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Noise Cancellation in Speech Signal Processing-A Review

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Abstract: Acoustic problems in the environment have gained attention due to the tremendous growth of technology that has led to noisy engines, heavy machinery, pumps, high speed wind buffeting and a myriad other noise sources. Exposure to high decibels of sound proves damaging to humans from both a physical and a psychological aspect. The problem of controlling the noise level in the environment has been the focus of a tremendous amount of research over the years. This paper describes a study of techniques for noise cancellation which can be applied at the input to standard receivers trained on noise-free speech. Such methods have been used in various applications, including communication systems, biomedical engineering, and industrial applications. In this review, we have classified the existing noise cancellation schemes and comprehensively explore various suggestions in each category as to demonstrate limitations of the existent techniques as well as effective contributions.

Keywords: Noise Cancellation, Noise reduction, Digital Signal processing, speech signal, Adaptive filters, Soft computing, speech analysis, Acoustic problem.

I. INTRODUCTION

In all practical situations, the received speech waveform contains some form of noise component. The noise may be a result of the finite precision involved in coding the transmitted waveform (quantization noise), or due to the addition of acoustically coupled background noise. Depending on the amount and type of noise, the quality of the received waveform can range from being slightly degraded to being annoying to listen to, and finally to being totally unintelligible. The problem of removing the unwanted noise component from a received signal has been the subject of numerous investigations. The pioneering work of Wiener and others give an optimum approach for deriving a filter that tends to suppress the noise while leaving the desired signal relatively unchanged. The design of these filters requires that the signal and the noise be stationary and that the statistics of both signals be known a priori. In practice, these conditions are rarely met.

The classical approach to noise cancellation is a passive acoustic approach. Passive silencing techniques such as sound absorption and isolation are inherently stable and effective over a broad range of frequencies. However, these tend to be expensive, bulky and generally ineffective for cancelling noise at the lower frequencies. The performance of these systems is also limited to a fixed structure and proves impractical in a number of situations where space is at a premium and the added bulk can be a hindrance. The shortcomings of the passive noise reduction methods have given impetus to the research and applications of alternate methods of controlling noise in the environment.

Various signal processing techniques have been proposed over the years for noise reduction in the environment. The explosive growth of digital processing algorithms and technologies has given an impetus to the application of these techniques to the real world.

Digital Signal Processors (DSPs) have shrunk tremendously in size while their processing capabilities have grown exponentially. At the same time the power consumption of these DSPs has steadily decreased following the path laid down by Gene's law. This has enabled the use of DSPs in a variety of portable hearing enhancement devices such as hearing aids, headsets, hearing protectors, etc.

There are two different approaches for electrical noise reduction. The first approach is passive electrical noise reduction techniques, such as those applied in hearing aids, cochlear implants, etc. where the signal and ambient noise are recorded using a microphone, noise reduction techniques such as spectral subtraction, the LMS algorithm, etc. are applied and the listener hears only the clean signal. One of the important assumptions of this technique is that the listener is acoustically isolated from the environment. This assumption is however not valid in a large particularly those number of situations where the ambient noise has a very large amplitude. In such situations, the second approach of Active Noise Cancellation (ANC) is applicable. ANC refers to an electromechanical or electroacoustic technique of cancelling acoustic disturbance to yield a quieter environment. The basic principle of ANC is to introduce a cancelling "antinoise" signal that has the same amplitude but

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the exact opposite phase, thus resulting in an attenuated residual noise signal. ANC has been used in a number of applications such as hearing protectors, headsets, etc.
The traditional wideband ANC algorithms work best in the lower frequency bands and their performance deteriorates rapidly as the bandwidth and the center frequency of the noise increases. Most noise sources tend to be broadband in nature and while a large portion of the energy is concentrated in the lower frequencies, they also tend to have significant high frequency components. Further, as the ANC system is combined with other communication and sound systems, it is necessary to have a frequency dependent noise cancellation system to avoid adversely affecting the desired signal.

a. Influence of noise on speech signal applications

The performance of any speech signal processing system is degraded in the presence of noise (either additive or convolution). This is due to the acoustic mismatch between the speech features used to train and test this system and the ability of the acoustic models to describe the corrupted speech.

When processing the speech signal, the quality of speech may be at risk from various sources of interference or distortions. Typical sources of interference are:

- Background noise added to the speech signal: for example – environmental noise or engine noise when talking on a mobile phone,
- Unintended echo occurring in closed spaces with bad acoustics,
- Acoustic or audio feedback: it occurs in two-way communication when the microphone in the telephone captures the actual speech of another person and the speech of the first person reproduced from loudspeakers, and sends them both back to the first person,
- Amplifier noise: an amplifier can produce additional thermal noise, which becomes noticeable during significant signal amplifications,
- Quantization noise created in the transformation of the analogue signal to digital: the interference occurs during sampling due to rounding up real values of the analogue signal,
- Loss of signal quality, caused by coding and speech compression.

Due to numerous sources of interference influencing the speech signal, when designing the system for speech signal processing, it is necessary to apply the techniques of noise cancellation and speech quality improvement. Before moving to the noise cancellation techniques, properties of speech and noise signals are described first.

b. Properties of the speech signal

Sounds created in the vocal tract have an effective frequency range of 300 Hz to 3400 Hz. Although speech has a wider frequency range, the band of 300 Hz to 3400 Hz encompasses a range sufficient for understanding speech, and is considered as a standard for speech transfer in telephony. From the aspect of frequency response, by moving articulators, the medium frequency and amplitude of the three main resonates i.e. formants are modified. Formants are defined as spectral peaks on the speech signal spectrum, expressed in open sounds or vowels. Most formants are created during resonance in the vocal tract (trachea and oral cavity). A formant with the lowest frequency is called f_1. Based on just the first two formants, f_1 and f_2, it is possible to distinguish between vowels. For instance - the vowel "u" has an f_1 frequency of 320 Hz and an f_2 frequency of 800 Hz, while the vowel "a" has an f_1 frequency of 1000 Hz and an f_2 frequency of 1400 Hz.

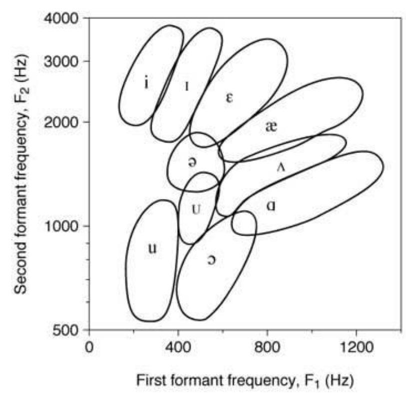

Figure 1: Graph of the f1 and f2 formant frequency range for 10 English vowels

Along with formants, the fundamental (basic) vocal chord vibration frequency of f0 is determined, the lowest frequency in the harmonic sequence. The fundamental frequency of an adult male voice ranges between 85 and 180 Hz, while this range in an adult female voice is 165 to 255 Hz. Vowels with a high fundamental frequency have a wide harmonic range in the speech signal spectrum, instead of a spectral peak. [12]

Based on the frequency properties described, it is possible to reduce different sounds in the speech signal. In certain situations, the difference between speech and noise is obvious. For instance, all noises below 300 Hz and above 3400 Hz may be suppressed by filtering out the speech signal through the filter band. Narrow-band noise, like the buzzing of the electricity network at a frequency of 50 Hz is also simple to eliminate by filtering out certain frequencies. If the noise has a very narrow frequency band, its filtering will not influence the understandability of speech. However, in numerous situations, the noise occurs on a wide-frequency band with random distribution, like environmental noise,

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music, engine noise etc. In such cases, the noise is much harder to separate and suppress from the signal, since it appears in the same frequency range as speech. From the aspect of signal power, noise is added to the clean speech signal. [13].

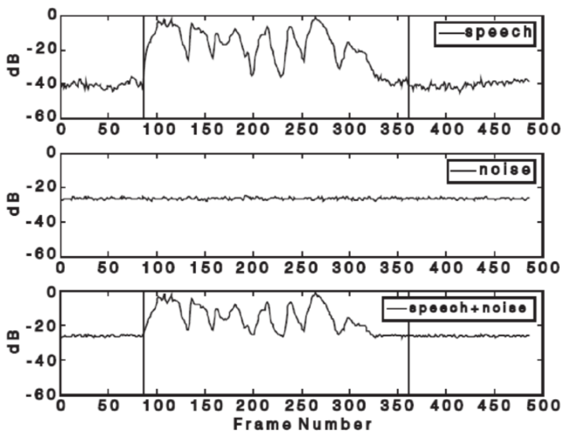

Figure 2: The influence of stationary noise has on speech signal

Although frequency properties of vowels are known, which makes the noise separation process much easier, consonants have a wide frequency range and are not easily separated from noise with filtering techniques.

C. Noise Properties

Different types of noise influence speech understandability in different ways, depending on their time and frequency properties. Noise can be classified in the following categories:

- Narrow-band noise – noise with a narrow frequency band,
- White noise – random noise with a flat signal power spectrum in theory. White noise contains all frequencies with the same intensity,
- Coloured noise – any wide-band noise which does not have a flat signal power spectrum. The best-known ones are: noise with a flat signal spectrum in the logarithmic scale (pink noise), noise in which the power density falls for 6 dB per octave (brown noise), environmental noise, engine noise etc.,
- Impulse noise – pulsing noise of a random amplitude and duration,
- Transient noise pulse – consisting of relatively long pulsing noises.

Noise is modeled with different mathematical methods for an easier classification and separation from the useful information in a signal. White noise is most often modeled as a stationary additive white Gaussian noise (AWGN). However, other types of noise are not stationary and all statistical noise parameters like mean value, variance and power spectrum vary in time. A non-stationary process can be modeled with a hidden Markov model (HMM). For instance, changes in the time domain of an impulse noise may be modeled with the Markov chain, containing a finitive number of stationary states and transitions. The number of states and transitions in the chain depends on noise properties [14].

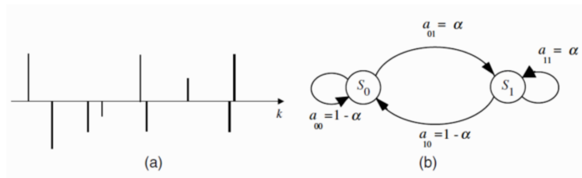

Figure 3: Impulse noise spectrum (a) and impulse noise Markov model (b)

d. Structure of Assessment

The associationsteps of this paper is as follows. The Introductory Section ends with a brief introduction of Noise cancellation and its necessity in speech signal processing. The part A, B and C in introduction shows a brief explanation about speech, noise and there properties.

In Section II,explains a General review of Noise cancellation Techniques using linear filtering,Many techniques have been proposed for the Noise cancellation for speech signals which are categorized in this section.

Section III and IV provide the information aboutthe review on recent researches in Noise cancellation in speech signals using time domain, frequency domain and spatial domain techniques.

Section V addressesthe issues for developing adaptive filtering structure for noise cancellation in speech signals.

Section VI and VII explains the issues for developing Feature Compensation and recursive filtering structures for noise cancellation in speech signals.

Section VII shows the observations, discussion and tabular comparison of different researches reviewed in previous sections. And a general conclusion of the paper, regarding review is presented in Section VIII.

II. LINEAR FILTERING OF DIGITAL SIGNAL

Prior to processing, the analogue signal must be transformed into the digital form. The procedure of transforming the analogue speech signal into a digital one creates additional noise during sampling, called quantization noise. However, already at the sampling frequency of 8 kHz and 16-bit sample resolution, the intensity of quantization noise is neglectable in comparison to other noise sources (microphone amplifier noise, environmental noise).

Once the analogue audio signal is transformed into a digital one, different techniques for noise cancellation and increasing speech signal quality are applied. The basic technique is linear filtering of the digital signal. Linear filtering encompasses signal processing in a time domain,

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reflected in a change of source signal spectrum content. The goal of filtering is to reduce unwanted noise components from the speech signal.

Usually, linear digital filters consist of two types: Finitive Impulse Response filters – FIR filters and Infinite Impulse Response filters – IIR filters.

In FIR filters, the output signal y[t] of a certain linear digital system is determined by convoluting input signal x[t] with impulse response h[t]:

$$y[t] = x[t] * h[t] \tag{1}$$

Where, t is the time domain value. Along with the time domain, digital filtering can also be conducted in the frequency domain.

Digital filters in the frequency domain are divided into four main categories: low-pass, band-pass, band-stop and high-pass [16].

The application of one of the listed band filters on a speech signal allows cancellation of stationary noise with a narrow frequency band. However, in most cases the noise is not stationary, and occurs in a wide frequency band along with speech, where the application of band filters does not provide satisfactory results. This is why other noise cancellation techniques are used that can filter the speech signal according to certain speech and noise properties.

Satorius, E.H. et al. studies, in many applications of Wiener filtering to noise cancellation an external reference noise input is required. However, if an external reference is not available, it is still possible to suppress additive noise using a Wiener linear prediction filter (LPF) provided the signal bandwidth is significantly less than the noise bandwidth. The purpose of this paper is to provide an analytical basis for bounding the performance of a digital LPF when applied to the problem of cancelling broadband additive noise from narrow-band signals [28].

A soft computing filtering approach is proposed for adaptive noise cancellation by Chunshien Li et al. The goal of noise cancellation is to extract the desired signal from its noise-corrupted version, using the proposed neuro-fuzzy system (NFS) as an adaptive filter. Traditional linear filtering may not be good enough to handle with the noise complexity. In the study, the NFS filter is trained in hybrid way using the well-known random optimization (RO) method and the least squares estimate (LSE) method for the noise cancelling problem [29].

Gharavi, Sam et al presented a new, hybrid RF/digital phase noise cancellation technique. The proposed phase noise cancellation technique estimates the phase noise using an RF delay-line-discriminator (DLD), digitizes the DLD output, performs proper digital signal processing (DSP) and then compensates for the phase noise at the digital baseband. This new technique is applicable to both transmitter and receiver and is independent of the modulation and waveform [30].

Paul, J.E. et al discusses two adaptive digital techniques for audio noise cancellation. The first technique, adaptive predictive Deconvolution, uses an adaptive linear predictor to estimate and cancel (time) correlated noise components on an audio signal. The second technique, adaptive filtering, employs two audio signal inputs, the first having the desired audio signal along with noise and the second sensing principally the noise. The second, noise signal is adaptively filtered and subtracted from the first signal cancelling noise components common to the two inputs [31].

As the quality factor of on-chip resonators does not scale with technology, the phase noise of an LC-oscillator can only be improved by consuming more power, while the benefits of circuit innovation are fundamentally limited. Although increasing current helps, it does come at a cost, and is ultimately limited by the maximum allowable amplitude, and how reliably small inductor values can be fabricated without Q-degradation. In Mikhemar, M et al propose a mixed-signal reciprocal-mixing cancellation technique that leads to a substantial reciprocal-mixing noise figure improvement independent of the LO phase noise [32].

III. NOISE CANCELLATION IN A TIME DOMAIN

Noise which occurs in the same frequency band as speech can be removed based on its statistical properties. The simplest separation and reduction of stationary noise is possible with the FIR filter in the time domain.

Filtering is performed on the framed input signal. Each frame of a digital speech signal can be described by the following vector:

$$x\ \ (n) = \{x(n), x(n-1), x(n-2), \ldots, x(n-N+1)\} \tag{2}$$

Where, N indicates the number of samples in the frame.

As previously mentioned, the noise signal is added to the speech signal. The speech signal vector containing noise can be described with the expression:

$$y(m) = x(m) + d(m) \tag{3}$$

Where, m is the time interval (frame) index, $x(m)$ the vector with clean speech samples, and $d(m)$ a vector with noise samples. This expression is based on the assumption that noise is stationary. In this case, speech and noise are independent, so the speech signal autocorrelation matrix containing noise conforms to the expression:

$$R\ \ (m) \equiv \langle y(m) y\ \ (m) \rangle = R\ \ (m) + R\ \ (m) \tag{4}$$

Where, $R_x(m)$ represents the autocorrelation matrix of the speech signal, and $R_d(m)$ the autocorrelation matrix of the noise. When the noise autocorrelation matrix is known, the autocorrelation matrix of the clean speech signal can be calculated according to the expression:

$$R\ \ (m) = R\ \ (m) - R\ \ (m) \tag{5}$$

If noise is stationary, the autocorrelation matrix of noise R_d does not change significantly from frame to frame. $R_d(m)$ can thus be estimated from breaks in the speech,

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while $R_y(m)$ is harder to estimate, since speech is quasi-stationary. Autocorrelation matrixes can be used for designing of a digital filter that will reduce noise in the speech signal. Filtering can be completed in the time domain and the frequency domain [13].

The time and frequency domain filtering schemes are investigated by Rahman, M.T. et al in [33]. The number of data points are optimized using a method described as selective truncation. In order to evaluate the performance of both the time and frequency domain filters, a series of tests is conducted using test signals. The training network parameters are optimized in order to speed up convergence.

Lowerre, J.M. proposed a method for cancelling noise in a multi-microphone situation which uses the estimate-maximize (EM) algorithm in the time domain. The development in the time domain of its use with a signal processing problem is presented. Two approximations are presented. The time-domain method will permit smaller data blocks to be used since no assumption of stationarity and estimates of the spectrum are used [34].

Nandkumar, S. et al presents a research in which first, the global objective speech quality measures show improved quality when compared to unconstrained dual-channel Wiener filtering and a traditional LMS-based adaptive noise cancellation technique, over a range of signal-to-noise ratios and cross-talk levels. Second, time waveforms and frame-to-frame quality measures show good improvement, especially in unvoiced and transitional regions of speech. Informal listening tests confirm improvement in duality as measured by objective measures [35].

Osterwise, C. et al proposed an adaptive noise cancellation technique for cancelling ambient electromagnetic interference from measurements taken in a noisy environment. A time-domain, non-recursive, block-processing algorithm was selected to generate the adaptive linear filter. Measurements in the near field of a clocked-logic electronic device in a noisy environment are compared with measurements of the same device in a noise-free environment to demonstrate that the algorithm properly removes ambient electromagnetic noise from the recorded signals [36].

IV. NOISE CANCELATION IN FREQUENCY AND SPATIAL DOMAIN

The main procedure of filtering in the frequency domain i.e. spectral filtering consists of the input signal analysis, filtering and synthesis of the filtered signal. The input signal analysis consists of framing and unitary transform from a time domain to a transform domain.

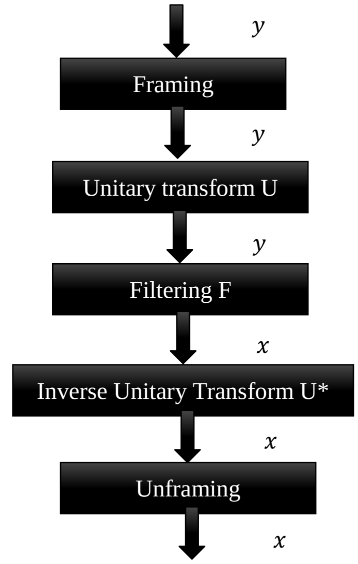

Figure 4: Spectral filtering procedure

The transform domain is most often the frequency domain. This is followed by filtering and return to the time domain, by the inverse unitary transform with unframing. Filtering primarily consists of the reduction of those frequencies whose power is below a certain threshold also called noise floor.

This filtering procedure can be described with the expression:

$$\hat{x}(m) = U(m)F(m)U^{*}(m)y(m) \qquad (6)$$

Where, U is the unitary matrix transform, conforming to UU*=I, and $F(m)$ is the gain or filter matrix. Input spectrum is obtained by transforming the input signal frame vector:

$$\boldsymbol{Y}(m) = U^{*}(m)\boldsymbol{y}(m) \qquad (7)$$

Output spectrum is calculated by filtering the input signal spectrum:

$$\widehat{\boldsymbol{X}}(m) = F(m)\boldsymbol{Y}(m) \qquad (8)$$

Finally, the output signal frame vector is calculated by applying the inverse transform to the output spectrum:

$$\widehat{\boldsymbol{x}}(m) = U(m)\widehat{\boldsymbol{X}}(m) \qquad (9)$$

The main goal of unitary transform is signal separation to a group of separate components, where it is easier to distinguish between the speech signal vector and the noise signal vector. Moreover, with the transform most of the speech signal energy is compressed into a relatively small number of coefficients, which facilitates processing. The most frequently used unitary transforms are the Discrete Fourier Transform (DFT), Discrete Cosine Transform (DCT) and the Karhunen-Loeve Transform (KLT) [17].

The discreet Fourier transform is widely used due to its fast and efficient means of calculating the transform and its inversion. It is also used due to its similarity with the human

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ear, which also conducts a certain Fourier analysis of the speech signal.
For DFT, kth column of the unitary matrix U equals the kth column of the Fourier transform matrix, defined by the expression:

$$u_k(m) = \frac{W_N^{-mM}}{\sqrt{N}}\left\{1, W_N^k, W_N^{2k}, \ldots, W_N^{(N-1)k}\right\}^T, \qquad W_N = e^{-i2\pi/N} \tag{10}$$

The discrete cosine transform is similar to DFT. DCTs are equivalent to DFTs of roughly twice the frame length (2N), operating on real data with even symmetry.
For DCT, the kth column and the nth row of the unitary matrix U are defined with the expression:

$$u'(m) = c\ \cos\frac{(2n+1)k\pi}{2N}, \qquad c = \frac{1}{\sqrt{2}} for\ k = 0 \qquad c = 1\ for\ k \neq 0 \tag{11}$$

After applying DFT spectral signal components can be analyzed as mutually independent with certain approximations, which significantly simplifies the noise separation procedure. Because framed speech signal is discontinued at frame endings DFT introduces certain distortions in the frequency domain. This is not the case with DCT as speech signal is framed with even symmetry; therefore no discontinuity related distortions exist. Moreover, DCT calculation is more efficient from DFT, since it is performed only on real numbers [13].
Tinati, M.A.et al proposed a novel method for cancellation of broadband/narrowband noise from speech signals. Independent component analysis (ICA) and wavelet packet approaches have been combined for blind noise separation from mixtures of speech signals. ICA method is used to estimate matrix A, which defines how the mixture signals have been mixed. Wavelet packets are used for de-correlation of approximation of noise and speech [37].

Adaptive filtering has been used for speech denoising in the time domain. During the last decade, wavelet transform has been developed for speech enhancement. Akhaee, M.A. et al are proposing to use adaptive filtering in the wavelet transform domain. author propose a hybrid method of using adaptive filters on the lower scales of a wavelet transformed speech together with the conventional methods (thresholding, spectral subtraction, and Wiener filtering) on the higher scale coefficients [38].

Daqrouq, K., studies that Speech enhancement is concerned with the processing of corrupted or noisy speech signal in order to improve the quality or intelligibility of the signal. Goal is to enhance speech signal corrupted by noise to obtain a clean signal with higher quality. However, the presence of noise in speech signals will contribute to a high degree of inaccuracy in a system that requires speech processing. This idea of noise cancellation for the speech signal was processed through the wavelet transform with neural networks [39].

In general, a signal subspace-based approach has a better performance result than the one with a method in Fourier domain. Ki-Man Kim et al Estimate the subspace on each subband, and design the optimum subband filter to minimize the signal distribution while reducing residual noise. A saving on computational complexity is achieved by subband domain processing [40].
Kuo, S.M. et al presents frequency-domain techniques for integrating noise reduction and echo cancellation algorithms. The self-excited method based on the short-term spectral magnitude technique is used for noise reduction. The integrated systems are implemented in frequency domain using both fast Fourier transform (FFT) and frequency-sampling filter (FSF) for splitting the time-domain signals into bandpass channels [41].

V. NOISE CANCELLATION USING ADAPTIVE FILTERING

With a basic concept first introduced by Widrow, the Adaptive Noise Canceller (ANC) removes or suppresses noise from a signal using adaptive filters that automatically adjust their parameters (Widrow et al. 1975). The ANC uses a reference input derived from single or multiple sensors located at points in the noise field where the signal is weak or undetectable. Adaptive filters then determine the input signal and decrease the noise level in the system output. The parameters of the adaptive filter can be adjusted automatically and require almost neither prior signal information nor noise characteristics.
However, the computational requirements of adaptive filters are very high due to long impulse responses, especially during implementation on digital signal processors. Convergence becomes very slow if the adaptive filter receives a signal with high spectral dynamic range (Haykin 2002), such as in non-stationary environments and colored background noise. In the last few decades, numerous approaches have been proposed to overcome these issues. For example, the Wiener filter, Recursive-Least-Square (RLS) algorithm, and the Kalman filter were proposed to achieve the best performance of adaptive filters (Albert et al. 1991, Kazemi et al. 2008, Ding et al. 2009). Apart from these algorithms, the Least Mean Square (LMS) algorithm is most commonly used because of its robustness and simplicity. However, the LMS suffers from significant performance degradation with colored interference signals (Vaseghi 2008). Other algorithms, such as the Affine Projection algorithm (APA), became alternative approaches to track changes in background noise; but its computational complexity increases with the projection order, limiting its use in acoustical environments (Sergio Ramirez Diniz 2008). An adaptive filtering system derived from the LMS algorithm, called Adaptive Line Enhancer (ALE), was proposed as a solution to the problems stated above. According to Widrow (Widrow et al. 1975, Widrow et al. 1976), ALE is an adaptive self-tuning filter capable of

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separating the periodic and stochastic components in a signal. The ALE detects extremely low-level sine waves in noise, and may be applied in speech with noisy environment. Furthermore, unlike ANCs, ALEs do not require direct access to the noise nor a way of isolating noise from the useful signal. In literature, several ALE methods have been proposed for acoustics applications. These methods mainly focus on improving the convergence rate of the adaptive algorithms usingmodified filter designs, realized as transversal Finite Impulse Response (FIR), recursive Infinite Impulse Response (IIR), lattice, and sub-band filters (Widrow et al. 1985, Cho 1990, Abid Noor et al. 2008, Jing et al. 2008).

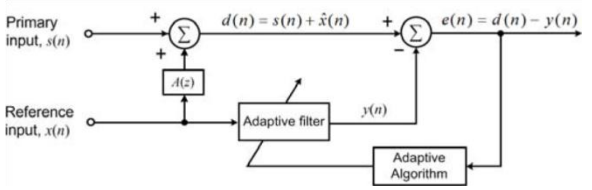

Figure 5: Block diagram of adaptive noise cancellation system

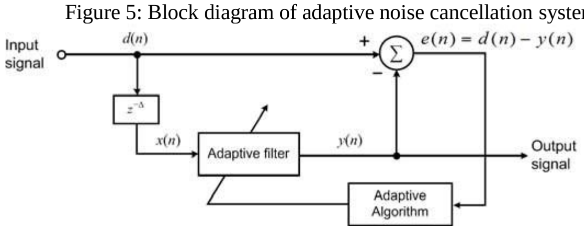

Figure 6: Block diagram of adaptive line enhancer

It is shown that for this application of adaptive noise cancellation, large filter lengths are required to account for a highly reverberant recording environment and that there is a direct relation between filter mis-adjustment and induced echo in the output speech. The second reference noise signal is adaptively filtered using the least mean squares, LMS, and the lattice gradient algorithms. These two approaches are compared in terms of degree of noise power reduction, algorithm convergence time, and degree of speech enhancement [42].

The effectiveness of noise suppression depends directly on the ability of the filter to estimate the transfer function relating the primary and reference noise channels. A study of the filter length required to achieve a desired noise reduction level in a hard-walled room is presented. Results demonstrating noise reduction in excess 10dB in an environment with 0dB signal noise ratio are presented by Pulsipher, D. et al in [43].

Mahbub, U. et al deals with a challenging task of cancelling both echo and noise in a single channel communication system. In this regard, first, a gradient based single channel adaptive least mean sqares (LMS) algorithm is developed to reduce the effect of echo. Next a spectral subtraction based single channel noise cancellation scheme is employed to reduce the effect of noise and residual echo. In order to overcome the problem of availability of a separate reference signal in single channel communication system, the delayed version of the echo and noise suppressed signal is used as the reference to the proposed adaptive filter algorithm [44].

Adaptive noise cancellation (ANC) is used widely to reduce noise from a noisy speech sound. However the least-mean-square (LMS) algorithm and its variants, such as the normalized (N)LMS, the modified (M)-LMS and the constrained stability (CS)-LMS algorithms do not perform well in ANC since the desired speech signal has a bad effect on the convergence rate and steady state misadjustment of these algorithms. Thus, Lin Bai et al propose a new adaptive algorithm that further relaxes the constraint in the CS-LMS algorithm. The new algorithm attempts to minimize the estimation error of the a posteriori error and the estimation is obtained using the concept of Taylor's expansion [45].

The filters, including a high-pass filter, an LMS adaptive filter and a combination of these two, were adopted to separate a speaker's voice from a noisy background.

VI. NOISE REDUCTION WITH RECURSIVE FILTERS

As opposed to procedures described thus far, recursive filters estimate clean speech signals based on filtering results from a previous frame and noise in the present frame. The basis for this group of filters was determined in 1960-ies by R. Kalman, with the proposal of a recursive solution for the problem of discreet data linear filtering. The Kalman filter is based on the algorithm of prediction and correction, with the assumption that a speech signal may be described with a linear stochastic model. In essence, Kalman filter algorithms predict a new state of the output signal based on the state from the previous frame, with a certain correction which is proportional to the estimate error. A set of mathematical equations of the Kalman filter enable the estimate and prediction of the clean speech signal with noise filtering [20].

The input noisy speech signal for frame n is defined in the state-space form, with the expression:

$$y(n) = \boldsymbol{h}x(n) + d(n) \qquad (12)$$

Where, $x(n)$ is the desired output signal, $d(n)$ the background white noise distributed by normal distribution, and h is the state transition matrix. The output signal model is described with the expression:

$$x(n) = Ax(n-1) + s(n) \qquad (13)$$

Where, A is the state transition matrix, and $s(n)$ is the process noise vector. Equations of the Kalman filter consist of a group of equations for the output signal estimate and a set of equations for the estimate correction.

The output signal estimate $\hat{x}(n)$ is defined based on the output signal prediction $x(n)$ and an adequate amplification k(n) of the prediction error e(n).

$$\hat{x}(n) = x\ (n) + k(n)e(n) \qquad (14)$$

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$$x\ \ (n) = A\hat{x}(n-1)$$

$$e(n) = y(n) - h\ \ x\ \ (n)$$

Optimum amplification vector $k(n)$ is determined recursively with Kalman filter correction equations. Diagram of the Kalman filter is shown in Figure 7.

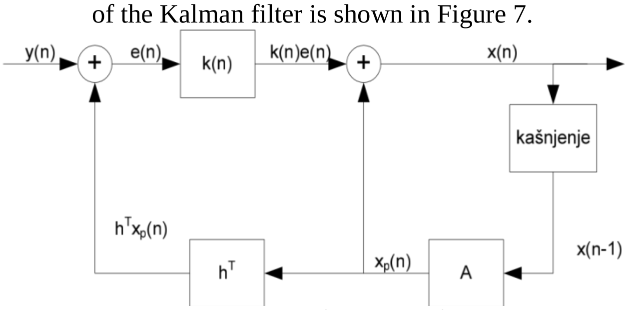

Figure 7: Diagram of the Kalman filter

Amplification vector coefficients are estimated by stochastic, not deterministic methods, which is why, in comparison with other groups of filters, the Kalman filter provides a better response to structural noise changes in the input signal. During implementation, a disadvantage of the Kalman filter are initial conditions (mean value and the variance of the state transition matrix), which must be known for the recursive algorithm to start [21].

Recently, a generalized singular value decomposition (GSVD)-based optimal filtering technique has been proposed for enhancing multimicrophone speech signals degraded by additive colored noise. The GSVD-based optimal filtering technique has a better noise reduction performance than standard beamforming techniques provided that the used filter length is large enough. In this paper, it is shown that the same noise reduction performance can be obtained with shorter filter lengths at a lower computational complexity by incorporating the GSVD-based optimal filtering technique in a generalized sidelobe canceller type structure, i.e., by adding an adaptive noise cancellation (ANC) postprocessing stage [46].

Liberti, J.C. et al investigate several adaptive noise-cancellation algorithms and their effectiveness in improving the quality of speech degraded by additive acoustic noise in mobile communications. A personal-computer system which was used to acquire test data and implement the algorithms is described. The algorithms studied include least mean squares (LMS), recursive least squares (RLS), a fast transversal filter (FTF) implementation of RLS, direct solution of the normal equation, and an adaptive notch filter [47].

Dargilington, D,J. et al describes an adaptive noise cancellation scheme for speech processing. Adaptive filters are implemented in sub-bands, based on a model of the human cochlea. A modification to the LMS structure is introduced which guarantees stability and convergence. This modification, a non-recursive normalisation, is used both in a wideband and in a sub-band implementation of the scheme. The effect of this normalisation is to cause the speech to be distorted, indicating that there is little benefit in using normalised LMS in a sub-band scheme, whether the application uses classical or intermittent noise cancellation [48].

Unfortunately, practical implementations of the Recursive Least Squares (RLS) algorithm are often associated with high computational complexity and/or poor numerical properties. Recently adaptive filtering was presented that was based on Matching Pursuits, have a nice tradeoff between complexity and the convergence speed. Sonbolestan, N. et al describes a new approach for noise cancellation in speech enhancement using the new adaptive filtering algorithm named fast affine projection algorithm (FAPA) [49].

VII. FEATURE COMPENSATION TECHNIQUIES

Together with speech signal noise cancellation techniques, techniques for compensating influence of noise on speech features where developed. These compensation methods aim at transforming MFCC feature vectors, in order to improve recognition accuracy of the noisy speech signal.

Based on the method of compensation, algorithms are divided into those based on parameters, or the stereo channel data. Algorithms based on stereo channel data compare clean speech samples with noisy samples, in order to learn statistical relations between them. The learned statistical relations are used for noise compensation on MFCC feature vectors. The multivariate Gaussian-based Cepstral normalization (RATZ) is the most common algorithm in this group. In parameter algorithms, the noise influence on feature vectors is described with a certain analytical function, containing a small group of statistical parameters. Code word dependent Cepstral normalization (CDCN) and Cepstral mean normalization (CMN) are the most common parameter algorithms [13].

Milner, B. et al examines the effect of applying noise compensation to improve acoustic speech feature prediction from noise contaminated MFCC vectors, as may be encountered in distributed speech recognition (DSR). A brief review of maximum a posteriori prediction of acoustic speech features (voicing, fundamental and formant frequencies) from MFCC vectors is made. Two noise compensation methods are then applied; spectral subtraction and model adaptation [50].

Gil Ho Lee et al, presents an approach to feature enhancement error compensation for noise robust speech recognition. The conventional feature enhancement techniques estimate the enhanced clean speech from the noise corrupted speech for improving speech recognition performance under noisy environments. During speech feature enhancement process, undesired residual error is generated because of incomplete property of the noise reduction. We apply the switching linear dynamic transducer (SLDT) to compensate this residual error [51].

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Hong Kook Kim et al, presents a set of acoustic feature pre-processing techniques that are applied to improving automatic speech recognition (ASR) performance on noisy speech recognition tasks. The principal contribution of this paper is an approach for cepstrum-domain feature compensation in ASR which is motivated by techniques for decomposing speech and noise that were originally developed for noisy speech enhancement. This approach is applied in combination with other feature compensation algorithms to compensating ASR features obtained from a mel-filterbank cepstrum coefficient front-end [52].

Hui Jiang et al, propose to compensate noise in the log-spectral domain for robust speech recognition based on a nonlinear environmental model. In this approach, starting from the original nonlinear speech distortion model in the feature domain, we derive the minimum mean square error (MMSE) estimation of clean speech signal given a noisy observation, which turns out to be an integral of a complex nonlinear function [53].

A feature compensation (FC) algorithm based on polynomial regression of utterance signal-to-noise ratio (SNR) for noise robust automatic speech recognition (ASR) is proposed by Cui, Xiaodong. In this algorithm, the bias between clean and noisy speech features is approximated by a set of polynomials which are estimated from adaptation data from the new environment by the expectation-maximization (EM) algorithm under the maximum likelihood (ML) criterion [54].

VIII. CONCLUSION & DISCUSSION

The performance of any speech signal processing system is degraded in the presence of noise (either additive or convolution). This is due to the acoustic mismatch between the speech features used to train and test this system and the ability of the acoustic models to describe the corrupted speech.

Various techniques for filtering the noise from a speech waveform has been studied. Most of these technique is based upon the concept tof adaptive filtering and takes advantage of the quasi-periodic nature of the speech waveform to supply a reference signal to the adaptive filter. Preliminary tests by authors indicate that the technique appears to improve the quality of noise speech and slightly reduce granular quantization noise. These technique also appears to improve the performance of the linear prediction analysis and synthesis of noisy speech.

It is also found from studies that, for the lower order FIR adaptive filter, RLS algorithm produce highest SNR and it is superior to LMS in its performance. But LMS is converging faster that RLS for the Finite Impulse response (FIR) filter Taps. Optimum Mu (LMS) and Lambda (RLS) values have been obtained by fixing the FIR Tap weight.

Acoustic noise cancellation ANC is best suited to remove ambient noise. The traditional wideband ANC algorithms work best in the lower frequency bands and their performance deteriorates rapidly as the bandwidth and the center frequency of the noise increases. Most noise sources tend to be broadband in nature and while a large portion of the energy is concentrated in the lower frequencies, they also tend to have significant high frequency components. Further, as the ANC system is combined with other communication and sound systems, it is necessary to have a frequency dependent noise cancellation system to avoid adversely affecting the desired signal.The major drawback of traditional single band ANC algorithms is that the performance deteriorates rapidly as the frequency of the noise increases. However, noise in real world conditions tends to be broadband with significant high frequency components.

Adaptive filtering has been used for speech denoising in the time domain. During the last decade, wavelet transform has been developed for speech enhancement. Spectral analysis of non-stationary signals can be performed by employing techniques such as the Adaptive filters like LMS, NLMS, STFT and the Wavelet transform (WT), which use predefined basis functions. Empirical mode decomposition (EMD) performs very well in such environments.

Also, Acoustic noise with energy greater or equal to the speech can be suppressed by adaptively filtering a separately recorded correlated version of the noise signal and subtracting it from the speech waveform. It is shown that for this application of adaptive noise cancellation, large filter lengths are required to account for a highly reverberant recording environment and that there is a direct relation between filter misadjustment and induced echo in the output speech. The second reference noise signal is adaptively filtered using the least mean squares, LMS, and the lattice gradient algorithms. These two approaches are compared in terms of degree of noise power reduction, algorithm convergence time, and degree of speech enhancement. Both methods were shown to reduce ambient noise power by at least 20 dB with minimal speech distortion and thus to be potentially powerful as noise suppression pre-processors for voice communication in severe noise environment.

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A. Tabular Comparison on Some Surveyed Literatures

Author	Research	Description
Tinati, M.A.	A novel method for noise cancellation of speech signals using wavelet packets	In this paper a novel method for cancellation of broadband/narrowband noise from speech signals is proposed. Independent component analysis (ICA) and wavelet packet approaches have been combined for blind noise separation from mixtures of speech signals. ICA method is used to estimate matrix A, which defines how the mixture signals have been mixed. Wavelet packets are used for de-correlation of approximation of noise and speech.
Akhaee, M.A.	Speech Enhancement by Adaptive Noise Cancellation in the Wavelet Domain	In this paper author proposing to use adaptive filtering in the wavelet transform domain. Authors propose a hybrid method of using adaptive filters on the lower scales of a wavelet transformed speech together with the conventional methods (thresholding, spectral subtraction, and Wiener filtering) on the higher scale coefficients.
Daqrouq, K.	Speech signal enhancement using neural network and wavelet transform	Speech enhancement is concerned with the processing of corrupted or noisy speech signal in order to improve the quality or intelligibility of the signal. Goal is to enhance speech signal corrupted by noise to obtain a clean signal with higher quality. However, the presence of noise in speech signals will contribute to a high degree of inaccuracy in a system that requires speech processing. This idea of noise cancellation for the speech signal was processed through the wavelet transform and neural networks.
Boll, S.	Suppression of acoustic noise in speech using two microphone adaptive noise cancellation	Acoustic noise with energy greater or equal to the speech can be suppressed by adaptively filtering a separately recorded correlated version of the noise signal and subtracting it from the speech waveform. It is shown that for this application of adaptive noise cancellation, large filter lengths are required to account for a highly reverberant recording environment and that there is a direct relation between filter misadjustment and induced echo in the output speech. The second reference noise signal is adaptively filtered using the least mean squares, LMS, and the lattice gradient algorithms. These two approaches are compared in terms of degree of noise power reduction, algorithm convergence time, and degree of speech enhancement.
Pulsipher, D.	Reduction of non-stationary acoustic noise in speech using LMS adaptive noise cancelling	Non-stationary acoustic noise with energy possibly equal to or greater than the speech is suppressed using a two microphone implementation of adaptive noise cancellation. The primary noise added to the speech is reduced by subtracting a filtered version of the second microphone reference noise. The reference noise filter is adaptively up dated using the Widrow-Hoff LMS algorithm. The effectiveness of noise suppression depends directly on the ability of the filter to estimate the transfer function relating the primary and reference noise channels. A study of the filter length required to achieve a desired noise reduction level in a hard-walled room is presented.
Mahbub, U.	Gradient based adaptive filter algorithm for single channel acoustic echo cancellation in noise	Conventional adaptive echo cancellation schemes are generally suitable for dual channel communication system and their performance degrades significantly in the presence of noise. This paper deals with a challenging task of cancelling both echo and noise in a single channel communication system. In this regard, first, a gradient based single channel adaptive least mean squares (LMS) algorithm is developed to reduce the effect of echo. Next a spectral subtraction based single channel noise cancellation scheme is employed to reduce the effect of noise and residual echo.
Lin Bai	A modified NLMS algorithm for adaptive noise cancellation	Adaptive noise cancellation (ANC) is used widely to reduce noise from a noisy speech sound. However the least-mean-square (LMS) algorithm and its variants, such as the normalized (N)LMS, the modified (M)-LMS and the constrained stability (CS)-LMS algorithms do not perform well in ANC since the desired speech signal has a bad effect on the convergence rate and steady state misadjustment of these algorithms. Thus, author propose a new adaptive algorithm that further relaxes the constraint in the CS-LMS algorithm. The new algorithm attempts to minimize the estimation error of the a posteriori error and the estimation is obtained using the concept of Taylor's expansion.
Liberti, J.C.	Evaluation of several adaptive algorithms for	The authors investigate several adaptive noise-cancellation algorithms and their effectiveness in improving the quality of speech degraded by additive acoustic

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	cancelling acoustic noise in mobile radio environments	noise in mobile communications. A personal-computer system which was used to acquire test data and implement the algorithms is described. The algorithms studied include least mean squares (LMS), recursive least squares (RLS), a fast transversal filter (FTF) implementation of RLS, direct solution of the normal equation, and an adaptive notch filter.
Darlington, D.J.	Sub-band, dual-channel adaptive noise cancellation using normalised LMS	An adaptive noise cancellation scheme for speech processing is described. Adaptive filters are implemented in sub-bands, based on a model of the human cochlea. A modification to the LMS structure is introduced which guarantees stability and convergence. This modification, a non-recursive normalisation, is used both in a wideband and in a sub-band implementation of the scheme. The effect of this normalisation is to cause the speech to be distorted, indicating that there is little benefit in using normalised LMS in a sub-band scheme, whether the application uses classical or intermittent noise cancellation
Hui Jiang	Nonlinear noise compensation in feature domain for speech recognition with numerical methods	Propose to compensate noise in the log-spectral domain for robust speech recognition based on a nonlinear environmental model. In this approach, starting from the original nonlinear speech distortion model in the feature domain, derive the minimum mean square error (MMSE) estimation of clean speech signal given a noisy observation, which turns out to be an integral of a complex nonlinear function. This work propose to use a numerical method to solve the above nonlinear integral. It requires higher computational complexity than the normal linear approximation methods but it is usually affordable since calculation is performed entirely in the pre-processing feature domain without involving any change in speech decoders.

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