Multichannel Speech Dereverberation Using GSC Beamforming with Different Adaptive Algorithms

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Abstract- Dereverberation of speech signals in a hands-free scenario by adaptive algorithms has been a research topic for several years now. However, it is still a difficult problem because of the nature of common room impulse response (RIR). RIR is generated artificially based on parameters of the room and its intensity depends on the size, shape, dimensions and materials used in the structure of the room. Beamforming is the classical method in the multichannel speech enhancement domain to suppress the noise at the microphone array output. GSC is the most prominently used for noise reduction as well as for interference rejection GSC beamformer with Least Mean Square (LMS), Normalized LMS (NLMS) and Recursive least square (RLS) are implemented with and without postfilter and their performance is evaluated under various noisy conditions. The GSC beamformer with RLS achieve better performance compared to GSC with LMS and NLMS algorithms. The performance metrics like Signal to Noise Ratio (SNR), Perceptual Evaluation of Speech Quality (PESQ) and Log spectral Distance (LSD) are used to validate our results.

Keywords- Speech Enhancement, GSC Beamforming, LMS, NLMS, RLS and post filters.

1.INTRODUCTION

In a variety of multimedia applications, speech and audio play a significant role as a human machine interface. However, Speech signal acquire by a distant microphone in an enclosed space is often degraded by reverberation. Reverberation is the combined effect of multiple reflections from the walls of the room and its intensity depends on the size, shape, dimensions and materials used in the construction of the room. This has a detrimental consequence on the perceived quality as well as the intelligibility of speech signal. Therefore, De-reverberation techniques play a key role in a variety of application.

In many speech communication applications like mobile phone, hearing aids, teleconference, etc., speech enhancement plays a crucial role. The main aim of speech enhancement is to improve the quality and intelligibility of degraded speech under various noisy conditions in real-time environments. Many speech enhancement techniques are introduced from the past few decades. Microphone array-based speech enhancement methods improve the quality as well as the intelligibility of corrupted speech when compared to single channel speech enhancement techniques.

Single channel speech enhancement techniques fail to find the direction of arrival and are unsuccessful in improving the desired signal strength. Beamforming gives the spatial information and improves the signal to noise ratio of the desired speech signal by attenuating the background noise from various noisy conditions. GSC beamforming plays a prominent role in the areas of noise cancellation due to its sidelobe canceling path.

2.RELATED WORK

Most of the popular De-reverberation algorithms are (a) Adaptive algorithms and (b) Blind Deconvolution algorithm. In Adaptive algorithms, preferred signal is given to the output. In the output, the algorithm coefficients are changed or adapted by using some adaptive algorithms such as LMS, RLS, NLMS. So that the output of algorithm is closely matches the desired signal. In Blind Deconvolution algorithm, no preferred signal is given to the output.

In this paper, Adaptive algorithms namely: LMS, NLMS, RLS have been implemented for De-reverberation of reverberated speech by using linear array of four microphones.

Beamforming or spatial filtering is a signal processing method used in sensor arrays for directional signal transmission or reception. This is achieved by combining elements in an antenna array in such a way that signals at particular angles experience constructive interference while others experience destructive interference. Beamforming can be used at both the transmitting and receiving ends in order to get spatial selectivity. The enhancement compared with omnidirectional reception/transmission is recognized as the directivity of the array.

Beamforming is the classical method in the multichannel speech enhancement domain to suppress the noise at the microphone array output. Using the spatial and temporal information, the signal to noise ratio is improved. Hence beamforming can also be called as spatial filtering. Beamformer forms a beam like a pattern towards source direction and enhances the degraded speech from background noise. Using a microphone array, the output of each microphone is combined to have an enhanced signal. There are two types of beamforming techniques: fixed beamforming and adaptive beamforming

A. Fixed Beamforming

Fixed beamforming generally describes a conventional technique where the antenna array pattern is obtained from fixed element weights that do not depend on the signal environment. Conversely, adaptive beamforming element weights that do depend on and can adapt to the signal environment via some feedback mechanism.

Fixed beamforming is a fundamental technique to enhance the speech signal where the weight of each microphone is fixed. The fixed beamformer can also be called as the data independent beamformer, as the weight coefficients will not depend on the microphone data. The types of fixed beamformer include Delay and Sum Beamformer (DSB), weighted and sum beamformer, filter and sum beamformer. Among these DSB is the most commonly used fixed beamformer where the desired signal is enhanced based on the delay on the microphone and is summed finally to have enhanced signal at the output as the weights are fixed, the desired speech signal is not enhanced completely using fixed beamformers. It fails in the reverberant environment to eliminate the diffuse noise. Due to this drawback, adaptive beamforming is addressed to enhance the quality of speech signal in noisy and reverberant environment.

B. Adaptive Beamforming

performs adaptive spatial signal processing with an array of transmitters or receivers. The signals are combined in a manner which increases the signal strength to/from a chosen direction.

In an adaptive beamforming technique, the weights are updated using adaptive algorithms. This beamforming is also called as data dependent beamformer as the weights are dependent on previous iteration weight coefficients. Also, they depend on the microphone array data statistics. Few of them are Linearly Constraint Minimum Variance (LCMV) beamformer, Minimum Variance Distortion Less Response (MVDR) beamformer, and Generalized Sidelobe Canceller (GSC). Among these GSC is the most prominently used for noise reduction as well as for interference rejection. It is easy to implement GSC Beamformer and Computational complexity is less when compared to other beamforming techniques. The filter weights of this beamformer are updated until error minimized to have enhanced speech signal at the GSC output. GSC beamformer with different adaptive filters are proposed under different noisy conditions.

4. PROPOSED OF GSC ADAPTIVE BEAMFORMING WITH POSTFILTER

In GSC with different adaptive filter under various noise conditions is proposed. Generalized Sidelobe Canceller structure is shown in Fig. 1. GSC structure has two parts. The upper part has a fixed beamformer. DSB is considered as fixed beamformer. The lower part has a blocking matrix and an adaptive filter (LMS, NLMS, RLS). Each block is explained in the below subsections.

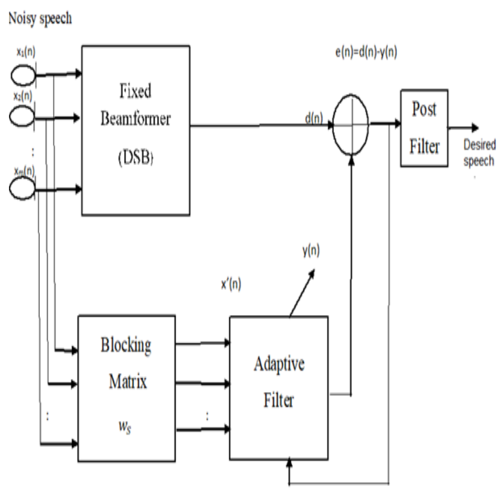

Fig .1 Structure of GSC Beamformer

DSB beamformer is a fixed beamformer used in improving SNR and finding the direction of arrival of the source signal. In the DSB structure, the microphones are placed in a linear manner by giving ‘d’ as the spacing between each microphone and angle ‘θ’ for receiving the input signal from a particular direction x_1(n), x_2 (n). . .. x_m(n) are inputs to microphone which combines the desired speech signal with a different type of

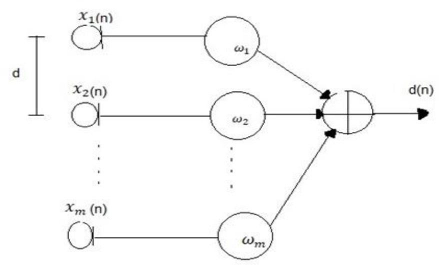

Fig.2 Delay and Sum Beamformer (DSB)

real-time noises. The delay between each microphone can give by angle θ of the incoming signal. The input of each microphone is delayed with angle θ and then summed to have an enhanced speech at the output of DSB which is shown in Fig.2.

The output of delay and sum beamformer is be defined by

$$\text{d(n)}=\frac{1}{M}\sum_{m=1}^{M} x_m(n-\tau_m) \quad (1)$$

Where d(n) is the DSB output, M is the number of microphones, x_m(n) is an incoming signal at the m^{th} microphone, τ_m time is the delay taken from source to each microphone. By modifying the phase weight, ψm(f) the main lobe position in the directivity pattern will be changed which is given by

$$\psi\text{m(f)}=2\pi\alpha(\text{m}-1)\text{ d} \quad (2)$$

Where

$$\alpha = \frac{\sin\theta}{\lambda}$$

θ is the direction of arrival of incoming signal and λ is used to determine the wavelength of frequency. By equation (2) time delay can be analyzed, as the phase shift in the frequency domain relates to a time delay in the time domain,

which is given as

$$\tau_m=\frac{\psi m(f)}{2\pi f} \quad (3)$$

$$\tau_m=\frac{2\Pi\alpha(m-1)d}{2\Pi f} \quad (4)$$

c = fλ

$$\tau_m=\frac{2\Pi\alpha(m-1)d\sin\theta}{c} \quad (6)$$

The fixed beamformer DSB with fixed amplitude weights denoted by $w_1, w_2 \ldots\ldots w_M$.From each microphone, the fixed weights are summed to have enhanced speech reference which is defined by d(n). The output of the fixed

beamformer is given by

$$d(n) = \overline{w}T_{\bar{x}(n)} \quad (7)$$

Where

$\overline{w}T$= $[w_{1,} w_2 \ldots\ldots w_M]$ is fixed weights vector of DSB

$\bar{x}$(n) is the microphone input vector.

B. Blocking Matrix

The GSC structure lower part has two blocks, the first block is Blocking Matrix (BM) $\overline{w}_s$ is used to block the speech signal and give output as noise reference. The blocking matrix is represented by

$$\begin{bmatrix} 1 & -1 & 0 & 0 \\ 1 & 0 & -1 & 0 \\ 1 & 0 & 0 & -1 \end{bmatrix}$$

This is used to know the spatial information on the adjacent microphones. The efficiency of the BM is decided by the number of microphones, as in this paper the number of microphones is taken as four, so the efficiency of the blocking matrix is three. The blocking matrix output is given by

$$\bar{x}'\text{(n)} = \overline{w_s x}(n) \quad (8)$$

$\bar{x}'$ (n) is an array of order M − 1, the incoming microphone signal is placed in the rows of the BM, the spatial information is completely used by the GSC beamformer because of BM in its structure.

C. Adaptive Filters

An adaptive filter with robust convergence rate is essential in speech enhancement. In the lower part of GS, the second block is an adaptive filter. In this paper adaptive filter plays a prominent role in reducing the error between the desired and noisy reference of a GSC. This can be achieved by using different adaptive algorithms in the adaptive filter input to the adaptive filter, where the weights are updated to enhance the corrupted speech at the GSC output. In the GSC with different adaptive filters is proposed in order to improve the performance of GSC in terms of speed and complexity. Here, we have introduced three adaptive filters like LMS, NLMS, RLS in the adaptive filter block of GSC. Adaptive algorithms are explained below.

1) LMS Algorithm

Least mean squares (LMS) algorithms are a class of adaptive filter used to mimic a desired filter by finding the filter coefficients that relate to producing the least mean square of the error signal (difference between the desired and the actual signal). In adaptive signal processing, the least-mean-squares (LMS) algorithm is extensively used due to its stable nature and simplicity while implementing. In stationary conditions, LMS shows the best steady-state performance. The standard LMS algorithm is explained in step-by-step manner below.

1. In the first step, the filter weight coefficients are initialized

$\overline{w}$(n)=$[w1(n)w_2(n)w_3(n) \ldots w_P(n) = 0]$ (9)

where P is the filter order.

2. In the second step, the adaptive filter output y (n) is calculated

y(n)=$\overline{w}T$(n)$\bar{x}'$(n) (10)

3. In the third step by using equation (11) the error signale(n) is calculated

e(n)=d(n)−y(n) (11)

4. Finally, by using (12), filter tap coefficients are updated

$\bar{w}(n+1) = \bar{w}(n) + \mu e(n)\bar{x}(n)$ (12)

Where μ is the step-size, the convergence rate of the filter weights is purely based on μ value. Equation (12) LMS weights update equation which used in adaptive filter block of GSC structure to update the degraded speech and to minimize the error. The computational complexity of LMS is given by the 2N number of additions/Subtractions and 2N+1 Multiplications/ Divisions with N=256.

2) NLMS Algorithm

The normalized LMS (NLMS) algorithm is in addition to the standard LMS algorithm. In NLMS the weight iteration to other. The step size μ in the NLMS algorithm is in a time-varying parameter which is used to calculate convergence of the adaptive filter. Step size μ is given as

$$\mu(n) = \frac{\alpha}{c+\|\bar{x}'(n)\|^2} \quad (13)$$

The convergence rate of NLMS is optimized by adaption

constant ‘α’ which ranges from

0<α<2,

‘c’ in the equation (13) is a constant term used for normalization of the filter which is limited to c< 1

Finally, the NLMS algorithm updates the filter coefficients by using the following equation.

$$\overline{w}(n+1) = \overline{w}(n) + \frac{\alpha}{c+\|\bar{x}'_{(n)}\|^2} e(n)\,\bar{x}'(n) \quad (14)$$

NLMS algorithms converge faster compared to LMS because of the normalization factor μ. The error e(n) of NLMS is less compared to the LMS algorithm. Computational Complexity [12] of NLMS is given by the 2N^2 + 2N number of additions/Subtractions and 2N^2 +3N Multiplications/ Divisions.

The NLMS algorithm has two distinct advantages over the least-mean-square (LMS) algorithm: 1) potentially-faster convergence speeds for both correlated and whitened input data and 2) stable behavior for a known range of parameter values (0 < < 2) independent of the input data correlation statistics.

3) RLS Algorithm

Recursive Least Squares (RLS) algorithm is robust adaptive algorithms to fasten the convergence rate compared to LMS and NLMS. By using the RLS algorithm the adaptive filter coefficients are found recursively to minimize the weighted least square of cost function corresponding with the input. RLS algorithm is strong in spontaneously adjusting the filter coefficients without knowing the input signal statistical information. At each instant, the RLS algorithms minimize the sum of squares of the desired speech signal estimated errors. Noise cancellation capacity is high compared to LMS and NLMS but requires complicated mathematical operations. Because of this RLS requires more computational resources. The RLS algorithm is explained below in a step-by-step manner.

coefficients are initialized

$\overline{w}(0) = [0\ 0\ 0 \ldots \ldots.\ 0\ 0\ ]T$

2. In the second step, the inverse matrix P(0) is initialized with the diagonal matrix maintaining the main diagonal with δ−1 value.

$\bar{x}'$ (n) = [x' (n)x'(n – 1) …x'(n – M + 1)]T (15)

where the $\bar{x}'$ (n) is adaptive filter input vector

3. In the final step, the RLS updated by calculating the following equations at each segment of the input signal.

$$\overline{w}(n) = \overline{w}(n - 1) + R(n)e(n), \quad (16)$$

$$R(n) = \lambda^{-1}\Pi(n)/(1 + \bar{x}'H(n)\Pi(n)) \quad (17)$$

$$\Pi(n) = P(n - 1)\, \bar{x}'(n), \quad (18)$$

$$P(n) = \lambda^{-1}P(n - 1)\, \lambda^{-1}R(n)\, \bar{x}'H(n)P\,(n - 1) \quad (19)$$

The error is estimated as follows

$$e\,(n) = d(k) - \overline{w}H\,(n - 1)\, \bar{x}'\,(n) \quad (20)$$

Computational Complexity of RLS is given by 3N^2 + 4N number of additions/Subtractions and 3N^2 +6N Multiplications/ Divisions.

4) Postfilter-

After GSC beamforming we use the postfilter is STWT i.e. the Stationary Tunable wavelet transform or also called Stationary wavelet transform (SWT) to remove the residual noise at the output of GSC.

The Stationary wavelet transform (SWT) is a wavelet transform algorithm designed to overcome the lack of translation-invariance of the discrete wavelet transform (DWT). Translation-invariance is achieved by removing the down samplers and up samplers in the DWT and up sampling the filter coefficients by a factor in the level of the algorithm. The SWT is an inherently redundant scheme as the output of each level of SWT contains the same number of samples as the input – so for a decomposition of N levels there is a redundancy of N in the wavelet coefficients. This algorithm is more famously known as "*algorithme à trous*" in French (word *trous* means holes in English) which refers to inserting zeros in the filters. It was introduced by Holschneider et al.

Application of postfilter-

A few applications of SWT are specified below.

- Pattern recognition
- Brain image classification
- Pathological brain detection

4. EXPERIMENTAL RESULTS

The performances of the proposed GSC beam former with different adaptive filters are shown in this unit. Consider a uniform linear array of four microphones and a sound with a spacing of 0.04m between each microphone. To estimate the GSC beamformer performance the clean speech is degraded with car, Restaurant, Babble, Station, Street, white noises under different SNR levels like -10, -5, 0, 5, 10dB.

The degraded speech is given as input to the fixed beamformer which is delay and sum beamformer where the degraded speech delay is calculated with weight coefficients and is summed to have speech reference at the output of DSB. In the next stage, BM output is given as input to LMS adaptive algorithms. In first stage the weights are updated to have enhanced speech at the GSC output. In the next stages similarly, the NLMS, RLS algorithms are applied to have improved performance with high quality and intelligibility enhanced speech at the GSC output shown in the fig. 5. To show the performance improvement of the proposed GSC beamformer objective measures like PESQ, output SNR, log spectral distance (LSD) are used. Lower the LSD higher the speech quality. These parameters are calculated as follows

Signal to Noise Ratio (SNR):

$$\text{SNR(dB)} = 10\, \boldsymbol{log} \frac{\sum_{k=0}^{N-1} x^2(k)}{\sum_{k=0}^{N-1} [\hat{x}(k) - x(k)]^2} \quad (21)$$

Log Spectral Distance(LSD):

$$D_{LS} = \sqrt{\frac{1}{2\Pi}\int_{-\pi}^{\pi}\left[10\log_{10}\frac{p(w)}{\hat{P}(\omega)}\right]^2 d} \quad (22)$$

The input speech signal is a reverberant noisy signal shown in table 1

Performance of reverberant and noisy input signal.

Noise type	Performance metrics	SNR in -10 dB	SNR in -5 dB	SNR in 0 dB	SNR in 5 dB	SNR in 10 dB
Babble	SNR	0.47	1.32	3.64	8.43	1.44
	PESQ	0.47	0.32	0.58	0.84	1.13
	LSD	3.67	3.28	2.93	2.63	2.37
Street	SNR	0.50	1.44	3.86	8.66	1.44
	PESQ	0.69	0.60	0.74	1.17	1.34
	LSD	3.30	2.95	2.64	2.38	2.16
Restaurant	SNR	0.44	1.32	3.69	8.54	1.44
	PESQ	0.36	0.61	0.79	1.03	1.28
	LSD	3.50	3.13	2.80	2.51	2.26
Car	SNR	0.54	1.53	4.17	9.22	1.48
	PESQ	0.67	0.85	1.09	1.30	1.44
	LSD	3.50	3.13	2.81	2.53	2.29
Station	SNR	0.42	1.24	3.42	7.99	1.41
	PESQ	0.66	0.92	1.16	1.37	1.48
	LSD	3.50	3.13	2.80	2.53	2.29
White	SNR	0.42	1.23	3.43	8.13	1.41
	PESQ	0.26	0.51	0.66	0.90	1.14
	LSD	3.73	3.33	2.98	2.67	2.39

Performances of GSC beamformer is verified with LMS, NLMS, And RLS by adding the reverberant speech signal with real- time noise like Car, Restaurant, Babble, Station, Street, White noises with different SNR level and their output SNR and PESQ and LSD values are shown in Table 2 and Table 3.

Table 2 Performance without Post Filter

SNR in dB	Noise Types	GSC WITH RLS			GSC WITH LMS			GSC WITH NLMS		
		SNR	PESQ	LSD	SNR	PESQ	LSD	SNR	PESQ	LSD
-10	Babble	1.16	2.45	2.54	25.89	3.76	4.32	0.25	1.10	4.80
	Street	1.68	2.70	2.65	27.32	3.77	4.56	0.63	1.29	4.12
	Restaurant	1.74	2.77	2.37	28.27	3.77	4.48	0.38	1.16	4.45
	Car	1.84	2.97	2.26	27.24	3.74	4.37	0.94	1.57	4.11
	Station	1.90	2.75	2.26	27.39	3.73	4.31	0.22	1.56	4.74
	White	2.04	2.84	2.25	27.20	3.71	4.44	1.65	1.34	4.44
-5	Babble	1.71	2.78	2.37	26.89	3.76	4.37	0.76	1.35	4.29
	Street	1.99	2.93	2.52	27.34	3.77	4.60	1.66	1.64	3.69
	Restaurant	2.12	3.02	2.23	27.72	3.77	4.47	1.13	1.51	3.97
	Car	2.10	3.12	2.16	27.30	3.75	4.41	2.52	1.87	3.67
	Station	2.16	2.95	2.18	27.36	3.75	4.34	0.65	1.94	4.24
	White	2.20	3.03	2.17	27.58	3.73	4.44	3.99	1.52	3.95
0	Babble	2.04	3.02	2.24	27.11	3.76	4.42	2.20	1.68	3.81
	Street	2.18	3.08	2.43	27.34	3.76	4.63	4.22	2.08	3.30
	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	Car	2.21	3.22	2.12	27.32	3.76	4.45	5.67	2.20	3.28
	Station	2.26	3.12	2.13	27.36	3.76	4.38	1.85	2.35	3.77
	White	2.26	3.17	2.14	27.48	3.74	4.46	7.75	1.79	3.52
5	Babble	2.19	3.17	2.19	27.22	3.76	4.46	5.29	2.04	3.40
	Street	2.25	3.17	2.38	27.34	3.76	4.65	3.05	2.39	2.96
	Restaurant	2.31	3.28	2.15	27.46	3.76	4.52	6.62	2.32	3.15
	Car	2.26	3.28	2.14	27.33	3.76	4.48	9.54	2.49	2.95
	Station	2.29	3.25	2.10	27.35	3.76	4.41	4.53	2.79	3.37
	White	2.29	3.28	2.14	27.43	3.75	4.48	1.11	2.11	3.14
10	Babble	2.25	3.27	2.18	27.28	3.76	4.50	9.23	2.34	3.05
	Street	2.28	3.27	2.36	27.34	3.76	4.67	1.13	2.67	2.68
	Restaurant	2.31	3.34	2.18	27.41	3.76	4.55	1.03	2.64	2.84
	Car	2.28	3.33	2.16	27.34	3.76	4.52	1.21	2.80	2.68
	Station	2.30	3.32	2.10	27.35	3.76	4.45	8.43	3.09	3.03
	White	2.30	3.33	2.16	27.39	3.75	4.51	1.30	2.44	2.83

Table 3 Performances with Post Filter

SNR in dB	Noise Types	POSTFILTER WITH RLS			POSTFILTER WITH LMS			POSTFILTER WITH NLMS		
		SNR	PESQ	LSD	SNR	PESQ	LSD	SNR	PESQ	LSD
-10	Babble	12.29	2.83	0.95	14.96	3.17	1.29	1.33	1.70	1.49
	Street	7.30	3.05	1.03	14.98	3.16	1.31	0.93	2.13	1.50
	Restaurant	11.13	3.21	0.93	14.97	3.15	1.32	2.01	2.36	1.41
	Car	9.27	3.22	0.93	14.98	3.17	1.30	2.09	2.37	1.41
	Station	9.97	2.98	1.04	14.98	3.16	1.30	0.81	2.21	1.48
	White	12.53	3.17	0.90	14.98	3.16	1.31	7.73	2.18	1.40
-5	Babble	13.94	3.04	0.89	14.97	3.17	1.29	4.03	1.80	1.39
	Street	9.39	3.15	0.97	14.98	3.16	1.30	2.87	2.25	1.40
	Restaurant	13.26	3.30	0.88	14.98	3.16	1.31	6.04	2.62	1.32
	Car	11.80	3.33	0.89	14.98	3.17	1.30	6.33	2.70	1.31
	Station	12.74	3.12	0.97	14.98	3.16	1.30	2.58	2.63	1.38
	White	14.13	3.28	0.85	14.98	3.16	1.31	2.05	2.43	1.31
0	Babble	14.66	3.19	0.85	14.97	3.17	1.30	1.14	2.10	1.29
	Street	12.00	3.23	0.92	14.98	3.16	1.30	8.47	2.79	1.31
	Restaurant	14.29	3.33	0.86	14.98	3.16	1.31	1.65	2.83	1.23
	Car	13.38	3.39	0.86	14.98	3.17	1.30	1.76	2.92	1.21
	Station	14.29	3.21	0.91	14.98	3.16	1.30	7.67	2.92	1.28
	White	14.79	3.36	0.83	14.98	3.16	1.31	4.47	2.66	1.21

		92	9	83	98	7	30	1	5	20
5	Street	13.61	3.27	0.83	14.98	3.16	1.30	2.17	2.97	1.21
	Restaurant	14.74	3.36	0.84	14.98	3.16	1.31	3.77	3.00	1.14
	Car	14.22	3.41	0.84	14.98	3.16	1.30	3.95	3.08	1.12
	Station	14.87	3.26	0.87	14.98	3.16	1.30	2.04	3.13	1.19
	White	15.00	3.39	0.82	14.98	3.16	1.31	7.60	2.85	1.13
10	Babble	15.00	3.34	0.81	14.98	3.16	1.30	5.56	2.72	1.11
	Street	14.40	3.32	0.86	14.98	3.16	1.30	4.56	3.09	1.13
	Restaurant	14.91	3.38	0.83	14.98	3.16	1.30	6.75	3.14	1.07
	Car	14.63	3.41	0.83	14.98	3.16	1.30	6.96	3.18	1.06
	Station	15.04	3.30	0.83	14.98	3.16	1.30	4.42	3.28	1.11
	White	15.06	3.39	0.82	14.98	3.16	1.30	10.32	3.02	1.06

At 10dB input SNR with white noise, proposed GSC without postfilter LMS gives an output SNR of 27.39dB, whereas for GSC without postfilter RLS and NLMS is 2.30dB and 1.30dB. Intelligibility measure PESQ for proposed GSC without postfilter LMS is 3.75dB whereas, for GSC without postfilter RLS and NLMS is 3.33dB and 2.44dB.

Using Postfilter at 10dB input SNR with white noise RLS gives an output of 15.06dB, whereas for LMS and NLMS is 14.98dB and 10.32dB at input speech signal is 1.41dB. Output SNR using RLS with Postfilter shows improved performance. Intelligibility measure PESQ for RLS with postfilter is 3.39dB whereas for LMS and NLMS with Postfilter is 3.16dB and 3.02dB at Same input speech signal as above. At an instance for 5dB input SNR with white noise, RLS with postfilter gives an output SNR of 15.00dB, whereas for LMS and NLMS is 14.98dB and 7.60dB at input speech signal is 8.13dB. Similarly, PESQ for RLS, LMS, NLMS are 3.39dB, 3.16dB, 3.02dB respectively, for this same input speech signal as above. These measure show that GSC Beamformer using Postfilter with RLS shows improved performance in terms of quality and intelligibility compared to LMS and NLMS.

The proposed GSC beamformer using postfilter with RLS adaptive filter gives better performance compared to GSC beamformer using NLMS and LMS and GSC beamformer using postfilter with NLMS and LMS.

5. CONCULSION

Multichannel Speech Dereverberation using GSC Beamforming with Different Adaptive Algorithms is proposed in this paper. Speech dereverberation with different adaptive algorithms like LMS, NLMS, RLS are implemented with Postfilter and their performances beamformer using postfilter with RLS is 15.06dB whereas LMS is 14.98dB and NLMS is 10.32dB under white noise condition. GSC beamforming using Postfilter with RLS, gives better result than GSC with LMS, NLMS. In proposed algorithms GSC with RLS gives improved performance in terms of speech quality and intelligibility.

REFERENCES

1)S. Siva Priyanka, T. Kishore Kumar (2019) “GSC Beamforming using Different AdaptiveAlgorithms for Speech Enhancement” Institute of electrical and electronics engineers 45670

2)S. Siva Priyanka, Kishore Kumar (2019) “GSC Adaptive Beamforming Using Fast NLMS Algorithm for Speech Enhancement” Institute of electrical and electronics engineers 160-165, 2019

3)S. Siva Priyanka, Kishore Kumar (2018) “Adaptive Beamforming using Zelinski-TSNRMultichannel Postfilter for Speech Enhancement” Institute of electrical and electronics engineers 43488

4)Randall Ali , Giuliano Bernardi (2019) “Methods of Extending a Generalized SidelobeCanceller With External Microphones” Institute of electrical and electronics engineers 27 (9), 1349-1363, 2019

5)Thomas Dietzen, Simon Doclo, Senior Member, Marc Moonen , and Toon van Waterschoot “Integrated Sidelobe Cancellation and Linear Prediction Kalman Filter for Joint Multi-Microphone Speech Dereverberation, Interfering Speech Cancellation, and Noise Reduction” Institute of electrical and electronics engineers 1-14, 2019

6)Chao Li, Ting Jiang, Sheng Wu “Speech Enhancement Based on Approximate Message Passing” Institute of electrical and electronics engineers, 187-198, 2020

7)Feng Ni, Yi Zhou, Hongqing Liu (2019) “A Robust GSC Beamforming Method for Speech Enhancement using Linear Microphone Array” Institute of electrical and electronics engineers,2019

8)K.V.Sridhar, T Kishore kumar (2019) “Performance Evaluation of CS Based Speech Enhancement using Adaptive and Sparse Dictionaries” Institute of electrical and electronics engineers 47735

9)S. Siva Priyanka (2017) “A Review on Adaptive Beamforming Techniques for Speech Enhancement” International Conference on Innovations in Power and Advanced Computing Technologies, 1-6, 2017

10)Nikolaos Dionelis, Mike Brookes, (2019) “Modulation-Domain Kalman Filtering for Monaural of electrical and electronics engineers 27 (4), 799-814, 2019

11)Pogula Rakesh, S.Siva Priyanka, T.Kishore Kumar (2017) “Performance Evaluation of Beamforming Techniques for Speech Enhancement” International Conference on Signal Processing, Communications and Networking, 2017

12)Yiteng Huang, Turaj Z. Shabestary, Alexander Gruenstein (2019) “HOTWORD CLEANER: DUAL-MICROPHONE ADAPTIVE NOISE CANCELLATION WITH DEFERRED FILTER COEFFICIENTS FOR ROBUST KEYWORD SPOTTING” Institute of electrical and electronics engineers, 6346-6350, 2019

13)Randall Ali, Toon van Waterschoot, Marc Moonen (2018) “GENERALISED SIDELOBE CANCELLER FOR NOISE REDUCTION IN HEARING DEVICES USING AN EXTERNAL MICROPHONE” Institute of electrical and electronics engineers, 521-525, 2018

14)Mohamed Salah, Bassant Abdelhamid (2019) “Improved Variable Step Size Regularized NLMS-Based Algorithm for Speech Enhancement” International Conference on Signal and Image Processing, 701-706, 2019

15)Pravin Nair, Ruturaj G. Gavaskar, Kunal N. Chaudhury (2020) “COMPRESSIVE ADAPTIVE BILATERAL FILTERING” Institute of electrical and electronics engineers, 2078-2082, 2020