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Multichannel Speech Dereverberation using Generalized Regression Neural Network

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Abstract: When the sound signal is recorded in a confined room, it gets corrupted by echo and background noise present in room. It also deteriorates the property of the dialogue signal and poses a question for numerous speech-related systems, which includes automatic speech recognition and speaker recognition. The Generalized Regression Neural Network (GRNN), which is a single-pass learning process, is renowned for its capability to quickly train on sparse data sets. In this paper, a GRNN-based approach is implemented, which deals with the unified effects of noisy and reverberant environment. The presented approach encompasses two phases: a preprocessing phase which contains framing and feature extraction and a dereverberation and denoising phase which uses the common regression neural network. The outcome of the suggested approach is verified in noisy circumstances for variations in noise, reverberation time and signal to noise ratios. The result of the experiment shows that the developed method operates superior than the existing technique for the actual quality measures. STOI is increased by 5.93% and PESQ is increased by 64.73%.

Keywords: *Reverberation, Dereverberation, Room Impulse Response (RIR), General Regression Neural Network (GRNN), Signal to noise ratio (SNR)*

1. Introduction

Extraction of the desired speech signal from reverberation and the unwanted background noise present in the room is the main objective of speech dereverberation. Speech deverberation acts as fundamental element in various real world applications, e.g., hearing aids, automatic speech recognition, speaker identification (SID), and mobile communication. Room reverberation is achieved by convolving the desired signal with RIR, and speech signals are distorted along with both time and frequency. It has a severe effect on the speech signal quality, also deteriorates the performance of speech processing systems significantly even when trained on large scale data [1]. In speech processing system reverberation still remains a well acknowledged challenge, specifically when it is subjected to background noise. Numerous dereverberation methods have been actively proposed in the past [2], [4]. Allen et al. [5] suggested two microphone speech dereverberation where the first signals were filtered into the frequency band, after which the delay variations were accounted for and applied to the filtered signals. For every band, the correlation among the two mike signals was determined and used to eliminate the reverberation effects as a gain factor for that band to remove the spectral bands with weak correlations. The proposed system is efficient in eliminating the speech's long-term echo.

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K. Lebart et al. [6] put forward a single channel spectral processing technique based on spectral subtraction to suppress the impact of late reverberation. The power spectrum of the reverberation is estimated using an algebraic prototype of late reverberation, which further deducts it from the power spectrum of the reverberant speech. This algorithm achieves a strong reduction of the reverberant energy. M. Wu et al. [7] suggested an algorithm in step one coloration effects are minimized by estimating for single channel speech dereverberation.

Inversefilter and spectral subtraction is used in the second step to mitigate late reverberation.

A recursive multichannel EM-based algorithm was suggested by B. Schwartz et al. [8]. In E-step, the Kalman filter is used to generate a new clean signal sample and the estimation is modified in M-step as per the Kalman filter system output. The reverberations are significantly reduced, and speech quality is increased by the proposed algorithm. K. Furuya et al. [9] proposed joint multichannel blind deconvolution and spectral subtraction for speech dereverberation. Early reflections are reduced by the inverse filter, and the remaining reverberations are suppressed by spectral subtraction. T. Nakatani et al. [10] developed methods of speech dereverberation depend on the basic property of speech signal called as harmonicity property. Two methods of dereverberation have been presented; in one approach, reverberant signals are converted into harmonic signals to estimate the average filter, while in another MMSE criterion is minimized to evaluate the quasi-periodicity of signals. With proposed methods, excellent quality speech dereverberation was achieved for 0.1 and 1.0 s reverberation time. Ina Kodrasi et al. [11] presented a partial multichannel equalization technique based on multiple input/output inverse theorem (P-MINT) to shorten the room impulse response and control the quality of the speech. The robustness of P-MINT is further increased by incorporating regularization. A computerized non-intrusive selection technique for the parameter of regularization is proposed, resulting in almost optimal quality of perceptual speech. The recommended algorithm was used to receive the best perceptual speech output in normalized P-MINT.

A lot of research has been done on dereverberation as well as denoising. M. Delcroix et al.[12] suggested a two-step speech dereverberation technique named linear predictive multi-input equalization (LIME) dependent on multichannel linear prediction (MCLP).An extension to the LIME method, which results in dereverberation with noise reduction in a colored noise acoustic environment, was proposed in [13]. The required speech is retrieved by filtering the residual with an auto-regressive (AR) speech estimate. Yoshioka et al. [14] presented a single channel estimate maximize speech dereverberation and noise drop technique. The anechoic speech was designed to be an all-pole system, whereas the reverberant speech was modeled as a process of auto regression. The reverberant speech is estimated in E-step while in M-step reverberation and speech parameters are estimated. A multichannel Wiener filter obtains dereverberation. O. Schwartz et al. [15] presented a multichannel minimum mean square error predictor for combined reduction of reverberation as well as noise. The estimator is a blend of minimum variance distortionless reaction beamformer and single-channel Wiener filter. The algorithm was verified for different source to microphone array distances and signals to noise ratios. S. Mosayyebpour et al. [16] recommended a single channel two-stage dereverberation algorithm for removing noise and reverberation. The first step is the estimation of the blind inverse filter by increasing the skewness of the LP remainder of the applied signal. Two stage spectral subtraction technique was used to minimize additive noise and reverberation in the second stage. C. Zheng et al. [17] proposed speech dereverberation and noise reduction technique in the linear prediction residual domain. A constrained MMSE LP residual estimator is used for it. This is based on the fact that additive components in the residual domain are late reverberation or noise.

In speech separation or improvement, deep neural networks (DNNs) commonly used in recent years [38]. Several studies [26], [27], [28], [29] reported significantly improved performance over traditional techniques of speech enrichment. In [30], Spectral mapping algorithm is presented by Han et al. to use a single DNN simultaneously to perform denoising and dereverberation. Their main principle is to learn to map the spectrum of noisy reverberant speech rather than fresh anechoic speech. In [31], Wu et al. presented reverberation-time-aware DNN based speech dereverberation. Depending on the reverberation time (T60), dereverberation quality is increased by choosing frame length and shift differently. RT60 is used in the DNN training and extraction of features as a control parameter. Reverberation time is projected in dereverberation stage to determine the proper frame length and shift for the feature extraction. In [32], Zhao et al. put forward a two-step DNN for denoising and dereverberation. Ratio masking is performed for denoising and then spectral mapping is done for dereverberation. In [33], Williamson and Wang proposed the use of DNN with supervised learning to dereverberate and denoise speech signal. For DNN based speech enhancement, they implemented a complex ideal ratio to mask utilizing anechoic speech as a required signal. In a single processing step, noise and reverberations are eliminated. In [34] Y. Zhao et al. proposed noisy and reverberant speech enhancement in which DNN is sequentially used to denoise and dereverberate. The clean phase is incorporated into the objective function to optimize the system permitted to realize a superior estimation of the magnitude of the spectrum. The suggested algorithm is investigated for various types of noise, SNR, RT60 and RIR.

Although GRNN is used in a wide variety of applications like target tracking [35, 36], Speech recognition [37], it can also be applied in speech dereverberation and denoising. The GRNN based multichannel speech dereverberation and denoising algorithm is presented. The main contribution of this work is single stage GRNN is used for multichannel dereverberation along with denoising and investigated for different room acoustic conditions.

The following is the structure of this paper. Noisy reverberant speech signal model is described at the begning of section 2. The proposed algorithm based on GRNN will then be introduced. The investigational arrangement is eleborated in Section 3. The performance evaluation results are summarized in Section 4. Section 5 terminates the paper by conclusion.

2. Algorithm Description

2.1. Signal Model

Considering a multichannel speech dereverberation system in enclosed environment, the signal received by n^{th} microphone is given by

$$y_n(k) = x_n(k) + v_n(k)$$

$$y_n(k) = s(k) * h_n(k) + v_n(k) \qquad (1)$$

Here, $y_n(k)$ represents signal received at the n^{th} microphone, $x_n(k)$ is reverberant speech signal, $h_n(k)$

represents n^{th} channel impulse response, $s(k)$ is the anechoic speech signal, $v_n(k)$ denotes noise signal collected up by the n^{th} mike and $*$ denotes linear convolution. Speech dereverberation aims to propose a technique including input $y_n(k)$ and output $\hat{s}(k)$, that is an estimate of $s(k)$. A mathematical model shows that $v_n(k)$ does not have any correlation with received reverberant signal $x_n(k)$ and $s(k)$ which is desired signal. So it is required to eliminate reverberations as well as noise from received reverberant and noisy signal to retrieve the clean speech.

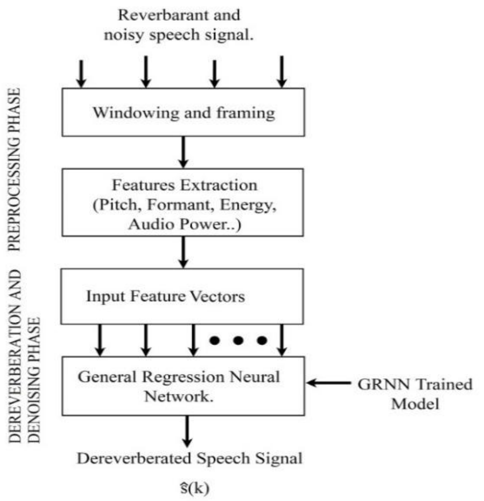


Fig.1. a) Speech dereverberation and denoising system using general regression neural network.

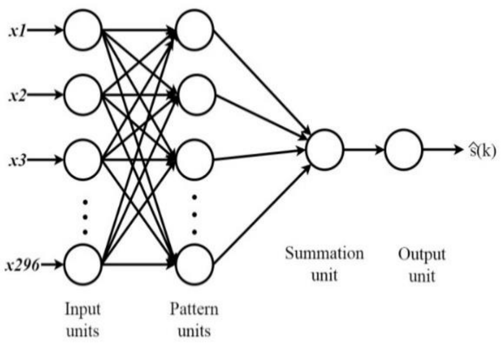


Fig.1 b) General regression neural network.

2.2. General Regression Neural Network for Speech Dereverberation and Denoising

Figure 1 shows the proposed system of speech dereverberation and denoising founded on a general regression neural network. The technique comprises of two parts: a preprocessing phase and a dereverberation and denoising phase. In the preprocessing stage, when a microphone array receives reverberant and noisy signal, the incoming signal is divided into frames by using windowing technique. After framing, features like periodogram, band power, pitch, energy etc. are extracted from each frame. These obtained features form the input feature vectors to the neural network used for dereverberation and denoising. Entire extracted aspects are concatenated and used for GRNN training. GRNN is trained with reverberant and noisy signal by using 30 samples from IEEE database. Trained model is used for testing purpose which is directly test on degraded signal with various SNRs, RT60 and noise. GRNN model have two hidden layer with size 30 and 1 respectively. The standardized radial basis function is utilized for training purpose. The GRNN is a Neural Network based on probability. This is normally used in many applications where accurate modelling is prime importance. [23], [24]. The main feature of this is to solve many types of regression challenges with a very minimal training time. The GRNN is implemented using four layers. The input is applied to the input layer of the GRNN, the patterns are extracted io the second layer, pattern layer. The summation is third layer and finally output layer.

For the given N inputs, the GRNN predicts the amount of M in a smaller amount of time identified by the propagation time. The value of M is supposed to be the approximate $\hat{\mathbf{s}}(\mathbf{k})$ of the required signal $\mathbf{s}(\mathbf{k})$. However N denotes values of the input feature vectors from input nodes, as shown in Fig.1b. GRNN approximates the projected M (N) (i.e.$\hat{\mathbf{s}}(\mathbf{k})$) like :

$$M(N) = \frac{\sum_{i=1}^{n} M_i \exp\left(\frac{-D_i^2}{2\sigma^2}\right)}{\sum_{i=1}^{n} \exp\left(\frac{-D_i^2}{2\sigma^2}\right)} \qquad (2)$$

$$D_i^2 = (N - N_i)^T . (N - N_i)$$

The σ is the smooth out factor for GRNN, and n is the amount of input data tests. The larger the value of σ make better the ability of the network to simplify, whereas smaller the value of σ decreases the capability of the network to oversimplify. The M (N), is the estimate which is a ratio of the summation of all the alleged values Mi, wherever individually observed value is assessed to its exponential rate by its Euclidean distance from N. The 'newgrnn' function utilized to construct the GRNN in the MATLAB setting [25]. In this research work GRNN inputs are the drawn features from a reverberant signal frame that establish the input features of the vectors x_1 to x_{296}. The output of GRNN signifies the approximate speech signal $\hat{s}(k)$ as shown in Fig .1b.

3. Performance Evaluation

3.1 Datasets and Experimental Setup

The implemented technique is evaluated with IEEE database(male and female speaker)[18]. Room with size

10m x 7m x 3m is simulated to generate RIRs. The 4 microphone array is used, and the distances between two microphones is 3 cm. The RIR is generated by keeping source and receiver microphones position fixed with the distance between them is 2m. In this experimentation, three incremental values of RT60 are examined, from 0.3 seconds to 0.9 seconds with an increment of 0.3 seconds. The RIR is generated by an image method [19]. For the training dataset, we used 30 reverberant sentences, RIR is generated with RT60 = 0.6s, signal to noise ratio is 0dB, and noise used is babble noise. We use 30 reverberant sentences for testing. The experimenstation utilized noise such as Babble and speech-shaped noise. For training and test data set, reverberant and noisy signals are produced by combining noise of required SNR with reverberant signal. In this paper noise of -5 dB, 0 dB, and 5 dB SNR is used. The signals are sampled at 8 kHz in this experiment. The incoming speech is divided into frames by a 23 ms hamming window with a 50 percent overlap between neighboring frames. We're using a 1024-point fast Fourier Transform (FFT) analysis. Time domain signal is resynthesized through the overlap add (OLA) method. The number of repetitions identified as 1000.

3.2. Evaluation Metrics

We examine the quality of speech in the experiments by using perceptual assessment of speech superiority (PESQ) [20]. PESQ range is -0.5 to 4.5. Speech intelligibility is evaluated by the use of short time objective intelligibility (STOI)[21]. Range of STOI is usually between 0 and 1. For PESQ and STOI, higher the scores better is the performance. Since we aim to eliminate room reverberation and background noise, clean-anechoic speech is utilized as a base signal for the estimation of objective metrics.

4. Evaluation Results

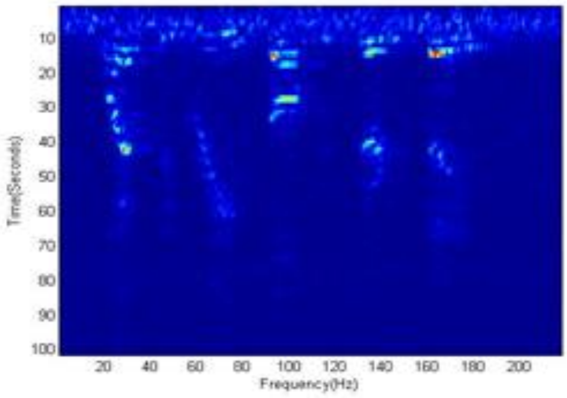
Table 1 - SSN Noise

	RT60 (S)	0.3			0.6			0.9		
	SNR(dB)	-5	0	5	-5	0	5	-5	0	5
PESQ	Unprocessed	1.22	1.57	1.89	1.20	1.50	1.77	1.25	1.45	1.67
	Two stage + TDR[32]	2.22	2.56	2.76	2.12	2.44	2.61	1.96	2.24	2.41
	GRNN	**3.80**	**3.97**	**3.99**	**3.81**	**3.93**	**3.97**	**3.47**	**3.90**	3.97
STOI (%)	Unprocessed	32.00	40.00	50.00	28.00	37.00	44.00	24.00	31.00	37.00
	Two stage + TDR[32]	82.90	87.60	90.00	80.80	86.30	88.90	77.90	83.50	85.90
	GRNN	**88.00**	**90.00**	**93.0**	**87.19**	**90.00**	**92.30**	**84.32**	**89.50**	**91.00**

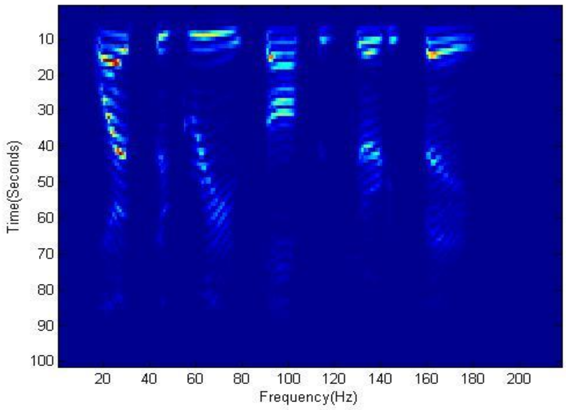
0

Table 2 –Babble Noise

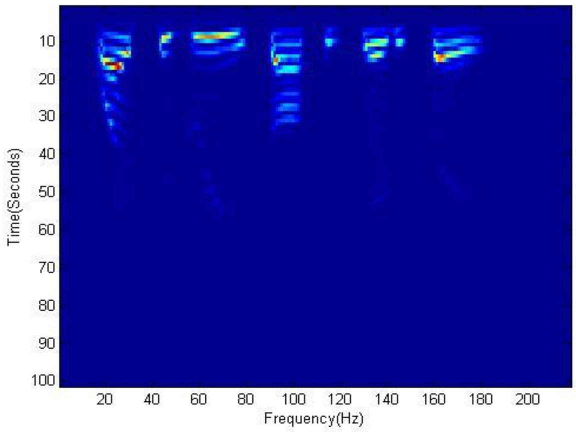
	RT60 (S)	0.3			0.6			0.9		
	SNR(dB)	-5	0	5	-5	0	5	-5	0	5
PESQ	Unprocessed	1.28	1.51	1.77	1.27	1.46	1.68	1.24	1.43	1.65
	Two stage + TDR[32]	2.27	2.57	2.76	2.14	2.43	2.61	1.95	2.22	2.40
	GRNN	**3.85**	**3.97**	**3.99**	**3.83**	**3.93**	**3.98**	**3.48**	**3.91**	**3.98**
STOI (%)	Unprocessed	20.0	30.0	40.0	20.0	30.0	40.0	10.0	20.0	30.0
	Two stage + TDR[32]	83.60	87.60	90.00	81.60	86.30	88.90	78.30	83.10	85.80
	GRNN	**88.15**	**90.74**	**93.48**	**87.99**	**90.09**	**92.35**	**84.38**	**89.58**	**91.03**



(a)



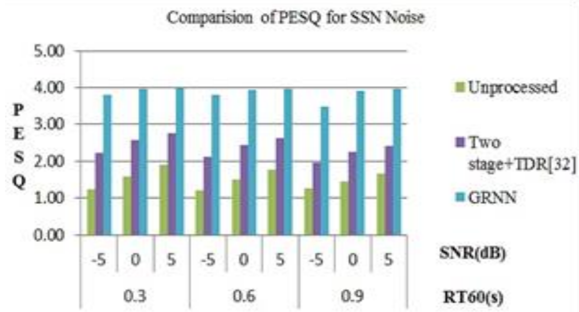
(b)

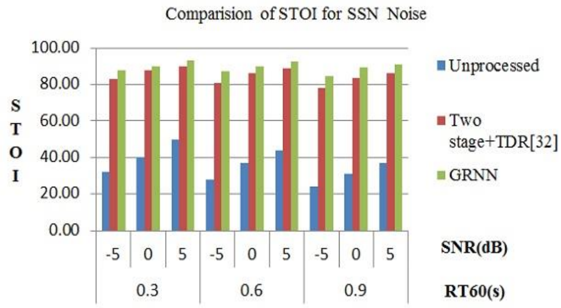


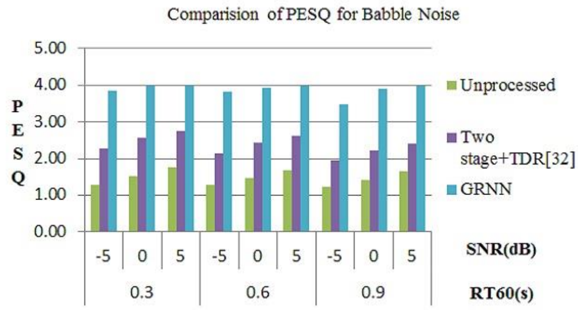
(c)

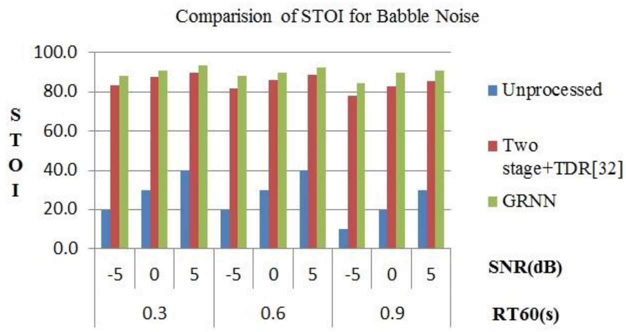
Table 1 summarizes the PESQ and STOI values for unprocessed and processed signals using GRNN with SSN noise under various reverberant and noisy environments. Table 2 shows the PESQ and STOI values of unprocessed and processed signals using GRNN with babble noise under various reverberant and noisy environments. The highlighted figures in table 1 and 2 shows the best result obtaind with SSN as well as babble noise respectively in terms of PESQ and STOI. Fig.3 provides an example of how the sentence " We find joy in the simplest things " is nhanced.

Fig. 3(a) provides a reverberant and noisy speech spectrogram of SSN noise at SNR = 5 dB and RT60 of 0.3 seconds. Figures 3 (b) and 3 (c) illustrate the spectrograms of anechoic speech and enhanced speech of presented GRNN based algorithm correspondingly. When the spectrograms of reverberant and noisy speech are compared with improved speech, it can be seen that the additive noise and smearing effects are effectively eliminated and the spectrotemporal patterns have been significantly recovered. This demonstrated the presented system can efficiently upgrade the quality of reverberant and noisy speech.









5. Conclusion

This paper presents GRNN based algorithm of speech dereverberation in reverberant as well as noisy environment.GRNN being a one pass learning algorithm, has the competence to get trained instantly using minimum samples. It is utilized to perform denoising and dereverberation of the reverberant and noisy signal. In order to study the impact of noise variations , noise SNR is varied within the range of -5dB to 5dB for each SSN and babble noise. Systematic evaluations using speech quality and objective speech intelligibility metrics show that our projected method improves quality of speech and lucidity of speech in a considerable variety of noisy and reverberant surroundings with fewer training samples compared to DNN based approach[32]. The results of the simulation show that the GRNN-based technique performs better than all others when considering denoising and dereverberation. The result of simulation demonstrates the capability of the GRNN architecture for denoising and dereverberation problems in the speech processing area. There are several opportunities for further research, such as the random position of the source in a closed room, variations in distance between source to receiver, testing of the algorithm in various noisy and reverberant conditions including more types of noise and online speech dereverberation and denoising using this algorithm. The future work would concentrate more on verifying this algorithm for random positions of the source in a closed room in various noisy and reverberant environments, which will include a wide variety of noise signals.

Author contributions

Seema Arote: Conceptualization, Methodology, Software, Field study **Vijay Mane:** Data curation, Writing-Original draft preparation, Software, Validation, Field study **Shakil Shaik:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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