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Design and Develop An Algorithm To Remove Noise Using Machine Learning Algorithm

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Abstract

Most hearing aids on the market today employ digital noise reduction techniques. Unlike previous analogue systems, these manufacturer-specific algorithms are designed to acoustically analyse the incoming signal and change the gain/output characteristics based on predefined rules. Hearing-impaired persons frequently utilise digital hearing aids to improve their speech intelligibility and quality of life. However, hearing aid performance is typically reduced owing to acoustic feedback, which causes further issues. This effect occurs when sound travels from the speakers to the microphone. This creates instability and a high-frequency oscillation, which hearing-impaired persons can feel if the volume exceeds their hearing limits. Furthermore, these effects restrict the maximum gain that the hearing aid can achieve and degrade sound quality when the gain is nearing the limit. Several feedback reduction approaches based on adaptive algorithms have been utilised to minimise auditory feedback. The purpose of this paper is for the researcher to design and create an algorithm to reduce noise using a machine learning method. Stationary noise is removed from the input audio stream during pre-processing. Using a machine learning technique, the original signal is separated from the noise, Post-processing and performance testing of the developed system.

Keywords: Digital noise reduction, amplification, algorithms, Dynamic Noise Reduction, spectrogram, modified Unet source separation, STFT, SNR, CNN.

1. Introduction

Hearing-impaired persons frequently utilize digital hearing aids to improve their speech intelligibility and quality of life. However, hearing aid performance is typically reduced owing to acoustic feedback, which causes further issues. This effect occurs when sound travels from the speakers to the microphone. This creates instability and a high-frequency oscillation, which hearing-impaired persons can feel if the volume exceeds their hearing limits. Furthermore, these effects restrict the maximum gain that the hearing aid can achieve and degrade sound quality when the gain is nearing the limit. Several approaches based on adaptive algorithms [1] for feedback reduction have been employed to decrease auditory feedback. Non-local diffusion filters [2], acoustic feedback reduction based on finite impulse response and infinite impulse response adaptive filters in digital hearing aids [3], and noise reduction Wiener filter [4] are some of the approaches used for speech noise reduction. Noise is reduced using filters such as adaptive filters or Wiener filters in the approaches described above. Adaptive filters have been used in several published implementations (least mean square, recursive least square, Kalman filters). Adaptive filters are optimum because they reduce the mean squared estimate error [5] and can be computed in real time. However, adaptive filters have the disadvantage of assuming that the process dynamics are linear, only providing a point estimate, and can only handle processes with additive, unmoral noise. The spectrum subtraction approach is a well-known noise reduction technique [6]. The noisy voice signal is first converted from the time domain into the frequency domain using the quick Fourier transform in this approach (FFT). The noise spectrum is then calculated during the speech pauses and subtracted from the noisy speech signal's frequency spectrum before the noisy speech signal is reconverted from the frequency domain to the time domain using the inverse FFT (IFFT) [7].

Although it is well known that the Wiener filter may have a negative impact on the speech signal, few studies have been conducted to demonstrate the intrinsic link between noise reduction and speech distortion. The object of changing the noise estimation by means of the Wiener filter and the rules for transforming the noisy speech signals from the time domain into the frequency domain and vice versa were considered in light of the described disadvantages of the noise reduction method using a Wiener filter, in order to allow adaptation to the non-linear transmission behavior of the human ear[8]. The digital hearing aid is developed with our suggested effective noise degradation architecture in this study to reduce the undesired noise signal from the original speech signal. To conduct frequency domain processing of the speech signal in our system, the continuous time domain signal is segmented into overlapping chunks called frames, and the frames are multiplied by a window function to eliminate spectral distortions [9].

1.1 Background

Electrical signals are ubiquitous because they are utilized in communication, entertainment, measuring equipment, imaging devices, control systems, and computers. Such signals are classified into two types: analogue signals, which are conveyed by constantly fluctuating quantities, and digital signals, which are limited to a finite range of discrete values (often just two, symbolized by 0 and 1). Analog signals are used in conventional telephones because the continually fluctuating pressure associated with sound waves is translated into continuously varying voltages of an electrical signal. Computers, on the other hand, often work with binary signals, which are sequences of zeros and ones.

Electrical signals are ubiquitous because they are utilized in communication, entertainment, measuring equipment, imaging devices, control systems, and computers. Such signals are classified into two types: analogue signals, which are conveyed by constantly fluctuating quantities, and digital signals, which are limited to a finite range of discrete values (often just two, symbolized by 0 and 1). Analog signals are used in conventional telephones because the continually fluctuating pressure associated with sound waves is translated into continuously varying voltages of an electrical signal. Computers, on the other hand, often work with binary signals, which are sequences of zeros and ones. Digital signals have two significant benefits. For starters, digital signals can be precisely duplicated. All you have to do is make sure that a zero does not become a one or vice versa. (You may do this by making the physical signals for zero and one very distinct, as well as by including redundancy, so that even if a zero sometimes becomes a one, the error is immediately repaired.) Second, digital signals are readily altered. You can accomplish a lot with digital signals since they are essentially a sequence of zeros and ones, and a computer can do anything specifiable to such a sequence. And what you're doing is referred to as digital signal processing.

1.1.1 Continuous Time Signals

Continuous-time signals are defined over a time continuum and are thus represented as a continuous independent variable. Analog signals are frequently used to refer to continuous-time signals. This sort of signal has amplitude and temporal continuity. These will have values at all times. The sine and cosine functions are the greatest examples of continuous time signals.

Figure 01. Continuous Time Signals

1.1.2 Discrete Time signals

Distinct signals are signals that are specified at discrete times. As a result, each independent variable has a different value. As a result, they are represented as a series of numbers. Although voice and visual signals may be represented in both continuous and discrete time formats, they are equivalent under specific conditions. Amplitudes have distinct features as well. A perfect illustration of this is a digital signal, which has discrete amplitude and time.

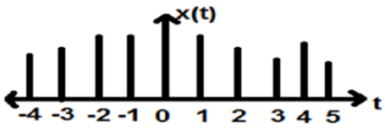

Figure 02. Discrete Time signals

1.1.3 Unit Impulse or Delta Function

A signal, which satisfies the condition, **$\delta(t)=\lim_{\epsilon\to\infty} x(t)\delta(t)=\lim_{\epsilon\to\infty} x(t)$** is known as unit impulse signal. This signal tends to infinity when t = 0 and tends to zero when t ≠ 0 such that the area under its curve is always equals to one.

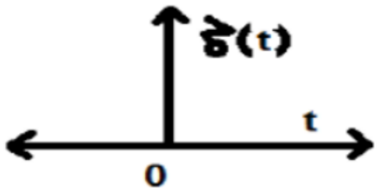

Figure 03. Impulse Signal

In a typical deep neural network, the output of ℓ-th layer can be expressed as:

$x_\ell=H_\ell(x_{\ell-1})$………………………………………………………………………………………………(1)

In Equation (1), where x_ℓ is the output of the ℓ-th layer, $x_{\ell-1}$ is the output of the $(\ell-1)$-th layer, and it is the input of the ℓ-th layer. $H_\ell(\cdot)$ is a composite function that is a non-linear transformation.

Deep neural networks have the problem of not learning effectively when the layer is deep. To address this limitation, ResNet [28] employed a skip connection, the input of which is appended to the output of the same layer as:

$$x_\ell = H_\ell(x_{\ell-1}) + x_{\ell-1} \quad \ldots\ldots\ldots (2)$$

ResNet's skip link allows the gradient to be transferred straight to the previous layers during learning, assisting in learning effectively in deeper architectures. However, when the input and output of the layer are summed, the information in the preceding levels gets weaker.

DenseNet [18] provides a method to concatenate the feature maps of all previous layers to address the drawbacks of ResNet skip connection discussed above. The l-th layer's output xl is written as:

$$x_\ell = H_\ell([x_0, x_1, \ldots, x_{\ell-1}]) \quad \ldots\ldots\ldots (3)$$

Where $[x_0, x_1, \ldots, x_{\ell-1}]$ refers to concatenation of the output feature map of layers 0 to $(\ell-1)$.

The diagnosis of mental illnesses, including depression, is based exclusively on inferences drawn from self-reported data and observed behaviour. Identifying people with established depression is usually not a clinical challenge with standard clinical instruments, but the potential for ambiguity, bias, and low reliability of important criteria for optimising treatment selection and improving outcomes, thereby reducing the economic and psychosocial burdens associated with hospitalisation, lost work productivity, and suicide. The diagnosis of mental illnesses, including depression, is based exclusively on inferences based on self-reported information and observed behaviour, guided by established categorization criteria.

1.2 Motivation

The motivating factor of this paper is that Real-world data, which is the input of the Machine Learning algorithms, are affected by several components; among them, the presence of noise is a key factor. Their must an approach that can easily filter the noise without hampering actual audio signal.

1.3 Aim of the paper

Create an algorithm to reduce noise using a machine learning method. In our experiment, adaptive noise reduction hearing aids give less amplification to noise than to speech. This is accomplished by detecting the frequencies (or times) when noise is stronger in comparison to speech and applying less amplification to those frequencies (or times).

1.4 Objective of the paper

1. To Pre-process of input audio signal that removes stationary noise
2. To Separate original signal from noise using machine learning algorithm

3. To develop Post processing and performance evaluation of designed system.

2. Review Of Literature

Wenjing Lu et al.[1] According to this paper, biomedical images and signals (for example, magnetic resonance imaging (MRI), computed tomography (CT), positron emission tomography (PET), whole slide images (WSIs), electrocardiogram (ECG), electroencephalogram (EEG), electromyography (EMG), and so on) are extremely useful for assessing a person's well-being. Doctors utilize pictures, signals, and clinical records as a specific media to identify an issue in a specific region of the body or organ. The advancement of image and signal processing over the last several decades has enabled automated analysis utilizing high-resolution and high-quality datasets.

Feng Miao , Rongzhen Zhao, Xianli Wang et al.[2] This paper focuses on improving the performance of the denoising method for vibration signals of rotating machinery by proposing a new method of signal demising based on the improved median filter and wavelet packet technology by analyzing noise component characteristics and relevant denoising methods. To begin, the median filter's window width is determined based on the sampling frequency so that impulsive noise and some white noise may be efficiently filtered out. Second, to eliminate the remaining white noise, an enhanced self-adaptive wavelet packet demising approach is employed. Following the preceding processing, relevant vibration signals are acquired. The method's performance was validated using simulation signals and rotor experimental vibration signals. Experiment findings show that the approach not only effectively eliminates mixed complex noises but also preserves fault character features, demonstrating that the suggested method outperforms the wavelet-domain median filter method.

Ali Abdullah Yahya, Jieqing Tan, and Lian Li et al. [3] This paper will concentrate on Noise produced during picture capture, broadcasting across analogue channels, and encoding or decoding frequently damaged video sequences, resulting in considerable image quality deterioration. As a result, emphasising the significance of noise reduction approaches for video sequences is required [1]. In addition to pattern recognition methods, noise reduction is a helpful tool for improving perceptual quality and increasing compression effectiveness [2]. This paper will concentrate on Noise produced during picture capture, broadcasting across analogue channels, and encoding or decoding frequently damaged video sequences, resulting in considerable image quality deterioration. As a result, emphasising the significance of noise reduction approaches for video sequences is required [1]. In addition to pattern recognition methods, noise reduction is a helpful tool for improving perceptual quality and increasing compression effectiveness [2].

Abdelshakour Abuzneid, Moeen Uddin, Shaid Ali Naz, Omar Abuzaghleh et al. [4] This study presents a method for eliminating noise from an audio stream. Filtering is accomplished by capturing the pattern of the noise signal. We have implemented our technique in MATLAB 7.0 in order to validate it. We studied the influence of the suggested algorithm on human speech and compared the findings to previous comparable work, the majority of which use basic algorithms and affect the voice signal. The findings demonstrate that the proposed method uses Voice over IP connection more efficiently and with fewer noises than similar existing algorithms.

Toshio Yoshizawa, Shigeki Hirobayashi , Tadanobu Misawa et al. [5] According to this publication, one of the most frequent methods for removing noise from a spectrum is spectrum subtraction. For frequency analysis, the spectrum subtraction approach, like many other noise reduction methods, employs the discrete Fourier transform (DFT). In DFT, there is typically a trade-off between frequency and temporal resolution. If the frequency resolution is poor, the noise spectra might overlap with the signal source spectrum, making extraction of the latter signal problematic. Similarly, if the temporal resolution is insufficient, it is impossible to discern fast frequency fluctuations. To overcome this problem, we used non-harmonic analysis (NHA) as a frequency analysis approach, which has excellent accuracy for disconnected frequency components and is only marginally impacted by frame length.

Naik D C, A Sreenivasa Murthy, Ramesh Nuthakki et al. [6] when noise damages speech information, this study focuses on the treatment of noisy speech signals in order to improve people's perception or better system comprehension. It is often difficult to maintain speech undistorted while decreasing noise, limiting the efficacy of speech enhancement systems that strike a balance between distortion of speech and noise reduction. With noisy speech with medium to high SNR, the aim is to create subjectively realistic signals by lowering noise levels, but with low SNR, the goal might be to reduce noise levels while maintaining intelligibility. This study includes a discussion of the necessity for speech improvement, its applications, and an overview of categorization and the many methodologies available, as well as a thorough literature analysis on speech enhancement techniques with diverse platforms.

Jakob Abeßer et al. [7] According to this study, the number of publications on acoustic scene categorization (ASC) in ambient audio recordings has steadily grown in recent years. The annual Detection and Classification of Acoustic Scenes and Events (DCASE) competition, which had its inaugural edition in 2013, was a major catalyst for this. So far, all tournaments have included one or more ASC tasks. This article reviews and organises existing techniques for data preparation, i.e., feature representations, feature pre-processing, and data augmentation, and for data modelling, i.e., neural network architectures and learning paradigms, with an emphasis on deep learning-based ASC algorithms. Finally, the article analyses existing algorithmic limits and open problems in order to foreshadow potential future advancements toward the real-world use of ASC systems.

C. Venkatesan1, P. Karthigaikumar et al. [8] This article focuses on medical expert systems, which are components of portable and smart healthcare monitoring equipment used in daily life. Arrhythmic beat classification is mostly utilised in the identification of electrocardiogram (ECG) abnormalities in order to diagnose cardiac issues. ECG data pre-processing and support vector machine-based arrhythmic beat classification are used in this work to differentiate between normal and abnormal patients. I A delayed error normalised LMS adaptive filter is utilised in ECG signal preprocessing to achieve high speed and low latency design with fewer computing components. Because the signal processing approach was created for remote healthcare systems, white noise reduction is the primary focus.

Hina Magsi, et al. [9] This study develops and analyses three distinct filtering techniques for reducing noise in medical health applications such as an EKG (ECG). The low pass filter removes noise at a low level, the moving average filter averages the signal values, and the Finite Impulse

Response (FIR) removes the high frequency components from the ECG and delivers the low frequency component, which is the desired information signal. The simulation findings show that the FIR filter outperforms the low pass and moving average filters in terms of decreasing attenuation in the ECG signal, making it suitable for medical health applications.

Yanqiu Zeng et al. [10] This study focuses on how Gaussian noise, an electronic noise generated by the random thermal motion of electronic components, degrades the quality and dependability of magnetic resonance (MR) pictures. This work proposes a hybrid demising method for MR images that is based on two poorly represented morphological components and one residual component. To begin, MCA is used to decompose a noisy MR image into cartoon, texture, and residual portions, which are then, demised using the Wiener filter, wavelet hard threshold, and wavelet soft threshold, respectively. Finally, combine all of the denoised sub images to create the denoised MR picture. The experimental findings demonstrate that the suggested technique outperforms each method individually in terms of mean square error and peak signal-to-noise ratio.

Guiji Tang , Xiaoli Yan , and Xiaolong Wang et al. [11] This study focuses on nonlinear time series denoising, which is required for effectively extracting information from observation sequences. An efficient chaotic signal denoising approach not only improves signal-to-noise ratio (SNR), but it can also maintain a good unpredictable denoised signal. However, the intrinsic features of chaos, such as great sensitivity to starting values and a broad spectrum, make noise reduction of contaminated chaotic signals difficult. To overcome these difficulties, an adaptive smoothing multistate morphological filtering (ASMMF) for reconstructing chaotic signals is presented. To reduce noise in polluted chaotic signals, a multiscale morphological filter is created adaptively based on the multiscale permutation entropy (MPE) of morphological filter residuals, and the contaminated signals are filtered.

Long Yu, Haonan Su, and Cheolkon Jung et al. [12] According to this article, low-light pictures have a poor dynamic range and significant noise due to a low signal-to-noise ratio (SNR). In this article, we propose a justnoticeable-difference (JND) transform for simultaneous augmentation and denoising of low-light pictures. Based on human visual perception, we accomplish both contrast improvement and noise reduction at the same time. First, we use contrast enhancement based on the perceptual histogram to properly assign a dynamic range while avoiding over-enhancing. Second, we use the JND transform to build a JND map based on an HVS response model using foreground and background brightness. The JND map is then refined using Weber's law and visual masking.

Tulasi Gayatri Devi et al. [13] This study focuses on image processing in the field of microscopy, which is becoming more prominent due to the usage of improved techniques for precise cell categorization. After the image has been processed using digital image processing techniques, the anomalies in the image may be properly recognised. Preprocessing is a crucial step that removes noise and other unwanted material. Pre-processing is necessary because noise causes inaccuracies in image processing algorithms. The initial step in pre-processing is to denoise the image. The quality of the entire image processing cycle is determined by the precision of denoising utilising filters. This study suggests filters for denoising microscopic pictures.

Vicent Mol´es-Cases, Gema Pi˜nero, Maria de Diego, and Alberto Gonzalez et al.[14] This study focuses on Personal Sound Zones (PSZ) systems, which use arrays of loudspeakers to deliver separate sound signals to numerous listeners inside a room. Weighted Pressure Matching (wPM) is one of the methods used to offer PSZ. It computes the set of filters necessary to give a desirable response in the listening zones while lowering the acoustic energy coming in the silent zones. This method may be written in both the time and frequency domains. In general, the time-domain formulation (wPM-TD) outperforms the frequency-domain formulation with shorter filters and delays (wPM-FD). wPM-TD, on the other hand, needs more computation to achieve the best filters. In this research, we present Weighted Pressure Matching with Subband Decomposition (wPM-SD), a unique approach to the wPM method that formulates a separate time-domain optimization problem for each of the subbands of a Generalized Discrete Fourier Transform (GDFT) filter bank.

Mingda Zhu And Na Liu et al. [15] According to this study, Low-Fled NMR technology has been widely employed in various fields, with the most typical approach being the employment of the CPMG sequence for T2 measurement. T2 spectrum inversion computation of Narcho sequence signal can yield important characteristics such as permeability, saturation, and fluid type of porous medium. T2 spectrum inversion calculations, on the other hand, are easily influenced by noise signals. One of the major issues with the use of low-field NMR technology is improving the signal-to-noise ratio (SNR) of echo signals. As a result, in order to achieve more accurate analysis findings, noise reduction technologies must be developed.

3. Proposed Methodology

The goal of a hearing aid with adaptive noise reduction is to offer less amplification to noise and more amplification to speech. This is accomplished by detecting the frequencies (or times) when noise is stronger in comparison to speech and applying less amplification to those frequencies (or times).

3.1 Algorithm Details: Dynamic Noise Reduction algorithm

1. The signal's spectrogram is computed.
2. Dynamically, a time-smoothed version of the supplied signal is computed with forward and backward movement of each frequency channel.
3. Unet source separation that is dynamically changed.
4. A filter smoothes the mask across frequency and time.
5. The mask is inverted and applied to the signal's spectrogram.
6. Get noise reduced signal

Modified Unet Source Separation is an audio separation model that can eliminate background noise and extract voices from an input audio file. In speech processing, the input voice is subjected to a Short Time Fourier Transform (STFT) and CNN is applied in frequency space. STFT produces a Complex Value consisting of Magnitude and Phase. Because of the nature of real values, magnitude estimate is simple, but phase estimation becomes difficult owing to the nature of complex values. When the Phase of the original material is utilised as is, there is no difficulty when the Signal-to-Noise Ratio (SNR) is high (low noise), but there is a problem when the SNR is low (high noise).

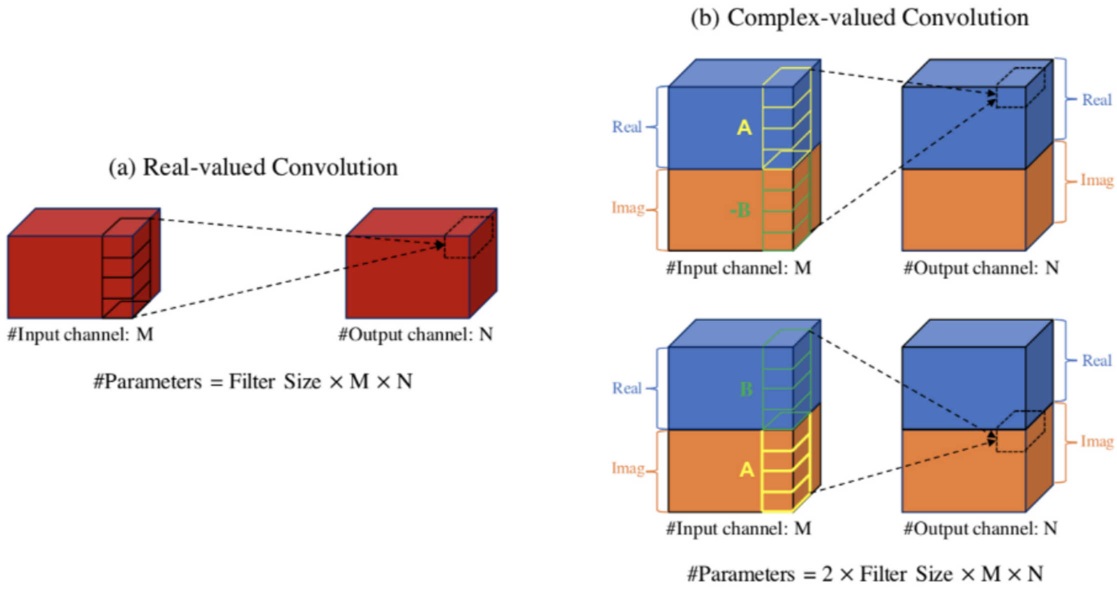

Figure 3.1 Illustration of (a) real-valued convolution and (b) complex-valued convolution

The Unet Source Separation architecture is as follows. The frequency components of the input audio are obtained using STFT and then transmitted through the Unet architecture using Complex Convolution. It then generates a mask and employs it to eliminate the noise before returning to the waveform through the Inverse Short-Time Fourier-Transform (ISTFT).

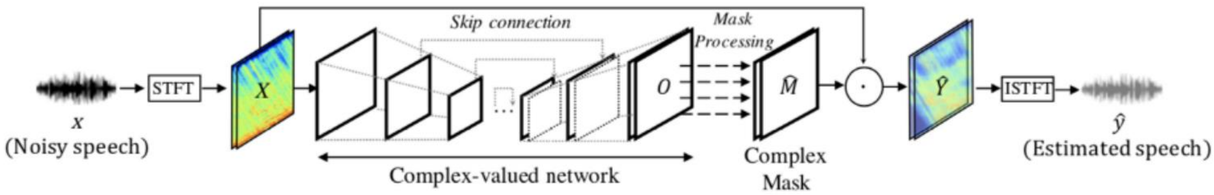

Figure 3.1 Illustration of speech enhancement framework with DCUnet.

CNN Working-

CNN’s were first developed and used around the 1980s. The most that a CNN could do at that time was recognize handwritten digits. It was mostly used in the postal sectors to read zip codes, pin codes, etc. The important thing to remember about any deep learning model is that it requires a large amount of data to train and also requires a lot of computing resources. This was a major drawback for CNNs at that period and hence CNNs were only limited to the postal sectors and it failed to enter the world of machine learning.

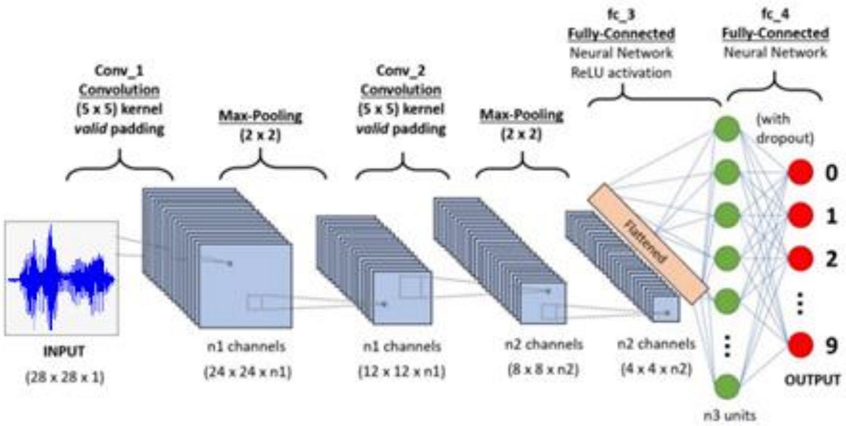

Figure 3.2 **CNN Working Flow**

In 2012 Alex Krizhevsky realized that it was time to bring back the branch of deep learning that uses multi-layered neural networks. The availability of large sets of data, to be more specific ImageNet datasets with millions of labeled images and an abundance of computing resources enabled researchers to revive CNNs. In deep learning, a **convolutional neural network** (**CNN/ConvNet**) is a class of deep neural networks, most commonly applied to analyze visual imagery. Several feedback reduction approaches based on adaptive algorithms have been utilised to minimise auditory feedback. The purpose of this paper is for the researcher to design and create an algorithm to reduce noise using a machine learning method. Stationary noise is removed from the input audio stream during pre-processing. Using a machine learning technique, the original signal is separated from the noise, Post-processing and performance testing of the developed system.Now when we think of a neural network we think about matrix multiplications but that is not the case with ConvNet. It uses a special technique called Convolution. Now in mathematics **convolution** is a mathematical operation on two functions that produces a third function that expresses how the shape of one is modified by the other. Audio file is first read into python script. Then this file is pre-processed using spatial domain filers. By using above mentioned approach the noise from the signal is get removed.

4. Result And Discussion

In the following tests, a hearing aid with adaptive noise reduction is used to offer less amplification to noise and more amplification to speech. This is accomplished by detecting the frequencies (or times) when noise is stronger in comparison to speech and applying less amplification to those frequencies (or times). In practise, the channel is subjected to noise (random signal). The noisy channel is now taken by creating AWGN (Additive White Gaussian Noise). The graph depicts the original signal as well as the noise signal. As seen in the graph, the noise signal affects the original analogue signal, when the signal is sampled at its Nyquist frequency. The samples are produced at the signal plus noise, resulting in incorrect sampling. After quantization, the quantization levels are interrupted by noise, and the quantization error rises. Because of the noise, the encoded signal is equally unpleasant. The goal is to reduce the noise in order to retrieve the original information.

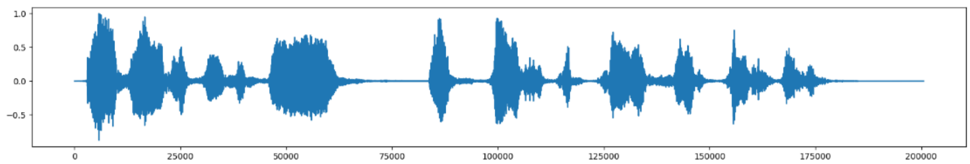

Figure 4.1 Original Audio signal

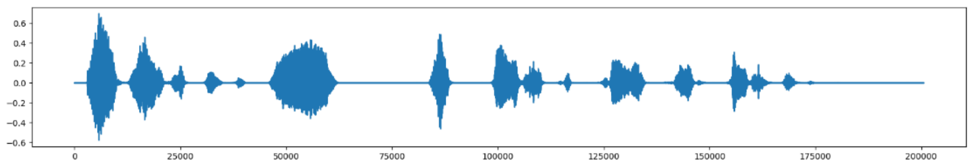

Figure 4.2 Audio signal after adding noise

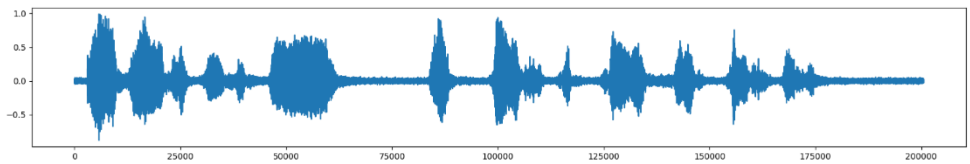

Figure 4.3 Noise Removed Audio signal

The above time-domain examination of an audio signal before and after adding and eliminating noise shows that the system produces a signal that is almost identical to the original audio file. In speech processing, the input voice is subjected to a Short Time Fourier Transform (STFT) and CNN is applied in frequency space. STFT produces a Complex Value consisting of Magnitude and Phase. Because of the nature of real values, magnitude estimate is simple, but phase estimation becomes difficult owing to the nature of complex values. Here, four audio samples are taken Noise removal is done on the different audio sample with five existing algorithm along with proposed algorithm. The SNR after noise removal is tabulated in table 4.1

	Kalman Filter	Boll Spectral Subtraction	White Gaussian Filter	LMS Adaptive filter	SDROM	Proposed system
Sample 1	28	43.5	49.1	53.4	59.27	62.14
Sample 2	24.9	45.7	45.6	52.1	59.56	63.41
Sample 3	28.8	48.2	49.9	56.6	59.08	63.69
Sample 4	27.5	44.8	47.1	58.8	59.33	61.94

Table 4.1 Signal to Noise Ratio (SNR) for various samples

From table 4.1 the graph of different noise removal algorithm is presented in figure 4.4. The graph is calculated by taking average of same algorithm reading into account.

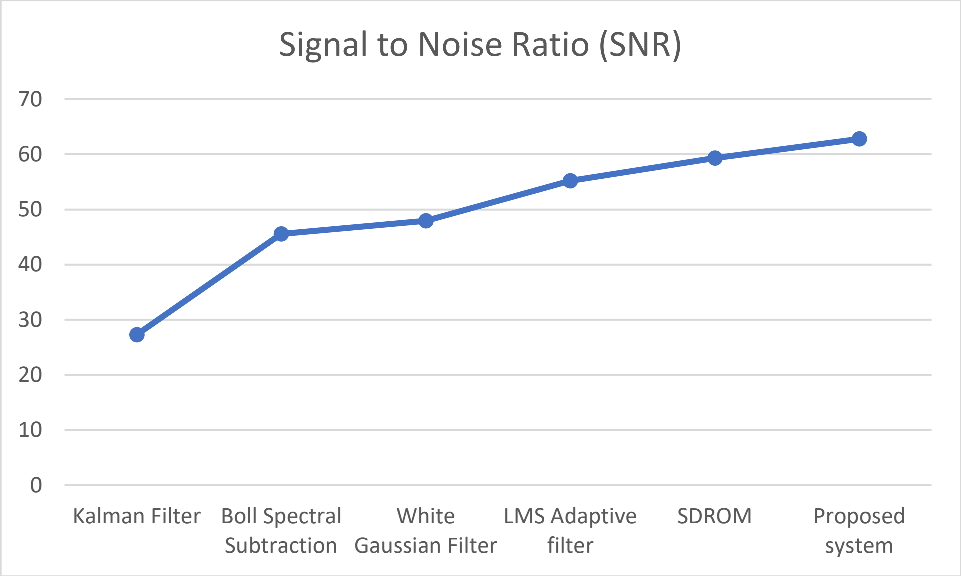

Figure 4.4 SNR of audio file with different noise removal algorithm

When the Phase of the original material is utilised as is, there is no difficulty when the Signal-to-Noise Ratio (SNR) is high (low noise), but there is a problem when the SNR is low (high noise). The value of SNR of proposed system is higher than that of every existing method.

5. Conclusion

However, hearing aid performance is typically reduced owing to acoustic feedback, which causes further issues. This effect occurs when sound travels from the speakers to the microphone. This creates instability and a high-frequency oscillation, which hearing-impaired persons can feel if the volume exceeds their hearing limits. Furthermore, these effects restrict the maximum gain that the hearing aid can achieve and degrade sound quality when the gain is nearing the limit. Several feedback reduction approaches based on adaptive algorithms have been utilised to minimise auditory feedback. Previous research has demonstrated that higher frequency resolution improves the precision of noise suppression for sound quality enhancement to an existing recording. The purpose of this paper is for the researcher to design and create an algorithm to reduce noise using a machine learning method. Stationary noise is removed from the input audio stream during pre-processing. Using a machine learning technique, the original signal is separated from the noise, Post-processing and performance testing of the developed system.

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