Active Noise Cancellation using Deep learning

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Abstract: **Active Noise Cancellation (ANC) is one of the most effective ways of reducing noise. The active noise reduction headphone is the most successful application of active noise control. Traditional active noise control methods are based on adaptive signal processing with the least mean square algorithm as the foundation. They are linear systems and do not perform satisfactorily in the presence of nonlinear distortions. In this project, ANC is formulated as a supervised learning problem and a deep learning approach, called deep ANC is proposed. Hybrid Active noise cancellation techniques which is the combination of feed forward and feedback techniques, in this project. Large scale multi conditioning is trained to achieve good generalization and robustness against a variety of noises. The goal of ANC systems is to generate an anti-noise with the same amplitude and opposite phase of the primary (unwanted) noise to cancel the primary noise. A Convolutional Recurrent Network (CRN) is trained to estimate the real and imaginary spectrograms of the cancelling signal from the reference signal so that the corresponding anti-noise can eliminate or attenuate the primary noise in the ANC system.**

Keywords: **Deep ANC, Convolutional Recurrent Network, Librosa, Denoise**

I INTRODUCTION

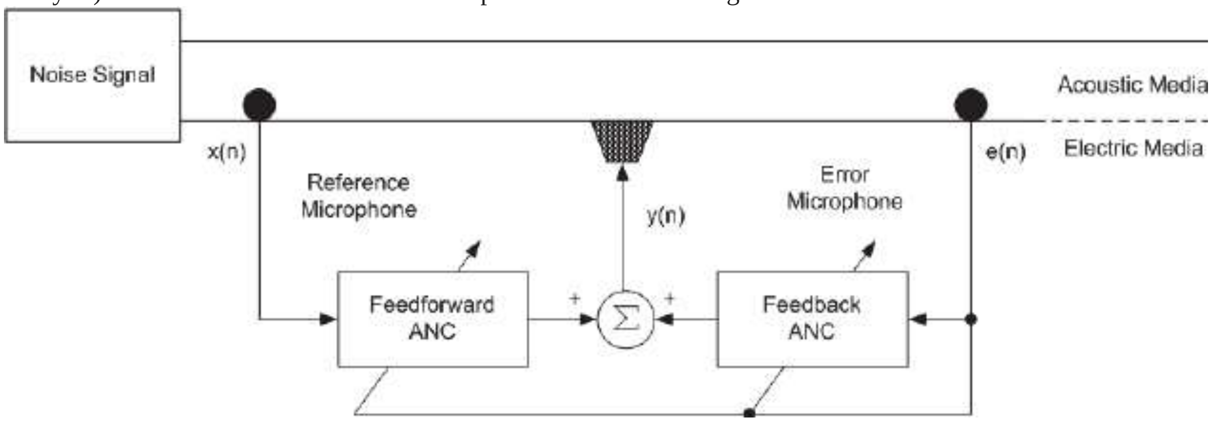
Noise in a communication system is undesirable or unwanted signals that get randomly added to the actual information carrying signal. Resultantly, it causes disturbances in the original signal being transmitted from one end to another.The presence of noise in the system causes interference in the signal being transmitted and this ultimately causes errors in the communication system. Practically, the addition of noise over the information carrying signal is an unavoidable phenomenon. And this interference automatically hinders the quality of the signal being transmitted. The consequences of exposing people to noise from various sources may vary from short term effects such as sleep disturbances to long term effects such as permanent hearing loss. To reduce the noise from source reaching our ear involves various methods which can be categorized into Active Noise Cancellation and Passive Noise Cancellation. Passive Noise Cancellation is the noise that headphones block out based on the physical design of the earcups. Based on the shape of the headphone earcups and how it fits over the head determines to a large degree how much noise the headphones can block out. This comes in handy when a user is listening to music or whatever desired sounds he wants to listen to.active noise cancellation is noise cancellation that works through powered electronic circuitry to produce noise cancellation. Passive noise cancellation is all about the physical, or you can say mechanical, design of the earcups. Active noise cancellation is a highly effective electronic method to reduce the effect of the noise in an environment. It is basically a generation of anti-noise which is equal in magnitude but opposite in phase with the noise. The anti-noise and the noise destructively interfere to remove the effects of noise from the path of the noise. They use both microphones and speakers to reduce or drown out the surrounding noise. They are majorly two types Active Noise cancellation feedforward active noise cancellation and feedback noise cancellation. The traditional approach to acoustics noise control uses passive techniques such as enclosures, barriers, and silencers to attenuate the undesired noise. These passive silencers are valued for their high attenuation over a broad frequency range; however, they are relatively large, costly, and ineffective at low frequencies. On the other hand, the ANC system efficiently attenuates low-frequency noise where passive methods are either ineffective or tend to be very expensive .Most importantly, ANC can block selectively. ANC is developed rapidly because it permits improvements in noise control, often with potential benefits in size, weight, volume, and cost. Blocking low frequency has the priority since most real life noises are below 1 KHz, for example engine noise or noise from aircrafts. Hence, the ANC project with deep learning technique is proposed. The Convolutional Recurrent Network concept used to train the data sets which contain speech signals, noise signal, and noiseless signals.

II EXISTING SYSTEM

Active noise control is a noise cancellation methodology based on the principle of superposition of acoustic signals, i.e. two superposed waveform signals cancel each other when they have the same amplitude but the opposite phase. ANC differs from passive noise control, e.g. by using sound-absorbing barriers like an earplug, and noise removal in signal enhancement where noise is removed by processing a noisy signal like noisy speech. Fundamentally, ANC is required to predict both the amplitude and phase of a noise signal at a given point in space ahead of time. While signal amplitude may be steady over time, signal phase changes all the time at any spatial location due to the nature of acoustic waves. Thus ANC is a very challenging problem, and in practice it can attenuate only low-frequency stationary noises. The FxLMS algorithm alleviates the effect of the secondary path by filtering the reference signal, x(t), with an estimate of the secondary path before feeding it to the controller .The secondary path is usually estimated separately as a finite impulse response filter (FIR) beforehand .In the existing system feed forward technique is used to remove noise from the reference signal. A typical feed forward ANC system consists of a reference microphone, a canceling loudspeaker, and an error microphone. The active noise controller takes the reference signal and error signal, sensed by the reference microphone and error microphone, respectively, as inputs to adapt the controller so that the canceling signal generated can superpose with the primary noise at the location to be silenced.Here, the mic is placed outside the ear cup and hears the outside noise before you can. It then processes the intrusive noise to create the anti-noise waves to cancel or neutralize the former. The existing paper says that the extension of active noise control (ANC) techniques to deal with nonlinear effects such as distortion and saturation requires the introduction of suitable nonlinear model classes and adaptive algorithms. Large sized models are typically used, resulting in an increased computational load, delayed convergence (and sometimes even algorithm instability), and other unwanted dynamical effects due to over parameterization. Also discusses the usage of polynomial Nonlinear Auto Regressive models with eXogenous variables(NARX) models and model selection techniques to reduce the model size and increase its robustness, for more efficient and reliable ANC. An offline procedure is devised to identify the controller model structure, and the controller parameters are successively updated with an adaptive algorithm based on the error gradient and on the residual noise.Simulation experiments show the effectiveness of the proposed approach. A brief analysis of the involved computational complexity is also provided.

III SYSTEM MODEL

Traditional active noise control (ANC) methods are based on adaptive signal processing adaptive filters that optimize filter characteristics by minimizing an error signal by Filtered-x least mean square (FxLMS) and its extensions. They are linear systems and do not perform satisfactorily in the presence of nonlinear distortions. In this project, paper We formulate ANC as a supervised learning problem and propose a deep learning approach, called deep ANC is proposed .Hybrid Active noise cancellation techniques which is the combination of feed forward and feed back techniques.In Feedforward active noise cancellation, the mic is placed outside the ear cup and hears the outside noise before user can. It then processes the intrusive noise to create the anti-noise waves to cancel or neutralize the former so the user can enjoy the sound. However, due to its outside placement, it is more in-tuned with the outsides and may not deliver the right sound to the listener, especially if the headphones or the earphones are not placed properly and can actually amplify the noise outside.Feedforward ANC gives results effectively in non linear distortions and wideband signals.In FeedBack ANC the mic is inside the ear cup and in front of the speaker, so it gets to hear the resulting signal in exactly the same way the listener does. As the mic hears the sound just as the user does, it can cancel out the noise. And if the headphones or earphones are worn incorrectly, it does not drastically affect the sound canceling. But since it clubs the sound and noise together, if this is not taken into the design account, that may lose out on the sound that makes your favorite music click. It gives accuracy against a variety of noises by feedback technique . To achieve both the advantages hybrid ANC is used which is a combination of both feedforward and feedback technique.Hybrid noise cancellation is a combination of feedforward and feedback mics and placing them both on the inside and outside of the ear cup. This kind of combination works to deliver the best result without drawbacks. It adapts and adjusts to the frequencies and delivers just the sound. Sometimes these earbuds come with an additional mic to capture additional sound and deliver it to the other party making it the perfect companion in workspaces.Active noise control is a noise cancellation methodology based on the principle of superposition of acoustic signals, i.e. two superposed waveform signals cancel each other when they have the same amplitude but the opposite phase.The goal of ANC systems is to generate an anti-noise with the same amplitude and opposite phase of the primary (unwanted) noise to cancel the primary noise. A convolutional recurrent network (CRN) is trained to estimate the real and imaginary spectrograms of the canceling signal from the reference signal so that the corresponding anti-noise can eliminate or attenuate the primary noise in the ANC system. Librosa library (python package for audio analysis) is used for the classification and separation of the audio signal.



BLOCK DIAGRAM OF HYBRID ANC

DATASET

The dataset includes the clean speech signal of man and the noisy signal. The dataset is stored in the .wav format and also trained in the same format.

"NOISE REDUCTION" PACKAGE IN PYTHON USING SPECTRAL GATING

"Noise reduce" package is a noise reduction algorithm in python that reduces noise in time-domain signals like speech, bioacoustics, and physiological signals. It relies on a method called "spectral gating" which is a form of Noise Gate. It works by computing a spectrogram of a signal (and optionally a noise signal) and estimating a noise threshold (or gate) for each frequency band of that signal/noise. That threshold is used to compute a mask, which gathers noise below the frequency-varying threshold.

The most recent version of "Noise reduce" comprises two algorithms:

Stationary Noise Reduction: Keeps the estimated noise threshold at the same level across the whole signal

Non-stationary Noise Reduction: Continuously updates the estimated noise threshold over time

Stationary Noise Reduction

The basic intuition is that statistics are calculated on each frequency channel to determine a noise gate. Then the gate is applied to the signal. This algorithm is based (but not completely reproducing) on the one outlined by Audacity for the **noise reduction effect** .The algorithm takes two inputs:

i. A noise clip containing prototypical noise of clip (optional)

ii. A signal clip containing the signal and the noise intended to be removed

Steps of the Stationary Noise Reduction algorithm

- A spectrogram is calculated over the noise audio clipStatistics are calculated over spectrogram of the noise (in frequency)
- A threshold is calculated based upon the statistics of the noise (and the desired sensitivity of the algorithm).
- A spectrogram is calculated over the signal.
- A mask is determined by comparing the signal spectrogram to the threshold
- The mask is smoothed with a filter over frequency and time.
- The mask is applied to the spectrogram of the signal, and is inverted If the noise signal is not provided, the algorithm will treat the signal as the noise clip, which tends to work .

Non Stationary Noise Reduction

The non-stationary noise reduction algorithm is an extension of the stationary noise reduction algorithm, but allows the noise gate to change over time.If the timescale of the signal occurs in known (e.g. a bird call can be a few hundred milliseconds), then the noise threshold is based on the assumption that events occurring on longer timescales .

Steps of the Non Stationary Noise Reduction algorithm

- Spectrogram is calculated over the signal
- A time-smoothed version of the spectrogram is computed using an IIR filter applied forward and backward on each frequency channel.
- A mask is computed based on that time-smoothed spectrogram
- The mask is smoothed with a filter over frequency and time,the mask is applied to the spectrogram of the signal

In this paper, use non-stationary noise reduction algorithm to denoise the signal

CRN DATA PREPROCESSING

The proposed CRN for deep ANC is shown in Fig. 6.1 and it takes Xr(m, c) and Xi(m, c)as input features for complex spectral mapping. To attenuate the primary noise at the location of the error microphone, deep ANC uses the ideal anti-noise (the primary noise) as the training target. The CRN is trained to map from the real and imaginary spectrograms of the reference signal to those of the canceling signal, Yr(m, c) and Yi(m, c). This is different from the methods that estimate only the magnitude spectrogram and use the phase spectrogram of the input signal to generate the estimated waveform output. Complex spectral mapping is chosen because of the importance of phase in active noise control. The complex spectrogram of the canceling signal goes through the Short Time Fourier transform to derive a waveform signal y(t). The anti-noise, which can be regarded as an estimate of the training target, is then generated by passing the canceling signal through the loudspeaker and secondary path.

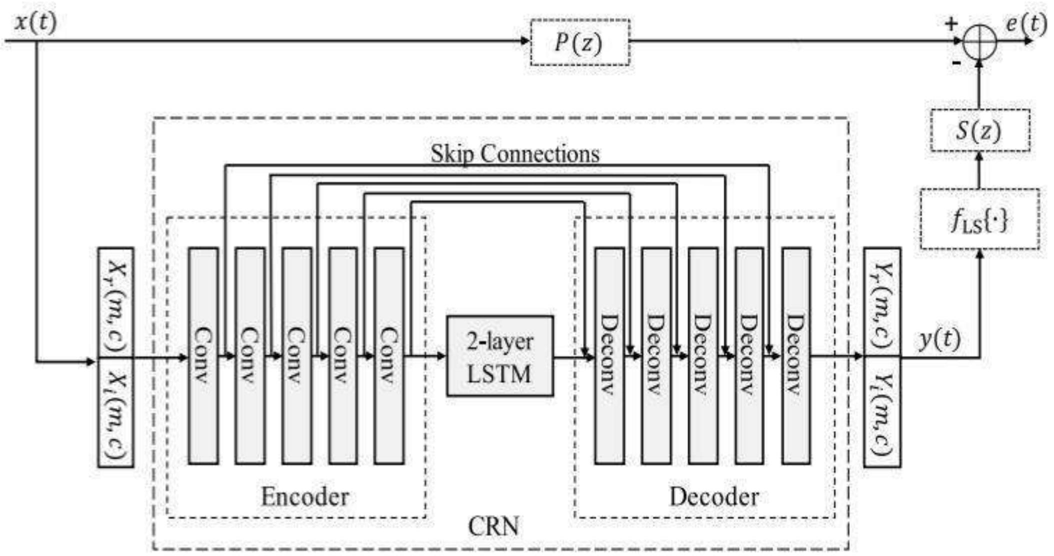


Diagram of CRN based deep ANC

CRN TRAINING STRATEGIES

Deep ANC can be trained to achieve noise cancellation no matter whether the reference signal is noise or noisy speech, by using proper training data and loss functions. Fig. 6.2 shows two training strategies for the deep ANC method:

Deep ANC trained with noise: The model trained this way aims to cancel any noise received at the reference microphone. To achieve this, noise signal n(t) is used as the reference signal and deep ANC is trained to completely eliminate the primary noise. The loss function is defined as:

$$L_n = \frac{\sum_{t=1}^{L} e^2(t)}{L}$$

where L is the length of the noise signal, and e(t) is defined as an error signal .

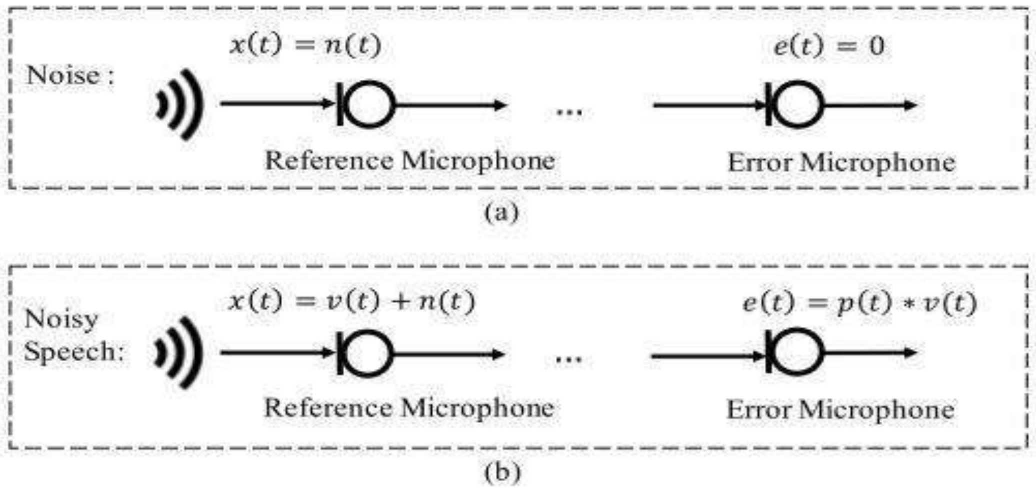
Deep ANC trained with noisy speech: The deep ANC models trained to cancel surrounding noise while preserving speech signal. The reference signal used to train this deep ANC system is a mixture of noise n(t) and speech v(t), and the corresponding primary signal d(t) is

$d(t) = p(t) * [v(t) + n(t)]$

$= p(t) * v(t) + p(t) * n(t)$ (5)

where $p(t) * n(t)$ and $p(t) * v(t)$ are, respectively, the noise and speech components of the primary signal. In order to attenuate only noise components and let speech pass through, the training target is set to the noise component, $p(t) * n(t)$,and the ideal error signal then is equivalent to $p(t) * v(t)$.The loss function used for training this deep ANC system is defined as:

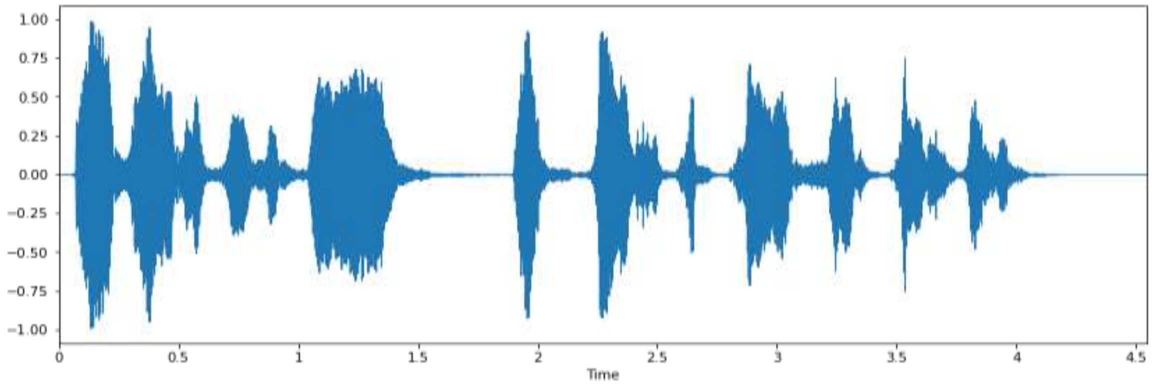
$$L_{ns} = \frac{\sum_{t=1}^{L} [e(t) - p(t) * v(t)]^2}{L}$$



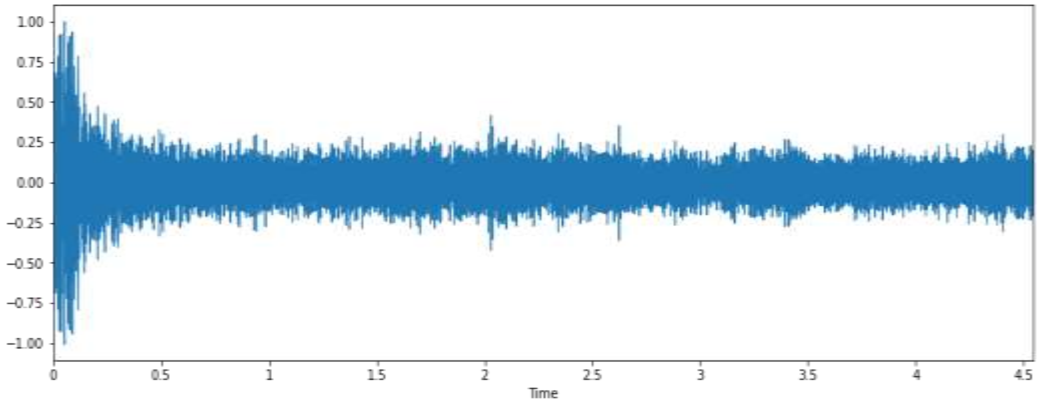
Training strategies for deep ANC when reference signalis (a) noise, and (b) noisy speech.

IV RESULT AND DISCUSSION:

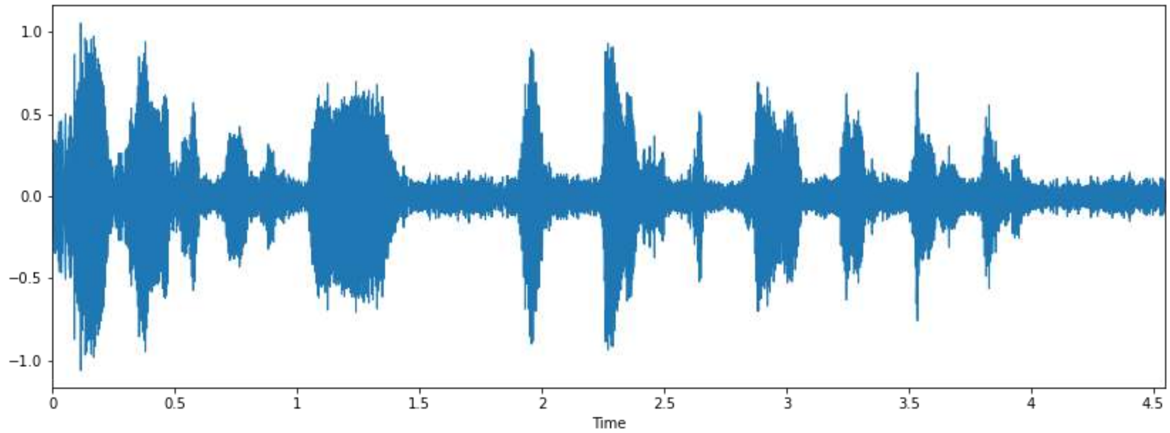
Clean speech signal



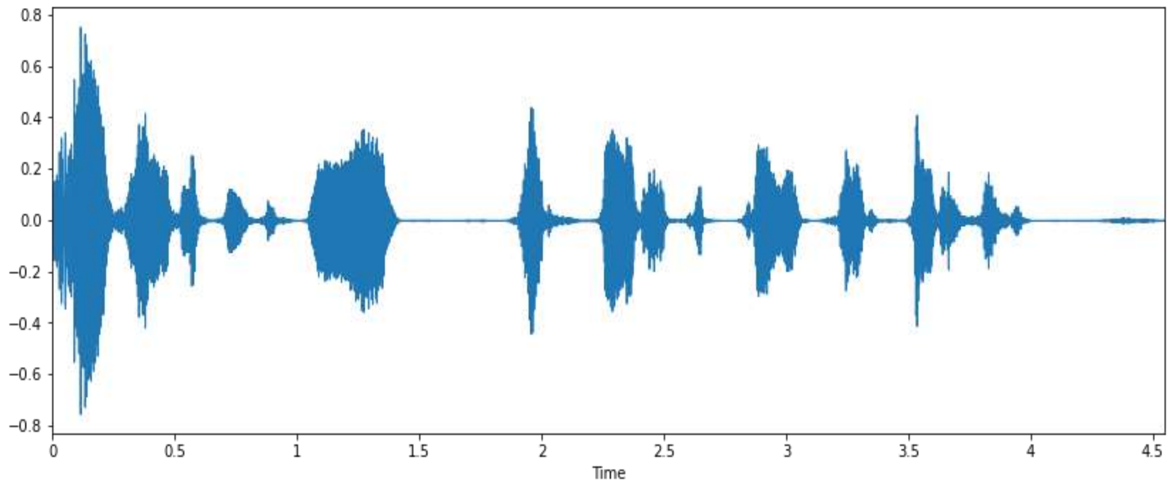
Noisy signal



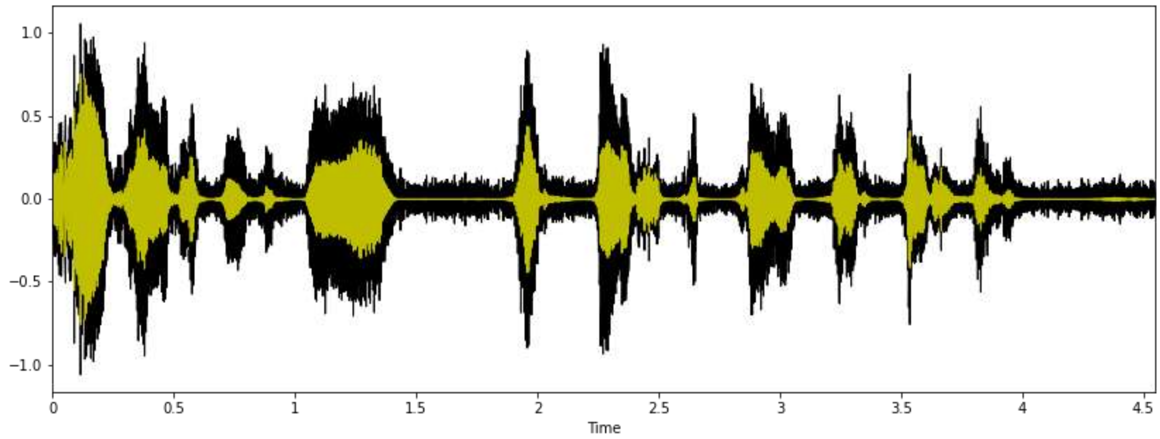
Noisy speech signal



Remove noise from noisy signal using "noisereduce" package (Denoised signal)



Waveplot to differentiate noisy audio and denoised audio



Black color indicates the Noisy audio and the yellow color indicates the denoised audio

SNR value for audio and denoised signal

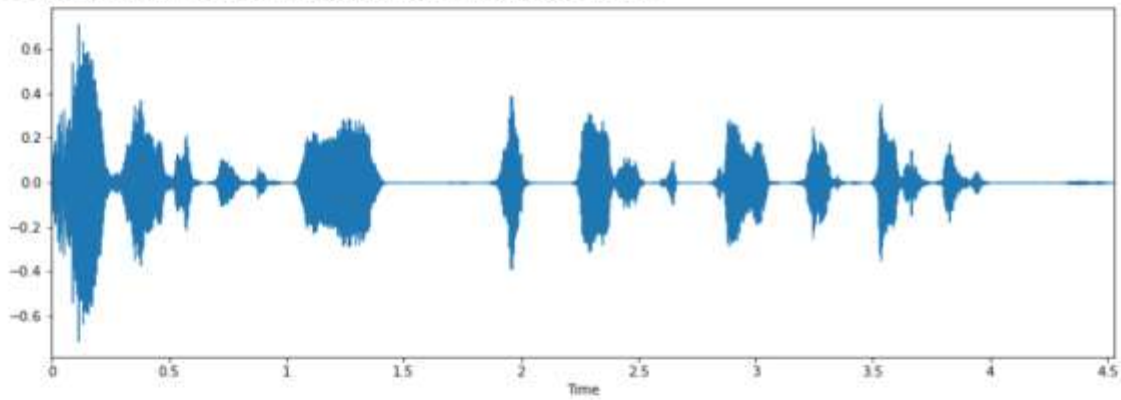
```
[18] snr=a/b
     log_value=math.log10(snr)

     snr_db=10 *log_value
     print(snr_db)

     5.985411505776574
```

Remove noise from denoised signal using CRN Training

<matplotlib.collections.PolyCollection at 0x7fd2e0410510>



Waveplot to differentiate denoised audio and CRN Trained audio (Noiseless audio)

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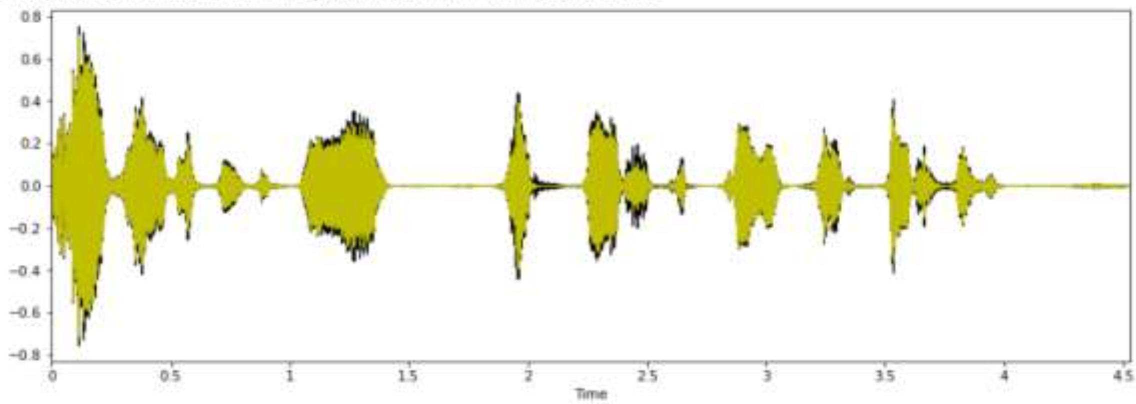

Black color indicates the denoised audio and the yellow color indicates the CRN trained audio

SNR value for denoised audio and CRN trained audio

```
s = s[: size_CRN_Trained_Audio]
num = np.dot(s.T , s)
den = np.dot((s - CRN_Trained_Audio).T,(s - CRN_Trained_Audio))
SNR = 10 * np.log10(num/den)
print('Value of SNR : ' + str(SNR))
```

```
Value of SNR : 14.849710464477539
```

V CONCLUSION:

The deep ANC approach is introduced for active noise control. A Convolutional Recurrent Network trained to estimate a canceling signal from the reference signal so as to remove or attenuate the primary noise.Using proper training data the deep ANC approach was trained. Large scale multi conditioning is trained to achieve good generalization and robustness against a variety of noises.. It has the intrinsic ability of modeling nonlinearities unavoidable in ANC systems. Unlike traditional methods, deep ANC is effective for wideband noise removal. The clean audio sample signal is generated and mixed with the noise and has been eliminated using the “Librosa” package with SNR of 5.98 db .The same is attained using CRN method with SNR of 14.84 db. Future work includes exploring time-domain methods for deep ANC, assessing robustness of deep ANC caused by changing error microphone position, and extending deep ANC to a multi-channel version.

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