achieve maximal noise suppression without adding perceptibly detectable speech distortion. Although effective filters may be created in the time domain, the majority of techniques now in use operate in the frequency domain. Working in the frequency domain has a variety of benefits, including but not limited to[58] :

1- The quick Fourier transform makes it possible to execute the filtering procedure extremely effectively.

2- There is a great degree of versatility in dealing with colored noise since the filters at different frequencies may be created and managed independently of one another.

3- Since the majority of our knowledge and understanding of speech production and perception is based on frequencies, we can easily apply this knowledge to the frequency domain to improve noise reduction performance.

According to our review, there are currently no perfect techniques or filters to remove noise from speech signals, but in order to achieve the best noise reduction, experts use filters with a variety of parameters or combine several different methods. Based on our review, we discussed various techniques for various authors in Table 1, and we will now discuss various techniques such as spectral subtraction and wiener filtering.

• First, speech enhancement is the technique of increasing the quality of a speech transmission by reducing background noise and other unpleasant noises. The clarity, consistency, and comprehension of a voice signal are typically used to determine its quality [59].

• The spectral subtraction method has been found to be a good method but not the best since it produces musical noise. And in [14], the spectral noise removal approach reduces background noise significantly while having minimal influence on speech intelligibility. Formal testing has revealed that at SNR = +5 dB, the improved speech has the same intelligibility as the untreated signal.

• Spectral subtraction in other author comparisons failed; in [22], when compared to Wiener filter and adaptive Wiener filter, SNR results were (spectral subtraction method SNR = 5.0439 dB, Wiener filtering method SNR = 4.9880 dB, adaptive Wiener filtering method SNR = 6.8726 dB) in the time domain. Here, adaptive Wiener filtering showed that it outperformed spectral subtraction and Wiener at both low and high SNR values, and it works in both the additive white Gaussian noise (AWGN) and colored noise scenarios.

• Another researcher uses the Wiener filter [38] when their results show that the suggested method consistently and successfully enhances all forms of noise examined. And the suggested approach produces an improved speech signal that is spectrally comparable to the clean speech signal and perceptually similar to the clean speech signal, where the result of the highest log-likelihood ratio (LLR) was 1.230 in 5 SNR (db).

• Another researcher used the Wiener filter but made some modifications to it, like [43], where they reached the result that approximately 14 to 15% of the SNR ratio increased by using the MNRM compared to the Wiener filter, and the highest SNR was in car noise, about 25.345 SNR (db).

• For more noise reduction, other authors used an adaptive Wiener filter but with TSNR and HRNR [25], and their result was more efficient. To improve the voice signal, two-step noise reduction approaches are applied. Then, harmonic regenerated noise reduction is applied to recreate the harmonics lost in the original signal. The experimental results suggest that employing the TSNR and HRNR methods improves the SNR of the input signal. When compared to TSNR, the HRNR approach produced the highest SNR, where the improvement in SNR (dB) in TSNR was 0.46 and in HRNR was 0.71.

• When FEDS and FAP were compared to classical adaptive filters like LMS, NLMS, AP, and RLS, the authors [19] found that RLS had the highest SNRI (db) at 29.7355. Compared to the LMS, NLMS, and AP algorithms, the RLS method offers a quicker

convergence speed. The FEDS and FAP algorithms outperform the LMS, NLMS, and AP algorithms and are comparable to the RLS algorithm. In another study [24], the authors found the RLS algorithm produces the highest SNR and outperforms LMS in terms of performance. However, with the Finite Impulse Response (FIR) filter taps, LMS converges quicker than RLS.

• When CNN is compared to filters, neural networks have been shown to be an effective technique. as well as CNN, which has been shown to be a viable technique for generalizing real-world noise suppression, and it is noticed that CNN in the training step takes a lot of time to process.

• Finally, from our review of different researchers' work, we notice that the most popular data bases that are used by the researchers are the NOIZUS data bases. This database comprises 30 sentences from the IEEE sentence database spoken by three male and three female speakers, and it is easily available in clean and noisy voices and does not need preprocessing. The Noisex-92 database is also available, but just the noisy file may need preprocessing, as is the TIMIT database. This dataset is not easily available for noisy voices, but in the field of recognition, it is available on many websites.

# 7. Conclusion

Noise reduction is an interesting and complex field to solve due to the fact that speech enhancement is affected by several types of noise, and there are many algorithms and techniques for noise reduction. In this paper, an overview of several noise reduction methods is discussed and compared with the performance that the other researcher reached with respect to various parameters.

In this review, we concluded that the most efficient filter is the adaptive Kalman filter for both stationary and non-stationary noise. The results show that it is better in white Gaussian (WGN) noise, but performance differs as the noise becomes usable in some cases. The Wiener filter is next, which works best when the noise is stationary. After that comes the adaptive filter algorithm LMS, which works well for low cost, complexity, and increasing the SNR in different noises and in color noise, but the RLS, FEDS, and FAP methods converge faster than the LMS. And then adaptive wiener, which performs well in both colored and additive white Gaussian noise (AWGN) and low and high SNR levels. Then spectral subtraction comes in on the list of good methods, but it produces residual noise, and its shortcoming is the use of noisy phases that produce a roughness in the quality of speech.

And in terms of neural network methods, they're rather good because, when compared to filtering methods, they found that neural networks execute more slowly. The deep learning de-noising method is the most complex and takes a very long time to complete, yet the results are subpar. ADALINE is the best of the neural network methods. The hardest noise to remove from a speech signal is non-stationary noise, and real-world unknown natural noise (mixed noise) is the hardest noise, followed by white Gaussian noise (WGN) and then colored noise.

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