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# Speech Enhancement Using Joint Time and DCT Processing for Real Time Applications

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**Abstract:** Deep learning based speech enhancement approaches provides better perceptual quality and better intelligibility. But most of the speech enhancement methods available in literature estimates enhanced speech using processed amplitude, energy, MFCC spectrum, etc along with noisy phase. Because of difficult in estimating clean speech phase from noisy speech the noisy phase is still using in reconstruction of enhanced speech. Some methods are developed for estimating clean speech phase and it is observed that it is complex for estimation. To avoid difficulty and for better performance rather than using Discrete Fourier Transform (DFT) the Discrete Cosine Transform (DCT) and Discrete Sine Transform (DST) based convolution neural networks are proposed for better intelligibility and improved performance. However, the algorithms work either features of time domain or features of frequency domain. To have advantage of both time domain and frequency domain here the fusion of DCT and time domain approach is proposed. In this work DCT Dense Convolutional Recurrent Network (DCTDCRN), DST Convolutional Gated Recurrent Neural Network (DSTCGRU), DST Convolution Long Short term Memory (DSTCLSTM) and DST Convolutional Gated Recurrent Neural Network (DSTDCRN) are proposed for speech enhancement. These methods are providing superior performance and less processing difficulty when compared to the state of art methods. The proposed DCT based methods are used further in developing joint time and magnitude based speech enhancement method. Simulation results show superior performance than baseline methods for joint time and frequency based processing. Also results are analyzed using objective performance measures like Signal to Noise Ratio (SNR), Perceptual Evaluation of Speech Quality (PESQ) and Short-Time Objective Intelligibility (STOI).

**Index Terms:** Speech Enhancement, Perceptual Evaluation of Speech Quality, Noise Reduction, Discrete transform, Recurrent Neural Network, Gated Unit, Signal to Noise Ratio.

## 1. Introduction

The goal of speech enhancement is to estimate clean speech from the corrupted speech and hence produces quality speech for listener comfort. However, processing of noisy speech introduces some distortion and to be taken care while

reducing the noise. A tradeoff between noise reduction and quality is always to be considered while using traditional speech enhancement methods like spectral subtraction, wiener filter and so on. All the traditional techniques uses Short Time Fourier Transform (STFT) for processing noisy speech [1,2]. It is noted that [3,4] the STFT based approaches, mask based approaches [5,6] and complex mask [7,8] uses noisy speech spectral amplitudes only and noisy phase remain untouched while processing [9]. At the reconstruction these approaches utilizes noisy speech phase for reconstruction of enhanced speech [3]. Due to complexity in processing noisy speech phase it is neglected in almost many algorithms. In this work DCT [9] and DST based speech enhancement approaches are proposed which considered phase while processing and for better performance.

Recent speech enhancement approaches uses deep learning models for noise reduction and quality improvement. Also mask based techniques like ideal binary mask [5], complex ratio masks [8] are developed for enhanced signal generation [9]. In this work deep neural network model using ideal mask and skip connections is proposed. This work utilizes Ideal Cosine Mask (ICM) and Ideal Sine Mask (ISM) as given in (7) and (9).

The enhanced speech resynthesis is based on phase is developing in time domain using the masks which are phase sensitive. Training strategies using convolution network is discussed using sliding window [10]. But the deep complex networks are introduced for better performance [11]. Complex valued spectrogram based neural network approaches provides benefits of cosine transform and Unet. But the complexities of phase based designs are still poses problems and this paper addresses the inbuilt phase processing transform using DCT. Also addresses the DCT and DST based approaches for speech enhancement.

## 2. State of Art and Insights of Proposed Method

The diagram of the proposed method is shown in Fig. 1. Here dense blocks are used in convolution network. Dense blocks provides better feature map by providing relevant information through different layers of network. Hence the correlation of frames can learn easily. It contains DCTNet, WNet, and a loss based fusion. WNet accepts the framed time domain input and DCTNet uses inbuilt phase and magnitude processing. To improve the quality of enhanced speech DCTNet and Wnet outputs are further processed using loss based fusion.

Input noisy speech is splitted into frames and applied to WNet and DCTNet. Fusion block accepts the output of mentioned networks and noisy speech for further processing [10].

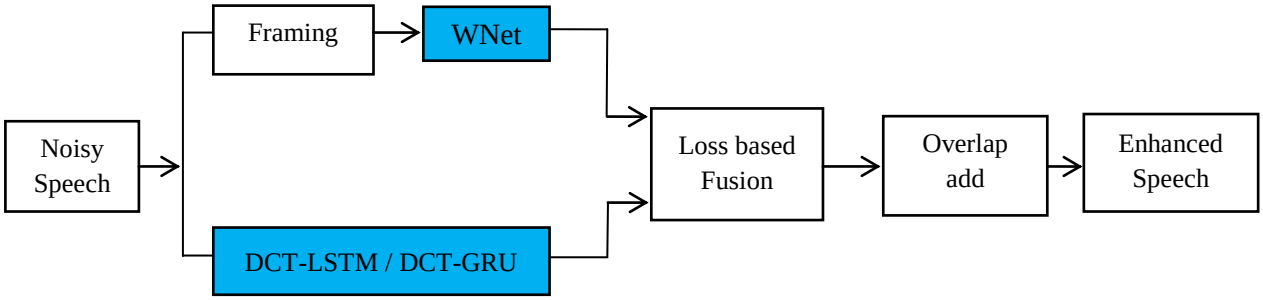



Fig. 1. Simplified Diagram of proposed Method

Gated neural units are used in gradient problem for RNN at the beginning and Long Short-Term Memory (LSTM) is one such variant. It uses the convolution operation [10] which applies convolution filters on input and output feature maps. Wnet uses GTCN as basic building block

DCT based model uses an intermediate processor in which the deep network is utilized. The backend and front end of processor utilizes an decoder and encoder respectively. The flow of encoder-processor-decoder architecture is shown in Fig. 2. Importance of encoder and decoder in proposed method is that the high-level features can easily extracted from input speech and can easily reconstrut the processed signal from lowlevel features at decoder stage. In this work the output of encoder is concatenate with input of decoder layer using skip connection for improved performance in the network.

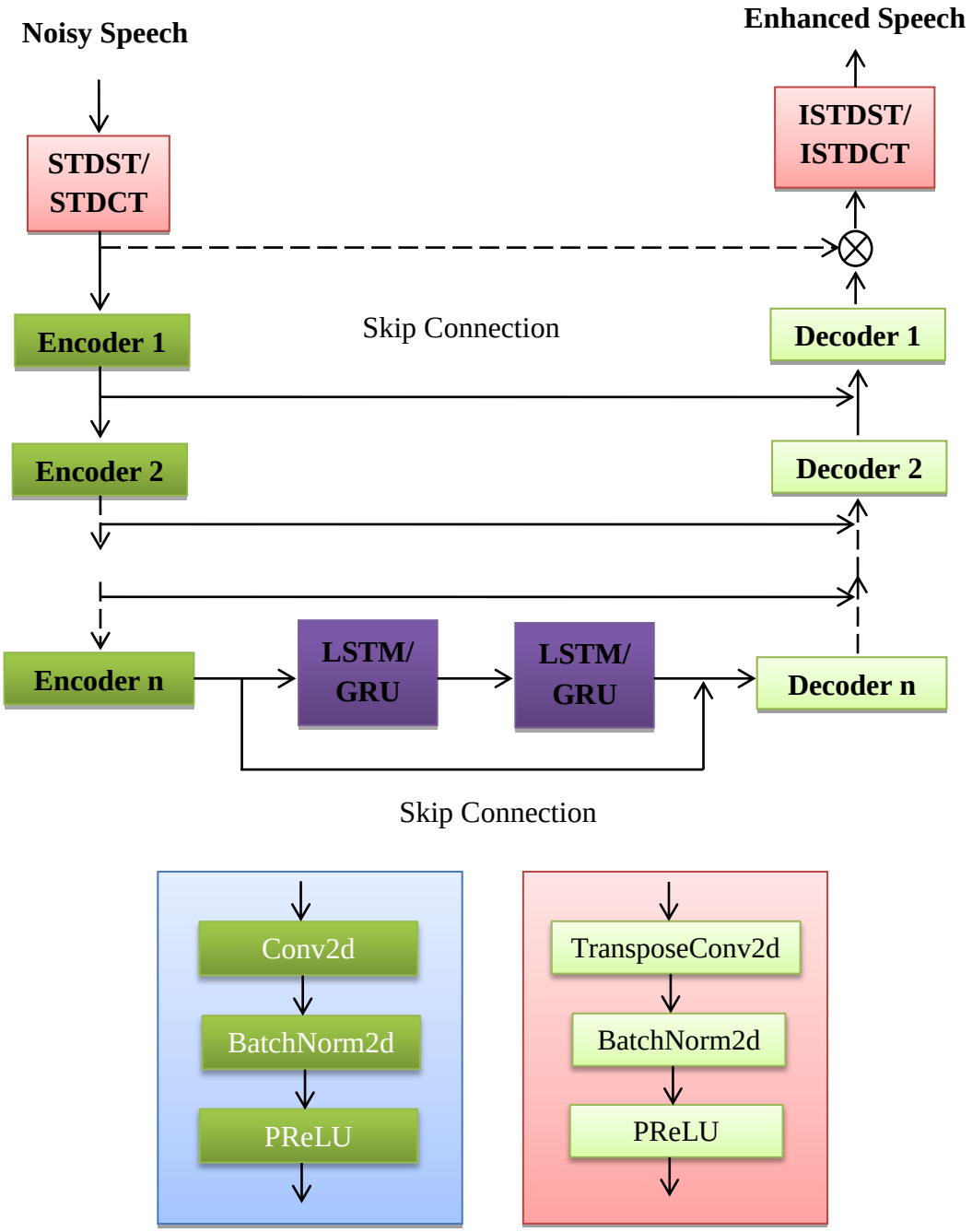



Fig. 2. Proposed encoder-decoder architecture using STDCT and STDST

### *2.1. Discrete domain Input features*

Speech enhancement using neural network uses either time domain or transform domain features [11,12]. For efficient enhancement more calculations and complex network is required to process the signal in low dimension domain like transform domain. Contrast to existed and commonly used DFT transform domain, this work proposes DST and DCT based transform domain for reduced complexity. Complexity of DFT results from its complex nature, wherein real and imaginary components are present [13,14]. Also the complexity in estimating clean speech motivated to process the signal using DST and DCT domains is discussed. The performance of proposed work is compared with different neural networks GCRN [15], SADUNET [16], and MASENET [17].

Performance of deep neural network models are studied using different transforms like DFT, DCT and DST in the literature. The motivation is that each transform has its own ability of energy compaction and to extract the required features from input signal. Speech signal can be decomposed using basis functions of different transforms for frequency related information. DCT transformation is real value based and hence results in reduced calculations as well. DCT and inverse DCT is obtained using (1) and (2) respectively.

$$X_c(k)=\sqrt{\frac{2}{N}}\beta(k)\sum_{n=0}^{N-1}x(n)\cos\left(\frac{\pi k(2n+1)}{2N}\right)\quad k=0,1,...,N-1 \tag{1}$$

$$x(n)=\sqrt{\frac{2}{N}}\sum_{k=0}^{N-1}\beta(k)X_c(k)\cos\left(\frac{\pi k(2n+1)}{2N}\right)\quad n=0,1,..,N-1 \tag{2}$$

Where,

$$\beta(k)=\begin{cases}\frac{1}{\sqrt{2}} & k=0\\ 1 & 1\le k\le N-1\end{cases} \tag{3}$$

Also the DST and IDST transforms are easily represented using (4) and (5) respectively

$$X_k=\sqrt{\frac{2}{N+1}}\sum_{n=1}^{n}x(n)\sin\left(\frac{n\pi k}{N+1}\right)\quad k=1,2,..,N \tag{4}$$

$$x(n)=\sqrt{\frac{2}{N+1}}\sum_{n=1}^{n}X_k\sin\left(\frac{n\pi k}{N+1}\right)\quad n=1,2,..,N \tag{5}$$

*2.2. Masks estimation and target training*

Proposed methods are developed based on estimation of masks during training stage. In this work two masks are used for DST and DCT transform domain deep covolution network [18]. Two masks are discussed in this work, one is Ideal Cosine Mask (ICM) and other is Ideal Sine Mask (ISM) .Cosine mask and sine mask are calculated using (7) and (9) respectively

$$S_{DCT}(t,f)=\frac{S_{DCT}(t,f)}{Y_{DCT}(t,f)}.S_{DCT}(t,f) \tag{6}$$

$$ICM(t,f)=\frac{S_{DCT}(t,f)}{Y_{DCT}(t,f)} \tag{7}$$

Where $S_{DCT}(t,f)$ are the clean speech DCT coefficients and $Y_{DCT}(t,f)$ is the noisy speech discrete cosine transform coefficients. ICM is the ideal cosine mask and *t,f* indicates the time frame and frequency bin respectively.

$$S_{DST}(t,f)=\frac{S_{DST}(t,f)}{Y_{DST}(t,f)}.S_{DST}(t,f) \tag{8}$$

$$ISM(t,f)=\frac{S_{DST}(t,f)}{Y_{DST}(t,f)} \tag{9}$$

Here $S_{DST}(t,f)$ is clean speech short time DST image, $Y_{DST}(t,f)$ is the noisy speech short time DST image and $ISM(t,f)$ is the ideal sine mask, where *t* and*f*indicates the time frame and frequency bin respectively.

In this work proposed methods performance under three activation functions is compared. Sigmoid, PReLU and tanh are used as activation functions in last layer and given the corresponding method numbers as method 1, method 2 and method 3 as follows

**Method-1:**

$$\hat{S}=Sigmoid((method(Y))*Y \tag{10}$$

**Method-2:**

$$\hat{S} = P\,\mathrm{Re}\,LU((method(Y))*Y \tag{11}$$

**Method-3:**

$$\hat{S} = \mathrm{Tanh}((method(Y))*Y \tag{12}$$

### *2.3. Loss Function*

Several loss functions are discussed in the literature for effective working of DNN [19,20]. Most traditional one is the Mean Square Error (MSE) [21,22]. But the characteristics of human hearing are not considered in this loss function [23]. The characteristics based on human hearing are taken into account when Scale Invariant Signal to Noise Ratio (SI-SNR) loss function is considered. Also perceptual based loss function is proposed in literature. Among the available ones the SI_SNR loss function holds well for encoder-decoder based architecture based DNN approaches. In this work SI_SNR (13) is used as loss function.

$$SI\_SNR = 10*\log_{10}\left(\frac{\|s_t\|_2^2}{\|e_n\|_2^2}\right) \tag{13}$$

Where $s_t = \frac{\langle \hat{s}, s \rangle . s}{\|s\|_2^2}$ and $e_n = \hat{s} - s$ . Here noise term in the denominator is obtained by subtracting the clean speech and enhanced speech.

Three loss functions are used in this work. Scale Invariant Signal to Noise Ratio (SI-SNR), Phase Constrained Magnitude (PCM), Time Frequency (TF) loss for optimizing the reconstructed speech [12] .

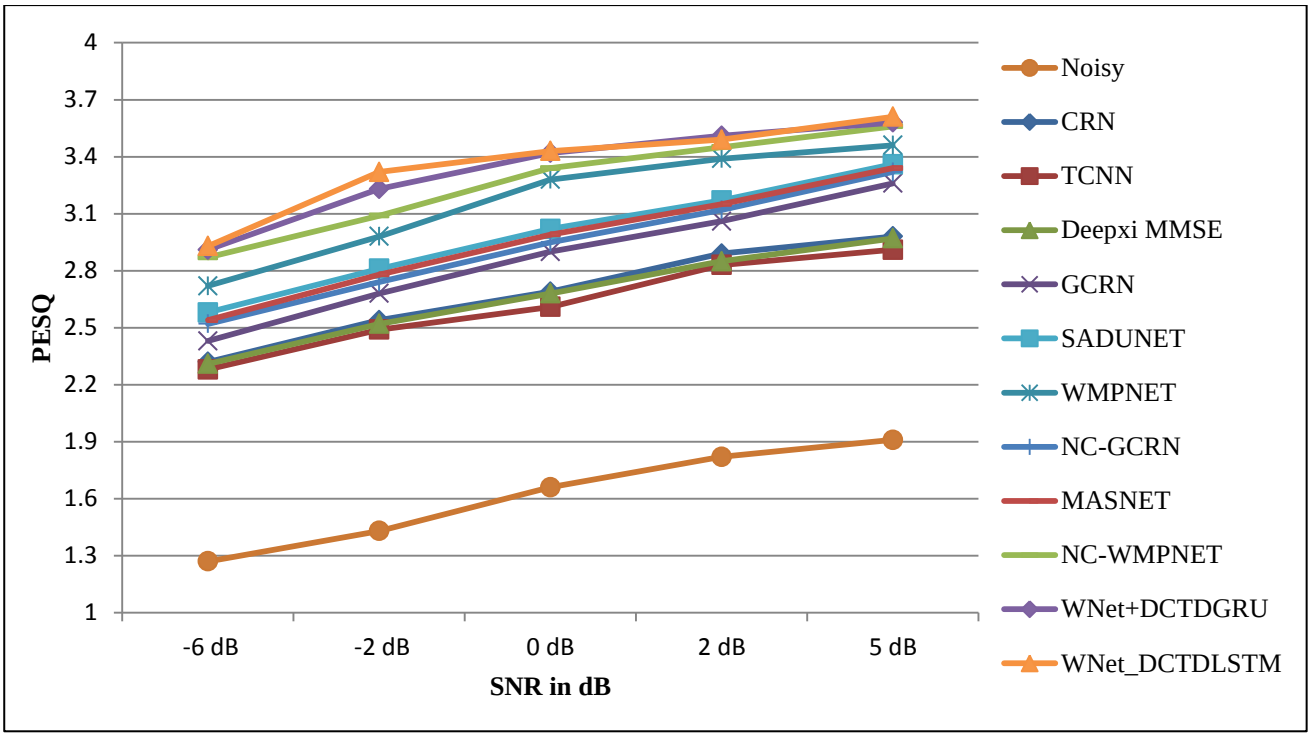
## 3. Results and Experiments

Simulations are performed by considering different noise environments and at different scenarios.

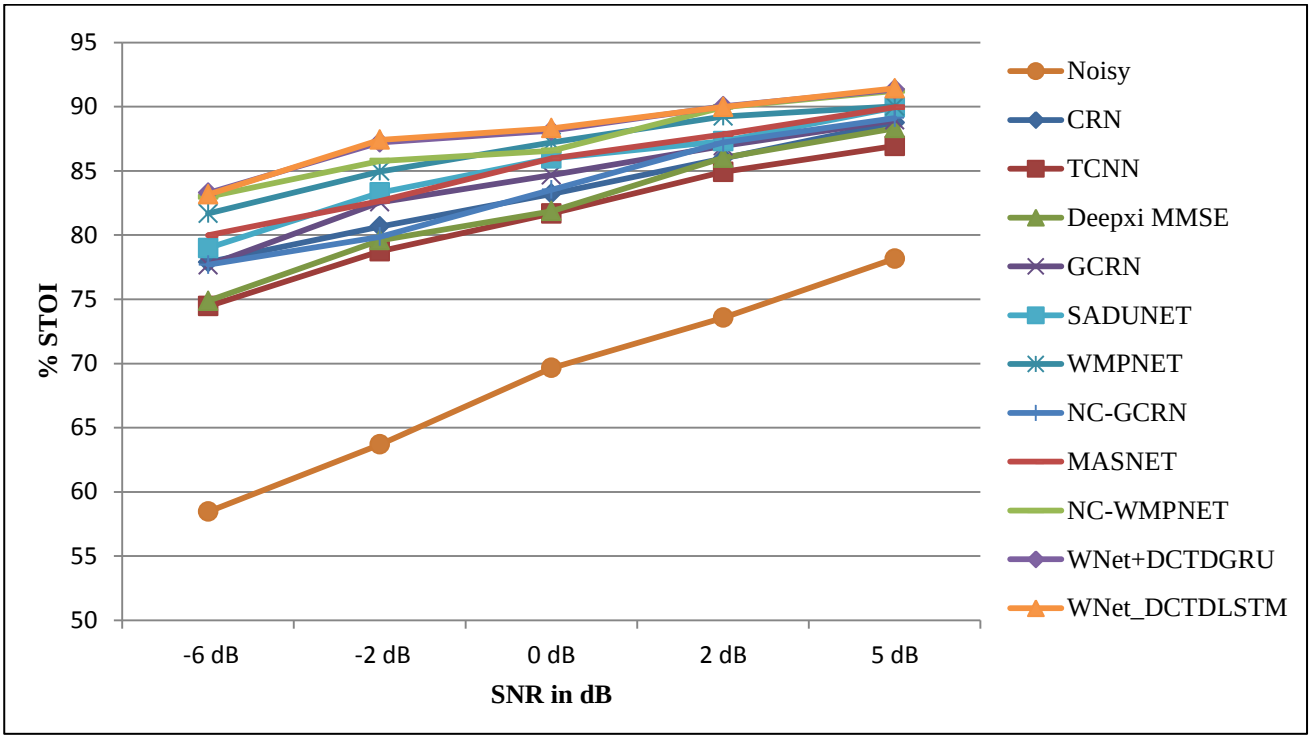
### *3.1. Baseline and result analysis*

Clean speech dataset from NOIZEUS database [24] is taken for training and testing. Noise database is considered for noise samples. Framing is done using hanning window of size 512 point and signal is sampled at 16KHz frequency. During processing short hop time of 8 ms is used. Clean speech signals are corrupted with noise environment at input SNRs of -6 dB, -3 dB, 0 dB, 3 dB and 6dB [23]. Performance of proposed method is analyzed using objective performance measures Perceptual Evaluation of Speech Quality (PESQ), Short Time Objective Intelligibility (STOI) and Signal to Noise Ratio (SNR) as shown in figures. The following baseline methods are compared with proposed method. The methods compared are CRN [12], TCNN [13], DeepXi [14], GCRN [15], SADUNET [16], MASENET [17], Proposed 1 ( WNet+DCTDGRU), Proposed 2 (WNet_DCTDLSTM).

In all these works Adam optimizer is considered. Number of epochs are set to 350 and the first 100 epochs are performed with 0.001 learning rate. This work utilizes different encoder layer and decoder layer channels of 1, 8, 16, 32, 64, 128, 256 and 256 LSTM nodes are choosen as line. The kernel parameter size is set to 5,1 and the stride for various layers as 2,1. Also the GRU nodes of 256 is set in this work. The simulation results of proposed method with baseline methods are given in Fig.3, Fig.4, Fig.5.

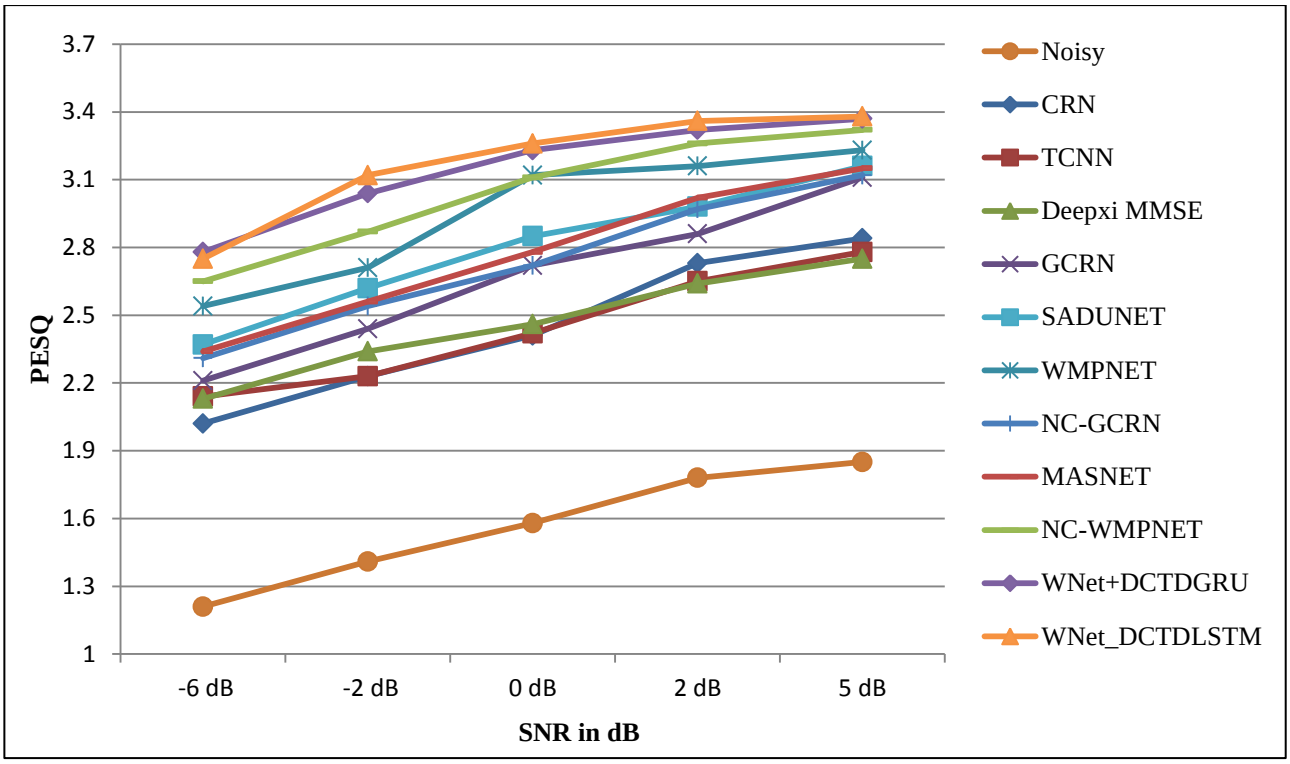



(a)

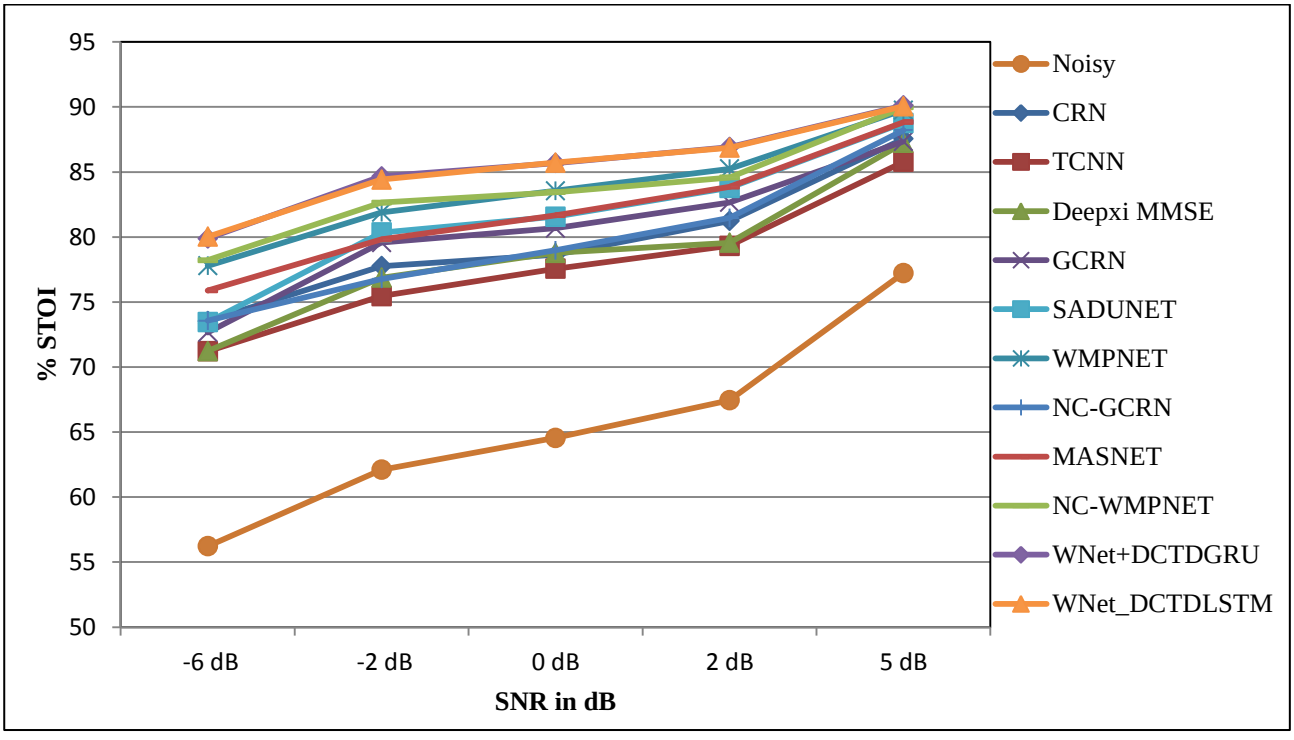



(b)

Fig. 3. Comparison of proposed method with baseline methods using objective performance measures under seen noise environments (a) PESQ (b) %STOI

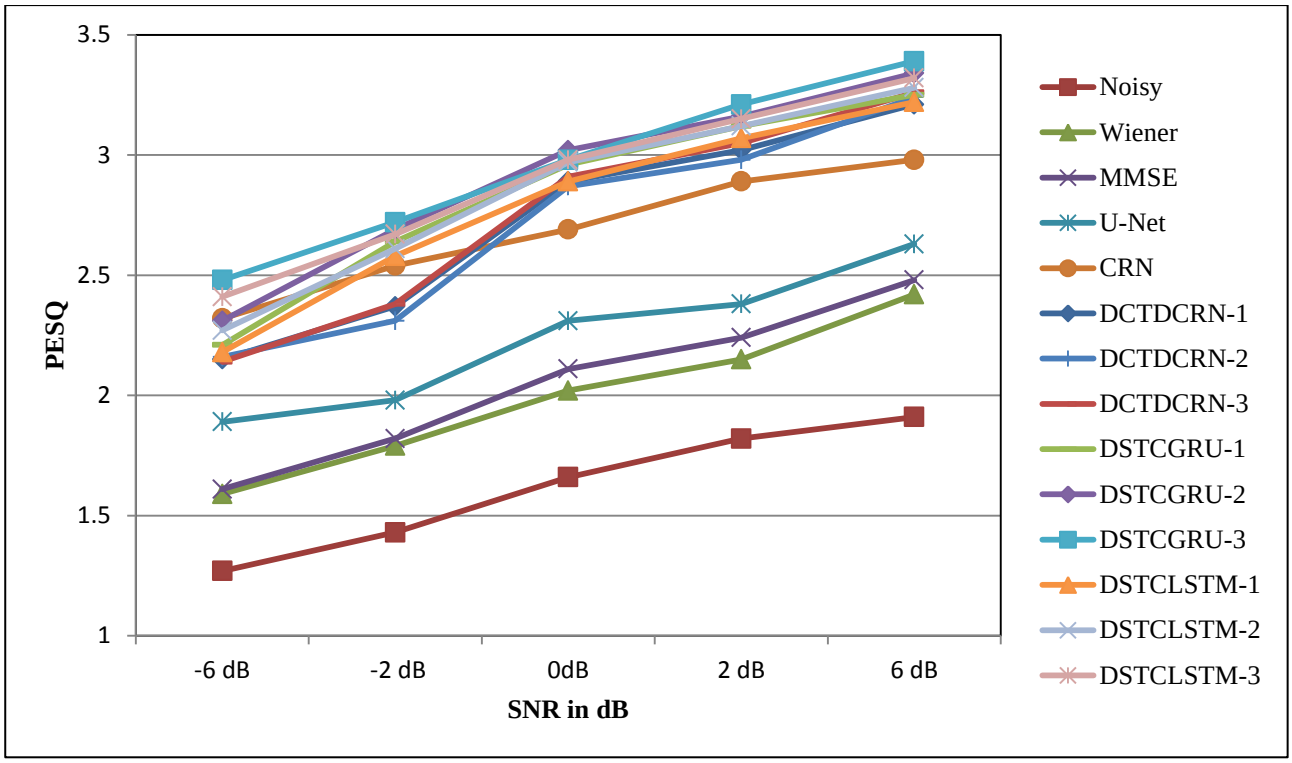



(a)

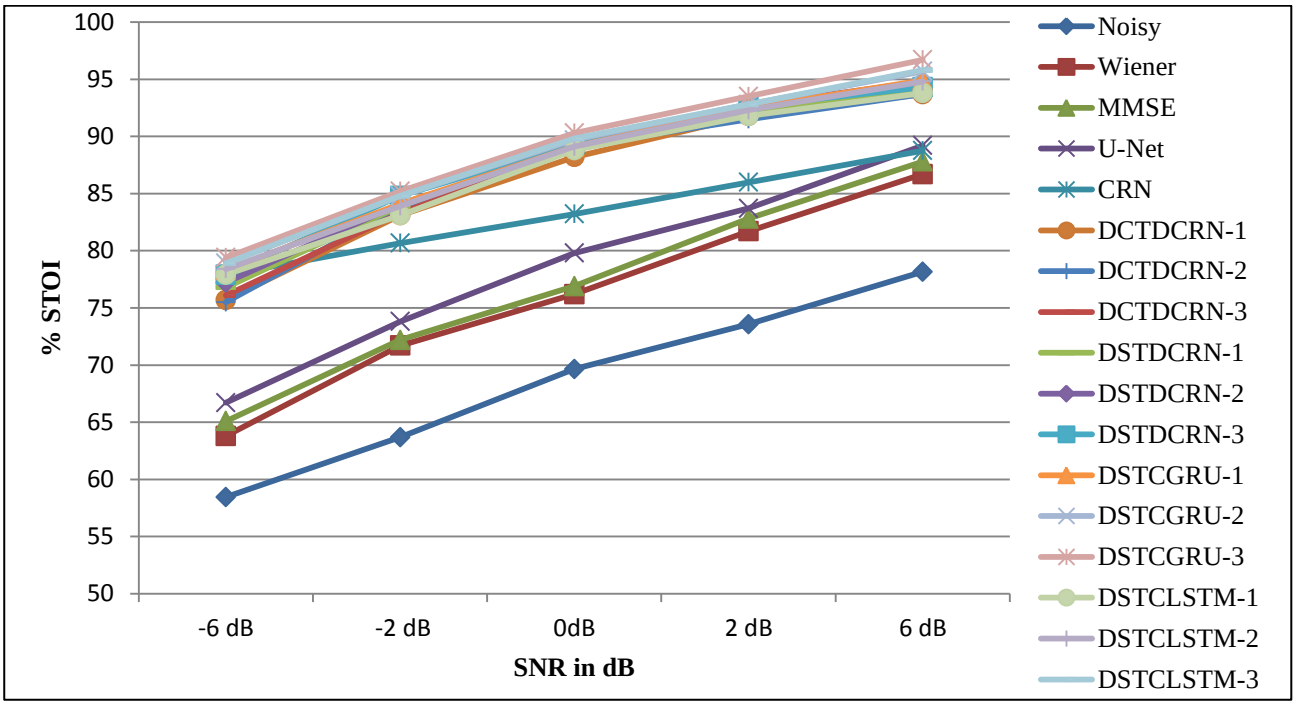



(b)

Fig. 4. Comparison of proposed method with baseline methods using objective performance measures under unseen noise environments (a) PESQ (b) %STOI




(a)




(b)

Fig. 5. Comparision of proposed method with baseline methods using objective performance measures under seen noise environments (a) PESQ (b) %STOI

It is observed from Fig.5 that the DSTCGRU-3 provides a PESQ of 2.48 at low SNR of -6 dB and 3.39 at high SNR of 6 dB. At 0 dB SNR it is observed that DSTCGRU-2 provides a high PESQ of 3.02. It is observed that the DST and DCT based convolutional recurrent neural network provides superior performance than to STFT based convolution neural network CRN and U-net model.

Fig.5. provides the comparison of STOI (In %) measure for existed and proposed methods. It is observed that DSTCGRU-3 provides better results. At low input SNR of -6 dB it is providing a value of 79.4 and a value of 96.7 at high input SNR of 6 dB. At 0 dB SNR DSTCGRU-3 provides a value of 90.3. At 0 dB SNR the methods DCTDCRN-2, DSTDCRN-3 and DSTCGRU-3 provides an STOI of 89.1, 89.3 and 90.3 respectively.

Table 1 provides the comparison of SNR measure for existed and proposed methods. It is observed that DSTCGRU-3 provides better results. At low input SNR of -6 dB it is providing a value of 3.95 and a value of 15.02 at high input SNR of 6 dB. At 0 dB SNR DSTCGRU-3 provides a value of 7.49. At 0 dB SNR the methods DCTDCRN-2, DSTDCRN-3 and DSTCGRU-3 provides an STOI of 5.96, 5.95 and 7.49 respectively

Tab1e 1. SNR Performance Comparison of proposed methods with existing methods

| SNR / Test | **-6 dB** | **-3 dB** | **0dB** | **3 dB** | **6 dB** | **Avg** |
|---|---|---|---|---|---|---|
| Noisy | -5.91 | -2.97 | 0.06 | 3.06 | 5.98 | 0.04 |
| Wiener | -4.86 | -1.68 | 1.14 | 4.47 | 7.05 | 1.22 |
| MMSE | -3.69 | -1.16 | 1.95 | 4.98 | 7.98 | 2.01 |
| U-Net | -2.75 | 1.54 | 3.89 | 7.34 | 9.12 | 3.82 |
| CRN | 1.93 | 4.71 | 6.62 | 9.57 | 11.97 | 6.96 |
| DCTDCRN-1 | 2.23 | 4.32 | 5.76 | 8.32 | 12.67 | 6.66 |
| DCTDCRN-2 | 2.66 | 4.87 | 5.89 | 8.86 | 12.98 | 7.05 |
| DCTDCRN-3 | 2.72 | 4.93 | 5.93 | 8.92 | 13.12 | 7.12 |
| DSTDCRN-1 | 2.41 | 4.43 | 5.82 | 8.46 | 12.78 | 6.78 |
| DSTDCRN-2 | 2.72 | 4.89 | 5.96 | 8.97 | 12.96 | 7.10 |
| DSTDCRN-3 | 2.87 | 5.02 | 5.95 | 8.68 | 12.95 | 7.09 |
| DSTCGRU-1 | 3.73 | 6.98 | 7.24 | 10.78 | 14.68 | 8.68 |
| DSTCGRU-2 | 3.89 | 7.12 | 7.35 | 10.89 | 14.84 | 8.81 |
| DSTCGRU-3 | **3.95** | **7.31** | **7.49** | **10.93** | **15.02** | **8.94** |
| DSTCLSTM-1 | 3.12 | 6.08 | 5.11 | 7.98 | 13.97 | 7.25 |
| DSTCLSTM-2 | 3.28 | 6.32 | 5.42 | 8.11 | 14.15 | 7.45 |
| DSTCLSTM-3 | 3.32 | 6.45 | 5.76 | 8.57 | 14.65 | 7.75 |

## 4. Conclusion

This work proposes a speech enhancement based on deep discrete sine and discrete cosine transform convolutional network. Also the developed techniques are combined with Wnet and joint time domain and DCT based in built phase processing technique is proposed. Experiments are performed on noisy speech samples and the simulation results shows that the proposed methods provide superior results with lesser parameters and calculations. DCT and DST based GRU processing model outperforms the existed approaches at low input and high input SNR corruption. Results show that proposed method shows improved performance in noise reduction (Signal to Noise Ratio) and providing intelligibility (STOI and PESQ) than to existing methods. Joint optimization based on time domain and DCT domain algorithms provides superior performance. This work opens development of different deep transform domain approaches for real time speech enhancement. Hybrid transform domains features can be utilized in deep neural network based algorithms and can be improved further with latest DNN models and transform domain features.

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## Conflict of Interest

The authors declare that they have no competing interests.

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