Speech Quality Enhancement through Noise Cancellation using an Adaptive Algorithm

Janak Kapoor, Ajita Pathak, Manish Rai, G.R Mishra

Abstract: **Noise when added to the speech signal deteriorates its quality and makes the speech signal meaningless for the listeners. The active noise cancellation technique can be used for cancelling this noise, recovering the original signal, and making it meaningful. But due to fast varying characteristics of speech signals along with high sensitivity of speech for surrounding noise the use of active noise cancellation on speech signals is quite challenging. In this paper, this challenge of estimation and cancellation of speech signal noise is analysed. The proposed noise cancellation model is implemented using human's speech, birds chirp, and airplane sound as surrounding noise signals. The active noise cancellation is applied using least mean square algorithm (LMS), normalized least mean square algorithm (NLMS) and recursive least mean square algorithm (RLS) for different types of noisy surroundings. The prediction accuracy and SNR of all the three algorithms for real-time human speech are also compared and discussed. The results are supported by root mean square EVM power analysis.**

Index Terms: Active noise cancellation, adaptive algorithms, speech signal, prediction accuracy, SNR, root mean square EVM power

I. INTRODUCTION

Speech is the fundamental means of communication in humans, uninterrupted and high-quality speech is always desirable for the transfer of information from the speaker to the listener. No matter how near or far the listener is, if speech signal is corrupted by the noise the fundamental goal of the transfer of information is highly challenged and misinterpretations may take place which results in the loss of important information [1,2]. Active noise cancellation proves to be a powerful tool to meet this challenge by providing noise-free communication between the speaker and the listener. Active noise cancellation is based on the principle of first predicting and then cancelling the noise signal through destructive interference. Noise cancellation may be divided into two thrust areas, the first is prediction and the second is a cancellation. A lot of research is been done and still, there is high scope of research in both the thrust areas of noise cancellation. The prediction of noise signals involves adaptive filtering techniques. Adaptive filtering is the combination of adaptive algorithms and adaptive filters.

Janak Kapoor is a Ph.D. candidate in the Dept. of Electronics and Communication Engineering, Amity University Lucknow, India (phone:9456469793, e-mail: janak_kapoor@rediffmail.com)
Ajita Pathak is Assistant Professor of Electronics and Communication Engineering Department, Amity University Lucknow, India (e-mail: apathak@amity.edu)
Manish Rai is Professor of Electronics and Communication Engineering Department, FET MJP Rohilkhand University Bareilly, India (e-mail: manishrai1968@gmail.com)
G.R Mishra is Professor of Physics and Electronics Department, Dr. RML Avadh University Ayodhya, India (e-mail: grmishra@gmail.com)

Adaptive algorithms are the set of operations based on mathematical equations which predict the filter parameters in a manner to reduce the difference between the desired signal and the predicted signal. Adaptive algorithms generate coefficients of the filters which make the filter output adapt with the change in the input signal and thus these filters are termed adaptive filters. The whole concept of active noise cancellation poses various challenges, a few of which are stated as: the first challenge is to predict the signal that is as similar as the original signal and the second challenge is to predict it in real-time at a rate as fast as to follow the changes in the original signal. The third challenge is the accurate prediction at a fast rate but with less complexity so that it can be easily implemented practically, the fourth challenge is precise cancellation of noise which is the sole aim of the whole noise cancellation process. The fifth challenge is to design such a system at a low cost which is an important factor in the widespread application of any new technology. In continuation to previously published work [1], this paper describes the approach to deal with the second and third of the stated challenges which are the fast convergence rate with low complexity of the cancellation system applied for prediction and cancellation of the real-time speech signal. A thorough literature review reveals that there are many methods [1]-[5] through which the coefficients of the filters can be varied to follow the time-varying characteristics of the signal. A DSP system to implement feedback adaptive active noise cancellation using FxLMS algorithm has been proposed by Jiun-Hung Lin et al. [6]. The most common approach is the one in which the mean square estimation error is minimized by recursively updating the filter coefficients on sample-to-sample bases. In this paper, the difference between the convergence rate and prediction accuracy of adaptive algorithms used to predict a speech signal is analysed, in comparison to the prediction of non-speech audible signals, which may be noise signals from vehicles, construction activity, industrial machinery, and animal noise. Simulation results justify the analyses and performance of the proposed model in comparison to the conventional models [7]-[11].

II. SPEECH SIGNAL Vs OTHER AUDIBLE SIGNALS

Sound is generated when air pressure varies with time at audible frequencies, this variation may be caused due to various reasons. In the case of musical instruments, this variation is caused due to vibration of strings as in the case of string instruments such as guitar, sitar, etc. In drum and dholak, this air pressure variation is caused due to vibration of the thin film when stroked by the hand or stick. Similarly, all sounds around us are caused due to air pressure variations resulting from various causes. But the sound when generated by vibrations of our vocal cord is called speech. The speech signal is quite different from the other sound signal as it has very large variations in frequency and a lesser number of silent intervals. Estimation of the speech signal is a more complex process in comparison to other sound signals, as other sound signals have much lower frequency variations, higher number of silent intervals and follow a continuous pattern on energy peaks of a short interval. These signals appear to be more deterministic for adaptive algorithms based on the principal of minimizing the mean square estimation error [12]-[15]. These characteristics of the speech signal are visible in the time domain plot and frequency domain plot of the speech signal given below. Figure 1-6 shows a bird chirp signal, airplane sound signal, truck noise signal, pure tone signal, real-time speech signal, and pre-recorded musical song signal. All the signals are analysed by their time-domain plot which gives the variation of the amplitude of the signal with respect to time. Array plot gives the array of amplitude with respect to uniformly spaced sample values ranging from 0 to 1000 samples, each sample equally spaced at an increment of 100. Power spectrum as given below, gives the probability with respect to the dB above-average power:

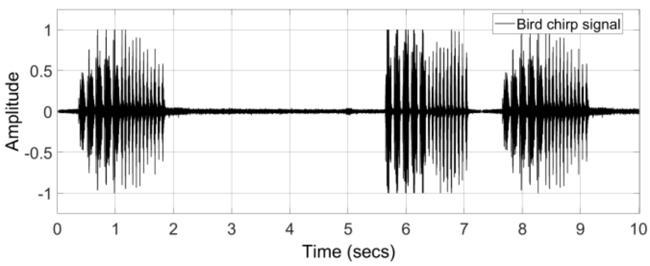
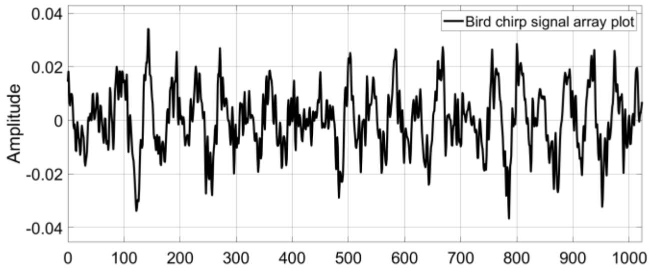


Figure 1(a)



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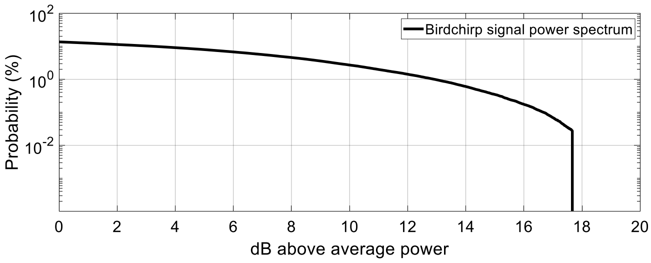


Figure 1(c)

Fig. 1 Time domain plot, array plot, and power spectrum of bird's chirp Sound

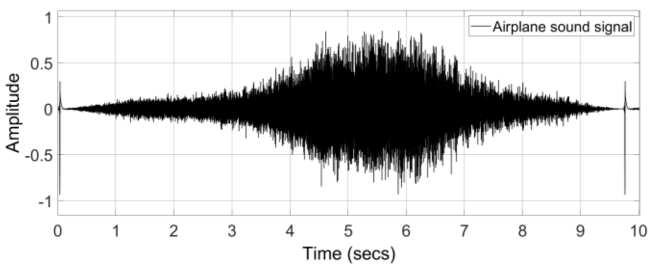
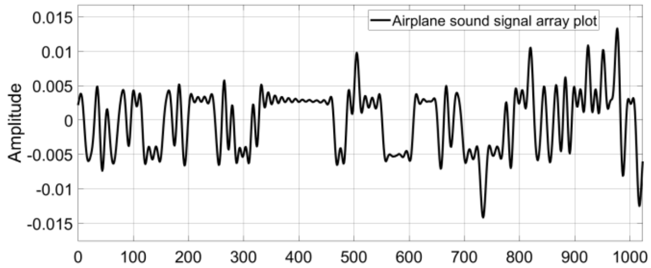


Figure 2(a)



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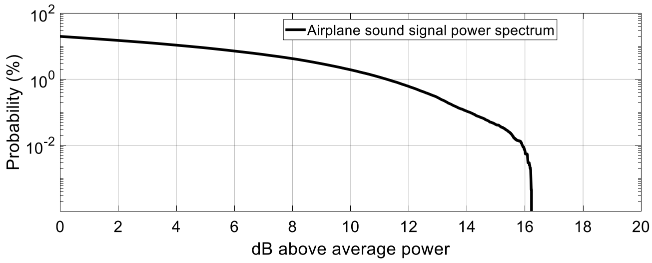


Figure 2(c)

Figure 2. Time domain plot, array plot, and power spectrum of airplane sound.

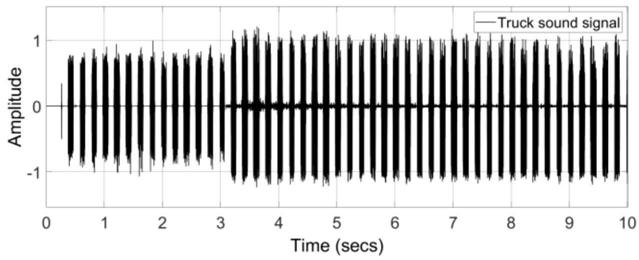
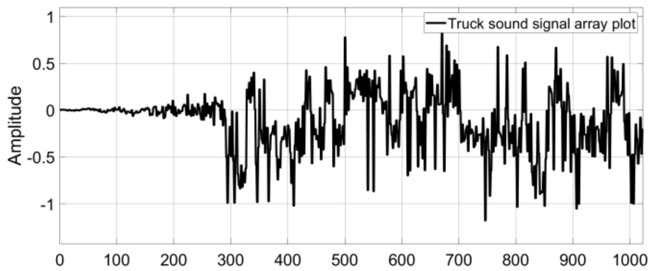


Figure 3(a)



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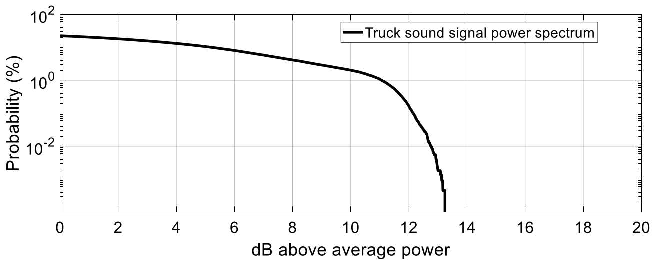


Figure 3(c)

Figure 3. Time domain plot, array plot, and power spectrum of truck sound.

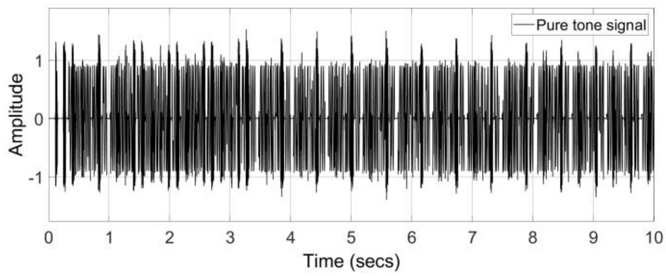
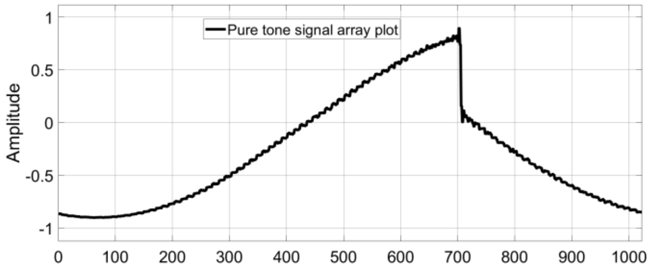


Figure 4(a)



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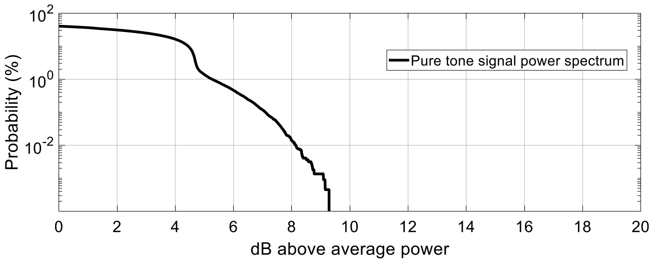


Figure 4(c)

Figure 4. Time domain plot, array plot, and power spectrum of pure tone sound.

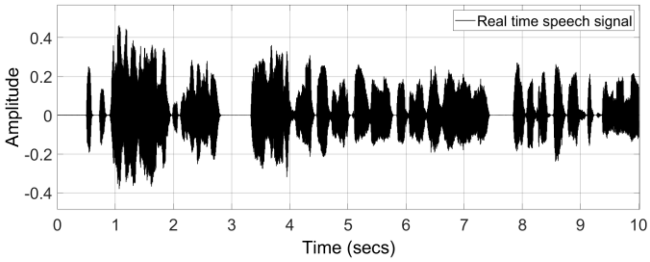
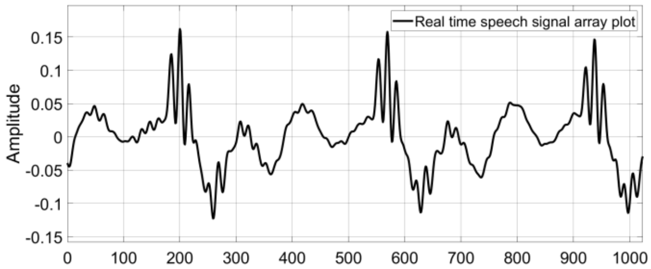


Figure 5(a)



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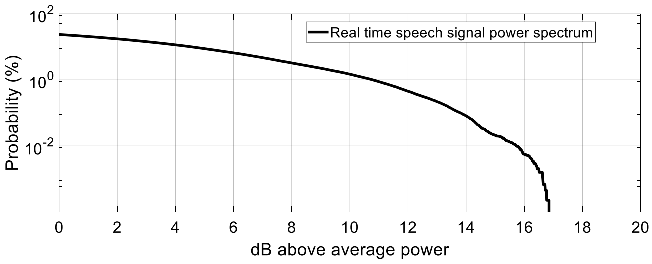


Figure 5(c)

Figure 5. Time domain plot, array plot, and power spectrum of real-time speech sound.

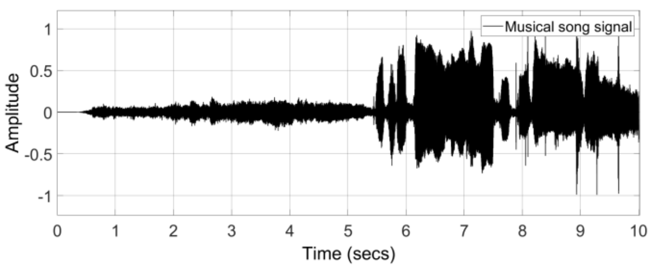


Figure 6(a)

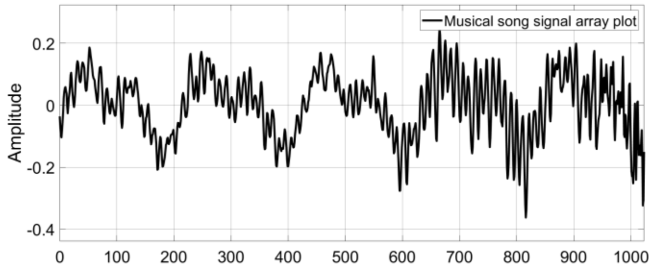


Figure 6(b)

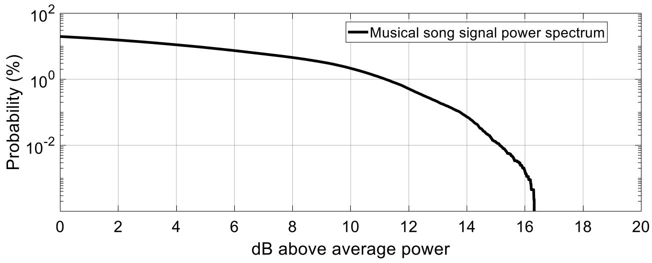


Figure 6(c)

Figure 6. Time domain plot, array plot, and power spectrum of musical song signal.

From figure 1-6 shown above, it is observed that a real-time speech signal shows a high amplitude variation, which is largely unrepetitive in a finite interval as compared to other signals, e.g. birds chirp signal has highly repetitive variations. Similarly, the truck and airplane noise signals also follow a repetitive pattern, whereas the pure tone sound signal is purely periodic. As a result of these repetitions, these signals become more easily predictable by adaptive filtering techniques as compared to the real-time speech signal. To predict the noise in the form of a speech signal the adaptive algorithm must have a high convergence rate. High convergence rate results in increased complexity, therefore in order to predict and cancel a speech signal, a trade-off between the convergence rate and the complexity of the algorithm is to be achieved. The algorithm that wins this trade-off is the one that is best suited for prediction and cancellation of real-time speech signal noise. This paper compares the three adaptive algorithms namely least mean square (LMS), normalized least mean square (NLMS) and recursive least mean square (RLS) for different types of noisy environments. Section III gives the mathematical analysis of convergence rate of different adaptive algorithms. Active noise cancellation model for cancellation of three different kinds of surrounding noise is proposed for analysis in section IV, Section V gives the simulation waveforms along with the comparative analysis of the results.

I. CONVERGENCE RATE OF ADAPTIVE ALGORITHMS: MATHEMATICAL ANALYSIS

The three adaptive algorithms namely the least mean square algorithm (LMS), normalised least mean square algorithm (NLMS), and the recursive least mean square algorithm (RLS) are all based on the basic principle of estimating the filter weights to minimize the mean square error between the filter output signal and the desired signal, the recursive mean square algorithm does the same by recursive computations of the mean square error the basic equation of computation of all the three algorithms are given as under:

$$y[n] = w^T[n-1]x[n]$$

$$e[n] = d[n] - y[n]$$

$$w[n] = w[n-1]\alpha + f(e[n]x[n]\mu)$$

For the least mean square (LMS) algorithm:

$$f(e[n]x[n]\mu) = x^*[n]\mu e[n]$$

For the normalized least mean square [NLMS] algorithm:

$$f(e[n]x[n]\mu) = \mu e[n]\frac{x^*[n]}{\epsilon + x^H[n]x[n]}$$

For the recursive least mean square (RLS) algorithm the equations are:

$$w[n] = w[n-1] + g^H[n]e[n]$$

$$Q[n] = \frac{Q[n-1]}{\gamma}x[n](1 - g[n]\,x^H\,[n])$$

$$g[n] = \frac{\gamma^{-1}x[n]Q[n-1]}{1 + \gamma^{-1}x^H\,[n]x[n]Q[n-1]}$$

TABLE 1
Notations

n	Present time index
$x[n]$	Input signal sample vector
$w[n]$	Filter weights
$e[n]$	Difference between estimated signal and desired signal
$g[n]$	Gain vector
$d[n]$	Desired signal response
$Q[n]$	Covariance matrix
α	Leakage factor (0 to 1)
γ^{-1}	Exponential weighting factor
ϵ	Small positive constant
μ	Step size
$y[n]$	Filtered output

As seen from the above equation the basic difference between the least mean square algorithm and normalized least mean square algorithm is that in the normalized least mean square algorithm the filter weights are updated using the normalized value of the buffered input samples at each step. To overcome the numerical instability a small positive constant parameter epsilon whose values range from 0 to 2 depending on the type of the input signal which may be single-precision floating-point, double-precision floating-point or a fixed-point input. In the recursive mean square algorithm, the equation is further changed with the inclusion of an additional gain vector for updating the filter weights. The gain vector depends on the normalized value of the product of inverse covariance matrix and inverse of the exponential weighting factor. All these changes in the basic least mean square algorithm are done to achieve stability with high convergence speed. Previous results published [1-4] have proved these changes to be very fruitful, as normalized least mean square algorithm is more widely used for adaptive filtering as compared to least mean square algorithm, due to its fast convergence rate and stability. Recursive least mean square algorithm has proved to be a far better choice for its higher adaption rate but suffered in case of its high mathematical complexity which hinders with smooth practical implementation. The performance of these algorithms for predicting various audio signals has been compared many times in the past by several researchers. Results analysed by them are available in the literature [16]-[25]. Jiun-Hung et al. [6] has reported maximal noise spectrum power reduction of 37.9 dB. But the one aspect which remains untouched is the performance comparison in the case of any audible signal with a human speech signal. As discussed above in section II, it is seen that characteristics of a speech signal are far different from any other audible signal so the performance of these algorithms should also be different for speech signal as compared with any other audible signal. This forms the basis of analysis in this research paper. Next sections give, a thorough performance analysis of least means square algorithm (LMS), normalised least mean square algorithm (NLMS) and the recursive least mean square algorithm (RLS) for speech signal noise and non-speech signal noise cancellation. Using the proposed model, the simulation results as given are analysed. Results bring forth the challenges and shortcomings of adaptive algorithms in the estimation and cancellation of a human speech signal.

II. PROPOSED MODEL

The model proposed for the comparative analysis of the three adaptive algorithms is shown in figure 7 given below. The model depicts the real-time scenario in which surrounding noise added to the desired signal corrupts the desired signal and makes it meaningless for the listener at the receiver end. The surrounding noise used for analysis is industrial machine noise in the form of airplane noise, animal noise in the form of bird's chirp sound, and human noise in the form of a real-time speech signal. The sum of the musical song with the surrounding noise is the input for the active noise cancellation (ANC) system which comprises of digital signal processor, the reference microphone, which provides the surrounding noise as a reference signal to the active noise cancellation (ANC) and the filtered output is obtained at the speaker.

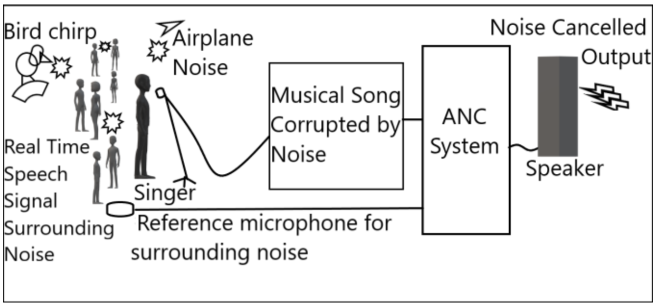


Figure 7. Proposed model with bird chirp, airplane fly by sound, and human speech signal as surrounding noise.

Figure 7 shows the proposed active noise cancellation model in which the singer is surrounded by people talking to each other resulting in a noisy environment, the song is recorded with this real-time speech signal background noise. The objective of implementing active noise cancellation, in this case, is to cancel the surrounding speech noise from the song so that the listener may be able to enjoy the actual song without surrounding noise. Similarly, aircraft noise and a bird's chirp sound are added to the singer voice resulting in corrupted song at the listener end, thus hindering the true essence of the song. The purpose of defining the three different kinds of noise is to study and analyse the effectiveness of the three adaptive algorithms in four different noisy environments. The analysis results hold significance in differentiating the performance of active noise cancellation algorithms applied for cancellation of machine noise, animal noise, human speech noise and the combination of the three as surrounding noise. Research outcome will prove to be a great help in understanding the prevalent shortcomings in active noise cancellation system. Overcoming these shortcomings will shape the prototype of more advanced noise cancellation systems of the future. The simulation results along with thorough analysis are described in the next section.

III. SIMULATION AND RESULTS

Simulink tool has been used to analyse the proposed model and results are given in figure 8 to figure13 below. The noise cancellation algorithms applied for comparative analysis are the basic least mean square algorithm (LMS), the normalized least mean square algorithm (NLMS) and the recursive least mean square (RLS) algorithm. Figures 8 (a), (b) and (c) given below, show the time domain plot of the musical song signal, real-time speech signal as surrounding noise and noise corrupted signal respectively. Whereas figures 8 (d), (e) and (f) given below represent the recovered signal after applying LMS, NLMS, and RLS algorithms respectively.

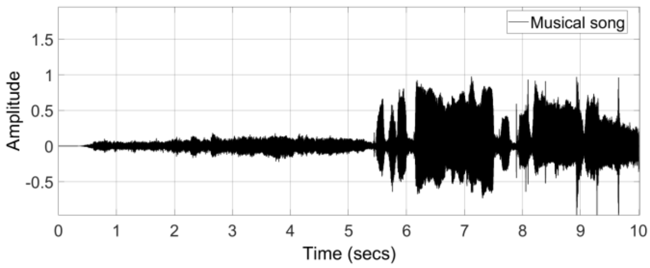


Figure 8(a)

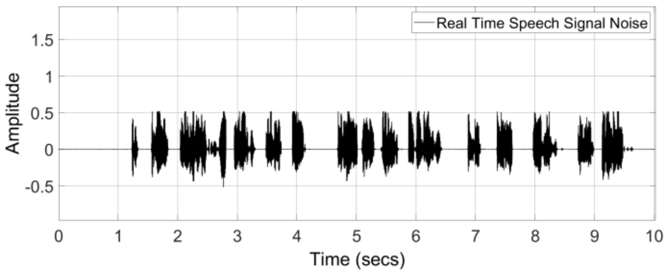
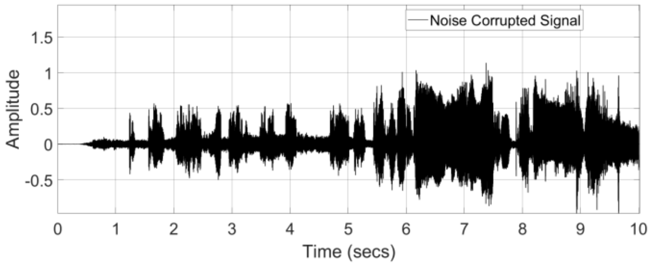


Figure 8(b)



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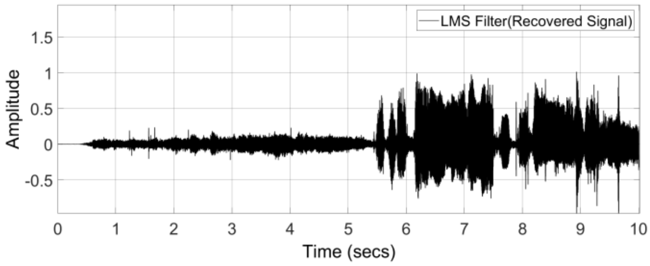
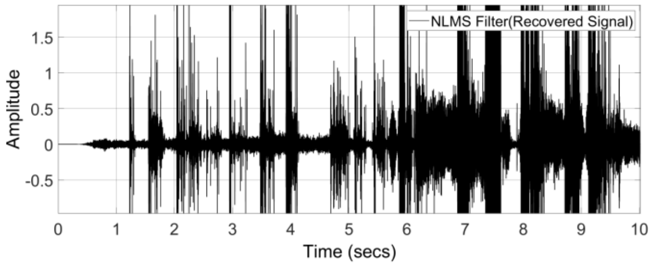


Figure 8(d)



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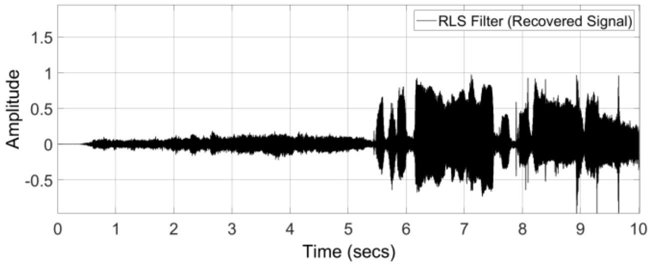


Figure 8(f)

Figure 8. Noise cancellation with real-time speech signal as surrounding noise.

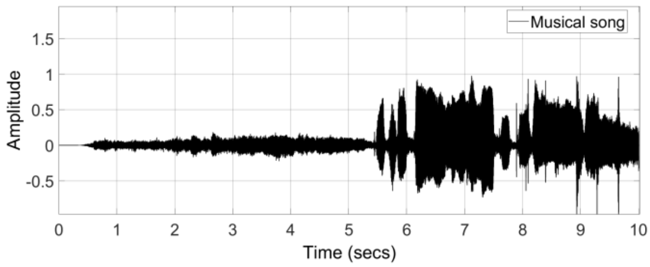
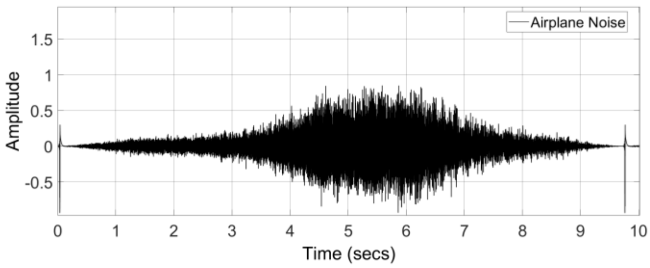


Figure 9(a)



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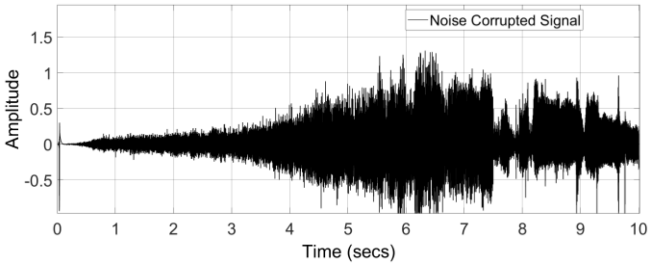

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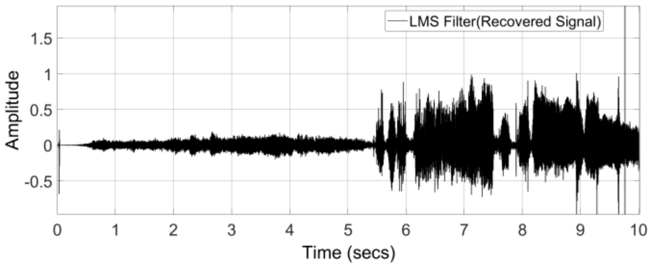
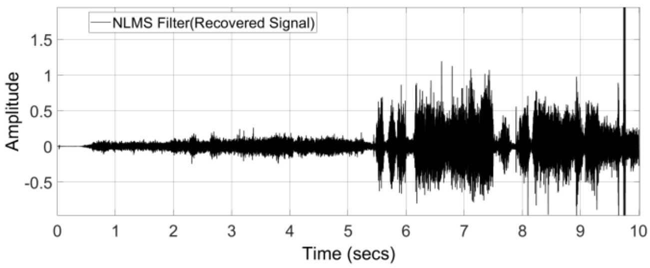


Figure 9(d)



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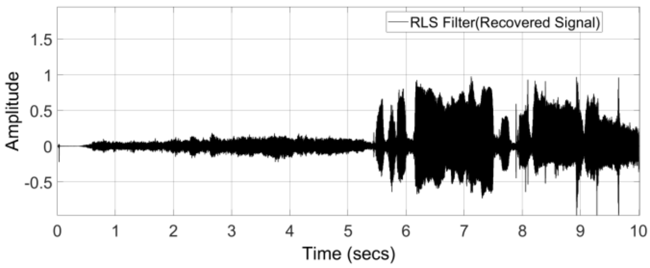

Figure 9(f)

Figure 9. Noise cancellation with airplane fly by sound as surrounding noise.

Figures 9 (a), (b) and (c) above, show the time domain plot of the musical song signal, airplane sound signal as surrounding noise and noise corrupted signal respectively. Whereas figures 9 (d), (e) and (f) show recovered signal after applying LMS, NLMS, and RLS algorithms respectively.

Similarly, figures 10 (a), (b) and (c) show the time domain plot of the musical song signal, birds chirp sound signal as surrounding noise and noise corrupted signal respectively. Figures 10 (d), (e) and (f) represent recovered signal after applying LMS, NLMS, and RLS algorithms:

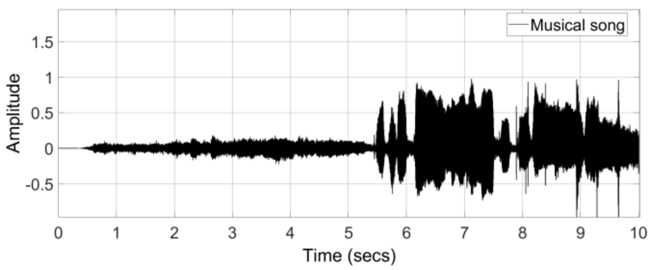

Figure 10(a)

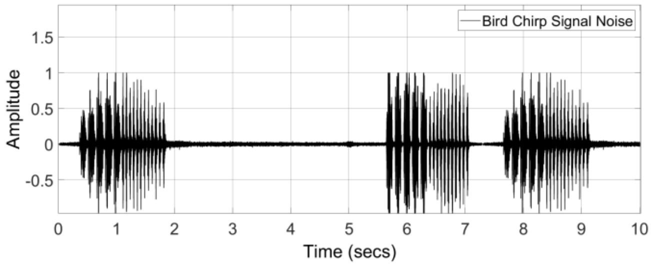

Figure 10(b)

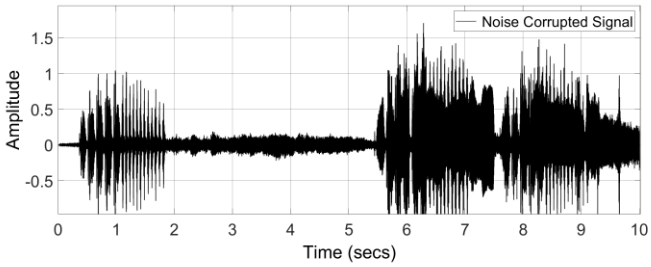

Figure 10(c)

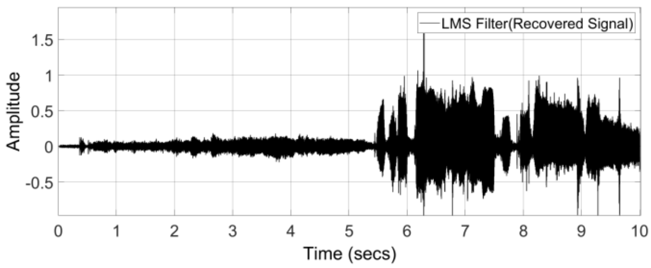

Figure 10(d)

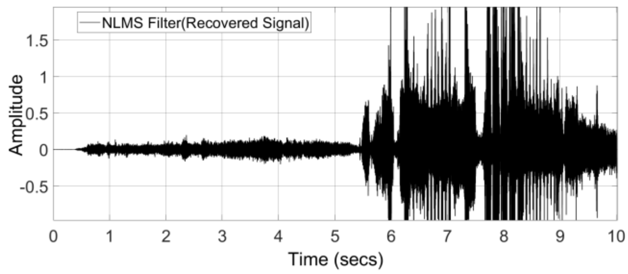

Figure 10(e)

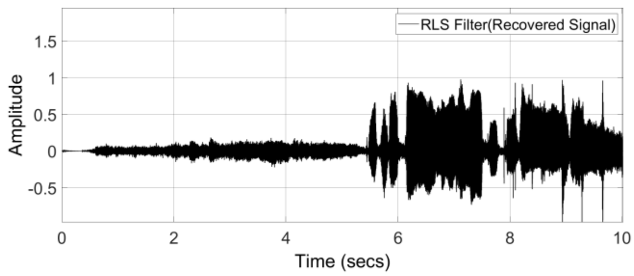

Figure 10(f)

Figure 10. Noise cancellation with bird chirp sound as surrounding noise.

As observed from the figures given above, we find that although all the three algorithms recover the original musical song signal after active noise cancellation of the surrounding noise which may be present in various forms, but their performance needs to be analysed. The performance of these three algorithms for cancelling different noise is analysed in terms of the convergence rate, mathematical complexity for achieving the same results and prediction accuracy. The convergence rate and prediction accuracy are observed from the array plot of filter weight. Filter weights are updated continuously by the adaptive algorithm to adapt with the varying input signal to reduce the error between the predicted signal and the input noise signal. By analysing the array plot, the difference between the convergence rate of various algorithms for different input noise signals is obtained. The filter weights are also used as the base parameter for calculating the prediction accuracy of the adaptive algorithms. Figure 11 to figure 13 show the array plot of adaptively updated weights for the least mean square (LMS), the normalized least mean square (NLMS) and the recursive least mean square (RLS) algorithms applied for the three different noise signals namely real-time speech signal, airplane sound signal, and birds chirp sound signal. The array plot gives the amplitude of filter weights plotted with respect to time in seconds. The number of weights considered here are 31 which are same for all the three algorithms. Weight amplitude varies rapidly in accordance with the rapidly changing noise. The convergence rate depends on the convergence of weights, faster the weights converge to the minimum, higher is the convergence rate. Prediction accuracy depends on the percentage of frequency the sample weights take a null value. Higher is the frequency, higher will be the prediction accuracy and vice versa. The performance of the three algorithms for three different surrounding noise is explained and proved by the simulation results as shown below.

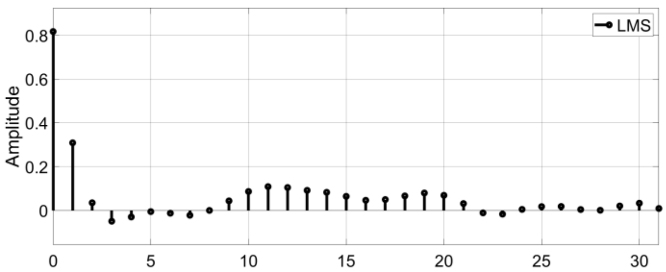

Figure 11(a)

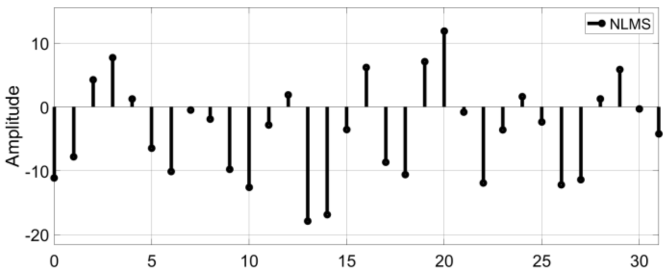

Figure 11(b)

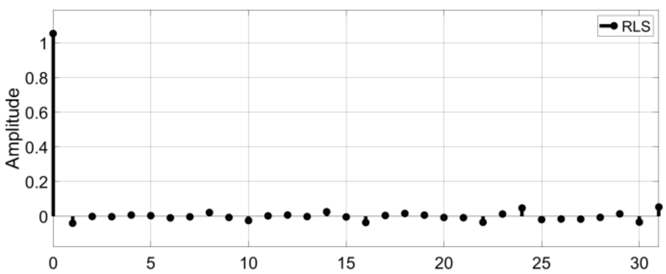

Figure 11(c)

Figure 11. Array plot of LMS, NLMS, and RLS filters for real-time speech signal as surrounding noise.

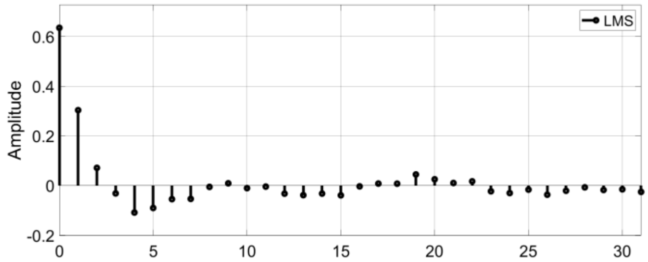

Figure 12(a)

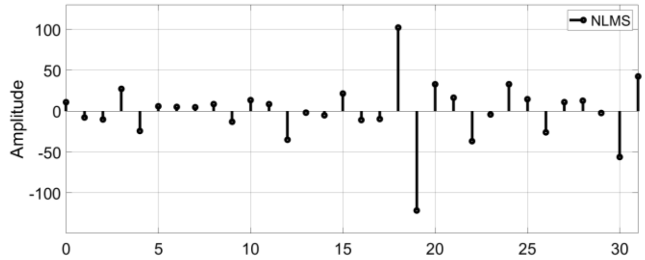

Figure 12(b)

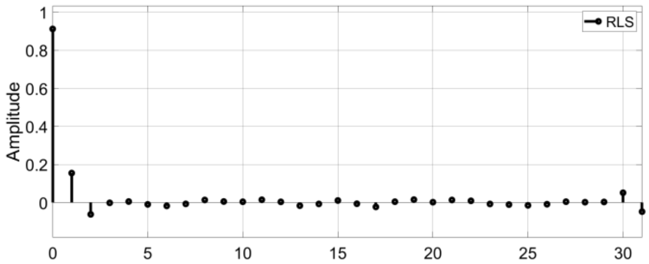

Figure 12(c)

Figure 12. Array plot of LMS, NLMS, and RLS filters for airplane sound as surrounding noise.

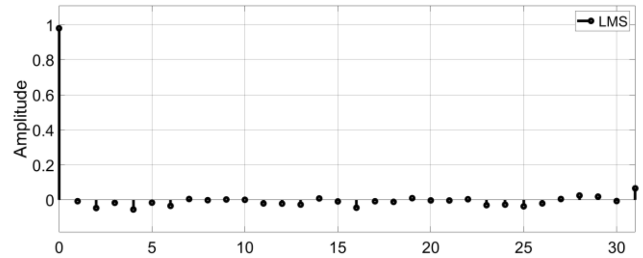

Figure 13(a)

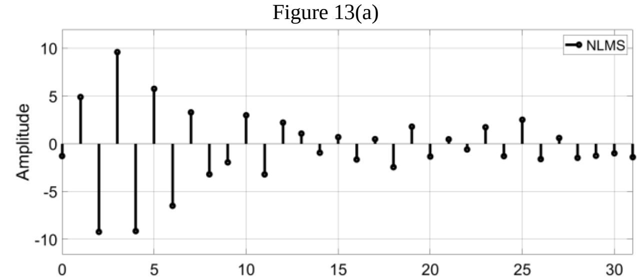

Figure 13(b)

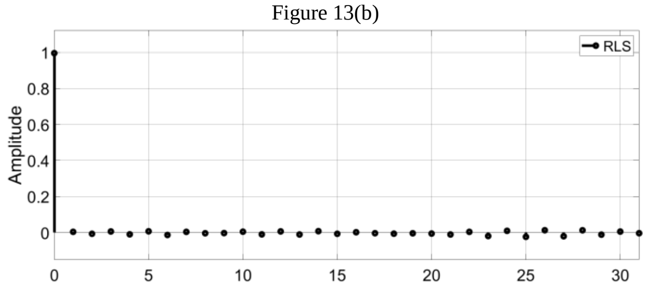

Fig.13(c)

Figure 13. Array plot of LMS, NLMS, and RLS filters for bird chirp sound as surrounding noise.

As observed from the plots shown above in figure 11 to figure 13, the amplitude of the filter weights varies in the range between -1 to 1 for LMS, -150 to 150 for NLMS and -2 to 2 for the RLS algorithm. The range of amplitude variation is highest in case of NLMS algorithm and lowest in the case of RLS algorithm for all the three surrounding noise signals considered for analysis. From the simulation plots it is observed that the convergence rate of the recursive least mean square (RLS) algorithm is the highest as compared to the least mean square (LMS) algorithm and normalized least mean square (NLMS) algorithm. The convergence rate of the least mean square (LMS) algorithm is better than the normalised least mean square (NLMS) algorithm. The normalized least mean square algorithm has the lowest convergence rate among the three. Comprehensive results are summarised in table 2 below:

TABLE 2
Comprehensive Analysis

Algorithm	Noise	Signal Statistics				
		Max		Min		Peak to Peak
		X	Y	X	Y	
LMS	Airplane	0	0.63	4	-0.1	0.74
	Bird Chirp	0	0.97	4	-0.54	0.1
	Human Speech	0	0.82	31	-0.23	0.1
NLMS	Airplane	18	0.1	19	-0.12	0.22
	Bird Chirp	3	0.95	2	-0.92	0.18
	Human Speech	25	0.17	0	-0.16	0.34
RLS	Airplane	0	0.91	2	-0.6	0.97
	Bird Chirp	0	0.99	25	-0.24	0.10
	Human Speech	0	0.91	31	-0.81	0.10

Table 2 above gives the signal statistics of the array plot of filter weights for different adaptive algorithms. As seen from the table the maximum value of the adaptive filter weight for all the three noise signals is at 0^{th} second for both least mean square (LMS) algorithm and recursive least mean square (RLS) algorithm. This means that in recursive least mean square (RLS) algorithm and least mean square (LMS) algorithm, the filter tends towards convergence from the initial value, whereas in the case of normalized least mean square (NLMS) algorithm the maximum value is obtained at the 18^{th} second for airplane noise, 3^{rd} second for bird chirp noise and 25^{th} second for the human speech noise. This observation proves the first fact that normalized least mean square (NLMS) algorithm have the lowest convergence rate among least mean square (LMS) algorithm and recursive least mean square (RLS) algorithm. Further analysis of table 2 shows that the distance between the maximum and minimum value is maximum for the human speech signal which is 31 seconds for both least mean square (LMS) algorithm and recursive least mean square (RLS) algorithms. Whereas it is 25 seconds for the normalized least mean square (NLMS) algorithm. For airplane noise: it is the minimum which is 4 seconds in the case of the least mean square (LMS) algorithm, 1 second in the case of normalized least mean square (NLMS) algorithm, and 2 seconds in the case of recursive least mean square (RLS) algorithm. This observation proves the major fact of this analysis that it is more difficult for all the adaptive algorithms to predict and actively cancel the human speech noise signal in comparison to animal noise or industrial machine noise. The reason behind this is already discussed in section II, that there is the larger number of variations and lesser repetitions in human speech as compared to animal noise, industrial machine noise. The other important observation from simulation results obtained is that for predicting human speech signal by least mean square (LMS) algorithm, six weights lie in the minimum threshold range of -0.005 to 0.005, whereas in the case of normalized least mean square (NLMS) algorithm the number of weights lying in the minimum threshold range of -0.005 to 0.005 is zero. In case of recursive least mean square (RLS) algorithm the number of weights lying in the minimum threshold range of -0.005 to 0.005 is nine which is the highest among the three. Thus, simulation results prove that the recursive least mean square (RLS) algorithm has a higher convergence rate and also is highly stable for the same step size as compared to the least mean square (LMS) and normalized least mean square (NLMS) algorithms. Further analysis shows that the convergence rate and stability of the recursive least mean square (RLS) algorithm is best in the case of birds' chirp sound, better in the airplane noise as compared to the real-time speech signal. The same is the case observed with normalized least mean square (NLMS) algorithm which shows the lowest convergence rate and lowest stability in the estimation of real-time speech signal as compared to better convergence rate and moderate stability in case of predicting the airplane sound signal. It is found best in case of bird's chirp noise signal. Similar characteristics are observed from the least mean square (LMS) algorithm which has the highest convergence rate, best stability for bird chirp signal, and lowest convergence rate, highest instability in the estimation of the real-time speech signal. The performance of the three algorithms is summarized and results obtained are in Table 3 given below:

TABLE 3
Result Summary in terms of convergence rate, stability, and complexity

Algorithm	Noise	Convergence Rate	Stability	Complexity
LMS	Airplane	Better	Better	Lowest
	Bird Chirp	Best	Best	
	Human Speech	Good	Good	
NLMS	Airplane	Average	Average	Average
	Bird Chirp	Average	Average	
	Human Speech	Average	Average	
RLS	Airplane	Better	Better	Highest
	Bird Chirp	Best	Best	
	Human Speech	Good	Good	

For further analysis the proposed noise cancellation model described above is categorized into four different cases. In case 1, 2 and 3 the desired signal is pre-recorded musical song and surrounding noise is real-time human speech, bird chirp sound and airplane sound respectively. Adaptive algorithms used are RLS, NLMS, LMS and the analysis criterion is filter weights generated by the adaptive algorithms. In case 4 the desired signal is pre-recorded musical song, adaptive algorithms used are RLS, NLMS, LMS and the analysis criterion is filter weights generated by the adaptive algorithms. But the surrounding noise now in this case is the combination of the real-time human speech, bird chirp sound and airplane sound. The purpose behind taking the four different cases is to evaluate the prediction accuracy of the adaptive algorithms for different kinds of surrounding noise. The sample of 31 filter weights generated for each algorithm for all the four cases are given below:

TABLE 4
Adaptive filter weights

Case	Noise	Sr. No.	RLS	NLMS	LMS
Case 1	Human Speech	1.	1.05	-0.27	0.95
		2.	-0.06	1.56	0.24
		3.	-0.01	2.02	-0.01
		4.	0.03	2.02	-0.00
		5.	0.01	-2.34	0.06
		6.	0.01	-0.77	0.08
		7.	-0.03	1.25	0.04
		8.	-0.02	1.16	0.01
		9.	0.03	-0.81	0.01
		10.	-0.01	-0.50	0.04
		11.	-0.03	-0.22	0.04
		12.	0.01	0.52	0.04
		13.	0.02	0.30	0.03
		14.	0.01	-0.24	0.02
		15.	-0.02	0.82	0.01
		16.	-0.01	-0.55	0.02
		17.	0.02	-0.64	0.04
		18.	-0.00	0.09	0.04
		19.	-0.02	1.42	0.03
		20.	-0.01	0.12	0.02
		21.	0.02	-1.32	0.03
		22.	0.00	-1.05	0.04
		23.	-0.02	1.70	0.03
		24.	-0.01	1.58	0.02
		25.	0.02	-1.69	0.01
		26.	0.00	-1.15	0.01
		27.	-0.03	1.70	0.01
		28.	0.01	1.58	0.01
		29.	0.02	-1.69	0.02
		30.	0.03	-1.15	0.04
		31.	-0.03	0.57	0.03
Case 2	Bird chirp	Sr. No.	RLS	NLMS	LMS
		1.	1.00	-1.30	-0.03
		2.	0.00	4.88	-0.03
		3.	-0.01	-9.24	-0.02
		4.	0.01	9.58	-0.02
		5.	-0.01	-9.15	-0.03
		6.	0.00	5.74	0.00
		7.	-0.00	-6.51	-0.00
		8.	-0.01	3.28	-0.00
		9.	0.01	-3.21	0.00
		10.	-0.01	-1.96	0.00
		11.	0.01	2.97	-0.02
		12.	0.01	-3.22	-0.02
		13.	0.00	2.20	-0.03
		14.	-0.00	1.05	0.01
		15.	-0.01	-0.95	-0.01
		16.	-0.00	0.68	-0.04
		17.	-0.01	-1.66	-0.01
		18.	-0.00	0.47	-0.01
		19.	-0.01	-2.46	0.01
		20.	0.00	1.78	-0.00
		21.	-0.00	-1.35	0.00
		22.	-0.01	0.45	-0.03
		23.	0.00	-0.61	-0.03
		24.	-0.00	1.72	-0.03
		25.	-0.01	-1.31	-0.04
		26.	-0.01	2.50	-0.02
		27.	-0.01	-1.62	0.00
		28.	0.00	0.59	0.02
		29.	-0.02	1.49	0.02
		30.	0.01	-1.27	-0.01
		31.	-0.02	-1.01	0.07
		Sr. No.	RLS	NLMS	LMS
		1.	0.91	10.85	0.63
		2.	0.15	-7.82	0.30

Case 3	**Airplane noise**	3.	-0.06	-10.25	0.07
		4.	-0.00	27.14	-0.03
		5.	0.01	-24.32	-0.11
		6.	-0.01	5.87	-0.09
		7.	-0.02	5.08	-0.05
		8.	-0.01	4.67	-0.05
		9.	0.01	8.49	-0.01
		10.	0.01	-13.07	0.01
		11.	0.00	13.37	-0.01
		12.	-0.02	8.45	-0.00
		13.	-0.01	-35.04	-0.03
		14.	0.01	-1.91	-0.04
		15.	-0.01	-5.14	-0.03
		16.	-0.02	21.40	-0.04
		17.	0.00	-10.90	-0.00
		18.	0.02	-9.67	0.01
		19.	0.00	102.08	0.01
		20.	0.02	-121.52	0.04
		21.	0.00	32.78	0.02
		22.	0.01	16.32	0.01
		23.	0.01	-36.78	0.02
		24.	-0.01	-4.15	0.01
		25.	-0.01	32.82	0.02
		26.	-0.01	14.47	-0.02
		27.	-0.01	-25.99	-0.03
		28.	-0.01	10.90	-0.02
		29.	0.00	12.65	-0.04
		30.	0.00	-2.37	-0.02
		31.	-0.05	-56.15	-0.01
Case 4	**Combined Noise**	**Sr. No.**	**RLS**	**NLMS**	**LMS**
		1.	1.00	0.51	1.02
		2.	0.01	-0.09	0.01
		3.	-0.01	-0.13	0.02
		4.	0.01	-0.32	0.01
		5.	-0.01	-0.27	-0.04
		6.	0.01	-0.10	0.03
		7.	-0.01	-0.06	-0.06
		8.	0.01	-0.14	0.04
		9.	0.00	-0.19	-0.04
		10.	-0.00	-0.12	0.08
		11.	-0.01	-0.01	-0.08
		12.	0.01	-0.01	0.06
		13.	-0.01	-0.02	-0.06
		14.	0.01	0.02	0.02
		15.	0.01	-0.02	-0.01
		16.	0.00	-0.19	-0.02
		17.	-0.00	-0.20	-0.01
		18.	-0.00	-0.03	-0.05
		19.	0.00	0.02	0.02
		20.	-0.01	-0.03	-0.01
		21.	0.01	0.02	0.07
		22.	-0.00	0.35	-0.06
		23.	0.00	0.28	-0.02
		24.	0.00	0.23	-0.02
		25.	0.00	0.23	-0.06
		26.	-0.00	0.23	-0.05
		27.	0.00	0.23	0.03
		28.	-0.00	0.21	0.03
		29.	-0.00	0.23	0.08
		30.	0.01	0.26	-0.02
		31.	-0.02	-0.27	-0.02

On the basis of the filter weights obtained for the four cases as listed above in table 4, it is observed that in case 4, the RLS algorithm has the highest prediction accuracy of 45.16%. In case, where the surrounding noise is real-time speech signal it has the best prediction accuracy of 9.67%. The calculated prediction accuracy of the three algorithms is given in table 5 below:

TABLE 5
Simulation results in terms of prediction accuracy

Algorithm	**Noise**	**Prediction Accuracy**
LMS	Airplane	6.45%
	Bird Chirp	25.8%
	Human Speech	3.22%
	Combined noise	<1%
NLMS	Airplane	<1%
	Bird Chirp	<1%
	Human Speech	<1%
	Combined noise	<1%
RLS	Airplane	19.35%
	Bird Chirp	38.70%
	Human Speech	09.67%
	Combined noise	45.16%

From the table given above, we find that the prediction accuracy for bird chirp signal is highest of 38.70% for RLS algorithm. When compared with LMS algorithm the prediction accuracy for bird chirp signal reduces to 25.8%. This means it is easier to predict and cancel the bird's chirp due to its highly repetitive pattern. One strange fact observed from the obtained results is the prediction accuracy of the RLS algorithm increases unprecedently when noise is applied in combined form. The RLS algorithm shows 45.16% prediction accuracy and the reason behind this increased accuracy is assumed to be the recursive nature of the algorithm. NLMS algorithms show the least convergence rate and prediction accuracy which is less than 1% in all the cases. This proves to be least suited for active noise cancellation applications. The findings are further proved by the simulation plots of power spectrum of the signals considered. Power spectrum of the input musical song, real-time speech signal noise, noise corrupted signal and the estimated signal output from the least mean square (LMS) algorithm, the normalized least mean square (NLMS) and the recursive least mean square (RLS) algorithm at sample rate of 44.1kHz is shown in figure 14 below:

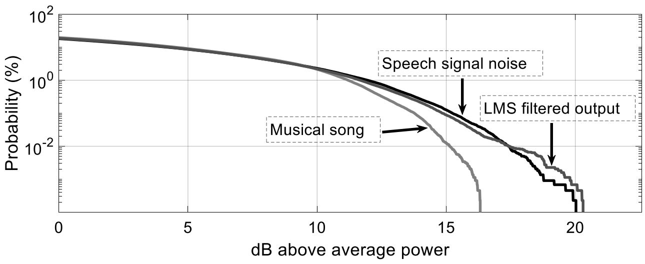

Figure 14(a)

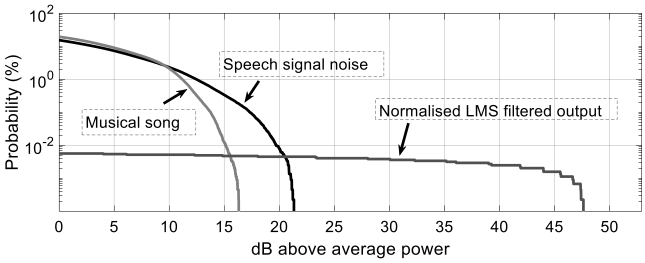

Figure 14(b)

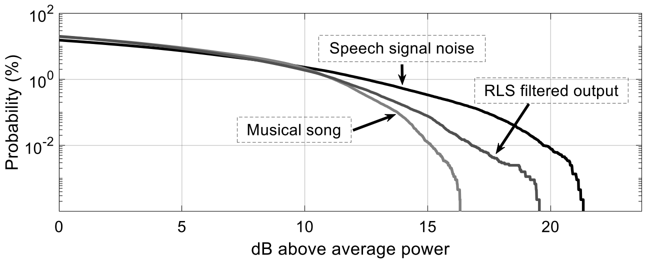

Figure 14(c)

Figure 14. Power spectrum of LMS, NLMS, and RLS filtered output showing recovered musical song after the cancellation of the speech noise signal.

As shown in figure 14 above, the average power is the same for the desired input musical song signal and the recovered signal output from recursive least mean square (RLS) algorithm. Whereas there is a large deviation in the case of normalized least mean square (NLMS) algorithm but small deviation in case of least mean square (LMS) algorithm. It justifies the proven fact that recursive least mean square (RLS) algorithm is much better in estimation and cancellation of real-time speech signal noise when compared to the least mean square (LMS) algorithm and the normalized least mean square (NLMS) algorithms. The prediction accuracy given in table 5 above is verified by results obtained by calculating the signal to noise ratio (SNR) of the desired signal for different noisy surroundings. SNR is calculated from modulation error ratio (MER) applied in digital communication applications. The concept of calculating MER using a reference signal input compared with received signal input is used in digital communication system for obtaining modulation efficiency. Ratio of average power of the reference signal to mean square error is termed as modulation error ratio. The same concept is used in this paper to calculate the signal to noise ratio of the desired input signal taken as the reference signal and the estimated signal generated by the adaptive algorithm is used as the input received signal. Table 6 below gives the signal to noise ratio (SNR) in dB for recovered signal in different surrounding noise.

TABLE 6
Signal to noise ratio

Algorithm	Noise	SNR (dB)
LMS	Airplane	29.94
	Bird Chirp	30.63
	Human Speech	28.83
	Combined noise	28.79
NLMS	Airplane	5.83
	Bird Chirp	-8.496
	Human Speech	36.99
	Combined noise	-9.952
RLS	Airplane	50.85
	Bird Chirp	41.09
	Human Speech	59.62
	Combined noise	39.09

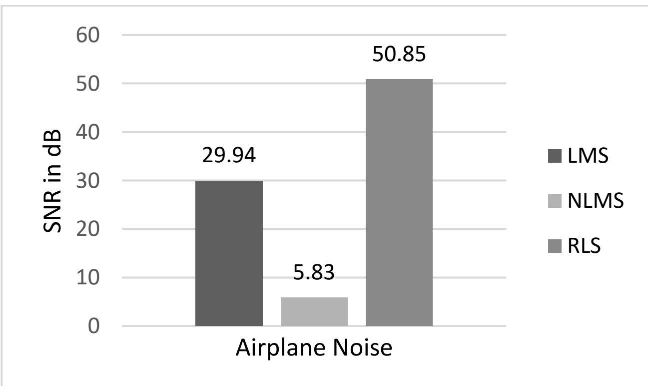

Figure 15(a)

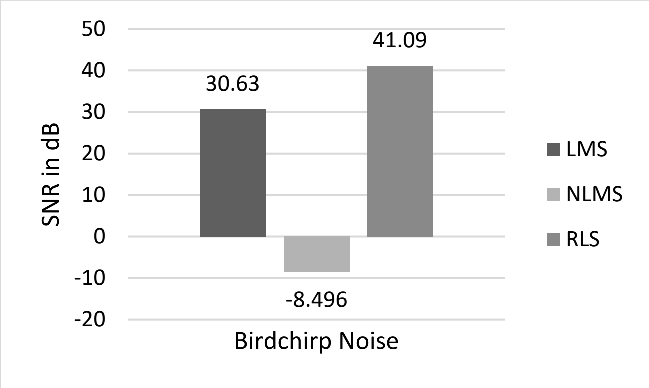

Figure 15(b)

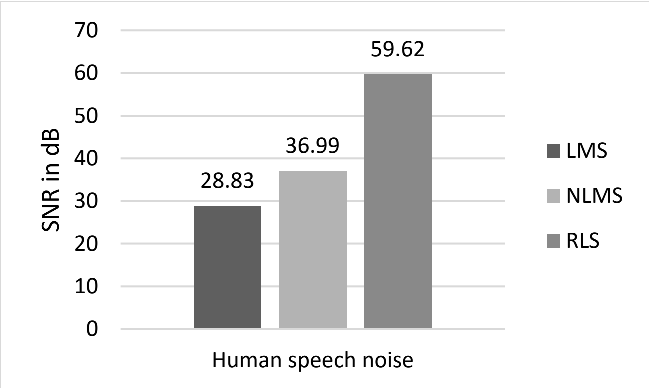

Figure 15(c)

Figure 15. Signal to noise ratio of recovered signal through LMS, NLMS and RLS algorithms for airplane noise, bird chirp noise and human speech noise.

It is seen that the RLS algorithm have highest prediction accuracy for bird chirp noise as well as highest SNR 41.09 dB as compared to 30.63 dB and -08.496 of LMS and NLMS algorithms respectively. Similarly, the SNR for the human speech noise is the highest 59.62 dB in case of RLS as compared to 36.99db of NLMS and 28.33db of LMS algorithm. The SNR in case of airplane noise is highest for RLS algorithm given as 50.85 dB and lowest 5.83 dB in NLMS algorithms. Similar results are obtained for the combined noise surrounding, highest prediction accuracy of 45.16% is verified by the highest SNR of 39.09 dB for RLS algorithm. However, better performance of RLS algorithm is reported by Suman et al. [8]. Further, Sayed et al. [5] has also reported faster convergence speed for RLS algorithm as compared with LMS, NLMS and AP algorithms. Our simulation results of table 6 justify the results of table 5, as clearly shown by the figures 15 (a), (b) and (c) respectively. Power of the noise signal and the recovered signal is another significant important parameter in active noise cancellation system. The noise signal and the estimated anti-noise signal add up to generate at least twice the total amount of power of reference noise signal which is minimized at the point of cancellation. The excess power dissipation of ANC is addressed by Ying Chen et.al [26]. Moreover, online secondary path modelling technique for auxiliary noise power scheduling algorithm is presented by Paulo et.al. [27] in ANC. We have used this concept of signal power in the active noise cancellation model for analysis of the adaptive algorithms. This is done by calculating the error vector measurement (EVM) parameter, that gives the performance indication of each algorithm in terms of the root mean square (RMS) power of the error vector between the reference signal and the received signal. The reference signal is the musical song signal and the received signal is the signal recovered after active noise cancellation i.e., the output of the adaptive filters. The root mean square EVM power is listed below in table 7 for the LMS, NLMS and RLS algorithms.

TABLE 7
RMS Error vector power

Algorithm	Noise	RMS EVM (dB)
LMS	Airplane	28.88
	Bird Chirp	8.194
	Human Speech	6.962
	Combined noise	29.3
NLMS	Airplane	338.2
	Bird Chirp	1298
	Human Speech	5.406
	Combined noise	1622
RLS	Airplane	2.871
	Bird Chirp	2.344
	Human Speech	0.3156
	Combined noise	3.556

The experimental results in table 7 indicates that the root mean square power of the error vector is the minimum with the RLS algorithm for all the three noise signals and also lowest for the combined noise surroundings. Therefore, our comparative analysis of results proves RLS algorithms to be best suited for adaptive noise cancellation application in three kinds of noisy surroundings as described in the proposed model.

IV. CONCLUSION

On implementation of the noise cancellation on the proposed model of analysis, it is concluded that the recursive least mean square (RLS) algorithm has the highest convergence rate as well as SNR and best stability in the estimation of the noise signal in all the three noisy surroundings namely real-time speech signal noise, airplane fly by noise and birds chirping noise. Moreover, this statement is further supported by the root mean square EVM power analysis for all three algorithms. The least mean square (LMS) has the second-best performance in terms of convergence rate and stability, the normalized least mean square (NLMS) algorithm lags among the three algorithms in the given noisy surroundings. Despite having a good convergence rate and stability recursive mean square algorithm suffers from high mathematical complexity for estimation and optimization of filter weights. This high complexity provides vast scope for further research to design adaptive filtering algorithms with reduced complexity, high convergence rate, and high stability. The other important finding from this analysis is the difference in characteristics behaviour of adaptive algorithms for real-time speech signal termed as human speech noise, noise from an airplane or industrial noise, and noise from a bird chirp or animal noise. It is observed and concluded from simulation results that human speech is far more unpredictable and difficult to estimate as compared to industrial machine noise and animal noise. Results show that all the three algorithms analysed have the lowest convergence rate, stability and prediction accuracy for estimation of human speech signal whereas the highest convergence rate, high stability and prediction accuracy for animal sound which follow a more repetitive pattern. Thus, are more easily estimated by adaptive filters. These findings hold significance to give a new direction to research in the field of adaptive filtering. It opens a new channel for research in the form that adaptive algorithms behave differently for different noise signals and the need of the hour is to design noise specific algorithms so that more efficient and less complex adaptive systems can be obtained at lower costs. A new term which may be coined from the findings of this paper is active noise specific cancellation. Researchers need to give a thought to this aspect in designing advanced, more robust, highly accurate next generation adaptive noise cancellation systems for the future.

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