SINGLE CHANNEL SPEECH ENHANCEMENT USING KALMAN FILTER

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Abstract

Single Channel Speech Enhancement Using Kalman Filter

Sujan Kumar Roy

The quality and intelligibility of speech conversation are generally degraded by the surrounding noises. The main objective of speech enhancement (SE) is to eliminate or reduce such disturbing noises from the degraded speech. Various SE methods have been proposed in literature. Among them, the Kalman filter (KF) is known to be an efficient SE method that uses the minimum mean square error (MMSE). However, most of the conventional KF based speech enhancement methods need access to clean speech and additive noise information for the state-space model parameters, namely, the linear prediction coefficients (LPCs) and the additive noise variance estimation, which is impractical in the sense that in practice, we can access only the noisy speech. Moreover, it is quite difficult to estimate these model parameters efficiently in the presence of adverse environmental noises. Therefore, the main focus of this thesis is to develop single channel speech enhancement algorithms using Kalman filter, where the model parameters are estimated in noisy conditions. Depending on these parameter estimation techniques, the proposed SE methods are classified into three approaches based on non-iterative, iterative, and sub-band iterative KF.

In the first approach, a non-iterative Kalman filter based speech enhancement algorithm is presented, which operates on a frame-by-frame basis. In this proposed method, the state-space model parameters, namely, the LPCs and noise variance, are estimated first in noisy conditions. For LPC estimation, a combined speech smoothing and autocorrelation method is employed. A new method based on a lower-order truncated Taylor series approximation of the noisy speech along with a difference operation serving as high-pass filtering is introduced for the noise variance estimation. The non-iterative Kalman filter is then implemented with these estimated parameters effectively.

In order to enhance the SE performance as well as parameter estimation accuracy in noisy conditions, an iterative Kalman filter based single channel SE method is proposed as the second approach, which also operates on a frame-by-frame basis. For each frame, the state-space model parameters of the KF are estimated through an iterative procedure. The Kalman filtering iteration is first applied to each noisy speech frame, reducing the noise component to a certain degree. At the end of this first iteration, the LPCs and other state-space model parameters are re-estimated using the processed speech frame and the Kalman filtering is repeated for the same processed frame. This iteration continues till the KF converges or a maximum number of iterations is reached, giving further enhanced speech frame. The same procedure will repeat for the following frames until the last noisy speech frame being processed.

For further improving the speech enhancement performance, a sub-band iterative Kalman filter based SE method is also proposed as the third approach. A wavelet filter-bank is first used to decompose the noisy speech into a number of sub-bands. To achieve the best trade-off among the noise reduction, speech intelligibility and computational complexity, a partial reconstruction scheme based on consecutive mean squared error (CMSE) is proposed to synthesize the low-frequency (LF) and high-frequency (HF) sub-bands such that the iterative KF is employed only to the partially reconstructed HF sub-band speech. Finally, the enhanced HF sub-band speech is combined with the partially reconstructed LF sub-band speech to reconstruct the full-band enhanced speech.

Experimental results have shown that the proposed KF based SE methods are capable of reducing adverse environmental noises for a wide range of input SNRs, and the overall performance of the proposed methods in terms of different evaluation metrics is superior to some existing state-of-the art SE methods.

I dedicate this work to my parents...

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Contents

List of Figures

List of Tables

List of Abbreviations

ACF	Autocorrelation function
AR	Auto-regressive
ARMA	Auto regressive moving average
ASR	Automatic Speech Recognition
CMSE	Consecutive mean squared error
DCT	Discrete cosine transform
DFT	Discrete Fourier transform
DWT	Discrete wavelet transformation
EM	Expectation maximization
FIR	Finite impulse response
HF	High-frequency
IT-KF	Iterative Kalman filter
IDFT	Inverse discrete Fourier transformation
IWF	iterative Wiener filter
KF	Kalman filter
LF	Low-frequency
LLR	Log-likelihood ratio
LP	Linear prediction
LPC	Linear prediction coefficient
PR	Perfect reconstruction
MAP	Maximum a-posteriori
MMSE	minimum mean square error
MSE	Mean squared error
NIT-KF	Non-iterative Kalman filter
PESQ	Perceptual evaluation of speech quality
SE	Speech enhancement
SNR	Signal-to-noise ratio
SSM	State-space model
WF	Wiener filter
WFB	Wavelet filter-bank

List of Symbols

$s(n)$	Clean speech
$y(n)$	Noisy speech
$u(n)$	Process noise
$v(n)$	Additive noise
$\hat{s}(n)$	Enhanced speech
$A_P(z)$	All-pole filter
$x(t)$	Excitation signal
$\epsilon(n)$	Prediction error
$\boldsymbol{R_{ss}}$	Autocorrelation matrix of clean speech $s(n)$
$\boldsymbol{A}$	LPC vector
$\boldsymbol{\Phi}$	Transition matrix
$\boldsymbol{\Sigma_x}$	Covariance matrix
$e(n)$	Measurement innovation
$\boldsymbol{K}(n)$	Kalman gain
$T_r()$	Trace operator
$E.$	Expectation operator
σ_v^2	Additive Noise Variance
σ_u^2	Process Noise Variance
$\hat{\boldsymbol{x}}(n\mid n)$	State vector
$s_h(n)$	Partially reconstructed HF sub-band speech
$s_l(n)$	Partially reconstructed LF sub-band speech
j_s	Last HF sub-band index

Chapter 1

Introduction

1.1 Overview of Speech Enhancement

Speech enhancement is essential in modern voice communication systems. Speech communication devices like cellular phones, handsfree equipment, human-to-machine speech processing systems, etc. are an integral part of our daily life. In real-life, the speech communication takes place in different noisy environments where the original clean speech could be degraded due to the presence of surrounding noises. These noises can range from stationary white noise to any non-stationary and/or colored noises such as street noise, car engine noise, babble noise, restaurant noise, etc. In many speech communication and processing systems, the desired clean speech is not available due to degradation by the ambient noises [1]. Therefore, noise reduction of speech has been an active area of research over the last few decades.

The performance of speech enhancement algorithms is evaluated according to the quality and intelligibility of the enhanced speech. In general, speech quality assessment falls into two categories; subjective and objective quality measures. Subjective quality measures are based on comparison of original and enhanced speech by a listener or a panel of listeners, where they rank the quality of the enhanced speech according to a predetermined scale. Objective quality measures are calculated from the original speech and the processed speech using some mathematical formulas. On the other hand, speech intelligibility is another quality measure to indicate how comprehensible a speech is in given conditions. The relationship between speech quality and intelligibility is not entirely understood, yet there exists some correlation between these two. Generally, speech perceived as *good* quality gives high intelligibility, and vice versa. However, there are speech samples that are rated as *poor* quality, and yet give high intelligibility, and vice versa [2]. Therefore, it is very important for a SE algorithm to maintain good quality as well as intelligibility of the enhanced speech.

Speech enhancement has been widely used as a front end tool for automatic speech recognition, telecommunications, hearing aids, etc. By improving the quality and intelligibility of the degraded speech using a SE method, it vastly improves the listening experience of users through these consumer applications. A brief description of speech enhancement applications is given below.

Automatic Speech Recognition: Automatic Speech Recognition (ASR) has been an important field of research since the 1950s. It can recognize human spoken words or sentences, and thus has many important real-world applications including person identification, human-robot communication, etc. The key requirement of these applications is to distinguish between similar sounding words. However, in practical applications, the speech recognition accuracy becomes degraded due to the sorrounding noise. SE in such situations is used as a front end tool of the ASR system to remove the unwanted noises or other interferences in the speech samples before the ASR software attempts to recognize the speech [3].

Telecommunications: One of the important applications of speech enhancement found in telecommunication systems is specifically mobile or cellular telephony. Due to the majority of the cell phone conversations taking place in noisy environments, namely automobiles, streets or public places, noise will inevitably be mixed up with the speech, making the conversation disturbing for the listener. A speech enhancement algorithm plays an important role in order to remove these unwanted noises, making the public conversation through cell phones more efficient [4].

Hearing Aids: The hearing aid devices consist of a microphone and amplifier including some DSP hardware. It is used by hearing impaired people. In adverse acoustic environments, individuals with hearing impairment may struggle to understand the speech content due to the interfering sounds, background noise, and reverberation. Like any other microphone, this is susceptible to picking up unwanted noise along with the speech. Therefore, a robust speech enhancement algorithm programmed on the DSP chip may improve the users listening experience [4].

Other Applications: In audio recording industry, speech enhancement plays a key role in removing different interferences like acoustic echo and reverberation. It is also used in air-ground communication, emergency equipment like elevator, SOS alarm, vehicular emergency telephones, VoIP, etc.

1.1.1 Categories of Speech Enhancement Algorithm

Speech enhancement algorithms are implemented based on certain assumptions depending on different applications. In general, these algorithms are classified based on the number of input channels or microphones (single/multiple microphones), and the domain of processing (time/transform domain). The time-domain or transform-domain speech enhancement algorithms can also be further classified as adaptive and non-adaptive depending on parameter estimation. In the single channel speech enhancement algorithm, one noisy mixture gives the overall spectral information of the degraded speech since there is only one microphone/channel available. On the other hand, in multi-channel speech enhancement, multiple microphones are available in order to capture the noisy mixtures which exhibit the advantage of incorporating both the spatial and the spectral information. However, multi-channel systems increase the system implementation costs and may not always be available. Therefore, single channel speech enhancement is of more interest in many speech processing applications [5].

The main focus of this thesis is to implement efficient single channel speech enhancement that can perform well in the presence of adverse environmental noises. For a single microphone speech $s(n)$, and additive noise $v(n)$ which may be white or colour noise, the noise corrupted speech signal $y(n)$ at time n is then represented as

$$y(n) = s(n) + v(n) \tag{1.1}$$

The general block diagram of single channel SE is shown in Figure 1.1, where the SE algorithm is to estimate the clean speech $s(n)$ from the noisy speech $y(n)$.

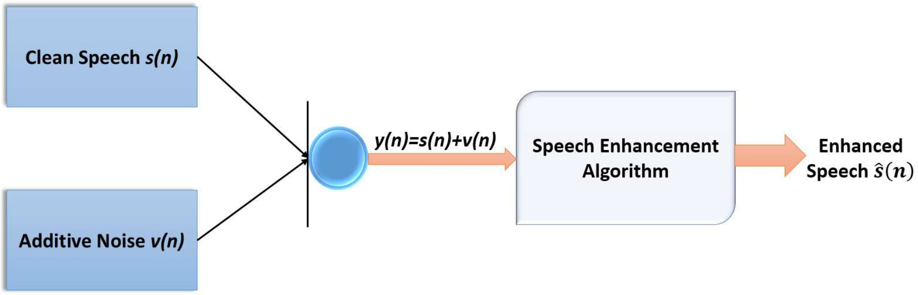


Figure 1.1: Block diagram of single channel speech enhancement.

1.1.2 Statistical Properties of Different Additive Noises

The main objective of speech enhancement algorithm is to estimate the clean speech $s(n)$ from the noise corrupted speech $y(n)$ through different noise reduction algorithms. However, it is a challenging task to eliminate or reduce the additive noise $v(n)$ in the noisy observation due to the random nature of the noise and the intrinsic complexities of the clean speech $s(n)$. In addition, different noises possess different statistical characteristics. Due to this reason, a speech enhancement algorithm may perform well for a particular type of noise, but not efficient for other types of noises. Therefore, it is important to understand the statistical characteristics of the additive noise $v(n)$ in order to develop an efficient speech enhancement algorithm for different environmental noises. Depending on the time or frequency characteristics, the additive noise $v(n)$ in (1.1) can be classified into the following categories.

- **White Noise:** It is defined as an uncorrelated noise process with a constant power spectral density. It is a wide-band noise which theoretically contains all frequencies within the signal bandwidth.

- **Non-stationary Noise:** In non-stationary noise, the power spectral density is not constant and changes over time. It is quite difficult to deal with this noise, since there is no prior information available about the characteristics of that noise.

- **Pink Noise:** Pink noise is a type of noise where the power spectral density (energy or power per Hz) is inversely proportional to the frequency of the signal. Therefore, the lower frequency components in pink noise have more power than the higher frequencies.

- **Restaurant Noise:** This type of noise contains multiple people talking in the background mixed in some cases with other noises coming from the kitchen or other utensil sounds. The spectral characteristics of restaurant noise are randomly changing as people carry on conversation to the neighbouring tables or the waiters interaction with guests during services.

- **Babble Noise:** This type of noise is encountered when a crowd or a group of people are talking together simultaneously (i.e. in a cafeteria, crowded classroom, or other places). It has the characteristics of time varying amplitudes. In addition, some of the noise frequencies may coincide closely with the original clean speech samples.

- **Street Noise:** The street noise includes vehicle's engine sound and other exhaust noise which increases with vehicle speed. The amplitude of this type of noise also changes rapidly.

- **Car Noise:** This type of noise contains car interior and engine sound during conversation through cell phone or other communication devices. It may also include break sound, tyre sound, and other exhaust sounds.

- **Train Noise:** Train noise contains its interior sounds, several distinct sounds such as the locomotive engine noise, and the wheels turning on the railroad track. It may also include horns, whistles, bells, and other noisemaking devices for both communication and warning.

- **Cockpit Noise:** This type of noise includes plane interior sound, engine sounds, and other exhaust sounds which may take place during the radio communication between the pilot and the air-traffic controller. This type of noise spectra may vary greatly as a function of the aircraft size and type and other associated parameters.

In general, speech enhancement algorithm can be thought of as an estimation problem, where an unknown signal (clean speech) is to be estimated in the presence of different types of noises, where only the noisy observation is available. Therefore, it is quite difficult for a particular speech enhancement algorithm to perform well across different types of noises [6].

1.2 Literature Review

Research on speech enhancement started more than 40 years ago at AT & T Bell Laboratories, with the pioneering work by Schroeder as mentioned in [7]. Schroeder proposed an analog implementation (consisting of bandpass filters, rectification and averaging circuitry) of spectral magnitude subtraction method for speech enhancement. Although there are many speech enhancement algorithms available nowadays, several existing algorithms (time-domain/transform- domain) for single channel speech enhancement are reviewed in this section which are closely related to this thesis, and will be implemented for comparison purposes.

1.2.1 Time-Domain Speech Enhancement Algorithms

Time-domain linear filtering approach for single channel SE is a popular one nowadays. In this approach, the SE problem is formulated as a filter design problem. More specifically, a filter should be designed such that it can reduce the additive noise level of the noisy speech as much as possible while not introducing any noticeable distortion in the enhanced speech [8]. Different types of linear filters can be designed in time-domain. One example of such an approach is the AR model based human speech production system. This model uses *all-pole* synthesis filtering techniques for estimating the LPC in noisy conditions. With the estimated LPCs, the approximated clean speech samples can be modeled. Kalman filter is also commonly used as a time-domain single channel speech enhancement method. The following subsections briefly review these important time-domain speech enhancement algorithms.

1.2.1.1 Speech Enhancement using LPC

LPC based speech enhancement algorithms can be thought of as a linear time varying system which is modelled by a digital filter with time-varying coefficients. In this type of noise reduction algorithms, the speech samples are represented by P^{th} order autoregressive (AR) model, where the speech production model parameters, namely, the LPCs are estimated from the noise corrupted speech [9].

Lim and Oppenheim in [10] introduced an LPC model based iterative scheme for enhancing the noise corrupted speech. These algorithms are based on the assumption of Gaussian excitation of the maximum a-posteriori (MAP) estimator where the LPC parameters are obtained from the clean speech. However, in noisy condition, the equations for solving the MAP estimator becomes non-linear which is difficult to solve. The authors of [10] suggested an iterative procedure which requires only a solution of a set of linear equations for LPC parameter estimation from noisy observations. This iterative procedure is referred to as linearized MAP (LMAP). This algorithm requires an initial estimate of the LPC parameters from noisy speech and then enhances the noisy speech by an appropriate application of an optimal filter. Then a new estimate of the LPC parameters is obtained by using the autocorrelation based method which is more accurate. The estimated speech samples are modeled with these new set of LPCs. The authors obtained the preliminary results of the enhanced speech after 2-3 iterations, where the formant bandwidth becomes very narrow, giving an unnatural sound and distorted estimated speech.

An improvement of LPC for noise reduction based on pitch synchronous addition method has been presented in [11]. It resolved the LPC estimation problem in noisy conditions. The idea is based on that the speech has a valid pitch period, which may hold up to 20-25 milliseconds for one utterance, and the speech is assumed to be stationary within this period. In addition, the amplitude of the waveform of the benchmark speech within each period remains constant. Using this property of speech, the authors synchronized the pitch period by applying the averaging operation which decreases the noise power if the speech samples are corrupted by an additive noise. Therefore, more accurate LPCs can be estimated from the processed speech which can guarantee the stability of the *all-pole* synthesis filter during LPC estimation. One shortcoming of this method is that it requires to estimate accurate pitch period in order to perform pitch synchronous operation, which is relatively difficult in noisy conditions.

The key point of LPC based speech enhancement is that the LPCs can be estimated accurately if the clean speech is available. In noisy conditions, however, the estimation of the LPCs becomes a very difficult task. In addition, the *all-pole* synthesis filter may not be stable in noisy conditions, which is an important condition for accurate LPC estimation. To overcome this shortcoming, numerous methods have been proposed in the literature. Unfortunately, a satisfactory solution for preserving the stability of the *all-pole* synthesis filter as well as accurate LPC estimation is never obtained. On the other hand, LPC can be used as an important model parameter for many speech enhancement methods, such as in Kalman filter where the state-space model is fromed with the LPCs. Therefore, it is still a demanding task to estimate LPCs in noisy conditions accurately. The next section gives a brief overview of some Kalman filter based speech enhancement algorithms.

1.2.1.2 Speech Enhancement using Kalman Filter

The Kalman filter (named after its inventor, Rudolf E. Kalman in 1960), was initially used for spacecraft, aircraft or other astrological signal analysis [12]. However, in the last two decades, KF based speech enhancement is an active area of research. In KF, speech is usually modeled as autoregressive (AR) process and represented in the state-space domain. The LPC and additive noise variance are two important parameter for Kalman filter implementation. It has several advantages over other speech enhancement methods, namely, it can maintain the non-stationary nature of the speech and does not need to assume the stationary condition within a small analysis frame as required for the other frequency-domain speech enhancement.

The Kalman filter based speech enhancement was first proposed by Paliwal and Basu in [13]. In this approach, it was shown that the Kalman filter outperform Wiener filter. However, the performance of the proposed algorithm was limited to reduce only white Gaussian noise. In this method, the linear prediction coefficients are estimated from clean speech, before being contaminated by white noise, which is however not true in practical applications. In [14], a neural network model for speech generation trained by dual extended Kalman filter was introduced where no justification for the non-linear system model was given. In [15], an iterative and sequential Kalman filter based speech enhancement algorithm has been proposed. This algorithm performs relatively well in terms of output SNR improvement. In addition, the authors of this paper also used higher-order statistics combindly with the Kalman filter in order to further improve the performance of the algorithm.

In [16], a Kalman filter based speech enhancement algorithm has been presented that is capable of reducing color noise. In this paper, new sequential estimation techniques have been developed for adaptive estimation of the unknown parameters. A perceptual Kalman filter based speech enhancement method has been proposed in [17, 18], where the perceptual weighting is used to replace the masking threshold. It avoids the frequency domain complexity and makes it suitable to estimate the state-space vector in time-domain. A Kalman filter based on wavelet filter-bank and psychoacoustic modeling for speech enhancement has been introduced in [19]. The adaptation of the Kalman filter in the wavelet domain has effectively reduced the non-stationary noise. The authors in this paper, also employed the perceptual weighting filter for exploiting the masking properties of the psychoacoustic model which is concatenated with the Kalman filter to further improve the intelligibility of the enhanced speech. In [20], a fast adaptive Kalman filter based algorithm has been proposed. In this method, the authors designed a coefficient factor for adaptive filtering, which is capable of estimating the additive noise from the degraded speech effectively.

A sub-band modulator Kalman filter based approach has been introduced in [21], where the noisy speech is decomposed into sub-bands and subsequently each sub-band is demodulated into its modulator and carrier components. The required parameters for Kalman filter namely LPCs and noise variance in this algorithm are estimated using the EM algorithm from each sub-band. Kalman filter is then implemented with the estimated parameters and applied to the modulators of all sub-bands instead of the sub-bands directly without altering the carriers. The full-band enhanced speech is obtained by adding all the modified sub-bands. In [22], speech enhancement based on robust Kalman filter as post-processor in the modulation domain has been introduced. In this algorithm, at first a conventional MMSE spectral amplitude algorithm is employed to the degraded speech as pre-filtering of the noisy speech. The LPC model parameters are estimated from the pre-filtered speech. In addition, two alternative methods are proposed for improving the stability of the *all-pole* synthesis filter that can be effectively used for the LPCs estimation. Finally, a Kalman filter is employed to the modulation domain of the pre-filtered speech as a post-processor for further improving the speech intelligibility. In [23], a restoration scheme of instantaneous amplitude and phase using Kalman filter for single channel speech enhancement has been introduced. In this algorithm, both of the amplitude and phase information has been restored from the noisy speech using Kalman filter in order to restore the clean speech samples. Although this algorithm performs well in different noisy conditions, it has some limitations. The main drawback of this method is that it assumes the clean speech samples for implementing the training set in order to estimate the LPC coefficients which is impractical. Another weak point of this algorithm is that it requires two different AR models in order to represent the amplitude and phase of the noisy speech which increases the computational complexity.

Gibson et al. in [24] have proposed to extend the use of the Kalman filter by incorporating a colored noise model in order to improve the enhancement performances for certain classes of noise sources. A disadvantage of the above mentioned Kalman filtering algorithms is that they do not address the model parameter estimation problem. Another weak point of this method is that the noise variance is estimated during the silent period of the noisy speech frame which implies that the use of voice activity detector (VAD) is needed. In [25], a fast converging iterative Kalman filter for speech enhancement has been introduced. This algorithm provides less residual noise in the enhanced speech as compared to the iterative scheme of Gibson, et al. [24]. This is achieved by the use of long and overlapped frames as well as a tapered window with a large side lobe attenuation for LPC analysis. In [26], iterative Kalman filtering for speech enhancement using overlapped frames has been introduced. In this paper, the authors proposed to use the overlapped windows for LPC analysis in order to reduce the background residual noise as found in the Gibson's iterative Kalman filter [24].

From the above literature review, it is clearly observed that the performance of Kalman filter based speech enhancement depends on the accuracy of the LPC and noise variance estimation in noisy conditions. As such, a key issue in Kalman filter based methods is to obtain accurate LPCs and noise variance from noisy speech.

1.2.2 Transform-Domain Speech Enhancement Algorithms

In transform-domain speech enhancement algorithms, the noisy speech samples are transformed into another domain (e.g., frequency domain, wavelet domain, etc.), in order to extract further details or other hidden information that may not readily be available in time-domain speech samples. Among different transform-domain speech enhancement algorithms, frequency-domain algorithms have been well studied over the past few decades. The main idea of the frequency-domain speech enhancement involves transforming the noisy speech into the frequency-domain via the discrete Fourier transform (DFT) and subtracting an estimate of the noise spectrum from the noisy spectrum, yielding an approximation of the spectrum of the clean speech, which is then converted back to the time-domain by the inverse DFT [27]. Spectral subtraction and Wiener filter based frequency-domain speech enhancement algorithms are very popular nowadays.

In order to deal with non-stationary noises, sub-band speech enhancement algorithms have also been investigated which works in other transform-domain (e.g., wavelet domain, DCT domain, etc.). In these algorithms, the noisy speech is decomposed into several critical sub-bands and then the desired information as required for speech enhancement is effectively estimated from the sub-bands[28]. Many transform-domain speech enhancement algorithms have been introduced in the last few decades. Among them, wavelet transform based algorithms for speech enhancement have been actively studied. Moreover, some speech enhancement algorithms have been introduced with the combination of wavelet filter-bank and other methods. The following subsections give a brief overview of some of the transform-domain single channel speech enhancement algorithms.

1.2.2.1 Speech Enhancement using Spectral Subtraction

The earliest and most commonly used method for speech enhancement is magnitude spectral subtraction. Since speech and noise are considered to be uncorrelated, if an estimate of the noise spectrum can be obtained for a particular noisy speech frame, then an estimate of the clean speech spectrum can be calculated by subtracting the estimated noise spectrum from the noisy spectrum. The estimated clean speech spectrum is represented as

$$\hat{S}(w) = Y(w) - \hat{V}(w) \tag{1.2}$$

where $\hat{S}(w)$ is the estimated frequency spectrum of the clean speech for a given frame, $Y(w)$ is the noisy spectrum of the same frame, and $\hat{V}(w)$ is the estimated noise spectrum. An estimate of the clean speech is recovered by applying the inverse discrete Fourier transformation (IDFT) to $\hat{S}(w)$, to give $\hat{s}(n)$. Since the human ear is relatively insensitive to phase, the phase angle of the noisy speech can be used when reconstructing the enhanced speech using IDFT.

Although the spectral subtraction based speech enhancement algorithm is relatively easier to implement, its effectiveness is heavily dependant on the accurate estimation of the additive noise spectrum of $v(n)$ which is a difficult task. The major drawback of this method is that it leaves residual noise with annoying noticeable tonal characteristics referred to as *musical noise* when the estimated noise spectrum is under-subtracted from the noisy spectrum. The enhanced speech also suffers from distortion if the estimated noise spectrum is over-subtracted from the noisy spectrum.

In order to address these issues, several modified spectral subtraction based algorithms have been proposed. In [29], an improved spectral subtraction for speech enhancement has been introduced that can reduce the *musical noise* effectively. However, this algorithm cannot resolve the speech distortion problem. In [30], spectral subtraction based speech enhancement using an adaptive spectral estimator has been introduced. In this algorithm, the authors try to reduce the *musical noise* and improve the quality of the enhanced speech by increasing the accuracy of the system spectral estimator. In addition, this algorithm is capable of reducing the stationary noises. In [31], spectral subtraction method for speech enhancement using an improved *a priori* MMSE has been proposed. In this paper, the authors have introduced an adaptive averaging factor to accurately estimate the *a priori* SNR for estimation of the additive noise spectrum. In [32], the authors introduced an improved spectral subtraction based speech enhancement algorithm that is capable of reducing the non-stationary noises. The authors in this paper used smooth spectrums to approximate the clean speech and noisy spectrums with auto-regressive (AR) model and constructed speech codebook and noise codebook. They employed the spectral subtraction using the speech and noise entry from codebooks, which obtained from the log-spectral minimization. However, the proposed algorithm can adapt to varying levels of noise only when speech is present, which is termed as the limitation of this algorithm. In [33], a multi-band spectral subtraction method based on auditory masking properties for speech enhancement has been developed. In this algorithm, a weighted recursive averaging method has been used to estimate the noise power spectrum. Finally, the spectrum of enhanced speech is obtained through a multi-band spectral subtraction and a gain function computed according to the subtraction factor.

The spectral subtraction based speech enhancement algorithms are popular for the simplicity of implementation. However, these algorithms have some major limitations. The performance of these algorithms fully depends on the estimation of the noise spectrum. In different noisy conditions, especially at low input SNRs, it is quite difficult to estimate the accurate noise spectrum from the degraded speech. Another weak point of these algorithms is that they require voiced activity detector in order to estimate the desired noise from the non-speech portion of the analysis speech. In addition, it is quite difficult for the spectral subtraction based algorithms to remove the *musical noise* completely. In order to address these issues, Weiner filter based speech enhancement techniques have been investigated over the past few decades. The next subsection briefly describes some existing Weiner filter based speech enhancement methods.

1.2.2.2 Speech Enhancement using Wiener Filtering

Wiener filter for speech enhancement was suggested as an improvement to the spectral subtraction by Lim and Oppenheim in [10]. In this method, a Wiener gain function $G(w)$ is calculated first, which is then multiplied with the noisy speech spectrum for attenuating the noise frequency components more precisely, namely,

$$S(w) = G(w)Y(w) \tag{1.3}$$

where *G(w)* is Wiener filter gain coefficient for a given frequency w which is defined as

$$G(w) = \frac{|Y(w)|^2 - |\hat{V}(w)|^2}{|Y(w)|^2}. \tag{1.4}$$

Here, $G(w)$ attenuates each frequency component by a certain amount depending on the power of the noise at that frequency w. If $|\hat{V}(w)|^2 = 0$, then $G(w) = 1$ and no attenuation takes place, i.e. there is no noise component at the frequency w, whereas if $|\hat{V}(w)|^2 = |Y(w)|^2$, then $G(w) = 0$ and the frequency component w is completely nulled. All other values of $G(w)$ between 0 and 1 scale the power of the signal by an appropriate amount.

In [34], an iterative Wiener filter (IWF) based speech enhancement algorithm has been proposed, where the complex LPC analysis has been used instead of the conventional LPC analysis. This method can estimate the desired speech spectrum more accurately, especially at low input SNRs. However, it introduces some background noise in the enhanced speech. In [35], perceptual Wiener filter based speech enhancement has been proposed, where Wiener filter with self adaptive averaging factor has been used to estimate *a priori* SNR for estimating the clean speech speech spectra, which may contain some *musical noise*. In order to remove the musical noise, a perceptual weighting filter based on simultaneous and temporal masking effects of the human auditory system is employed to the processed speech. In addition, an unvoiced speech enhancement algorithm is also integrated with the scheme to improve the intelligibility of the enhanced speech. Although this algorithm in general performs well, a little bit distortion was introduced in the enhanced speech. In [36], sub-band cross-correlation compensated Wiener filter combined with harmonic regeneration for speech enhancement has been introduced which is capable of reducing the color noises. In this algorithm, a nonlinear sub-band Bark scale frequency spacing approach has been used to reduce the additive color noise effectively. It can also restore the original harmonic features in the enhanced speech that are lost due to the additive noise effect. In addition, it can also reduce the distortion in the enhanced speech. However, this algorithm is not suitable for different adverse environmental noises. In [37], speech enhancement based on sub-band Wiener filter with pitch synchronous analysis has been introduced. This algorithm used the perceptual filter-bank to provide a good auditory representation as well as good perceptual quality in the enhanced speech. Sub-band Wiener filter based pitch synchronous analysis, on the other hand, reduces the drawback of the fixed window shifting problem as introduced in some existing Wiener filter based approaches. In order to increase the inter frame similarities, the analysis window shift is performed based on the pitch period, which is estimated by using the clipping level method. For further improvement, Wiener filter using *a priori* SNR with adaptive parameter is employed to each sub-band. The weak point of this method is that it requires accurate estimation of the pitch period, which is relatively difficult to realize in noisy conditions.

In general, the advantage of the Wiener filter based speech enhancement is that it is straightforward and relatively easier to implement. However, it has some limitations. One limitation is that it cannot remove the *musical noise* significantly in the enhanced speech. Also the performance of this algorithm is somewhat dependent on the accuracy of the *a prior* SNR estimation.

1.2.2.3 Speech Enhancement using Wavelet

The wavelet transform has been widely used in various signal processing fields nowadays. It is a powerful tool for non-stationary speech signal analysis, which can simultaneously represent both the time and frequency information of the analysis speech through the multiresolution analysis principle. Moreover, it can decompose an analysis speech into a set of sub-bands with different frequency resolutions. From the decomposed sub-bands, further details or other hidden information can be extracted that may not appear in the Fourier domain. Therefore, some researchers have exploited the wavelet filter-bank approach for implementing speech enhancement. In this section, some existing single channel speech enhancement algorithms based on the wavelet filter-bank are discussed briefly.

In [38], speech enhancement through reducing the noise components in the wavelet domain has been introduced. In this algorithm, a semisoft thresholding is employed to the decomposed wavelet coefficients of the degraded speech in order to reduce the additive noise components while keeping the important information of the speech. To do this, the unvoiced region of the noisy speech is classified first and then thresholding is applied in a different way which can prevent the quality degradation of the unvoiced sounds during the denoising process. However, it is quite difficult to estimate the desired threshold under different noisy conditions. In addition, in noisy conditions, the unvoiced part of the speech sample can be filled up with the additive noise, which makes the unvoiced classification difficult. In [39], speech enhancement based on wavelet using the Teager energy operator has been proposed. The authors in this paper used the time adoption of the wavelet thresholds where the time dependence is introduced by approximating the Teager energy of the wavelet coefficients. An advantage of this algorithm is that it does not require an explicit estimation of the noise level or the *a priori* knowledge of the SNR, which is usually needed in most of the spectral subtraction and Wiener filter based speech enhancement algorithms. However, it still needs to estimate the Teager energy from the decomposed subbands. In noisy conditions, it is sometimes difficult to estimate the Teager energy appropriately.

Speech enhancement based on efficient hard and soft thresholding using wavelet has been proposed in [40]. The noise as well as the analysis speech are estimated from the detailed coefficients of the first scale. Then, both the hard and soft thresholding are applied successively where the regions for hard thresholding are identified according to the estimated *a prior* SNR in the wavelet domain. Soft thresholding is applied to the rest of the regions. Therefore, this algorithm fully depends on an accurate estimation of the *a prior* SNR in noisy condition for applying the soft thresholding or hard thresholding. In [41], speech enhancement based on masking thresholding in wavelet domain has been proposed where the auditory system characteristics are used to generate the masking threshold. Moreover, the *a priori* SNR is estimated from the wavelet domain instead of Fourier domain depending on the masking threshold used for a particular frequency bin. However, this algorithm depends on the accuracy of the *a prior* SNR as well as masking threshold estimation. In [42], speech enhancement using a bivariate shrinkage based on redundant wavelet filter-bank has been introduced. In this paper, the authors found appropriate wavelet structures which are more suitable for speech enhancement based on bivariate shrinkage method. This method was originally proposed for image enhancement. However, the authors in this paper adapt this method for single channel speech enhancement.

1.3 Motivation

From the aforementioned literature review, the spectral subtraction method suffers from the *musical noise* that is introduced in the enhanced speech. Although, Wiener filter is an improved version of the spectral subtraction, it also has the same issue. In addition, in these two algorithms, the speech samples are assumed to be stationary in an analysis speech frame. However, in a real scenario, speech is non-stationary in nature. That means, both of these algorithms fail to maintain the non-stationary nature of the analysis speech samples.

Wavelet transform based speech enhancement algorithms, on the other hand, overcome the non-stationary signal analysis problems by maintaining the non-stationary nature of the analysis speech samples during sub-band decomposition. Using the benefits of the sub-band speech, several speech enhancement algorithms have been introduced in the literature. Among them, the hard and soft thresholding based methods are popular. However, it is quite difficult to decide when hard/soft thresholding is suitable to apply. In addition, hard thresholding sometime fails to reduce the additive noise components in critical sub-bands where both the speech and additive noise components remain balanced. Although, the soft thresholding can remove some of these noise components in such situation, it takes the risk of degrading the quality of the enhanced speech. In order to address these issues, speech enhancement algorithms based on the masking properties of the human auditory system have been proposed. However, human auditory masking is a complicated process which is only partially understood as the threshold of hearing (audibility) is unique from person to person and even changes with persons age, which makes it more complicated. Moreover, in noisy condition, it is quite difficult to generate the appropriate masking threshold.

The Kalman filter has been recently used as a powerful tool for single channel speech enhancement. However, it is known that the performance of the Kalman filter based speech enhancement depends on the accuracy of the LPC and noise variance estimation in noisy conditions. Some of the existing Kalman filter based speech enhancement algorithms reported in the literature assume that the clean speech and additive noise information are available for the LPC and noise variance estimation. This assumption makes these algorithms impractical, since in a practical scenario, we can access only the noisy speech. Moreover, it is quite challenging to estimate these model parameters in noisy conditions. Therefore, Kalman filter based speech enhancement algorithm, including optimal parameter estimation in noisy conditions has been an active research area in the recent years.

1.4 Objective of the Thesis

The main objective of this thesis is to develop Kalman filter based single channel speech enhancement algorithms capable of reducing adverse environment noises. As the LPCs and noise variance are the two important state-space model parameters for Kalman filter implementation, in this thesis, depending on these parameter estimation techniques, three SE approaches are proposed.

In the first approach, a non-iterative Kalman filter based speech enhancement algorithm is proposed, which operates on a frame-by-frame basis. In this proposed method, the state-space model parameters, namely, LPCs and noise variance are estimated first in noisy conditions. For LPCs estimation, speech smoothing and autocorrelation based combined method is proposed. A new method based on a lower-order truncated Taylor series approximation of the noisy speech along with a difference operation serving as high-pass filtering is introduced for the noise variance estimation. The proposed non-iterative Kalman filter is then implemented with these estimated parameters effectively.

In order to enhance the speech enhancement performance as well as parameter estimation accuracy in noisy conditions, an iterative Kalman filter based speech enhancement method is presented as the second approach, which also operates on a frame-by-frame basis. For each frame, the state-space model parameters of the KF are estimated through an iterative procedure. The Kalman filtering iteration is first applied to each noisy speech frame, reducing the noise component to a certain degree. At the end of this first iteration, the LPCs and other state-space model parameters are re-estimated using the processed speech frame and the Kalman filtering is repeated for the same processed frame. This iteration continues till the KF converges or a maximum number of iterations is reached, giving further enhanced speech frame. The same procedure will repeat for the following frames until the last analysis speech frame being processed.

For further improving the speech enhancement result, a sub-band iterative Kalman filter is proposed as the third approach. A wavelet filter-bank is first used to decompose the noisy speech into a number of sub-bands. To achieve the best trade-off among the noise reduction, speech intelligibility and computational complexity, a partial reconstruction scheme based on the proposed consecutive mean squared error (CMSE) is used to synthesize the HF and LF sub-bands such that the iterative Kalman filter is employed only to the partially reconstructed HF sub-band speech. Finally, the enhanced HF sub-band speech is combined with the partially reconstructed LF sub-band speech to reconstruct the full-band enhanced speech.

1.5 Organization of the Thesis

The rest of this thesis is organized as follows:

Chapter 2: This chapter first describes the human speech modeling system with the LPC analysis, the conventional LPC estimation process, and the mathematical details of the conventional Kalman filter. It then introduces the proposed non-iterative and iterative Kalman filter based speech enhancement algorithms, the proposed LPC estimation algorithm in noisy condition, and a novel algorithm for the excitation noise variance estimation. Comparative study of the proposed Kalman filter based approaches with other existing competitive methods is also presented.

Chapter 3: This chapter gives detailed description of the wavelet and filter-bank material followed by the proposed sub-band iterative Kalman filter based speech enhancement algorithm. It focuses on partial reconstructions of the high-frequency and low-frequency sub-bands using the proposed CMSE based synthesis approach, and a comparative study of the proposed method with other existing competitive methods.

Chapter 4: This chapter provides detailed of simulation results and discussions of the proposed methods for various noisy conditions, including the simulation setup, test database description for clean speech and noise, and performance evaluation methods. Some existing state-of-the art speech enhancement algorithms are also simulated for comparison in this chapter in order to justify the merit of the proposed methods.

Chapter 5: This chapter gives some concluding remarks and directions for future research.

Chapter 2

Speech Enhancement using Kalman Filter

2.1 Introduction

This chapter is concerned with Kalman filter based speech enhancement techniques. It is known to be an adaptive minimum mean square error (MMSE) filter that provides a computationally efficient and recursive solution for estimating a signal from noisy observations. The main theory of the KF is based on state-space model, where LPC and additive noise variance are two important parameters of this model. In addition, the performance of the KF based speech enhancement depends on the estimation accuracy of these parameters in noisy conditions. Therefore, this chapter first introduces the human speech modeling technique using the LPC analysis, the LPC estimation techniques in noise-free case, the existing LPC estimation methods in noisy conditions, and the mathematical details of the conventional Kalman filter based speech enhancement. It then introduces the proposed non-iterative KF based speech enhancement, including the proposed estimation techniques for state-space model parameters, namely LPC and noise variance, in noisy conditions. It also gives the details of the proposed speech enhancement using iterative KF, including some simulation results.

2.2 Human Speech Modeling using LPC Analysis

Linear prediction (LP) is often used as a fundamental tool for modeling the human speech. Generally speaking, human speech is random in nature, but the correlation between speech samples could be exploited for the purpose of predicting future speech samples in a linear manner. This idea called linear prediction, has been used to generate correlated speech samples. The speech generation model associated with the vocal tract is thus closely related to the phonemic representation of the speech that can be compactly represented by the linear prediction coefficient (LPC) [43, 44].

The anatomy human speech production is shown in Figure 2.1 [43]. In general, human speech is produced by a source of sound energy (e.g. the larynx) modulated by a transfer function (filter) that matches the shape of the supralaryngeal vocal tract, as shown in Figure 2.1. When a person speaks, the lungs work like a power supply of the speech production system. Speech is produced by an excitation signal generated in the throat, which is modified by resonances due to the shape of the vocal, nasal and pharyngeal tracts. The excitation produces two types of signal, voiced and unvoiced. Voiced speech is produced when the glottal pulses created by periodic opening and closing of the vocal folds. These periodic components are characterized by their fundamental frequency f_0. On the other hand, the unvoiced speech is produced through the continuous air flow pushed by the lungs [43]. This

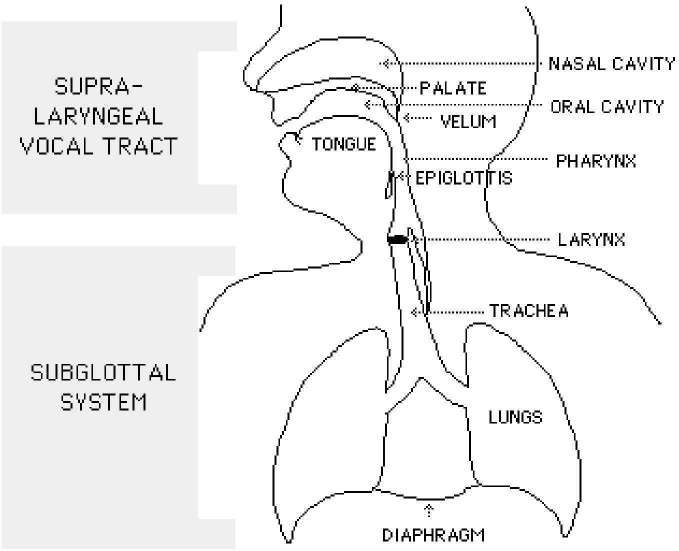


Figure 2.1: The anatomy of human speech production system.

system is referred to as the source filter model of speech production. A block diagram of the source filter model is shown in Figure 2.2.

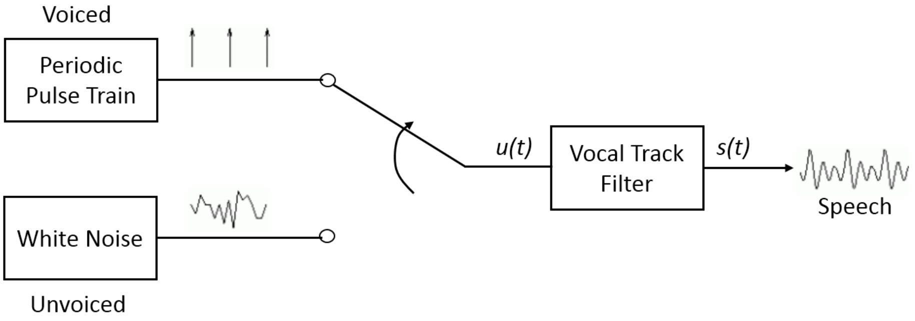


Figure 2.2: Source filter model of human speech production system.

In the linear prediction analysis, the human vocal tract can be modeled as an infinite impulse response system for producing the speech. Originally in 1960, Gunnar Fant proposed a linear model of speech production in which glottis and vocal tract are fully uncoupled. In this model, an *all-pole* filtering system is used to model the vocal tract as shown in Figure 2.3.

The key to linear prediction analysis is the linear predictive filter which allows the value of the next sample to be determined by a linear combination of the previous samples [45]. For example, at a particular sample point n, the speech sample $s[n]$ as shown in Figure 2.2 (the sampled version of $s(t)$) can be represented as a linear sum of the P previous samples, i.e,

$$\hat{s}[n] = a_1 s[n-1] + a_2 s[n-2] + ... + a_P s[n-P] = \sum_{i=1}^{P} a_i s[n-i] \tag{2.1}$$

where $\hat{s}[n]$ is the prediction of $s[n]$, $s[n-i]$ is the i^{th} previous sample of $s[n]$, P is the linear prediction order, and a_i's are called the linear prediction coefficients. Using the

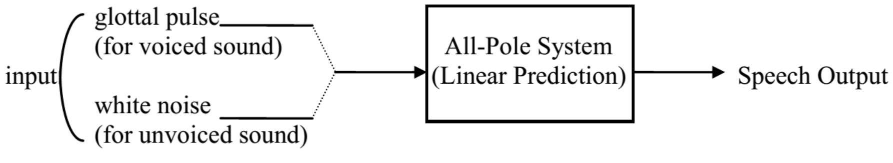


Figure 2.3: Linear prediction model for human speech production.

all-pole filtering system, the linear model of speech production is represented as

$$S(z) = GU(z)\frac{1}{1-\sum_{i=1}^{P} a_i z^{-i}} = \frac{GU(z)}{A_P(z)} \tag{2.2}$$

where $S(z)$ and $U(z)$ are the z-transforms of the speech and the excitation signals, i.e., $s[n]$ and $u[n]$, respectively, G is the input gain factor, P is the linear prediction order, $H(z) = \frac{G}{A_P(z)}$ is the all-pole synthesis filter, and $A_P(z)$ is an FIR (finite duration impulse response) system whose transfer is given by

$$A_P(z) = 1 - \sum_{i=1}^{P} a_i z^{-i} \tag{2.3}$$

By taking the inverse z-transformation and rearranging to equation (2.2), the speech $s[n]$ can be expressed as

$$s[n] = \sum_{i=1}^{P} a_i s[n-i] + Gu[n] \tag{2.4}$$

which states that the speech samples can be modeled as a weighted sum of the P previous samples plus the excitation signal.

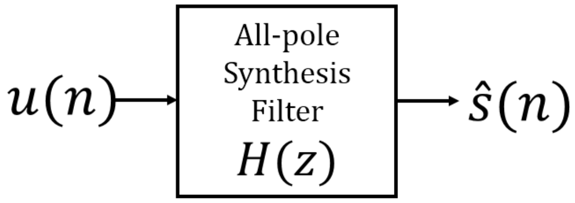


Figure 2.4: All-pole filtering system for speech production .

The excitation signal $u[n]$ is the input of the all-pole filtering system as shown in Figure 2.4, which is either a sequence of regularly spaced pulses called voiced speech or unvoiced speech. It is mainly assumed as white noise in the all-pole system, with zero mean and unit variance. In LP theory, $u[n]$ is usually called the residual error or simply error, which is represented as $\epsilon[n] = Gu(n)$ [46]. For a given speech signal $s[n]$ with LP parameters $a_i, i = 1, 2, 3, ..., P$, the residual error $\epsilon[n]$ can be estimated as

$$\epsilon[n] = s[n] - \hat{s}[n] = s[n] - \sum_{i=1}^{P} a_i s[n-i] \tag{2.5}$$

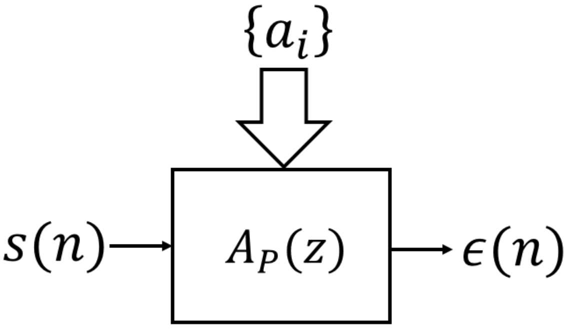


Figure 2.5: Estimation of residual error $\epsilon[n]$ using the prediction filter.

which is simply the output of the prediction filter excited by the speech samples $s[n]$ as shown in Figure 2.5.

The crucial task of LP modelling of speech is to accurately estimate the linear prediction coefficients (LPCs). The next section describes the conventional LPC estimation process in details.

2.2.1 Conventional LPC Estimation in Noise-free Case

In the conventional LPC estimation method, the analysis speech samples are considered as noise-free, that means it assumes the availability of the clean speech. There are two methods for LPC estimation, i.e., autocorrelation and covariance based methods. In this thesis, only the autocorrelation based technique is used in LPC estimation.

In general, the linear prediction coefficients a_i's are estimated by minimizing the expectation of the residual energy $\epsilon^2[n]$ or $E[\epsilon^2[n]]$ as [46]

$$\begin{aligned} E[\epsilon^2[n]] &= E[(s[n] - \sum_{i=1}^{P} a_i s[n-i])^2] \\ &= E[s^2[n]] - 2\sum_{i=1}^{P} a_i E[s[n]s[n-i]] + \sum_{i=1}^{P} a_i \sum_{j=1}^{P} a_j E[s[n-i]s[n-j]] \\ &= r_{ss}(0) - 2\boldsymbol{r}_{\boldsymbol{ss}}^T \boldsymbol{A} + \boldsymbol{A}^T \boldsymbol{R}_{\boldsymbol{ss}} \boldsymbol{A} \end{aligned} \tag{2.6}$$

where $\boldsymbol{R}_{\boldsymbol{ss}} = E[\boldsymbol{s}\boldsymbol{s}^T]$ is the autocorrelation matrix of the input vector $\boldsymbol{s}^T = [s[n-1], s[n-2], \ldots, s[n-P]]$, $\boldsymbol{r}_{\boldsymbol{ss}} = E[s[n]\boldsymbol{s}]$ is the autocorrelation vector and $\boldsymbol{A}^T = [a_1, a_2, \ldots, a_P]$ is the LPC vector.

From equation (2.6), the gradient of the mean square prediction error with respect to the LPC vector $\boldsymbol{A}$ is given by

$$\frac{\partial}{\partial \boldsymbol{A}} E[\epsilon^2[n]] = -2\boldsymbol{r}_{\boldsymbol{ss}}^T + 2\boldsymbol{A}^T\boldsymbol{R}_{\boldsymbol{ss}} \tag{2.7}$$

where the gradient vector is defined as

$$\frac{\partial}{\partial \boldsymbol{A}} = (\frac{\partial}{\partial a_1}, \frac{\partial}{\partial a_2}, \ldots, \frac{\partial}{\partial a_P})^T \tag{2.8}$$

The least mean square error solution is obtained by setting equation (2.7) to zero and rearranging the terms, i.e.,

$$\boldsymbol{A}^T\boldsymbol{R}_{\boldsymbol{ss}} = \boldsymbol{r}_{\boldsymbol{ss}}^T \tag{2.9}$$

Taking the transpose on both sides of equation (2.9), we get

$$(\boldsymbol{A}^T)^T\boldsymbol{R}_{\boldsymbol{ss}}^T = (\boldsymbol{r}^T)_{\boldsymbol{ss}}^T \tag{2.10}$$

We know that the transpose of a transpose matrix is the original matrix. Thus, $(\boldsymbol{A}^T)^T = \boldsymbol{A}$ and $(\boldsymbol{r}^T)_{\boldsymbol{ss}}^T = \boldsymbol{r}_{\boldsymbol{ss}}$. Here, $\boldsymbol{R}_{\boldsymbol{ss}}$ is a symmetric metrix, and we know that the transpose of a symmetric metrix is the matrix itself, i.e., $\boldsymbol{R}_{\boldsymbol{ss}}^T = \boldsymbol{R}_{\boldsymbol{ss}}$. Therefore, rearranging equation (2.10), we get

$$\boldsymbol{A}\boldsymbol{R}_{\boldsymbol{ss}} = \boldsymbol{r}_{\boldsymbol{ss}} \tag{2.11}$$

from which the linear prediction coefficient vector is solved as

$$\boldsymbol{A} = \boldsymbol{R}_{\boldsymbol{ss}}^{-\boldsymbol{1}}\boldsymbol{r}_{\boldsymbol{ss}} \tag{2.12}$$

or equivalently,

$$\begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ \vdots \\ a_P \end{bmatrix} = \begin{bmatrix} r_{ss}(0) & r_{ss}(1) & r_{ss}(2) & \ldots & r_{ss}(P-1) \\ r_{ss}(1) & r_{ss}(0) & r_{ss}(1) & \ldots & r_{ss}(P-2) \\ r_{ss}(2) & r_{ss}(1) & r_{ss}(0) & \ldots & r_{ss}(P-3) \\ \vdots & \vdots & \ddots & \vdots & \\ r_{ss}(P-1) & r_{ss}(P-2) & r_{ss}(P-3) & \ldots & r_{ss}(0) \end{bmatrix}^{-1} \times \begin{bmatrix} r_{ss}(1) \\ r_{ss}(2) \\ r_{ss}(3) \\ \vdots \\ r_{ss}(P) \end{bmatrix} \tag{2.13}$$

The matrix $\boldsymbol{R}_{\boldsymbol{ss}}$ is called Toepiltz matrix which is symmetric with only P elements provided that each diagonal element being identical. The Levinson-Durbin recursion can be used to solve the matrix in order to get the linear prediction coefficients a_i's

[46]. In noise-free case, the LPC synthesis filter is stable, that means all the roots of the denominator are inside the unit circle. Therefore, the estimated LPC coefficients are accurate. However, in practice, we can access only the noisy speech. Therefore, the next section describes the proposed LPC estimation method in noisy condition.

2.2.2 Existing LPC Estimation Methods in Noisy Conditions

The conventional LPC estimation technique requires that the spectral parameters be estimated from the clean speech. This is because the LPCs are directly related to the pole locations of the *all-pole* synthesis filter, which in principle are functions of formant frequencies. When noise is introduced, however, the pole locations are changed and the *all-pole* synthesis filter may no longer be stable, which leads to wrong estimation of the LPCs. Moreover, the estimated LPCs contain severe temporal variations as compared to those obtained from the clean speech. Therefore, these coefficients may no longer represent the proper configurations and shapes of the glottal source and the vocal tract system. On the other hand, the spectrum of the LPC synthesis filter exhibits formant shifting and the bandwidth becomes wider, leading to an overall degradation in the quality of the reconstructed speech. Therefore, it is a very challenging task to estimate the LPC coefficients from the noisy speech.

To overcome this problem, numerous methods have been proposed in the last few decades. However, obtaining a satisfactory solution preserving the stability of the *all-pole* LPC synthesis filter, and providing an accurate estimation of the linear prediction coefficients is still a challenging task. It is important to note that the additive noise $v(n)$ changes the speech generation process from AR model to an auto regressive moving average (ARMA) process. Therefore, the LPC parameters estimated from a noise corrupted speech using an *all-pole* synthesis filter become biased, which is proportional to the inverse of the signal-to-noise ratio [47]. For noisy speech $y(n) = s(n) + v(n)$, where $s(n)$ is the clean speech and $v(n)$ is the zero mean white noise, the biased autocorrelation function (ACF) is written as

$$\begin{aligned} \hat{R}_{yy}(n) &= \hat{R}_{ss}(n) + \hat{R}_{vv}(n) \\ &= \hat{R}_{ss}(n) + \sigma_v^2\delta(n) \end{aligned} \tag{2.14}$$

where σ_v^2 is the additive noise variance, $\hat{R}_{vv}(n)$ is the biased ACF of the additive noise $v(n)$, $\hat{R}_{yy}(n)$ and $\hat{R}_{ss}(n)$ are the ACF of the noisy speech $y(n)$ and that of the clean speech $s(n)$, respectively.

The main idea here is to subtract the noise power from the ACF of the noisy speech $\hat{R}_{yy}(n)$ at zero lag, $n = 0$. To do this, an iterative noise subtraction based method for the LPC estimation has been introduced in [48], where noise compensation is achieved by gradually subtracting a noise power estimated from the ACF of the noisy speech. The main drawback of this method is that it assumes the noise variance to be known. Instead of deriving the exact noise variance, the adaptive method proposed in [49] determines a suitable bias that should be subtracted from the zero-lag of the ACF of the noisy speech. In this method, the stability of the *all-pole* LPC synthesis filter is ensured when the noise variance is less than the minimum eigenvalue of the autocorrelation matrix. In [47], the noise periodogram is obtained first by applying a simplified noise PSD estimator on the calculated noisy periodogram. Then, the effect of noise on the spectral parameters is decreased by gradually subtracting values of the resulting noise autocorrelation coefficients from the coefficients derived from the noisy speech. The LPCs are estimated from the absolute value of the estimated coefficients. This method ensures a significant decrease in the degrading effect of noise while the estimated LPCs are more accurate. Higher order Yule-Walker equation has been used in [50], where $\hat{R}_{ss}(0)$ is not involved in the evaluation of $\hat{R}_{ss}(n)$ from the noisy speech $y(n)$ for all lags other than zero. This method was developed only for estimating the LPCs from the white noise corrupted speech and under the assumption that the noise variance is known. Another shortcoming of this method is that the energy of the additive noise spreads all over the autocorrelation lags of the analysis speech, which may lead to a substantial increase in the variance of the estimated spectral parameters.

2.3 Conventional Kalman Filter for Speech Enhancement

The theory of Kalman filter is established on state-space model where a state equation models the dynamics of a signal generation process, an observation equation, on the other hand, models the noisy and distorted nature of the signal. The linear prediction coefficients and additive noise variance are two important state-space model parameters for KF implementation. The operation principle of the KF includes a prediction step and a correction step. In the prediction step, it estimates the *a posteriori* error covariance by using the previous samples of the state-space model. The KF basically reduces the additive noise effect by minimizing the *a posteriori* error covariance achieved at each step through recursive procedures. To do this, in the correction step, the *a posteriori* error covariance is processed recursively until its minimization. The overall operation is performed on a frame-by-frame basis. In this way, at the end of the recursive procedure, the additive noise is statistically minimized [51].

The clean speech $s(n)$ is modeled as a P^{th} order auto-regressive (AR) process as given by

$$s(n) = \sum_{i=1}^{p} a_i s(n-i) + u(n) \tag{2.15}$$

and the noisy speech is defined as

$$y(n) = s(n) + v(n) \tag{2.16}$$

where $s(n)$ is the n^{th} sample of the clean speech, $y(n)$ is the n^{th} sample of the noisy observation, a_i is the i^{th} LPC coefficient, $u(n)$ and $v(n)$ are uncorrelated Gaussian white noise sequences with zero mean and the variances σ_u^2 and σ_v^2, respectively.

This system can be represented by the following state-space model (SSM), where the bold faced letters represent vectors or matrices
State Equation:

$$\boldsymbol{x}(n) = \boldsymbol{\Phi}\boldsymbol{x}(n-1) + \boldsymbol{G}u(n) \tag{2.17}$$

Observation Equation:

$$y(n) = \boldsymbol{H}\boldsymbol{x}(n) + v(n) \tag{2.18}$$

In the above SSM,

1. $\boldsymbol{x}(n)$ is a P-dimensional signal vector, or the state parameter vector at time n which can be expressed as

$$\boldsymbol{x}(n) = [s(n-p+1) \quad s(n-p+2) \quad \ldots \quad s(n)]^T \tag{2.19}$$

2. $\boldsymbol{\Phi}$ is a $P \times P$-dimensional state transition matrix that relates the states of the

process at times $n-1$ and n which can be written as

$$\boldsymbol{\Phi} = \begin{bmatrix} 0 & 1 & 0 & \dots & 0 \\ 0 & 0 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & 1 \\ a_p & a_{p-1} & a_{p-2} & \dots & a_1 \end{bmatrix},$$

3. $\boldsymbol{G}$ and $\boldsymbol{H}$ are the $P \times 1$ input vector and the $1 \times P$ observation row vector, respectively, which can be represented as

$$\boldsymbol{H} = \boldsymbol{G^T} = \begin{bmatrix} 0 & 0 & 0 & \dots & 1 \end{bmatrix},$$

4. $y(n)$ is the observation measurement of the SSM at time n.

If $\boldsymbol{x}(n)$ and $y(n)$ are assumed to be jointly Gaussian, the Kalman filter gives an optimal estimate of the $\boldsymbol{x}(n)$ given the noisy data $y(n), y(n-1), ..., y(1)$. For such a Gaussian distribution, the optimal estimate is called the minimum mean squared error (MMSE) estimate as given by

$$\hat{\boldsymbol{x}}(n|n) = E[\boldsymbol{x}(n)|y(n), y(n-1), ..., y(1)] \tag{2.20}$$

The corresponding *a posteriori* estimation error covariance $\boldsymbol{\Sigma_x}(n|n)$ is then defined as

$$\boldsymbol{\Sigma_x}(n|n) = E[\boldsymbol{\epsilon}(n|n)\boldsymbol{\epsilon}^T(n|n)] \tag{2.21}$$

where $\boldsymbol{\epsilon}(n|n)$ is the *a posteriori* estimation error which is defined as

$$\boldsymbol{\epsilon}(n|n) = \boldsymbol{x}(n|n) - \hat{\boldsymbol{x}}(n|n) \tag{2.22}$$

Similarly, the one step prediction error also called the *a priori* estimation error $\boldsymbol{\epsilon}(n|n-1)$ of $\boldsymbol{x}(n|n)$ and the associated *a priori* error covariance matrix $\boldsymbol{\Sigma_x}(n|n-1)$ are defined as

$$\boldsymbol{\epsilon}(n|n-1) = \boldsymbol{x}(n|n) - \hat{\boldsymbol{x}}(n|n-1) \tag{2.23}$$

$$\boldsymbol{\Sigma_x}(n|n-1) = E[\boldsymbol{\epsilon}(n|n-1)\boldsymbol{\epsilon}^T(n|n-1)] \tag{2.24}$$

The goal here is to find an equation that computes an *a posteriori* state estimate as a linear combination of an *a priori* estimate (also called prediction) and a weighted difference between the actual measurement and the one-step measurement prediction [51]. More specifically, it is possible to write an update equation for the new estimate $\hat{\boldsymbol{x}}(n|n)$ by combing the old estimate $\hat{\boldsymbol{x}}(n|n-1)$ with the measurement prediction as

$$\hat{\boldsymbol{x}}(n|n) = \hat{\boldsymbol{x}}(n|n-1) + \boldsymbol{K}(n)[y(n) - \boldsymbol{H}\hat{\boldsymbol{x}}(n|n-1)] \tag{2.25}$$

where $y(n) - \boldsymbol{H}\hat{\boldsymbol{x}}(n|n-1)$ is called the measurement innovation, which is defined as

$$e(n) = y(n) - \boldsymbol{H}\hat{\boldsymbol{x}}(n|n-1) \tag{2.26}$$

The measurement innovation reflects the discrepancy between the predicted measurement $\boldsymbol{H}\hat{\boldsymbol{x}}(n|n-1)$ and the actual measurement $y(n)$. The innovation $e(n)$ is a special stochastic process that plays a central role in the development of the Kalman filter theory [51, 52]. The $P \times P$ matrix, $\boldsymbol{K}(n)$ in equation (2.25) is called Kalman gain which also plays a very important role. The Kalman gain vector $\boldsymbol{K}(n)$ should be determined such that the *a posteriori* error covariance is minimized. Substitution of equation (2.18) into (2.25) gives

$$\hat{\boldsymbol{x}}(n|n) = \hat{\boldsymbol{x}}(n|n-1) + \boldsymbol{K}(n)[\boldsymbol{H}\boldsymbol{x}(n) + v(n) - \boldsymbol{H}\hat{\boldsymbol{x}}(n|n-1)] \tag{2.27}$$

By substituting equation (2.27) into (2.21) and rearranging the terms, we get

$$\boldsymbol{\Sigma}_{\boldsymbol{x}}(n|n) = E[[(\boldsymbol{I}-\boldsymbol{K}(n)\boldsymbol{H})\epsilon(n|n-1)-\boldsymbol{K}(n)v(n)][(\boldsymbol{I}-\boldsymbol{K}(n)\boldsymbol{H})\epsilon(n|n-1)-\boldsymbol{K}(n)v(n)]^T] \tag{2.28}$$

where $\boldsymbol{\epsilon}(n|n-1)$ is the error of the *a prior* estimate, which is uncorrelated with the measurement noise $v(n)$. Therefore, equation (2.28) is re-written as

$$\boldsymbol{\Sigma}_{\boldsymbol{x}}(n|n) = [\boldsymbol{I}-\boldsymbol{K}(n)\boldsymbol{H}]E[\epsilon(n|n-1)\epsilon^T(n|n-1)][\boldsymbol{I}-\boldsymbol{K}(n)\boldsymbol{H}]^T+\boldsymbol{K}(n)E[v(n)v^T(n)]\boldsymbol{K}^T(n) \tag{2.29}$$

Considering $\sigma_v^2 = E[v(n)v^T(n)]$ and using equation (2.24) into (2.29) gives

$$\boldsymbol{\Sigma}_{\boldsymbol{x}}(n|n) = [\boldsymbol{I} - \boldsymbol{K}(n)\boldsymbol{H}]\boldsymbol{\Sigma}_{\boldsymbol{x}}(n|n-1)[\boldsymbol{I} - \boldsymbol{K}(n)\boldsymbol{H}]^T + \boldsymbol{K}(n)\sigma_v^2\boldsymbol{K}^T(n) \tag{2.30}$$

Equation (2.30) is the error covariance update equation where $\boldsymbol{\Sigma}_{\boldsymbol{x}}(n|n-1)$ is the prior estimate of $\boldsymbol{\Sigma}_{\boldsymbol{x}}(n|n)$.

The diagonal elements of the covariance matrix $\boldsymbol{\Sigma}_{\boldsymbol{x}}(n|n)$ contain the mean squared error (MSE). We know that the sum of the diagonal elements of a matrix is the *trace* of that matrix. Therefore, the MSE may be minimized by minimizing the *trace* of $\mathbf{\Sigma}_{\boldsymbol{x}}(n|n)$. Rewriting equation (2.30) as

$$\begin{aligned}\mathbf{\Sigma}_{\boldsymbol{x}}(n|n) = \mathbf{\Sigma}_{\boldsymbol{x}}(n|n-1) - \boldsymbol{K}(n)\boldsymbol{H}\mathbf{\Sigma}_{\boldsymbol{x}}(n|n-1) - \mathbf{\Sigma}_{\boldsymbol{x}}(n|n-1)\boldsymbol{H}^T\boldsymbol{K}^T(n) \\ + \boldsymbol{K}(n)[\boldsymbol{H}\mathbf{\Sigma}_{\boldsymbol{x}}(n|n-1)\boldsymbol{H}^T + \sigma_v^2]\boldsymbol{K}^T(n) \quad (2.31)\end{aligned}$$

and taking the trace on both sides of (2.31) rearranging the terms, we get

$$\begin{aligned}T_r[\mathbf{\Sigma}_{\boldsymbol{x}}(n|n)] = T_r[\mathbf{\Sigma}_{\boldsymbol{x}}(n|n-1)] - 2T_r[\boldsymbol{K}(n)\boldsymbol{H}\mathbf{\Sigma}_{\boldsymbol{x}}(n|n-1)] \\ + T_r[\boldsymbol{K}(n)(\boldsymbol{H}\mathbf{\Sigma}_{\boldsymbol{x}}(n|n-1)\boldsymbol{H}^T + \sigma_v^2)\boldsymbol{K}^T(n)] \quad (2.32)\end{aligned}$$

Taking the partial derivative on both sides of the equation (2.32) with respect to $\boldsymbol{K}(n)$ gives

$$\frac{dT_r[\mathbf{\Sigma}_{\boldsymbol{x}}(n|n)]}{d\boldsymbol{K}(n)} = -2[\boldsymbol{H}\mathbf{\Sigma}_{\boldsymbol{x}}(n|n-1)]^T + 2\boldsymbol{K}(n)[\boldsymbol{H}\mathbf{\Sigma}_{\boldsymbol{x}}(n|n-1)\boldsymbol{H}^T + \sigma_v^2] \quad (2.33)$$

from which $\boldsymbol{K}(n)$ can be computed by setting the left side of (2.33) to zero as

$$\boldsymbol{K}(n) = \mathbf{\Sigma}_{\boldsymbol{x}}(n|n-1)\boldsymbol{H}^T[\boldsymbol{H}\mathbf{\Sigma}_{\boldsymbol{x}}(n|n-1)\boldsymbol{H}^T + \sigma_v^2]^{-1} \quad (2.34)$$

Using the equations (2.34), (2.25), and (2.26), the update equation of the current state $\hat{\boldsymbol{x}}(n|n)$ is given by

$$\hat{\boldsymbol{x}}(n|n) = \hat{\boldsymbol{x}}(n|n-1) + \boldsymbol{K}(n)e(n) \quad (2.35)$$

The update equation for the error covariance matrix with optimal gain is obtained through the substitution of equation (2.34) into (2.31), namely,

$$\begin{aligned}\mathbf{\Sigma}_{\boldsymbol{x}}(n|n) &= \mathbf{\Sigma}_{\boldsymbol{x}}(n|n-1) - \boldsymbol{K}(n)\boldsymbol{H}\mathbf{\Sigma}_{\boldsymbol{x}}(n|n-1) \\ &= (\boldsymbol{I} - \boldsymbol{K}(n)\boldsymbol{H})\mathbf{\Sigma}_{\boldsymbol{x}}(n|n-1) \quad (2.36)\end{aligned}$$

Finally, the enhanced speech sample $\hat{s}(n)$ at time n is given by

$$\hat{s}(n) = \boldsymbol{H}\hat{\boldsymbol{x}}(n|n) \quad (2.37)$$

The above KF based speech enhancement algorithm is summarized below

Initialization:

$$\hat{\boldsymbol{x}}(0|0) = 0 \tag{2.38}$$

$$\boldsymbol{\Sigma}_{\boldsymbol{x}}(0|0) = [0]_{p\times p} \tag{2.39}$$

Time update (predictor):

$$\hat{\boldsymbol{x}}(n|n-1) = \boldsymbol{\Phi}\hat{\boldsymbol{x}}(n-1|n-1) \tag{2.40}$$

$$\boldsymbol{\Sigma}_{\boldsymbol{x}}(n|n-1) = \boldsymbol{\Phi}\boldsymbol{\Sigma}_{\boldsymbol{x}}(n-1|n-1)\boldsymbol{\Phi}^T + \boldsymbol{G}\sigma_u^2\boldsymbol{G}^T \tag{2.41}$$

Measurement update (corrector):

$$e(n) = y(n) - \boldsymbol{H}\hat{\boldsymbol{x}}(n|n-1) \tag{2.42}$$

$$\boldsymbol{K}(n) = \boldsymbol{\Sigma}_{\boldsymbol{x}}(n|n-1)\boldsymbol{H}^T(\boldsymbol{H}\boldsymbol{\Sigma}_{\boldsymbol{x}}(n|n-1)\boldsymbol{H}^T + \sigma_v^2)^{-1} \tag{2.43}$$

$$\hat{\boldsymbol{x}}(n|n) = \hat{\boldsymbol{x}}(n|n-1) + \boldsymbol{K}(n)e(n) \tag{2.44}$$

$$\boldsymbol{\Sigma}_{\boldsymbol{x}}(n|n) = (\boldsymbol{I} - \boldsymbol{K}(n)\boldsymbol{H})\boldsymbol{\Sigma}_{\boldsymbol{x}}(n|n-1) \tag{2.45}$$

Estimated speech (at time n):

$$\hat{s}(n) = \boldsymbol{H}\hat{\boldsymbol{x}}(n|n) \tag{2.46}$$

The above procedures are repeated for the following speech frames and continued until the end of all frames to be processed. At the end of processing all noisy speech frames, the ultimate enhanced speech $\hat{s}(n)$ is obtained. The next section gives the proposed speech enhancement based on non-iterative Kalman filter.

2.4 Proposed Non-Iterative Kalman Filter based Speech Enhancement

In this section, we propose a non-iterative Kalman filter for speech enhancement, in which the state-space model parameters, namely, LPC and noise variance, are estimated from the noisy speech. The new method is not limited to reduce only the white Gaussian noise, rather it is expected to reduce the different environmental noises. For LPC estimation, a combined speech smoothing and autocorrelation method is proposed. A new method based on a lower-order truncated Taylor series approximation of the noisy speech along with a difference operation serving as high-pass filtering is also introduced for the noise variance estimation. The Kalman filter is then developed with these estimated parameters.

It is noted that the $P \times P$ dimensional Kalman gain function $\boldsymbol{K}(n)$ (2.34) has been used in the conventional Kalman filter. The update equation (2.35) indicates that the *a priori* estimate $\hat{\boldsymbol{x}}(n|n-1)$ is a $P \times 1$ dimensional matrix which is added with $\boldsymbol{K}(n)e(n)$ that should also be $P \times 1$ dimensional according to the linear algebra operation. Therefore, in the proposed non-iterative Kalman filter, the modified $P \times 1$ dimensional $\boldsymbol{K}(n)$ is obtained as

$$\boldsymbol{K}(n) = [\boldsymbol{\Sigma_x}(n|n-1)\boldsymbol{H}^T(\boldsymbol{H}\boldsymbol{\Sigma_x}(n|n-1)\boldsymbol{H}^T + \sigma_v^2)^{-1}]\boldsymbol{H}^T \tag{2.47}$$

The proposed algorithm works on a frame-by-frame basis, each frame containing N speech samples. The proposed non-iterative KF based speech enhancement is summarized as follows

Initialization:

$$\hat{\boldsymbol{x}}(0|0) = 0 \tag{2.48}$$

$$\boldsymbol{\Sigma_x}(0|0) = [0]_{p \times p} \tag{2.49}$$

$$\boldsymbol{\Phi} = \begin{bmatrix} 0 & 1 & 0 & \dots & 0 \\ 0 & 0 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & 1 \\ a_p & a_{p-1} & a_{p-2} & \dots & a_1 \end{bmatrix} \tag{2.50}$$

For $n = 1 \quad to \quad N$ **do**

Time update (predictor):

$$\hat{\boldsymbol{x}}(n|n-1) = \boldsymbol{\Phi}\hat{\boldsymbol{x}}(n-1|n-1) \tag{2.51}$$

$$\boldsymbol{\Sigma_x}(n|n-1) = \boldsymbol{\Phi}\boldsymbol{\Sigma_x}(n-1|n-1)\boldsymbol{\Phi}^T + \boldsymbol{G}\sigma_u^2\boldsymbol{G}^T \tag{2.52}$$

Measurement update (corrector):

$$e(n) = y(n) - \boldsymbol{H}\hat{\boldsymbol{x}}(n|n-1) \tag{2.53}$$

$$\boldsymbol{K}(n) = [\boldsymbol{\Sigma}_{\boldsymbol{x}}(n|n-1)\boldsymbol{H}^T(\boldsymbol{H}\boldsymbol{\Sigma}_{\boldsymbol{x}}(n|n-1)\boldsymbol{H}^T + \sigma_v^2)^{-1}]\boldsymbol{H}^T \tag{2.54}$$

$$\hat{\boldsymbol{x}}(n|n) = \hat{\boldsymbol{x}}(n|n-1) + \boldsymbol{K}(n)e(n) \tag{2.55}$$

$$\boldsymbol{\Sigma}_{\boldsymbol{x}}(n|n) = (\boldsymbol{I} - \boldsymbol{K}(n)\boldsymbol{H})\boldsymbol{\Sigma}_{\boldsymbol{x}}(n|n-1) \tag{2.56}$$

Estimated speech (at time n):

$$\hat{s}(n) = \boldsymbol{H}\hat{\boldsymbol{x}}(n|n) \tag{2.57}$$

End for

The above procedure is repeated for the following frames and continued until the end of the last noisy frame, yielding the ultimate enhanced speech $\hat{s}(n)$.

2.4.1 Proposed Noise Variance Estimation Algorithm

The noise variance σ_v^2 is estimated using a new method proposed based on a lower-order truncated approximation of Taylor series. The clean speech samples given in equation (1.1) can be well approximated locally at any point on a curve by a lower order polynomial, which can be thought of as a truncated local Taylor series approximation. The main idea here is to apply a low-order difference operation, which is simply an approximation to a certain order differentiation of the truncated series so that the lower order terms are eliminated, while leaving behind only a high-order terms, mainly composed of high-frequency noise components, from which the noise variance is estimated. The differentiation can be represented mathematically as a convolution of the noisy observation with an FIR (finite-duration impulse response) template as shown in Table 1 [53].

Table 1: Derivative Templates.

Template (w)	Differentiation Order
[-1 1]	First Derivative
[1 -2 1]	Second Derivative
[1 -3 3 -1]	Third Derivative
[1 -4 6 -4 1]	Forth Derivative

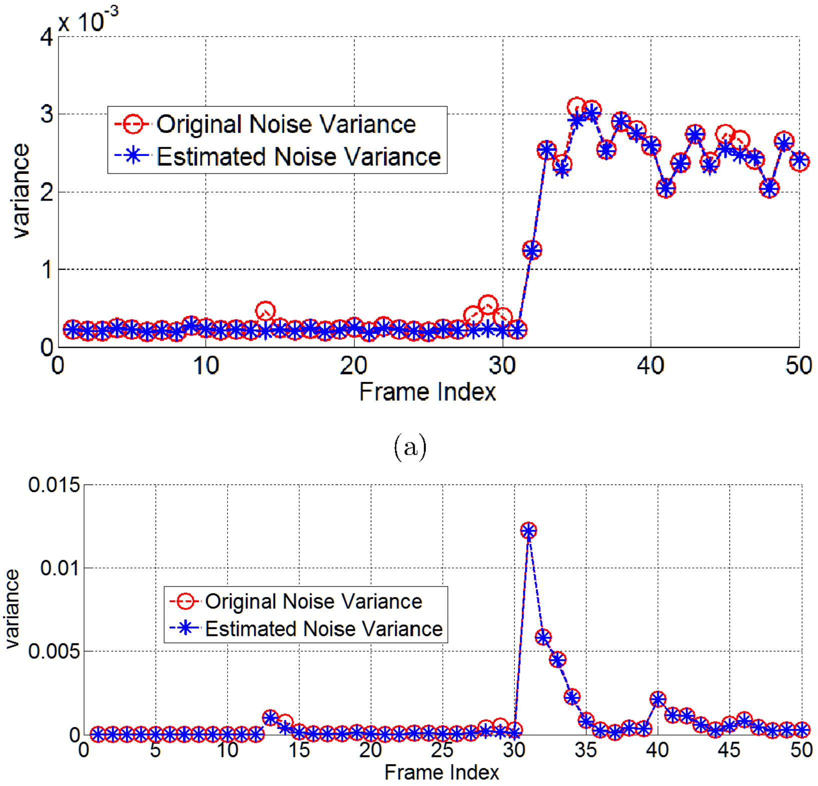
With the difference operation, the noisy speech $y(n)$ is processed as

$$\hat{y}(n) = \frac{1}{M}\sum_{i=0}^{M-1} w[i]y[n-i] \tag{2.58}$$

where $w[i]$ is the derivative template coefficients and M is the length of the template w. Finally, the additive noise variance σ_v^2 is estimated from $\hat{y}(n)$ using the sample variance formula,

$$\sigma_v^2 = \frac{1}{N}\sum_{n=1}^{N} (\hat{y}(n) - \bar{\mu})^2 \tag{2.59}$$

where $\bar{\mu}$ is the sample mean of $\hat{y}(n)$ and N is the number of sample points in the analysis speech.



(a)

(b)

Figure 2.6: Performance comparison between the original and the estimated noise variance, (a) non-stationary noise, (b) restaurant noise experiment. Speech samples are taken from the TIMIT database (input SNR=0dB).

Figure 2.6 shows the performance comparison between the estimated noise variance and the original noise variance in the cases of non-stationary and restaurant noises, respectively (input SNR=0dB). From Figure 2.6, it is observed the estimated noise variance is very close to the original noise variance, even at 0dB input SNR.

2.4.2 Proposed LPC Estimation Algorithm

Here, we propose an LPC estimation algorithm based on speech smoothing and autocorrelation. First, the smoothing is used as a pre-processing of the noisy speech $y(n)$ which can remove some unwanted high-frequency noise components in advance. The simplest smoothing can be done with a simple rectangular window serving as an FIR filter. For example, a 3-point smooth (i.e., the window width is $m = 3$) at sample point n is represented as

$$\hat{y}(n) = \frac{y(n-1) + y(n) + y(n+1)}{3} \tag{2.60}$$

where $\hat{y}(n)$ is the n^{th} sample of the smoothed speech.

There are many different smoothing kernels or windows available, such as, *triangular*, *rectangular*, Hamming window, etc. [53]. However, the choice of the smoothing kernel depends on the domain of processing as well as applications to be considered. The following table shows some smoothing kernels used in most applications.

Table 2: Different Smoothing Kernels

Smoothing Kernel (w)	Kernel Name
[1 1 1]	3-point boxcar (sliding average)
[1 1 1 1 1]	5-point boxcar (sliding average)
[1 2 1]	3-point triangular window
[1 2 3 2 1]	5 point triangular window

The width of the smoothing kernel m is usually chosen to be an odd integer, so that the smooth coefficients are symmetrically balanced around the central point. In the proposed LPC estimation algorithm, the smoothing is performed with a 5-point rectangular kernel $w = [1 \quad 1 \quad 1 \quad 1 \quad 1]$ for the sample points $n = 3$ to $N - 2$, where N is the number of sample points in each analysis speech frame. Here, the rectangular kernel is used since it is fitted well in time-domain rather than other smoothing kernels. It is observed that the smoothing operation cannot be performed for the first two points or for the last two points within each frame. In general, for an m-width smoothing kernel, there will be $(m-1)/2$ points at the beginning, and $(m-1)/2$ points at the end of the analysis speech for which a complete m-width smooth cannot be calculated like the other points. This phenomenon is called the edge effects and the lost points problem. In order to address this issue, $(m-1)/2$ points zero padding is done at the beginning and the end of the analysis speech frame.

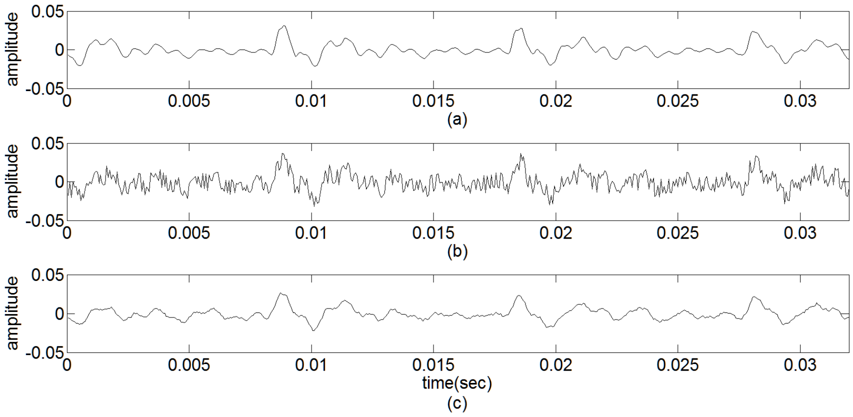


Figure 2.7: (a) clean speech (male) frame, (b) white noise (input SNR=5dB) corrupted frame, and is the corresponding smoothed speech frame.

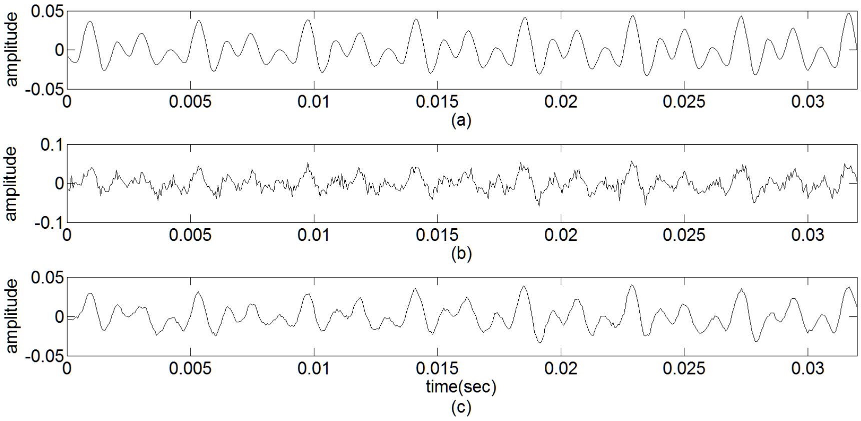


Figure 2.8: (a) clean speech (female) frame, (b) non-stationary noise (input SNR=5dB) corrupted frame, and is the corresponding smoothed speech frame.

The underlying principal is to perform smoothing on a sample-by-sample basis within each analysis speech frame. The general smoothing operation can be represented mathematically using the convolution operation between the noisy speech $y(n)$

and the smoothing kernel w as

$$\hat{y}(n) = \frac{1}{m}\sum_{i=0}^{m-1} w(i)y[n-(m-1)/2+i] \tag{2.61}$$

It is noted that the convolution equation (2.61) is modified slightly as compared to the conventional convolution so that the smooth coefficients are symmetrically balanced around the central point. Figure 2.7 and 2.8 show the effect of smoothing process, where the clean speech is corrupted by the white and non-stationary noises (input SNR=5dB).

The smoothing can never reduce the additive noise effects completely, since the noise components are spreaded out over a wide range of frequencies, and smoothing simply reduces the noise in part of its frequency range. Although it can remove some *high-frequency* noise components, it underestimates the contribution of the *low-frequency* noise components, which is hard to estimate visually because there are so few *low-frequency* components in the noisy speech. This remaining low-frequency noise components can affect the LPC estimation accuracy of the autocorralation method. In order to remove such noise components effectively, the estimated noise variance σ_v^2 in (2.59) is subtracted from the zero-lag of $\hat{R}_{yy}(n)$ in (2.62), where $\hat{R}_{yy}(n)$ is the ACF of $\hat{y}(n)$. Generalizing the result given in equation (2.14), the noiseless $\hat{R}_{ss}(n)$ is estimated as

$$\hat{R}_{ss}(n) = \begin{cases} \hat{R}_{yy}(n) - \sigma_v^2\delta(n), & n = 0 \\ \hat{R}_{yy}(n), & otherwise \end{cases} \tag{2.62}$$

where

$$\hat{R}_{yy}(n) = \sum_{i=0}^{N-1+P} \hat{y}[i]\hat{y}[n-i] \tag{2.63}$$

and $\hat{y}(n)$ is the smoothed speech samples, σ_v^2 is the estimated noise variance obtained from equation (2.59). Using the same procedure of the equation (2.13), the estimated ACFs $\hat{R}_{ss}(n)$ can be represented in matrix notation as

$$\begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_P \end{bmatrix} = \begin{bmatrix} \hat{R}_{ss}(0) & \hat{R}_{ss}(1) & \dots & \hat{R}_{ss}(P-1) \\ \hat{R}_{ss}(1) & \hat{R}_{ss}(0) & \dots & \hat{R}_{ss}(P-2) \\ \vdots & \vdots & \ddots & \vdots \\ \hat{R}_{ss}(P-1) & \hat{R}_{ss}(P-2) & \dots & \hat{R}_{ss}(0) \end{bmatrix}^{-1} \times \begin{bmatrix} \hat{R}_{ss}(1) \\ \hat{R}_{ss}(2) \\ \vdots \\ \hat{R}_{ss}(P) \end{bmatrix} \tag{2.64}$$

By solving equation (2.64) using the Levinson-Durbin recursion, the LPC coefficients a_i's are estimated [45, 49] effectively.

It is important to understand the link between the spectrum of a speech and its prediction coefficients. To do this, using equation (2.2) and (2.3) and setting $z = e^{j\omega}$, the spectrum of speech $s[n]$ is represented as

$$S(e^{j\omega}) = \frac{G^2 |U(e^{j\omega})|^2}{|1 - \sum_{i=1}^{P} a_i e^{-jwi}|^2} \tag{2.65}$$

It is noted that $U(e^{j\omega})$ is termed as the prediction error in the linear prediction theory which is assumed to be white Gaussian noise with zero mean and unit variance. Therefore, its magnitude spectrum is assumed to be constant, i.e., $|U(e^{j\omega})| = 1$ for all ω [46]. Then equation (2.65) reduces to

$$S(e^{j\omega}) = \frac{G^2}{|1 - \sum_{i=1}^{P} a_i e^{-jwi}|^2} \tag{2.66}$$

Therefore, the spectrum of a speech signal can be modeled by the frequency response of an *all-pole* filter, whose parameters are the linear prediction coefficients [46]. Figure 2.9 shows the spectra of the clean, the degraded, and the estimated speech corresponding to the frequency response of an all-pole filter in the presence of non-stationary noise (SNR=0dB), where the LPCs are obtained from these speech samples separately. It is observed that the estimated spectra (solid line) is closer to the clean speech spectra (dashed line). In particular, the shape of the first two formants is better preserved in the estimated spectra as compared to the clean speech spectra (dashed line). From Figure 2.10, it is also observed that the estimated spectra (solid line) is a close approximation to the clean speech spectra (dashed line) in the presence of pink noise.

2.5 Proposed Speech Enhancement Algorithm using Iterative Kalman Filter

In the non-iterative KF method proposed in the previous section, the model parameters are estimated in non ideal case. Although it performs relatively well in different noisy conditions, yet it has some limitations, especially at low SNRs where the accuracy of the estimated LPC decreases. The possible phenomenon of this effect may introduce some *musical noise* as well as distortion in the enhanced speech.

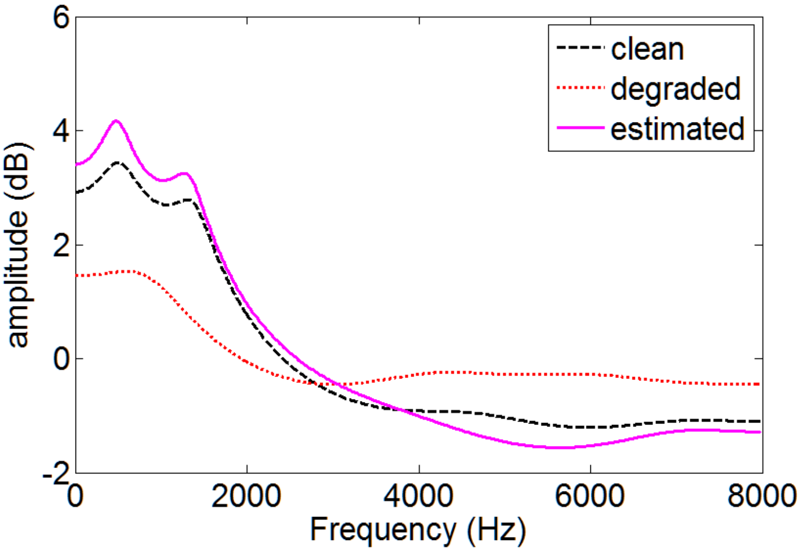


Figure 2.9: Power spectra comparison between the clean speech (dashed), degraded speech (dotted), and estimated speech (solid), in the presence of non-stationary noise (Input SNR= 0dB).

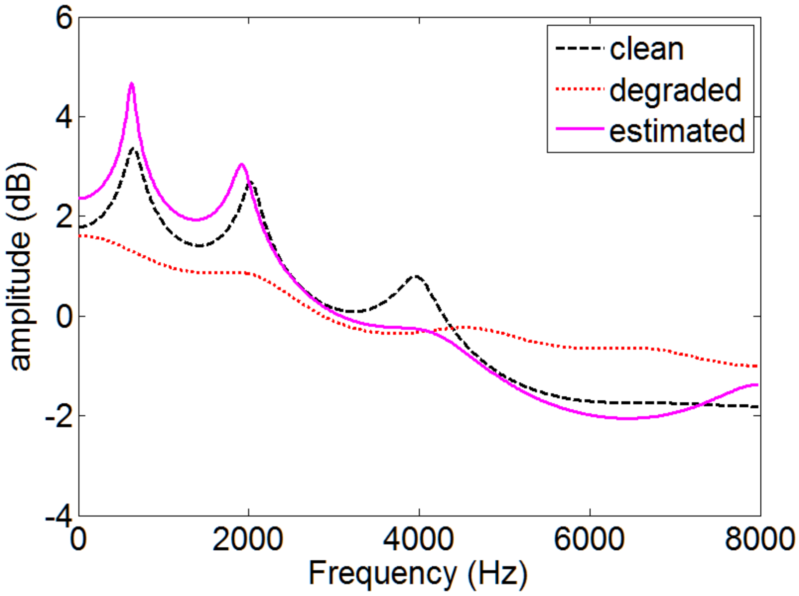


Figure 2.10: Power spectra comparison between the clean speech (dashed), degraded speech (dotted), and estimated speech (solid), in the presence of pink noise (Input SNR = 0dB).

In order to enhance the SE performance as well as parameter estimation accuracy in noisy conditions, an iterative Kalman filter based SE method is presented in this section, which also operates on a frame-by-frame basis but contains two loops of iterations, called inner and outer loops for each frame. In the inner loop, the state-space model parameters of the KF are updated sample-by-sample through an iterative procedure. The additive noise components are reduced significantly when the inner loop is completed for one entire frame. Then, the LPCs and other state-space model parameters are re-estimated from the same processed speech frame for the 2^{nd} inner loop iteration. The outer loop iterative procedure stops when the KF converges or the preset maximum number of iterations is exhausted, giving the further enhanced result of the same speech frame to the input noisy speech frame. The same procedure will repeat for the following frames until the end of all analysis speech frames being processed.

For each frame of N samples, we set D as the maximum number of iterations. The proposed iterative KF based speech enhancement can be summarized below.

Estimate LPCs from $y(n)$, yielding $a_k, k = 1, 2, 3, \ldots, P$. Let $\hat{s}^{(0)}(n) = y(n), n = 1, 2, 3, \ldots, N$.

For $j = 1 \quad to \quad D$ **do** [outer loop]

Initialization:

$$\hat{\boldsymbol{x}}^{(j)}(0|0) = 0 \tag{2.67}$$

$$\boldsymbol{\Sigma_x}^{(j)}(0|0) = [0]_{p\times p} \tag{2.68}$$

$$\boldsymbol{\Phi}^{(j)} = \begin{bmatrix} 0 & 1 & 0 & \ldots & 0 \\ 0 & 0 & 1 & \ldots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \ldots & 1 \\ a_p & a_{p-1} & a_{p-2} & \ldots & a_1 \end{bmatrix} \tag{2.69}$$

For $n = 1 \quad to \quad N$ **do** [inner loop]

Time update (predictor):

$$\hat{\boldsymbol{x}}^{(j)}(n|n-1) = \boldsymbol{\Phi}^{(j)}\hat{\boldsymbol{x}}^{(j)}(n-1|n-1) \tag{2.70}$$

$$\boldsymbol{\Sigma_x}^{(j)}(n|n-1) = \boldsymbol{\Phi}^{(j)}\boldsymbol{\Sigma_x}^{(j)}(n-1|n-1){\boldsymbol{\Phi}^{(j)}}^T + \boldsymbol{H}^T\sigma_u^2\boldsymbol{H} \tag{2.71}$$

Measurement update (corrector):

$$e^{(j)}(n) = \hat{s}^{(j-1)}(n) - \boldsymbol{H}\hat{\boldsymbol{x}}^{(j)}(n|n-1) \tag{2.72}$$

$$\begin{aligned}\boldsymbol{K}^{(j)}(n) = {} & [\boldsymbol{\Sigma_x}^{(j)}(n|n)\boldsymbol{H}^T(\boldsymbol{H}\boldsymbol{\Sigma_x}^{(j)}(n|n)\boldsymbol{H}^T \\ & + \sigma_v^2)^{-1}]\boldsymbol{H}^T\end{aligned} \tag{2.73}$$

$$\hat{\boldsymbol{x}}^{(j)}(n|n) = \hat{\boldsymbol{x}}^{(j)}(n|n-1) + \boldsymbol{K}^{(j)}(n)e^{(j)}(n) \tag{2.74}$$

$$\boldsymbol{\Sigma_x}^{(j)}(n|n) = (\boldsymbol{I} - \boldsymbol{K}^{(j)}(n)\boldsymbol{H})\boldsymbol{\Sigma_x}^{(j)}(n|n-1) \tag{2.75}$$

Estimate enhanced speech (at time n):

$$\hat{s}^{(j)}(n) = \boldsymbol{H}\hat{\boldsymbol{x}}^{(j)}(n|n) \tag{2.76}$$

```
    End for [inner loop]
    If $|1 - k_1^{(j)}||\hat{a}_P| < 1$ (where $k_1^{(j)}$ is the $1^{st}$ element of $\boldsymbol{K}^{(j)}(n)$) [KF Converges]
        Output the enhanced speech $\hat{s}(n)$ and stop.
        End for [outer loop]
    Else
        Re-estimate LPCs $a_k (k = 1, 2, 3, \ldots, P)$ from the $j^{th}$ processed frame $\hat{s}^{(j)}(n)$.
Repeat for [outer loop]
```

The above procedure is repeated for the following frames and continued until the end of the last frame, resulting in ultimate enhanced speech $\hat{s}(n)$.

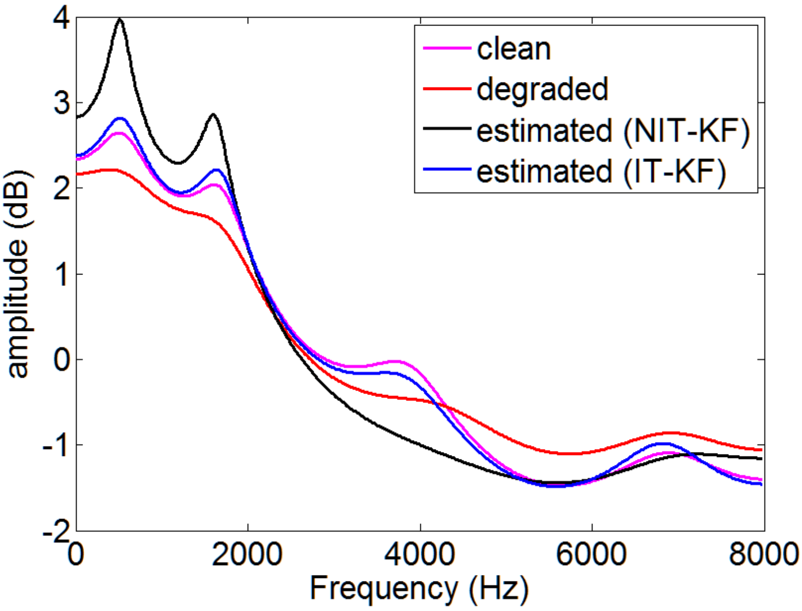


Figure 2.11: Power spectra comparison between the clean speech (magenta), degraded speech (red), estimated(NIT-KF) (black), and estimated(IT-KF) (blue) in presence of the non-stationary noise (Input SNR = 0dB).

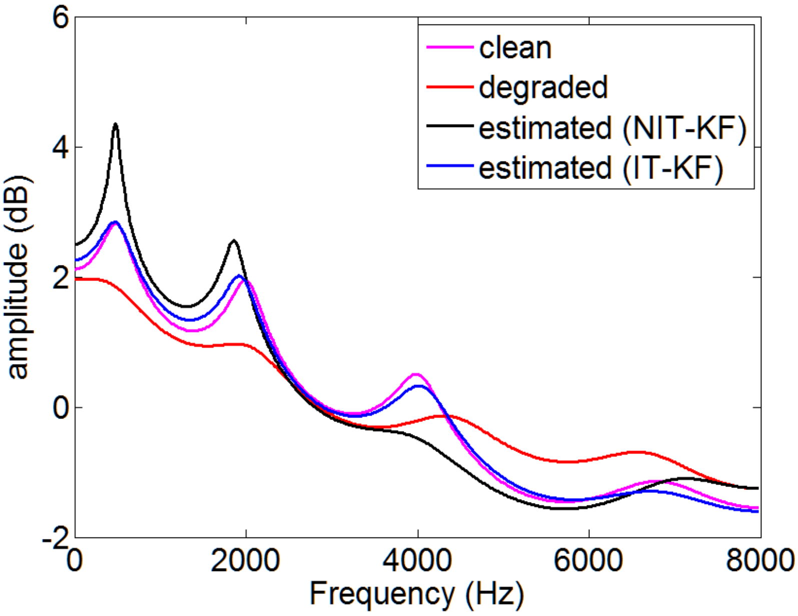


Figure 2.12: Power spectra comparison between the clean speech (magenta), degraded speech (red), estimated(NIT-KF) (black), and estimated(IT-KF) (blue) in the presence of the pink noise (Input SNR = 0dB).

In this proposed method, the LPCs are re-estimated for several times using the enhanced speech frame resulting from the inner iteration of the Kalman filter. Figures 2.11 and 2.12 compare the estimated speech spectra used in the non-iterative (NIT-KF), and iterative (IT-KF) Kalman filter based methods with the clean speech and the degraded speech spectra in the presence of non-stationary and pink noises, respectively with input SNR=0dB.

From Figure 2.11, it is observed that the estimated speech spectra obtained from the enhanced speech frame provided by the iterative Kalman filter estimated(IT-KF) (blue) is closer to the clean speech spectra (magenta) than the estimated spectra (black) obtained from the non-iterative Kalman filter estimated(NIT-KF) method. In particular, the shapes of all the four formants are better preserved in the estimated(IT-KF) (blue) as compared to the clean speech spectra (magenta). From Figure 2.26, it is also observed that the estimated(IT-KF) (blue) is also closer to the clean speech spectra (magenta) in the presence of pink noise. In the overall comparison, it is clearly observed that the estimated(IT-KF) (blue) can preserve all the formant frequencies effectively, while the estimated(NIT-KF) (black) sometimes fails as compared to the clean speech spectra (magenta).

2.6 Performance Comparisons of the Proposed Methods

To evaluate the performance of the proposed methods, we use the NOIZEUS speech corpus database, which is composed of 30 phonetically balanced sentences belonging to six speakers [1]. The speech is sampled at 16 kHz and corrupted by white Gaussian, babble and car noises taken from the Noisex-92 database [54] for a wide range of input SNR (-10dB to 15dB). The LPC order considered in this simulation is $P = 8$. The criteria used for the performance evaluation is the perceptual evaluation of speech quality (PESQ) [55]. PESQ takes values between 1 (worse) and 4.5 (best). The detailed description of PESQ will be discussed in chapter 4.

The performances of the proposed methods based on the non-iterative Kalman filter (Proposed-NIT-KF), iterative Kalman filter (Proposed-IT-KF) are evaluated and compared with some existing methods, namely, LPCs enhancement in iterative Kalman filtering (LPC-IT-KF) [26] and fast converging iterative Kalman filtering based method (FC-IT-KF) [25].

Figure 2.13 shows the performance comparison between the proposed methods and other existing methods in terms of PESQ for the white, babble and car noise experiments. From Figure 2.13, it is observed that the proposed method performs much better than the existing methods consistently even at low SNRs in all three noises. This is attributed to the good overall reduction of the background noise, residual noise and distortion.

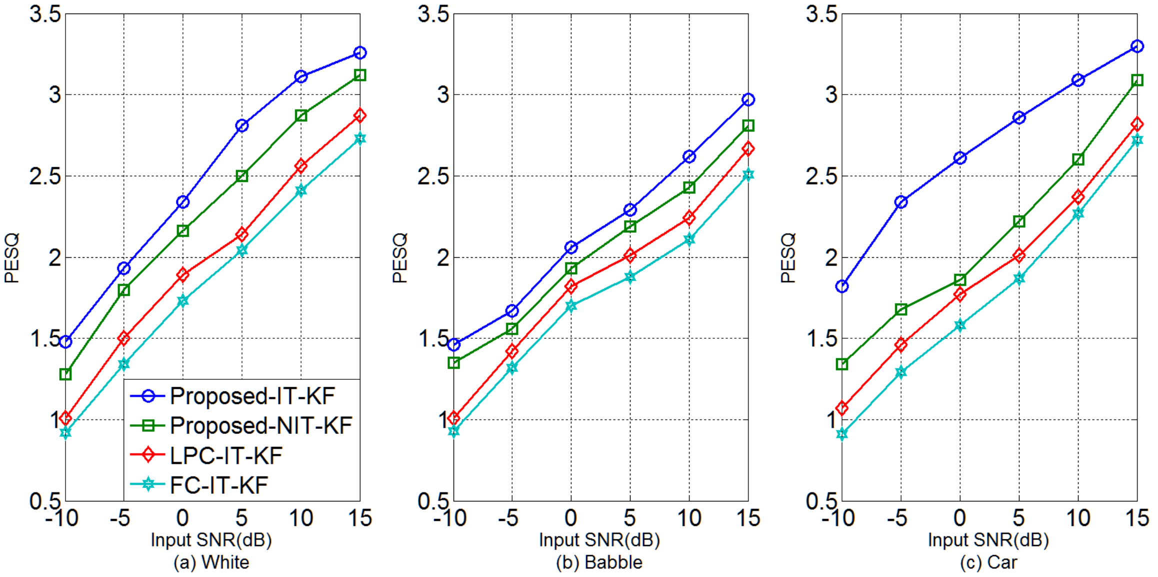


Figure 2.13: Performance comparison between the proposed methods and other existing competitive methods in terms of PESQ. The speech utterances are corrupted by (a): White, (b): Babble and (c): Car noises for a wide range of input SNRs(-10dB to 15dB).

Other extensive simulation results for the proposed methods in the presence of other environmental noises will be shown and discussed in Chapter 4.

2.7 Conclusion

In this chapter, at first, some background material including human speech modeling using LPC analysis, conventional LPC estimation in noise-free and noisy conditions, conventional KF for speech enhancement has been introduced. In the conventional KF, the state-space model parameters, namely, LPC and noise variance are estimated from the clean speech and noisy speech, respectively, which is impractical. In order to overcome these limitations, we proposed a non-iterative Kalman filter based speech enhancement approach, where the LPC and noise variance are estimated from noisy speech. In addition, for LPC estimation in noisy conditions, a smoothing and autocorrelation based combined method has been proposed. A new method based on lower-order truncated approximation of Taylor series along with a difference operation serving as high-pass filtering, for the estimation of the noise variance was also proposed. Moreover, the proposed parameter estimation methods perform well in different environmental noises, which compactly make the non-iterative Kalman filter to reduce the environmental noises. Some existing Kalman filter based methods, on the other hand, are limited to reduce only white noise as mentined in the literature [13].

The non-iterative Kalman filter, however, introduce some *musical noise* and distortion in the enhanced speech. In order to improve the speech enhancement accuracy as well as parameter estimation in noisy conditions, an iterative Kalman filter based speech enhancement method has been proposed as the second approach, where the state-spate model parameters of the Kalman filter have been estimated through a two-loop iteration process. It is important to note that the LPC coefficients have been updated based on the partially enhanced speech in each frame for a better accuracy, thus making the iterative Kalman filter method better than the non-iterative Kalman filter. Specifically, unlike the besic version of Kalman filter, which is to reduce only white noise, the iterative version of Kalman filter was proposed for colored noise corrupted speech enhancement. In addition, it can update better Kalman filter parameters through iterations as well as improve speech enhancement performance over the non-iterative Kalman filter.

Through simulation studies, we have found that the proposed methods are capable of reducing the adverse environmental noises significantly for a wide range of input SNRs, and outperform several existing methods in the literature.

Chapter 3

Proposed Speech Enhacement Algorithm using Sub-band Iterative Kalman Filter

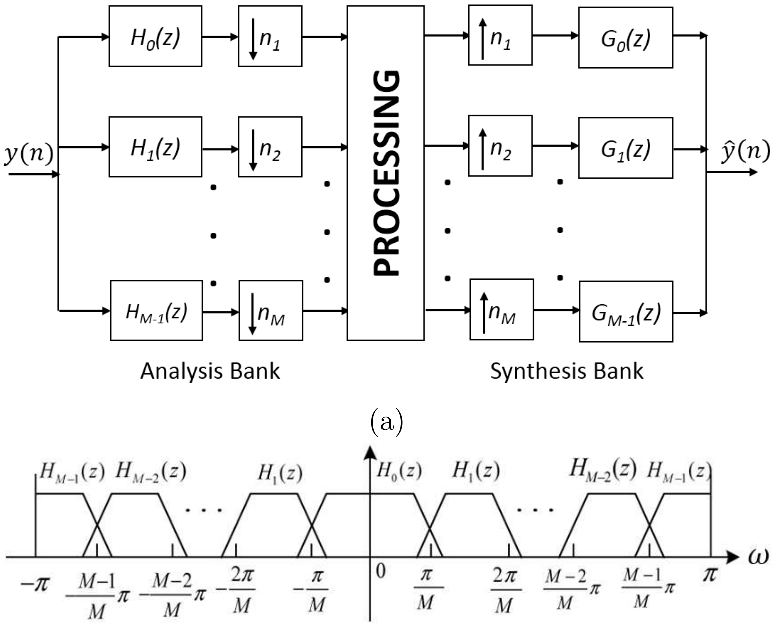
3.1 Introduction

The iterative Kalman filter based speech enhancement presented in chapter 2 performs better than existing Kalman filter based methods. This is because it can reduce the residual noise in the enhanced speech by employing better Kalman filter parameters through iterations. However, some *musical-like* artifacts still remain in the enhanced speech. Moreover, the enhanced speech also suffers from a little bit distortion, which can degrade the quality of the enhanced speech. In order to further improve the speech quality, a sub-band iterative Kalman filter based speech enhancement algorithm is proposed in this chapter, where a wavelet filter-bank is used to decompose the noisy speech into a set of sub-bands prior to Kalman filtering. It is important to note that the decomposed sub-bands contain some hidden information that may not be available in the full-band noisy speech. As such, in the new method, the state-space model parameters of the Kalman filter, namely, the LPCs and the excitation noise variance, are estimated from the sub-band speech rather than the full-band noisy speech as done in the previous two approaches. The estimated model parameters have better accuracy than those estimated from the full-band noisy speech, leading to a better performance of the sub-band iterative Kalman filter based speech enhancement algorithm. The following sections first introduce the wavelet and filter-bank fundamentals, and then present the sub-band iterative Kalman filter based approach, including the parameter estimation from the sub-bands of noisy speech. Finally, simulation results will be provided to show the performance of the proposed sub-band Kalman filter based method followed by concluding remarks.

3.2 Wavelets and Filter-bank

The wavelet filter-bank in general is an array of band-pass filters that separates the input signal into multiple components, where each one carrying a single frequency sub-band of the original signal [56]. The generated sub-bands contain further details or other hidden information of the analysis signal that may not readily be available in the full-band signal yet could be exploited by processing each sub-band separately. The decomposition process performed by the wavelet filter-bank is called analysis process and the output of each analysis process is referred to as a sub-band signal. The reconstruction process is called synthesis process, which is to reconstruct the original complete signal from sub-band signals. The main requirement for wavelet filter-bank design is to meet the perfect reconstruction (PR) criterion which intuitively means that the signal does not get corrupted by the filter-bank. Moreover, in a PR system, there is no error at the output, meaning that the output is simply a time-delayed copy of the input signal [57].

Multirate filter-banks are the general building blocks for sub-band decomposition. Figure 3.1 shows an M-channel filter-bank structure where $H_i(z)$'s and $G_i(z)$'s are the analysis and synthesis filters respectively. The characteristics of these filters depend on the application to be used and the dimensionality of the problem. The multi-layered wavelet filter-bank structure shown in Figure 3.1 decomposes the input signal into a series of different frequency space, called the multi-resolution analysis of a signal in different scales which can demonstrate different frequency characteristics of a signal. More specifically, a two-channel filter-bank decomposes the analysis signal into two parts, one is detail part and the other is approximation part. The detail part contains the high-frequency information of the signal, and the approximation part, on the other hand, contains the low-frequency information of the signal. A multi-channel filter-bank can be implemented by performing a series of two-channel



(a)

(b)

Figure 3.1: (a) Block diagram of an M-channel filter-bank structure, and (b) approximate frequency responses of analysis filters.

decomposition, where the approximation or detail part can be further decomposed again in order to obtain further detail and approximation part in a higher scale. The level of decomposition for extracting the essential information from the sub-band signals depends on the applications. Also, the multiple band decomposition may be obtained by simultaneously applying an M-channel filter-bank directly [58]. In general, the sub-band decomposition should be properly carried out such that it provides the following advantages.

- Give sufficient information for both analysis and synthesis procedures.
- Reduce the computational time sufficiently.
- It is relatively easier to implement.
- It can analyze the signal at different frequency bands with different resolutions.
- It decomposes the signal into a coarse approximation and detail information.

Using the advantages of the sub-band decomposition, many speech enhancement algorithms have been introduced in the literature. Most of these algorithms combine wavelet filter-bank with other methods in order to improve the performance of the speech enhancement. Here, we mainly focus on the wavelet sub-band decomposition process, and consider both the two-channel and multi-channel decomposition cases.

3.2.1 Two-channel Filter-bank Structure

A 2-channel filter-bank is shown in Figure 3.2,

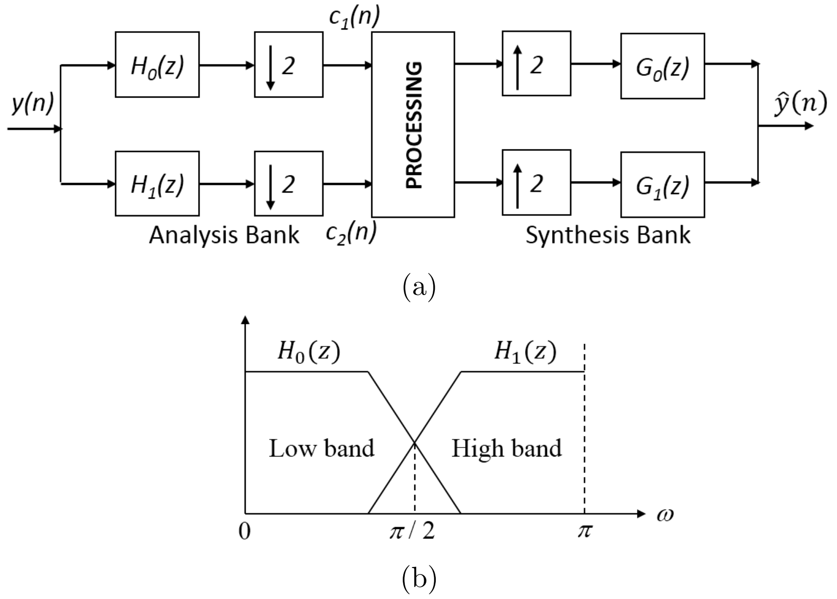


Figure 3.2: (a) Block diagram of a simple two-channel filter-bank structure, and (b) approximate frequency responses of analysis filters.

where a discrete time signal $y(n)$ enters the analysis bank composed of filters $H_0(z)$ and $H_1(z)$ which separate the frequency content of the input signal in frequency bands of equal width. Further, $H_0(z)$ and $H_1(z)$ are a low-pass and a high-pass filters, respectively. The output of each filter contains half-band the frequency content of the original signal $y(n)$, with an equal sampling rate [57]. The two outputs together contain the same frequency content as the original signal $y(n)$, but the amount of data is doubled. Therefore, downsampling by a factor two, denoted by $\downarrow 2$, is applied to the outputs of the filters in the analysis bank. Reconstruction of the original signal is possible using the synthesis filter bank and the rate-reduced two-channel signals [59]. In the synthesis bank, the signals are upsampled by $\uparrow 2$ and passed through the synthesis filters $G_0(z)$ and $G_1(z)$ respectively. The filters in the synthesis bank provide the same characteristics as compared to the filters in the analysis bank.

Finally, the reconstructed signal $\hat{y}(n)$ is obtained by summing up the outputs of the filters in the synthesis filter-bank. The output signals, $c_1(n)$, and $c_2(n)$ of the analysis filter-bank are called the sub-bands. It is important to note that the efficient use of the up-sampling and down-sampling in the analysis and synthesis bank does not guarantee the exact reconstruction of the original input signal $y(n)$. In order to design a practical filter-bank, PR condition of the filter-bank have to be met [60], which is described in the next subsection.

3.2.2 Perfect Reconstruction of Two-channel Filter-bank

Figure 3.2 is used here as an example to drive the PR conditions. Consider N_0 and N_1 be the length of the low-pass and high-pass filters $H_0(z)$ and $H_1(z)$, respectively in the analysis bank as shown in Figure 3.2. Then the input-output relation is represented as

$$\hat{Y}(z) = T_0(z)Y(z) + T_1(z)Y(-z) \tag{3.1}$$

where $T_0(z)$ and $T_1(z)$ are given by

$$T_0(z) = \frac{1}{2}[G_0(z)H_0(z) + G_1(z)H_1(z)] \tag{3.2}$$

$$T_1(z) = \frac{1}{2}[G_0(z)H_0(-z) + G_1(z)H_1(-z)] \tag{3.3}$$

The transfer functions $T_0(z)$ and $T_1(z)$ are called the distortion and aliasing transfer functions of the system. In order to design a PR filter-bank, it is necessary to find $H_k(z)$ and $G_k(z)$ such that the output is a delayed copy of the input. That means, the filters have to satisfy the following two conditions

$$G_0(z)H_0(z) + G_1(z)H_1(z) = z^{-n_0} \tag{3.4}$$

$$G_0(z)H_0(-z) + G_1(z)H_1(-z) = 0 \tag{3.5}$$

where n_0 indicates a time delay and equation (3.5) indicates the aliasing free conditions, which can be satisfied by choosing

$$G_0(z) = H_1(-z), and \quad G_1(z) = -H_0(-z) \tag{3.6}$$

The above condition implies that in the synthesis bank, the impulse response of the low-pass filter $g_0[n]$ is obtained by altering the sign of the impulse response of the high-pass filter $h_1[n]$, i.e.;

$$g_0[n] = (-1)^n h_1[n] \tag{3.7}$$

and similarly we have

$$g_1[n] = (-1)^{n+1} h_0[n] \tag{3.8}$$

where $h_0[n]$ and $h_1[n]$ are the impulse responses of the low-pass and high-pass filters in the analysis bank while $g_0[n]$ and $g_1[n]$ are the low-pass and high-pass filters in the synthesis bank.

If equations (3.4) and (3.5) are satisfied, the output of the two-channel filter-bank in Figure 3.2 is a delayed version of the input signal, i.e.;

$$\hat{Y}(z) = z^{-n_0} Y(z) \tag{3.9}$$

Rearranging equation (3.6) yields

$$H_1(z) = G_0(-z), and \quad G_1(z) = -H_0(-z) \tag{3.10}$$

Submitting the equation (3.10) into (3.4) gives

$$H_0(z)G_0(z) - H_0(-z)G_0(-z) = P_0(z) - P_0(-z) = z^{-n_0} \tag{3.11}$$

where $P_0(z)$ denotes the product of the two low-pass filters, $H_0(z)$ and $G_0(z)$, namely,

$$P_0(z) = H_0(z)G_0(z) \tag{3.12}$$

Equation (3.11) indicates that the product of all the odd terms of the two low-pass filters, $H_0(z)$ and $G_0(z)$ must be zero, except for order n_0 where the even order terms are arbitrary. The delay parameter n_0 must be odd which is usually the center of the filter $P_0(z)$. These observations indicate that the coefficients of $P_0(z)$ can be written as

$$p_0[n] = \begin{cases} 0, & \text{if } n \text{ is odd and } n \neq n_0 \\ 1, & \text{if } n = n_0 \\ arbitary, & \text{if } n \text{ is even} \end{cases} \tag{3.13}$$

Consequently, the two-channel PR filter-bank design reduces to two steps

1. Design a filter $P_0(z)$ that satisfies equation (3.13).
2. Factorize $P_0(z)$ into $H_0(z)$ and $G_0(z)$, then use equation (3.10) to compute $H_1(z)$ and $G_1(z)$ respectively.

3.2.3 M-channel Filter-bank

The PR condition for the M-channel filter-bank is given by

$$T_0(z) = z^{-m_0}, \quad T_k(z) = 0, \quad k \neq 0 \tag{3.14}$$

where

$$T_k(z) = \frac{1}{M} \sum_{i=0}^{M-1} G_i(z) H_i(zW^k) \tag{3.15}$$

and $W = e^{-j2\pi/M}$. $T_o(z)$ is the amplitude and phase distortion transfer function, whereas the remaining transfer functions $T_1(z), T_2(z), ..., T_M(z)$ are aliasing transfer functions. For a given filter length, the number of coefficients to be found is directly proportional to the number of channels M.

In this thesis, wavelet filter-bank is used to decompose the noisy speech into a set of sub-bands. For sub-band decomposition, wavelet packet tree decomposition technique is used, which provides more sophisticated analysis of a non-stationary signal, since it decomposes the signal not only in the approximation part, but also in the detail part [61]. An example of 4-level wavelet packet tree decomposition has shown in Figure 3.3, in which $W_{j,n}$ represents the n^{th} node of the j^{th} level decomposition, where $j = 1, 2, 3, \ldots$ and $n = 2^j - 1$. The decomposed sub-bands at each level are organized as low-frequency to high-frequency, which are represented by $W_{j,0}, W_{j,1}, W_{j,2}, \ldots, W_{j,2^j-1}$.

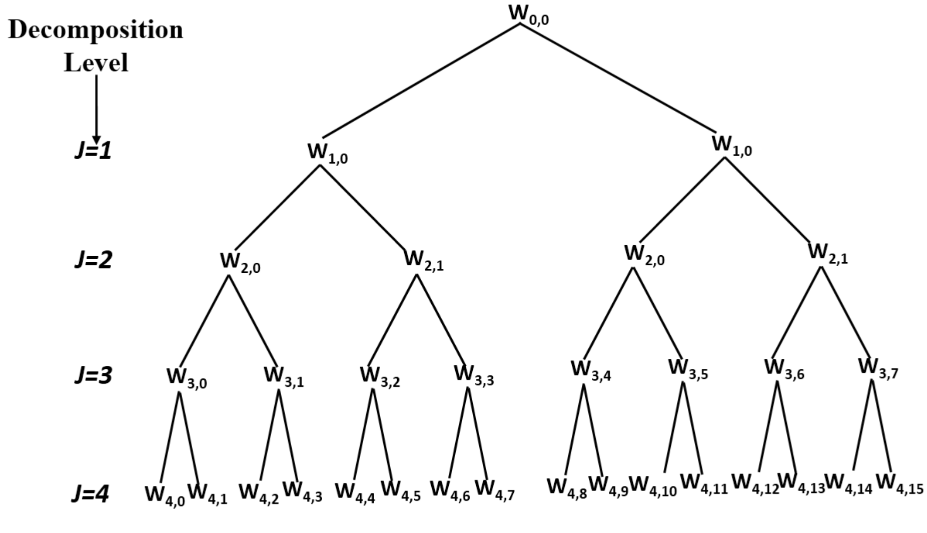


Figure 3.3: A four-level wavelet packet tree decomposition structure.

3.3 Proposed Speech Enhancement Algorithm using Sub-band iterative Kalman Filter

In this section, a sub-band iterative Kalman filter based speech enhancement is proposed. In the proposed algorithm, a 4-level wavelet packet tree decomposition using the wavelet '*sym13*' [62] is first used to decompose the noisy speech $y(n)$ (equation 1.1) into 16 sub-bands. It is important to note that the wavelet packet coefficients at every sub-band can be reconstructed independently by using the wavelet packet reconstruction algorithm so that the length of the reconstructed sub-bands are equal to the given signal (at the same sampling rate) [61]. Here, 16 reconstructed sub-bands, represented by $y_i(n)$, $i = 1, 2, \ldots, 16$ are used prior to Kalman filtering. Note that the lowest sub-band index $i = 1$ denotes the highest frequency sub-band in this proposed algorithm. From the decomposed sub-bands, it is observed that most of the HF components of the additive noise $v(n)$ reside in the higher-order sub-bands. The lower-order sub-bands, on the other hand, mainly contain the low-frequency components of the clean speech $s(n)$. Moreover, these low-frequency components in the lower-order sub-bands have the intelligible speech components that need to be preserved in order to maintain good quality in the enhanced speech. To achieve the best *trade-off* among the noise reduction, speech intelligibility, and computational complexity, a partial reconstruction scheme based on consecutive mean squared error (CMSE) is proposed to synthesize the HF and LF sub-bands such that an iterative Kalman filter is employed only once to the partially reconstructed HF sub-bands $y_h(n)$ rather than all the decomposed sub-bands ($y_i(n)$, $i = 1, 2, 3, \ldots, 16$) of the noisy speech $y(n)$ as done by some existing sub-band Kalman filter based speech enhancement methods. In the proposed algorithm, the state-space model (SSM) parameters, namely, LPC and additive noise variance are estimated from $y_h(n)$. It is also found that $y_h(n)$ contains the vast majority of the HF components of the additive noise $v(n)$. Therefore, the noise variance σ_v^2 can be estimated effectively from $y_h(n)$ rather than the full-band noisy speech $y(n)$. It is also observed that the noise variance σ_v^2 estimated from $y_h(n)$ is more closer to the original noise variance as compared to the noise variance estimated from the full-band noisy speech $y(n)$. The partially reconstructed LF sub-bands $y_l(n)$, on the other hand, keep unchanged since this part mainly contains the clean speech components.

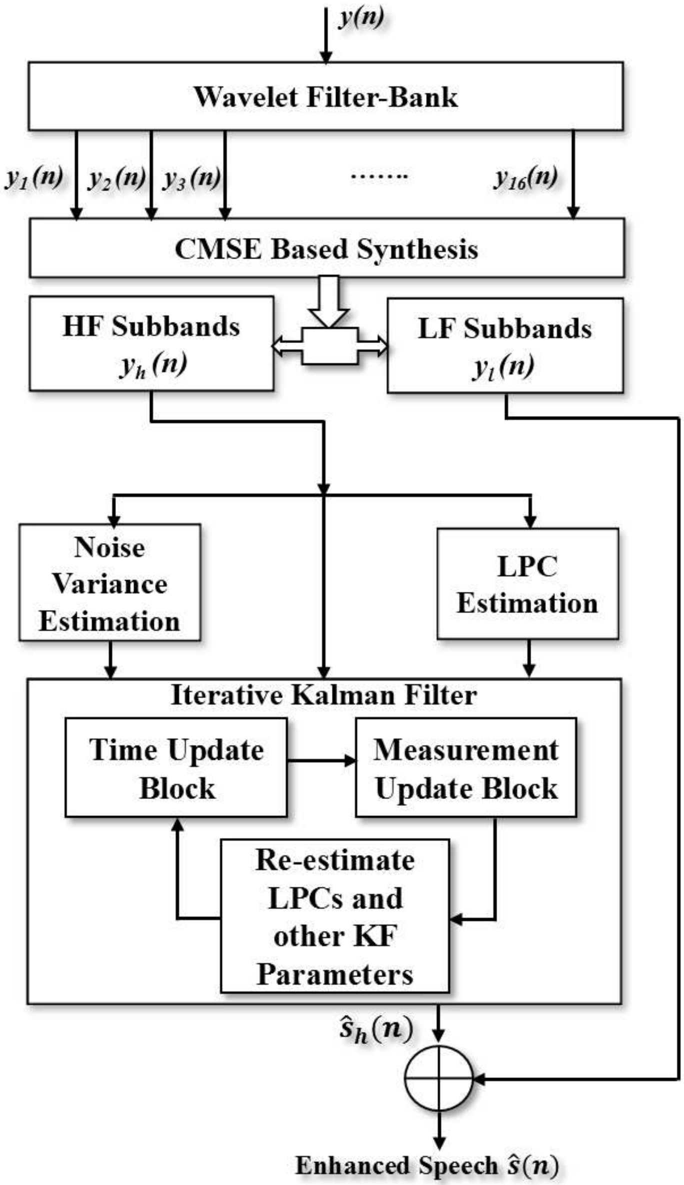


Figure 3.4: Block-diagram of the proposed sub-band iterative Kalman filter for single channel speech enhancement.

Finally, the enhanced speech of the partially reconstructed HF sub-bands $\hat{s}_h(n)$ provided by the proposed sub-band iterative Kalman filter is combined with the partially reconstructed LF sun-bands $y_l(n)$ to reconstruct the full-band enhanced speech $\hat{s}(n)$. This approach can save more CPU computational time as well as better speech enhancement accuracy than some existing sub-band Kalman filter based methods in the literature. The overall block-diagram of the proposed algorithm is shown in

Figure 3.4.

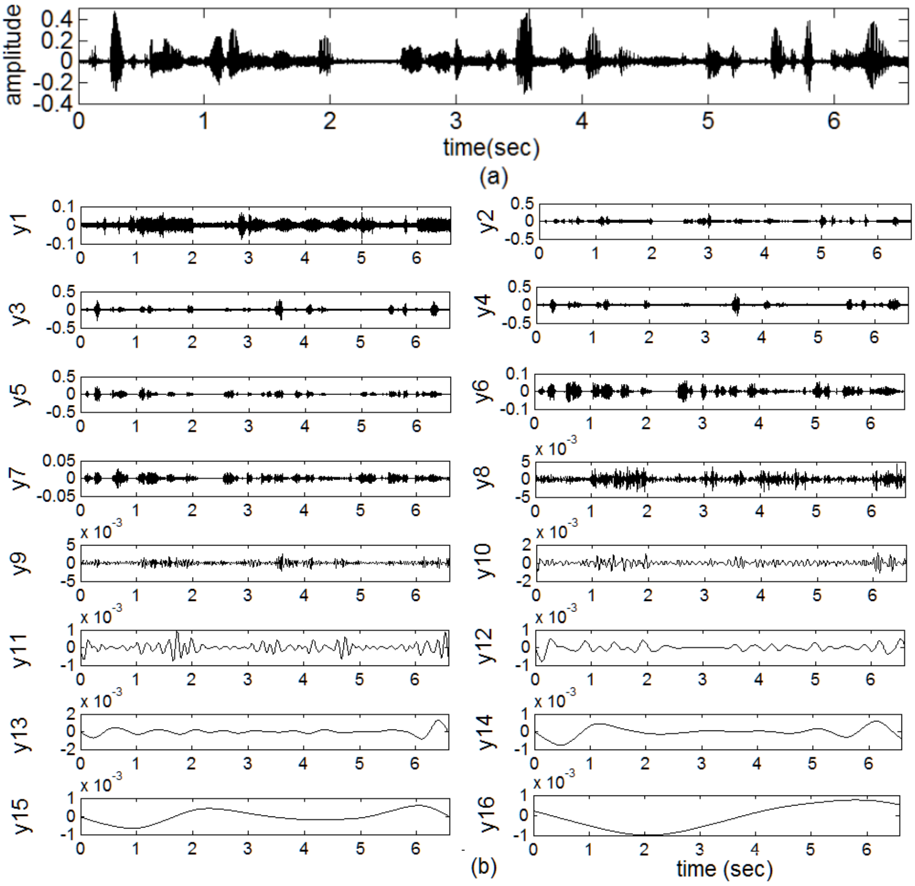


Figure 3.5: (a) Speech sample (TIMIT database) corrupted by babble noise (SNR=10dB), (b) the corresponding 16 reconstructed subbands.

Figure 3.5 shows an example of a 4-level wavelet packet tree decomposition to noisy speech $y(n)$ and the corresponding 16 reconstructed sub-bands $y_i(n), i = 1, 2, \ldots, 16$. The constituent modules of the proposed algorithm are explained in the following subsections.

3.3.1 CMSE Based Synthesis

Here, the mean square error between two consecutive subbands, called consecutive mean square error (CMSE) is used to decide what sub-bands are reconstructed into the HF band for Kalman filtering. The CMSE is defined as

$$E_k = CMSE(y_k\left(n\right), y_{k+1}(n)) = \frac{1}{N}\sum_{n=1}^{N}\left(y_k\left(n\right) - y_{k+1}\left(n\right)\right)^2 \tag{3.16}$$

where $k = 1, 2, \ldots, 15$ is the sub-band index, N is the number of the sub-band speech samples. The underlying principle is to find $k = j_s$, the index of the last HF sub-band, such that no significant difference between the two consecutive CMSE values, namely E_{j_s} and E_{j_s+1}, is observed. Specifically, we compute E_k and E_{k+1} for $k = 1, 2, \ldots, 15$ until their difference is very small or negligible. Then such a value of k is denoted as j_s. This empirical criterion is derived from extensive experiments. Once the value of j_s is identified, the partially reconstructed HF and LF sub-band speeches are, respectively, given by

$$y_h\left(n\right) = \sum_{i=1}^{j_s} y_i(n) \tag{3.17}$$

$$y_l\left(n\right) = \sum_{i=j_s+1}^{16} y_i(n) \tag{3.18}$$

Figure 3.6 shows the CMSE values for the 16 sub-bands of the noisy speech $y(n)$ shown in Figure 3.5. From Figures 3.5 and 3.6, it is clearly observed that the 9^{th} subband is the last sub-band to be used for the partial reconstruction of the HF band. In general, the value of j_s depends on the input speech samples, the noise types, and the input SNR.

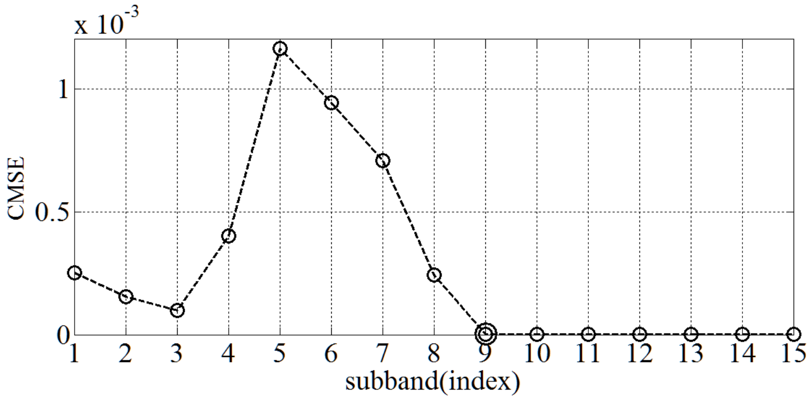


Figure 3.6: The CMSE values corresponding to the sub-band speeches in Fig. 3.5. The double circle indicates the j_s.

3.3.2 Proposed Sub-band Iterative Kalman Filter

The proposed sub-band iterative Kalman filter speech enhancement algorithm is applied to $s_h(n)$ while keeping $s_l(n)$ unchanged. It works on a frame-by-frame basis, including two loops, namely, the inner and the outer loop. For each frame, in the inner loop, the state-space model parameters of the KF are updated sample-by-sample through an iterative procedure. The additive noise components are reduced significantly when the inner loop completed for one entire frame. Then, the LPCs and other state-space model parameters are re-estimated from the processed speech for the 2^{nd} inner loop iteration. The outer loop iteration stops when the Kalman filter converges or the preset maximum number of iterations is exhausted, giving the further enhanced speech frame $\hat{\boldsymbol{s_h}}(n)$ to the noisy speech frame $\boldsymbol{s}_h(n)$. The same procedure will repeat for the following frames until the end of all noisy speech frames being processed.

The state-space model of the proposed sub-band iterative Kalman filter is represented by the following two equations, where the bold faced letters represent vectors or matrices

State Equation:

$$\boldsymbol{x}(n) = \boldsymbol{\Phi x}(n-1) + \boldsymbol{H}^T u(n) \tag{3.19}$$

Observation Equation:

$$z(n) = \boldsymbol{Hx}(n) + v(n) \tag{3.20}$$

Here $\boldsymbol{x}(n)$ is a P-dimensional signal vector, or the state parameter vector at time n which can be expressed as

$$\boldsymbol{x}(n) = [y_h(n-p+1) \quad y_h(n-p+2) \quad \dots \quad y_h(n)]^T \tag{3.21}$$

In (3.19), $u(n)$ is called the process noise and $\boldsymbol{\Phi}$ is a $P \times P$-dimensional state transition matrix, which is given as

$$\boldsymbol{\Phi} = \begin{bmatrix} 0 & 1 & 0 & \dots & 0 \\ 0 & 0 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & 1 \\ a_p & a_{p-1} & a_{p-2} & \dots & a_1 \end{bmatrix},$$

where a_i is the i^{th} LPC coefficient, P is the LPC order, and $\boldsymbol{H}$ is the $1 \times P$ observation row vector as given by

$$\boldsymbol{H} = \begin{bmatrix} 0 & 0 & 0 & \dots & 1 \end{bmatrix}.$$

In (3.20), $z(n)$ is the observation measurement of the state-space model at time n and $v(n)$ is the measurement noise.

For each frame of N samples, we set D as the maximum number of iterations. The proposed iterative KF based speech enhancement can be summarized below.

Estimate LPCs $a_k, k = 1, 2, 3, \ldots, P$, from the sub-band noisy speech $z(n)$. Let $\hat{s_h}^{(0)} = z(n), n = 1, 2, 3, \ldots, N$.

For $j = 1 \quad to \quad D$ **do** [outer loop]

Initialization:

$$\hat{\boldsymbol{x}}^{(j)}(0|0) = 0 \tag{3.22}$$

$$\boldsymbol{\Sigma_x}^{(j)}(0|0) = [0]_{p \times p} \tag{3.23}$$

$$\boldsymbol{\Phi}^{(j)} = \begin{bmatrix} 0 & 1 & 0 & \ldots & 0 \\ 0 & 0 & 1 & \ldots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \ldots & 1 \\ a_p & a_{p-1} & a_{p-2} & \ldots & a_1 \end{bmatrix} \tag{3.24}$$

For $n = 1 \quad to \quad N$ **do** [inner loop]

Time update (predictor):

$$\hat{\boldsymbol{x}}^{(j)}(n|n-1) = \boldsymbol{\Phi}^{(j)} \hat{\boldsymbol{x}}^{(j)}(n-1|n-1) \tag{3.25}$$

$$\boldsymbol{\Sigma_x}^{(j)}(n|n-1) = \boldsymbol{\Phi}^{(j)} \boldsymbol{\Sigma_x}^{(j)}(n-1|n-1) {\boldsymbol{\Phi}^{(j)}}^T + \boldsymbol{H}^T \sigma_u^2 \boldsymbol{H} \tag{3.26}$$

Measurement update (corrector):

$$e^{(j)}(n) = \hat{s_h}^{(j-1)} - \boldsymbol{H} \hat{\boldsymbol{x}}^{(j)}(n|n-1) \tag{3.27}$$

$$\begin{aligned} \boldsymbol{K}^{(j)}(n) = [&\boldsymbol{\Sigma_x}^{(j)}(n|n) \boldsymbol{H}^T (\boldsymbol{H} \boldsymbol{\Sigma_x}^{(j)}(n|n) \boldsymbol{H}^T \\ &+ \sigma_v^2)^{-1}] \boldsymbol{H}^T \end{aligned} \tag{3.28}$$

$$\hat{\boldsymbol{x}}^{(j)}(n|n) = \hat{\boldsymbol{x}}^{(j)}(n|n-1) + \boldsymbol{K}^{(j)}(n) e^{(j)}(n) \tag{3.29}$$

$$\boldsymbol{\Sigma_x}^{(j)}(n|n) = (\boldsymbol{I} - \boldsymbol{K}^{(j)}(n) \boldsymbol{H}) \boldsymbol{\Sigma_x}^{(j)}(n|n-1) \tag{3.30}$$

Estimate enhanced speech (at time n):

$$\hat{s_h}^{(j)}(n) = \boldsymbol{H} \hat{\boldsymbol{x}}^{(j)}(n|n) \tag{3.31}$$

```
    End for [inner loop]
    If $|1 - k_1^{(j)}||\hat{a}_P| < 1$ (where $k_1^{(j)}$ is the $1^{st}$ element of $\boldsymbol{K}^{(j)}(n)$) [KF Converges]
        Output the enhanced speech $\hat{s_h}(n)$ and stop.
        End for [outer loop]
    Else
      Re-estimate LPCs from the $j^{th}$ processed frame $\hat{s_h}^{(j)}(n)$, giving a new set of
      $a_k$'s, $k = 1, 2, 3, \ldots, P$.
Repeat for [outer loop]
```

The above procedure is repeated for the following frames and continued until the last frame being processed, resulting in ultimate enhanced speech $\hat{s}_h(n)$ for all the frames. Finally, the full-band enhanced speech $\hat{s}(n)$ is obtained as

$$\hat{s}(n) = \hat{s}_h(n) + y_l(n) \tag{3.32}$$

3.3.3 Parameter Estimation

The LPC coefficients used in the sub-band iterative Kalman filter are updated based on the partially enhanced speech in each frame for a better accuracy. In addition, it can preserve the formant frequencies of the speech more precisely. Figure 3.7 shows the estimated spectra (dashed), which can preserve the shapes of all the four formants as compared to the clean speech spectra (solid).

As mentioned earlier, the noise variance σ_v^2 is estimated from $y_h(n)$ rather than the full-band noisy speech $y(n)$, since $y_h(n)$ contains the vast majority of the additive noise components. Noted that the noise variance estimated using the proposed algorithm is already presented in section 2.4.1. Accordingly, we apply the difference operation to $y_h(n)$, namely,

$$\hat{y_h}(n) = \frac{1}{M} \sum_{i=0}^{M-1} w[i] y_h[n-i] \tag{3.33}$$

where w is the derivative template (Table 1, chapter 2) and M is the length of w.

Finally, σ_v^2 is estimated from $\hat{y_h}(n)$ using the sample variance formula,

$$\sigma_v^2 = \frac{1}{N} \sum_{n=1}^{N} \left(\hat{y_h}(n) - \bar{\mu}\right)^2 \tag{3.34}$$

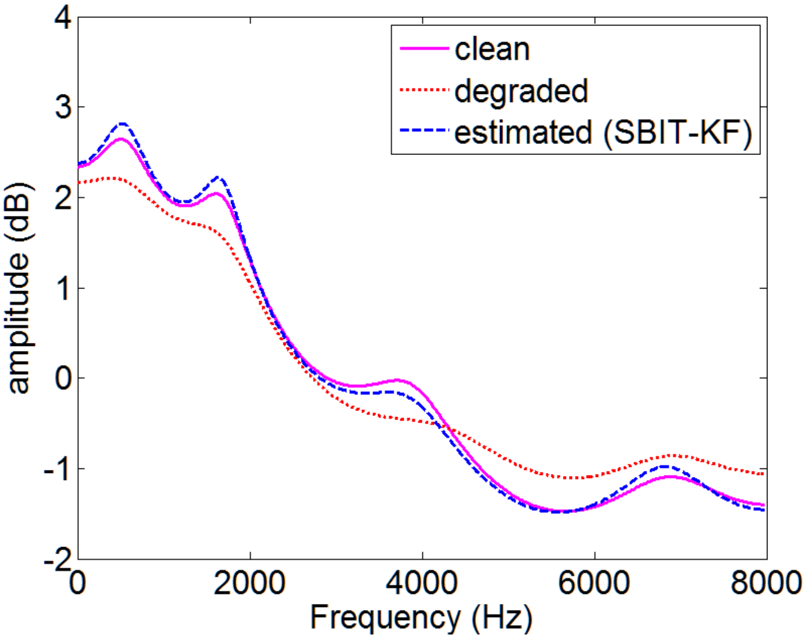


Figure 3.7: Power spectra comparison between the clean speech (solid), degraded speech (dotted), and estimated (SBIT-KF) speech (dashed) in the presence of babble noise (SNR = 0dB).

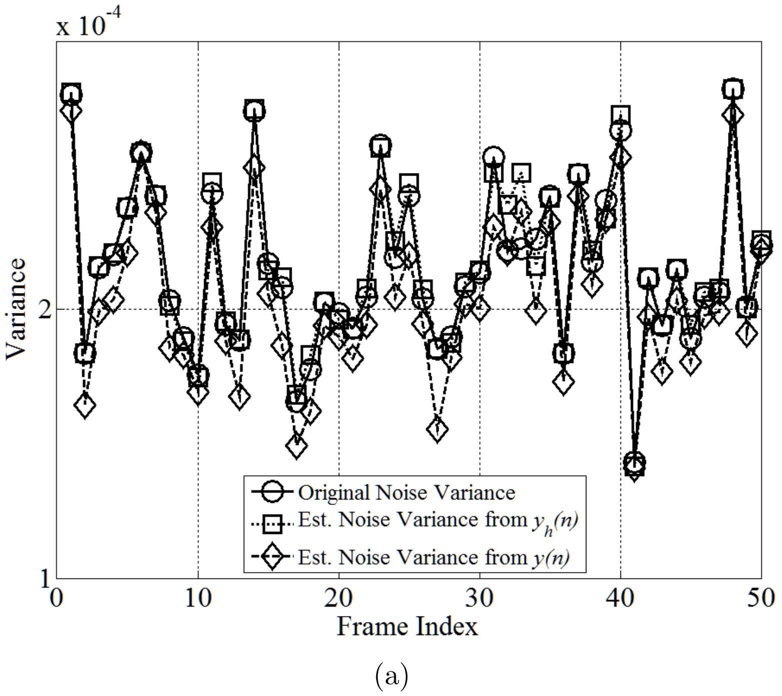
where $\bar{\mu}$ is the sample mean of $\hat{y_h}(n)$ and N is the number of sample points in the analysis speech.

Figure 3.8 shows the performance comparison between the original noise variance and the estimated noise variances obtained from the partially reconstructed HF sub-band speech $y_h(n)$ and full-band noisy speech $y(n)$, in the presence of white Gaussian and non-stationary noises (input SNR=-5dB), respectively.

From Figure 3.8, it is observed that the noise variance σ_v^2 of the additive noise $v(n)$ estimated from $y_h(n)$ approaches closely to the original noise variance, even at low input SNR (-5dB) in both noise types. The noise variance estimated from the full-band noisy speech $y(n)$, on the other hand, deviates a bit from the original noise variance.

3.4 Performance of the Proposed Method

In this simulation study, the same simulation setup as in section 2.6 is used. In addition, the Wavelet function used in the computation of the wavelet filter-bank is *sym13*, order-13 least asymmetric orthogonal wavelet [62]. The proposed sub-band iterative



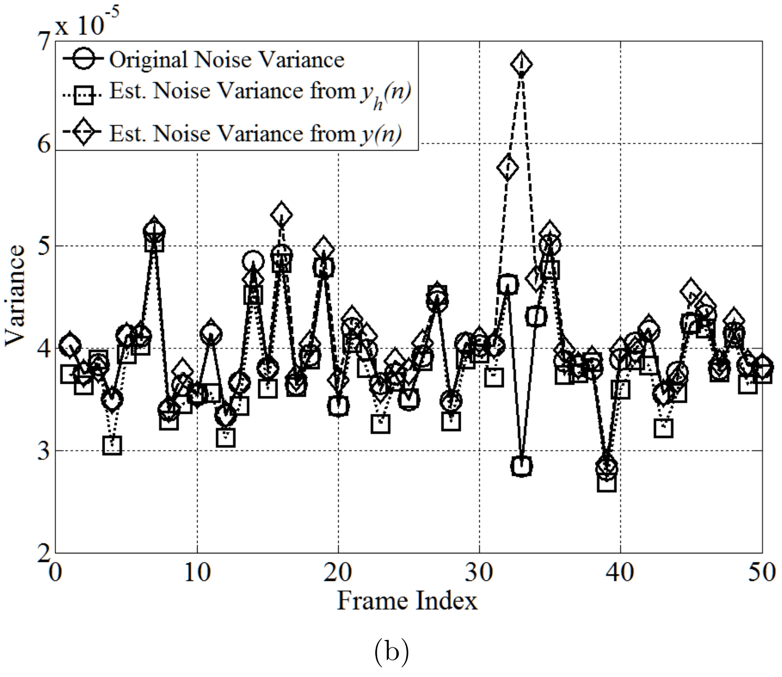


Figure 3.8: Performance comparison between the original and estimated noise variances obtained from the partially reconstructed sub-band speech $y_h(n)$ and full-band noisy speech $y(n)$, respectively, (a) white Gaussian, (b) non-stationary noise experiment. Speech utterances are taken from the TIMIT database (input SNR=-5dB).

Kalman filter based method (Proposed-SBIT-KF) is evaluated and compared with the proposed iterative KF (Proposed-IT-KF), non-iterative KF (Proposed-NIT-KF) and the existing methods, namely, LPCs enhancement in iterative Kalman filtering (LPC-IT-KF) [26] and fast converging iterative Kalman filtering based method (FC-IT-KF) [25].

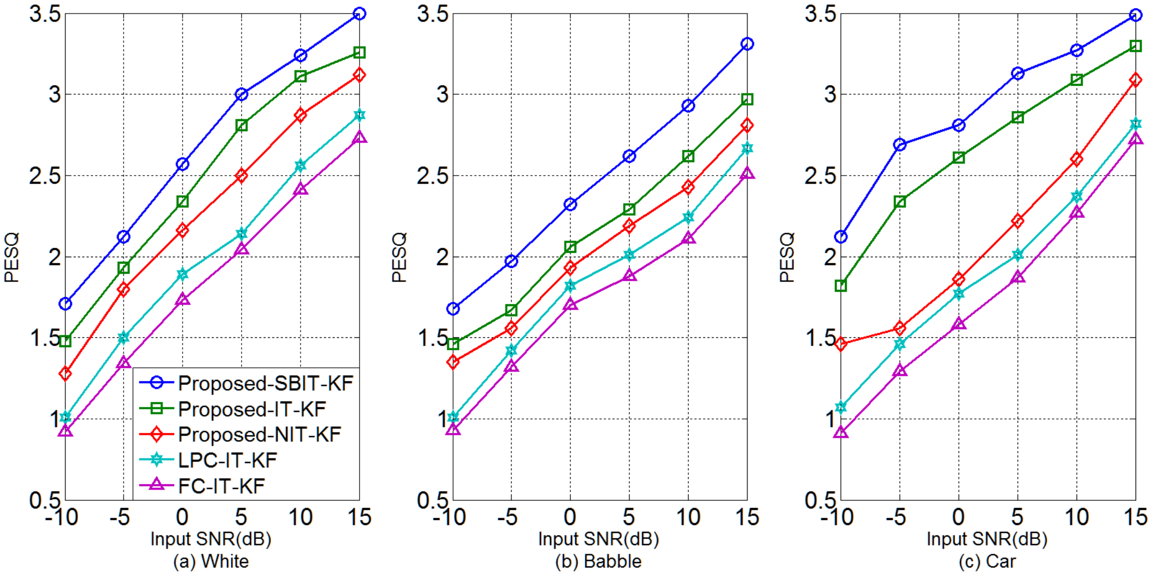


Figure 3.9: Performance comparison between the proposed methods and other existing competitive methods in terms of PESQ. The speech utterances are corrupted by (a): White, (b): Babble and (c): Car noises for a wide range of input SNRs(-10dB to 15dB).

From Figure 3.9, it is seen that the proposed sub-band iterative KF based method performs better than the proposed non-iterative and iterative KF as well as the existing methods consistently, in terms of PESQ for all the three types of noises. In addition, the performance of the existing competitive methods is worse than all the three proposed methods at all input SNRs. This is attributed to the good overall reduction of background noise, residual noise and distortion. More detailed simulation results of the proposed methods in the presence of other adverse environmental noises will be shown and discussed in Chapter 4.

3.5 Conclusion

In this chapter, at first, some background materials, including wavelet and filter-bank, two-channel PR filter-bank, M-channel PR filter-bank, and wavelet packet tree decomposition, have been introduced. Although the iterative Kalman filter performs well than non-iterative Kalman filter in chapter 2, however, some *musical-like* artifacts as well as a bit distortion still remains in the enhanced speech. For further improving the SE results, this chapter introduced the proposed sub-band iterative KF based proposed SE method, where a wavelet filter-bank is used first to decompose the noisy speech into a set of sub-bands. A consecutive mean square error (CMSE) based scheme has been proposed to make partial reconstruction of the HF and LF sub-bands such that the iterative Kalman filter is applied to the partially reconstructed HF sub-band speech only, while keeping the LF sub-bands unchanged. Then the partial enhanced speech provided by the iterative Kalman filter is combined with the partially reconstructed LF sub-band speech to reconstruct the full-band enhanced speech. In the proposed method, the state-space model parameters have been estimated from the sub-band speech rather than the full-band noisy speech, which provides better accuracy. In addition, in the proposed method, the iterative Kalman filter is applied only to the partially reconstructed HF sub-band speech rather than all the decomposed sub-bands as done in some existing sub-band Kalman filter based methods in the literature. Therefore, our method can reduce the computational complexity to a certain extent.

The experimental results show that the proposed method performs better than the existing methods for different environmental noises. It is also observed that the proposed sub-band KF method outperforms other two Kalman filter based methods presented in chapter 2.

Chapter 4

Simulation Results and Discussions

4.1 Experimental Setup

To illustrate the efficiency of the proposed methods, extensive computer simulations are conducted, where the clean speech sentences are taken from the NOIZEUS speech corpus [1], and TIMIT database[63], respectively. The NOIZEUS speech corpus database is composed of 30 phonetically balanced sentences belonging to six speakers. 30 speech utterances, including 15 male and 15 female speakers are also selected from the TIMIT database. The duration of the sentences taken from both of the database is in between 2 to 4 seconds. The experiments are performed in the presence of 9 types of noises, namely, the white Gaussian, non-stationary, restaurant, babble, street, car, pink, train, and cockpit noises for a wide range of input SNRs (-10dB to 15dB). Among the noise samples, white Gaussian, babble, car, pink, and cockpit (f16) are taken from the Noisex-92 database [54]. Restaurant, street, and train noises are taken from the NOIZEUS speech corpus database [1], and the non-stationary noise is computer generated. The speech and noise are sampled at 16 kHz. A rectangular window of 32 milliseconds is used for framing the test speech and the LPC order used here is 8. The proposed Kalman filter based speech enhancement algorithms are implemented in time-domain, where the rectangular window is fitted well during framing and no overlapping is considered. The whole experiments are performed in Matlab 8.1.

4.2 Performance Evaluation Methods

As for the assessment of the enhanced speech quality, various objective measures, namely, the perceptual evaluation of speech quality (PESQ), signal to noise ratio (SNR), segmental SNR (seg. SNR), and Log-likelihood ratio (LLR) are used. The detailed description of these evaluation metrics are given below.

PESQ: In recent years, perceptually motivated measures have been popularly used in measuring the speech quality. The PESQ evaluation metric is widely accepted as an industrial standard for objective voice quality evaluation according to the ITU-T recommendation P.862 [55]. PESQ includes a complex sequence of processing steps to produce a set of distortion scores as a function of time and frequency. A simplified block-diagram of the PESQ is shown in Figure 4.1.

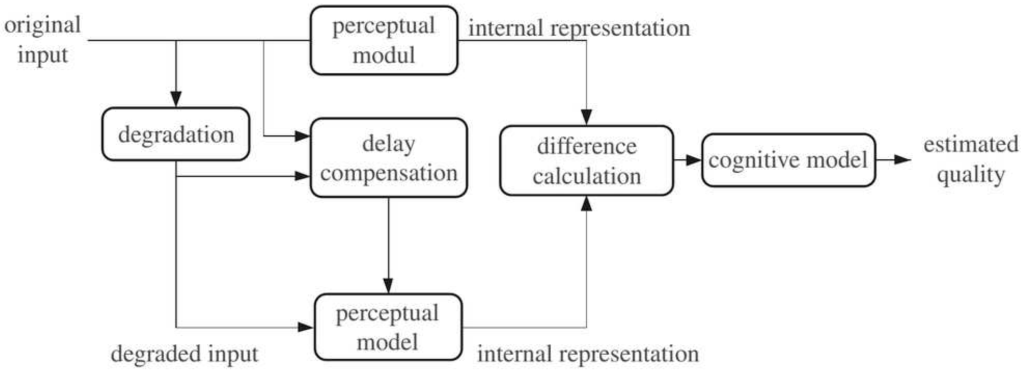


Figure 4.1: Simplified block-diagram of the PESQ evaluation.

PESQ uses a perceptual model to convert the input and the degraded speech into an internal representation. The degraded speech is time-aligned with the original signal to compensate for the delay that may be associated with the degradation. The difference in the internal representations of the two signals is then used by the cognitive model to estimate the PESQ score. PESQ takes values between 1 (worst) and 4.5 (best) [55, 64].

SNR: Signal-to-Noise Ratio (SNR) is one of the oldest and widely used objective measures. It is defined as the ratio of signal power to the noise power, often expressed in decibels. A ratio higher than 1:1 (greater than 0 dB) indicates more signal than noise. It is mathematically simple to calculate, but requires both distorted and undistorted (clean) speech samples [2, 64]. SNR can be calculated as follows

$$SNR = 10log_{10}\frac{\sum_{n=1}^{N} s^2(n)}{\sum_{n=1}^{N} [s(n) - \hat{s}(n)]^2} \tag{4.1}$$

where $s(n)$ is the clean speech, $\hat{s}(n)$ is the distorted speech, and N the number of samples.

Segmental SNR: The classical definition of SNR is not well related to the speech quality for a wide range of distortions. To have a more complete evaluation of the noise reduction performance, we also consider the segmental SNR, which correlates well with the level of noise reduction regardless of the existing distortion in the speech. In addition, it is less sensitive to the misalignments between the original and distorted speech which occurs during the global SNR calculation. Therefore, it is an efficient performance evaluation metric for the speech enhancement algorithm than the global SNR [64]. Segmental SNR is calculated in short frames, and then averaged over a number of frames [2, 64]. It is defined as

$$Seg_{SNR} = \frac{10}{M}\sum_{m=0}^{M-1} log_{10}\frac{\sum_{n=Lm}^{Lm+L-1} s^2(n)}{\sum_{n=Lm}^{Lm+L-1}[s(n) - \hat{s}(n)]^2} \tag{4.2}$$

where L is the frame length (number of samples), and M the number of frames in the signal ($N = ML$).

The frame length is normally set between 15 to 20 ms. Since the logarithm of the ratio is calculated before averaging, the frames with an exceptionally large ratio is somewhat weighed less, while frames with low ratio is weighed somewhat higher. It can be observed that this matches the perceptual quality well, i.e., frames with large speech and no audible noise does not dominate the overall perceptual quality, but the existence of noisy frames stands out and will drive the overall quality lower. However, if the speech sample contains excessive silence, the overall segmental SNR values will decrease significantly, since silent frames generally show large negative segmental SNR values. In this case, silent portions should be excluded from the averaging using speech activity detectors. In the same manner, exclusion of frames with excessively large or small values from averaging generally results in segmental SNR values that agree well with the subjective quality [2]. A typical value for the upper and the lower ratio limit is 35 and 10 dB [64].

LLR: The LLR is also used in this work as it is an important tool for measuring the efficiency of the enhanced speech. It is a distance measure that can be directly calculated from the LPC vector of the clean and distorted speech [64]. Therefore, it is also called an LPC based object measure. It is calculated as follows

$$LLR = log(\frac{\boldsymbol{A}_e^T \boldsymbol{R}_c \boldsymbol{A}_e}{\boldsymbol{A}_c^T \boldsymbol{R}_c \boldsymbol{A}_c}) \tag{4.3}$$

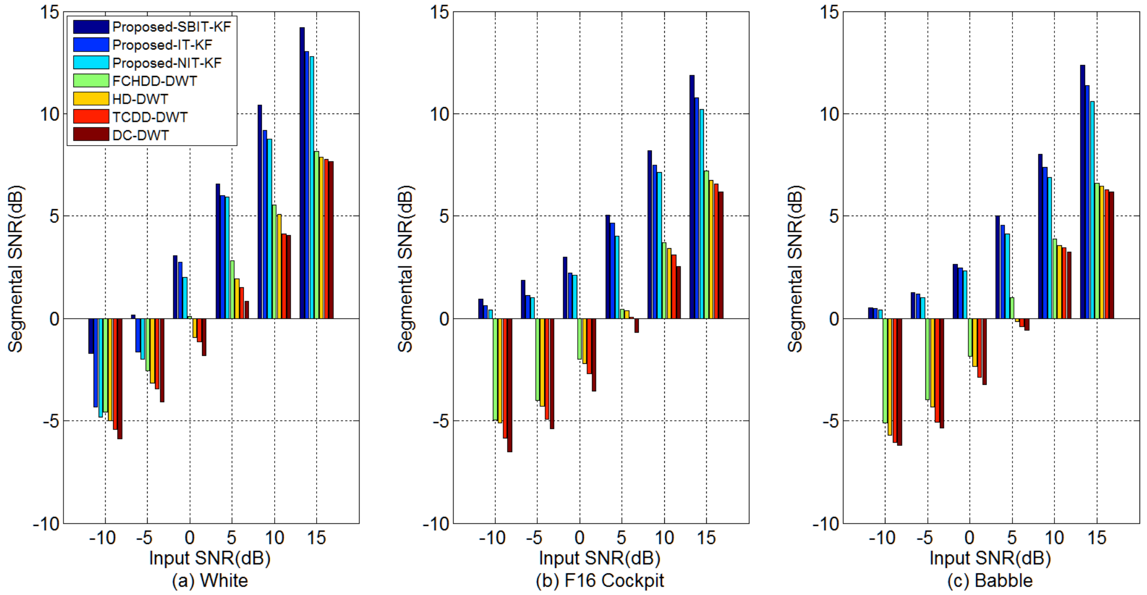
where $\boldsymbol{A}_c$ is the LPC vector for the clean speech, $\boldsymbol{A}_e$ is the LPC vector for the enhanced speech, $\boldsymbol{A}^T$ is the transpose of $\boldsymbol{A}$, and $\boldsymbol{R}_c$ is the auto-correlation matrix for the clean speech.

The less value of the LLR means that the enhanced speech contains less distortion as well as better SNR improvement [64].

4.3 Performance Comparisons between the Proposed and Existing Methods

The performances of the proposed methods are evaluated and compared against some existing state-of-the art speech enhancement methods in terms of the aforementioned evaluation metrics. In the first comparative study, 30 speech utterances are taken from the TIMIT database and the experiment is performed in the presence of white Gaussian, F16 Cockpit, and babble noises for a wide range of input SNRs(-10dB to 15dB). The performance of the Proposed-NIT-KF, Proposed-IT-KF, and Proposed-SBIT-KF are compared with the existing competitive methods, namely, the bivariate two-channel DWT (TC-DWT), three-channel double density DWT (TCDD-DWT), higher-density discrete wavelet(HD-DWT), and four-channel double density discrete wavelet transformation (FCHDD-DWT) based methods introduced by Hamid Reza Tohidypour et all. in 2015 [42].

The experimental results presented in Figure 4.2 reveal that the proposed methods consistently outperform the existing methods in terms of segmental SNR (dB) for all the three noise types. Overall, the proposed sub-band iterative KF gives the best result, then followed by the proposed iterative and the non-iterative KF based methods, but all the three proposed methods perform much better for all input SNRs than the existing methods. In particular, the existing methods provide very poor performance at low input SNRs. At high input SNRs, although the existing methods perform relatively well, yet not as good as the proposed methods.

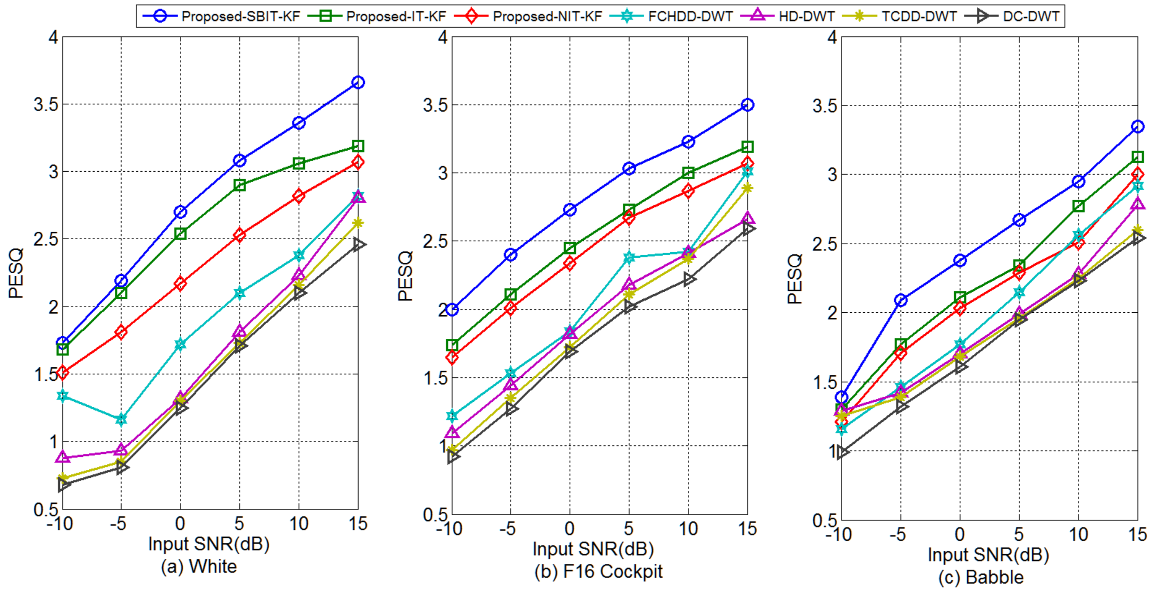


(a) White

(b) F16 Cockpit

(c) Babble

Figure 4.2: Performance comparison between the proposed and existing competitive methods in terms segmental SNR (dB). The speech utterances are corrupted by (a): White, (b):F16 Cockpit, and (c): Babble noises for a wide range for input SNRs(-10dB to 15dB).



(a) White

(b) F16 Cockpit

(c) Babble

Figure 4.3: Performance comparison between the proposed and existing methods in terms of PESQ. The speech utterances are corrupted by (a): White, (b): F16 Cockpit, and (c): Babble noises for a wide range for input SNRs(-10dB to 15dB).

The PESQ results shown in Figure 4.3 indicates that the proposed methods perform better for all input SNRs in the three noisy cases than the existing methods. It is also observed that the PESQ results of the existing methods below 1 at low input SNRs, which is termed as the worst performance according to the ITU-T standard of PESQ [55]. Among the existing methods, FCHDD-DWT relatively performs well than others. However, the average PESQ of FCHDD-DWT is still lower than the proposed non-iterative KF based method which provides relatively lower performance among the proposed methods.

To illustrate the efficiency of the proposed methods in the presence of other environmental noises, such as car, street, train, and restaurant noises, another experiment is performed, where the speech samples are taken from NOIZEUS speech corpus database [1]. The experiments are conducted for a wide range of input SNRs (0dB to 15dB). The experimental results of the proposed methods (Proposed-NIT-KF, Proposed-IT-KF,and Proposed-SBIT-KF) are compared with the existing methods, namely the Wiener filter and harmonic regeneration based combined method (WF-HRG), sub-band Wiener filter (SB-WF), and Wiener filter (WF) based methods introduced by Ch.V. Rama Rao et all. in 2012 [36] in terms of the segmental SNR (dB) and PESQ.

The segmental SNR (dB) results shown in Figure 4.4 reveal that the proposed methods outperform existing Wiener filter based methods for all input SNRs in the four noisy cases. It is also observed that the proposed methods always provide positive segmental SNR improvement, even at low input SNRs for all the experiments. The Wiener filter based methods, on the other hand, provide very poor performance at low input SNRs, even the improved segmental SNRs are negative for all noise experiments. In addition, at high input SNRs, such as at 15dB, the improved segmental SNRs of the existing methods are less than 5dB, while for the proposed methods, it is greater than 10dB which is regarded as excellent performance. In general, the higher value of the segmental SNR (dB) indicates the weaker speech distortions as well as better perceived quality in the enhanced speech. Through the extensive simulation results, it is clearly observed that the proposed methods noticed lowest distortion in the enhanced speech for all the four experiments than the existing methods.

From Figure 4.5, it is seen that the proposed methods provide significant PESQ improvement than the existing Wiener filter based methods for all input SNRs of the

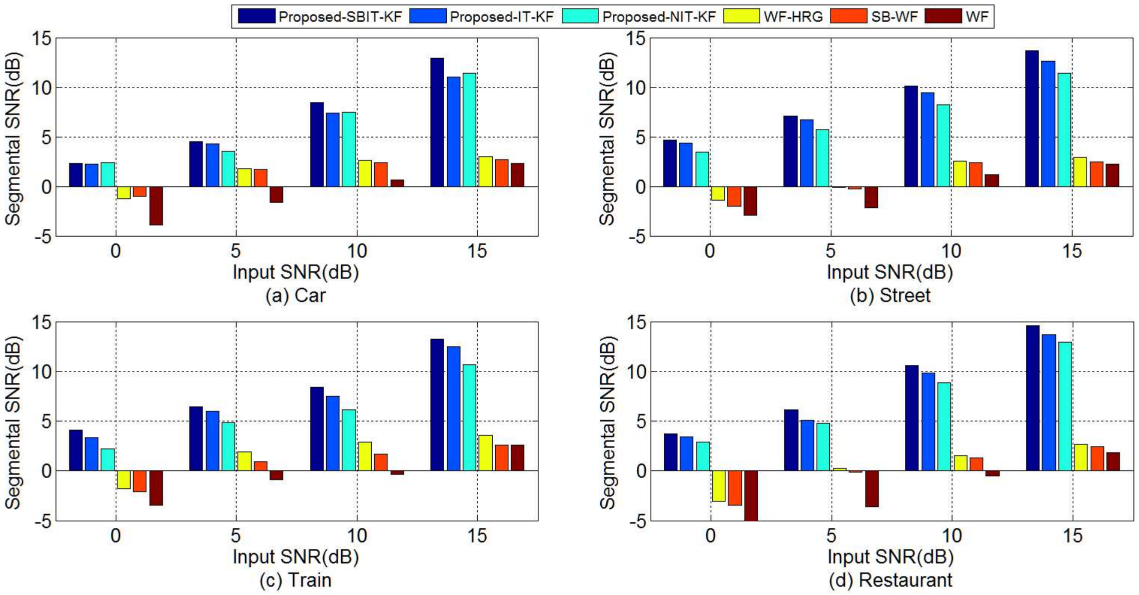


Figure 4.4: Performance comparison between the proposed and other existing methods in terms of segmental SNR (dB). The speech utterances are corrupted by (a): Car, (b):Street, (c): Train, and (d): Restaurant noises for a wide range of input SNRs(0dB to 15dB).

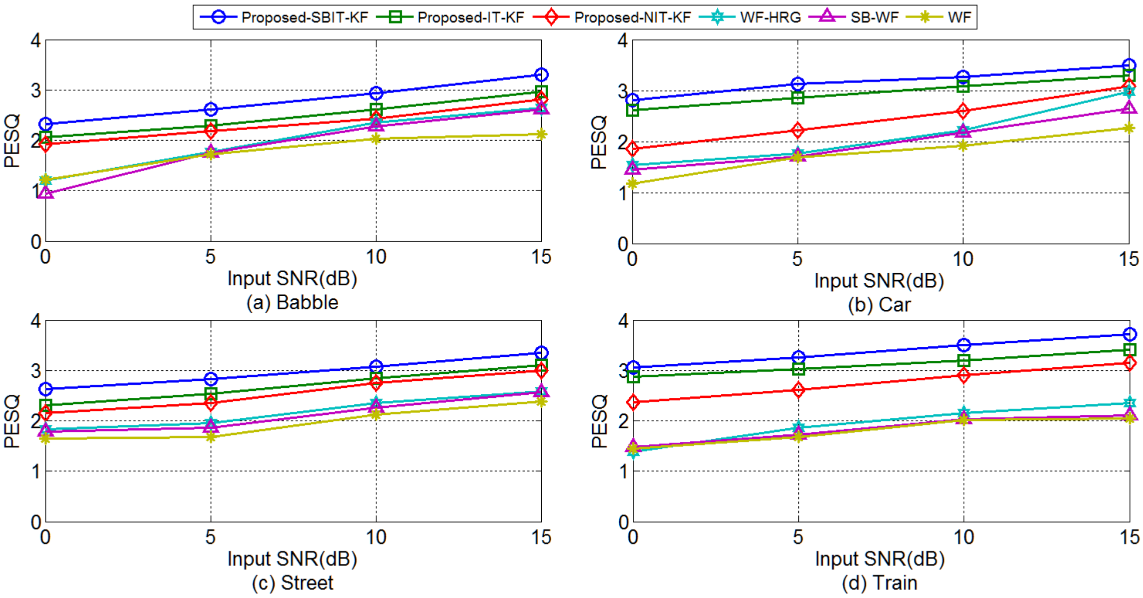


Figure 4.5: Performance comparison between the proposed and other existing methods in terms of PESQ. The speech utterances are corrupted by (a): Car, (b): Street, (c): Train, and (d): Restaurant noises for a wide range of input SNRs(0dB to 15dB).

four noise experiments. It is also noted that at low input SNR, say at 0dB, the PESQ improvement of the existing methods is close to 1, while it is greater than 2 for the proposed methods. At high input SNR, say at 10dB, a significant PESQ improvement is found for the proposed methods (always above 3) as opposed to existing methods (always below 3) for all the four experiments. Among the proposed methods, the sub-band iterative KF, followed by the iterative and non-iterative KF outperform the existing Wiener filter based methods for all the four experiments.

4.4 Comprehensive Performance Comparisons between the Proposed Methods

To illustrate graphically the efficiency achieved by the proposed methods, the spectrograms for the clean, noisy and enhanced speech in the presence of white Gaussian and non-stationary noises at 5dB input SNR are shown in Figure 4.6 and Figure 4.7 respectively.

From Figures 4.6 and 4.7, it is shown that there is a little bit residual noise remaining in the enhanced speech provided by the non-iterative KF based method, while noticeable improvement is found for the iterative KF. For sub-band iterative KF, it removes the wide-band residual noise components significantly in the enhanced speech and provides a better resolution in the speech spectral peaks and a very low residual noise floor in the enhanced speech.

To illustrate the efficiency of the proposed methods in terms of the four evaluation metrics, a comprehensive simulation study is conducted in the presence of 9 types of noises for the SNR range of -10dB to 15dB. For performing these experiments, 30 speech sentences are taken from the TIMIT database. The main goal of this simulation study is to show that the proposed methods perform the best across different environmental noises, where most of the speech conversations take place.

The segmental SNR results presented in Figure 4.8 indicates that the sub-band iterative KF relatively performs better for all noise experiments as compared to the iterative and non-iterative KF. However, the iterative and non-iterative KF also provide noticeable segmental SNR improvement for all experiments.

The PESQ results presented in Figure 4.9 also indicates that the sub-band iterative KF performs much better than other two proposed methods. Specifically, at 15dB

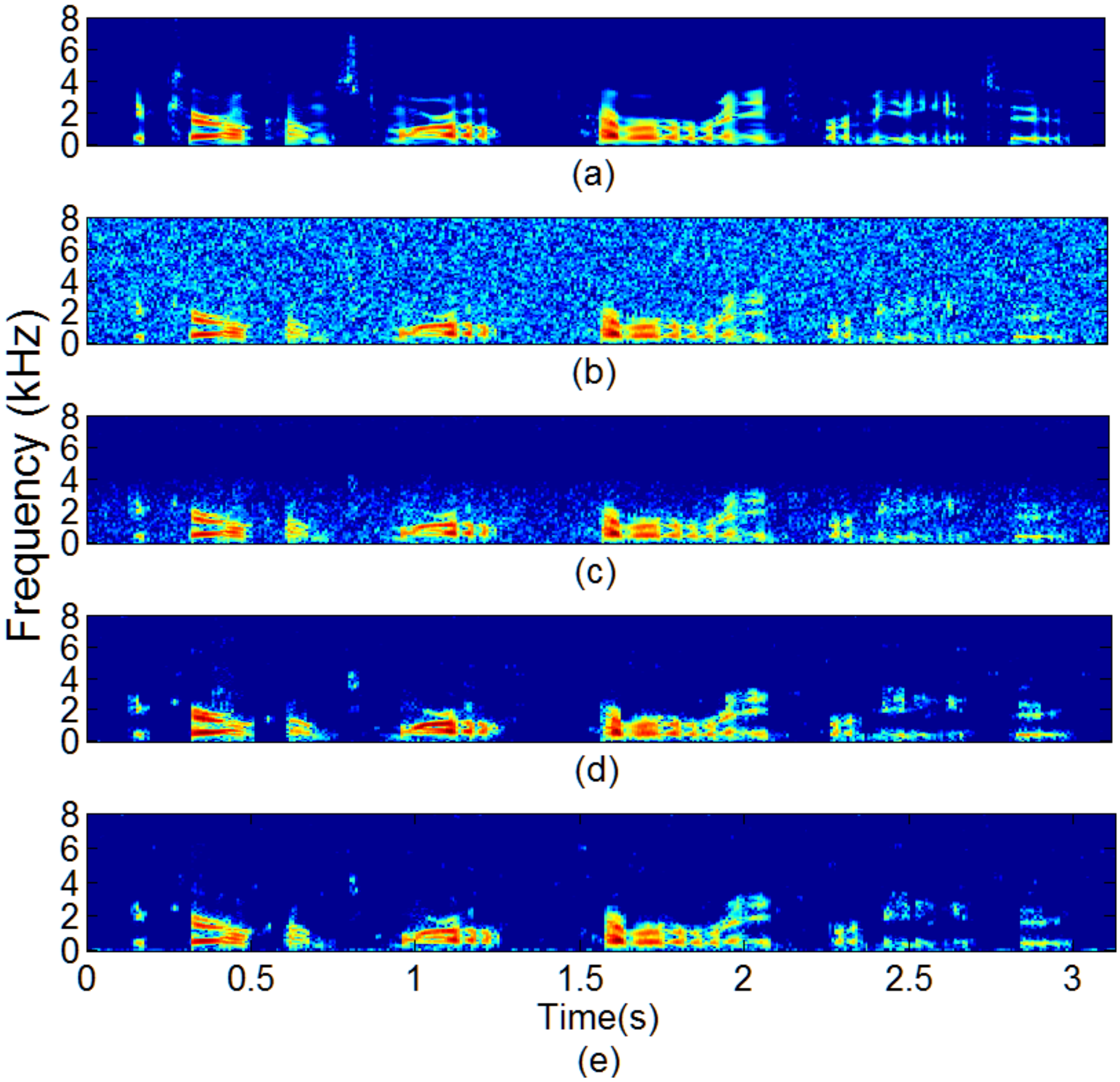


Figure 4.6: Spectrograms of (a): clean speech, (b): noisy speech, and enhanced speech (c,d,e) obtained through using the Proposed-NIT-KF, Proposed-IT-KF, and Proposed-SBIT-KF, respectively in the presence of white Gaussian noise (input SNR=5dB).

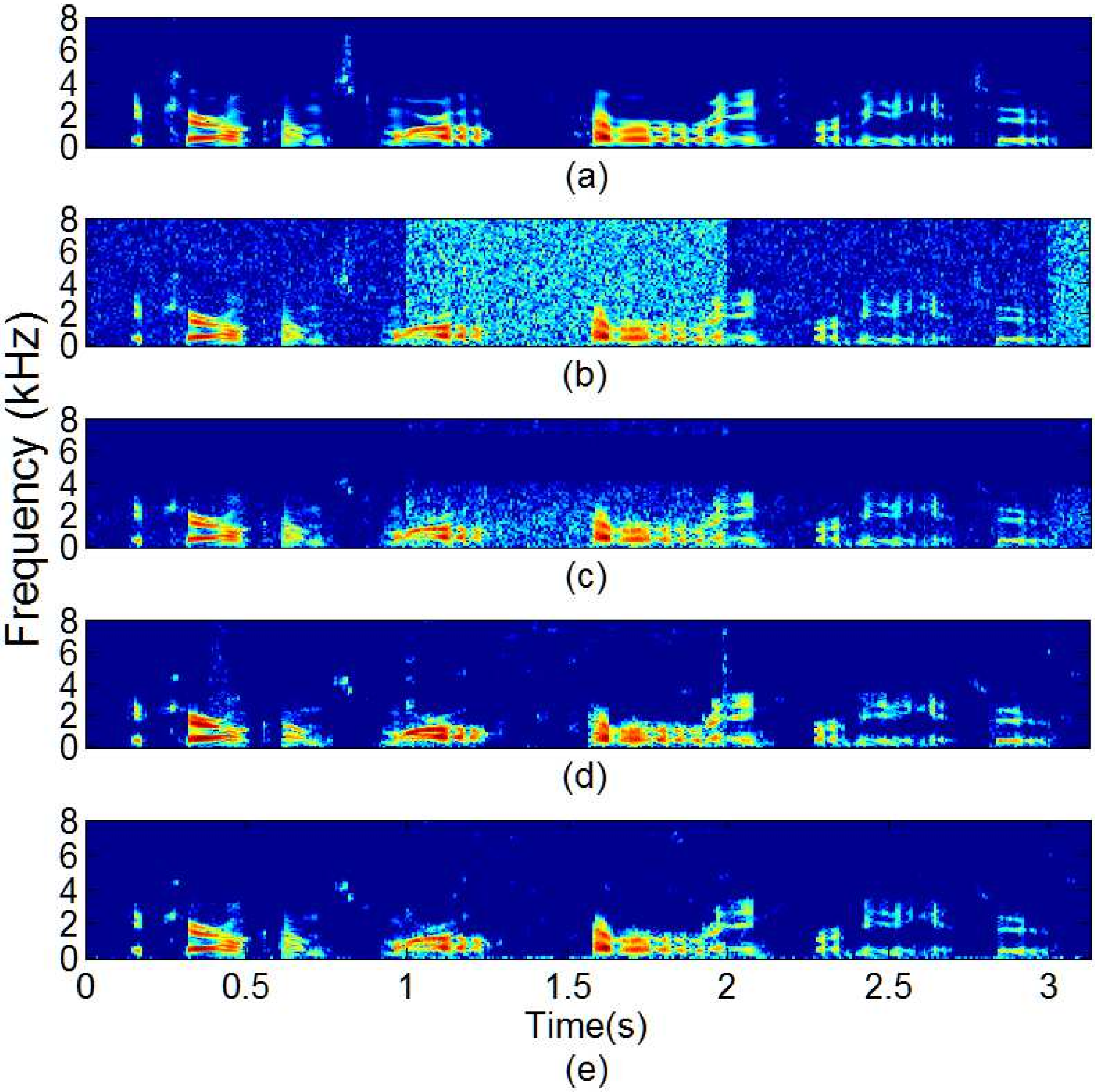


Figure 4.7: Spectrograms of (a): clean speech, (b): noisy speech, and enhanced speech (c,d,e) obtained through using the Proposed-NIT-KF, Proposed-IT-KF, and Proposed-SBIT-KF, respectively in the presence of non-stationary noise (input SNR=5dB).

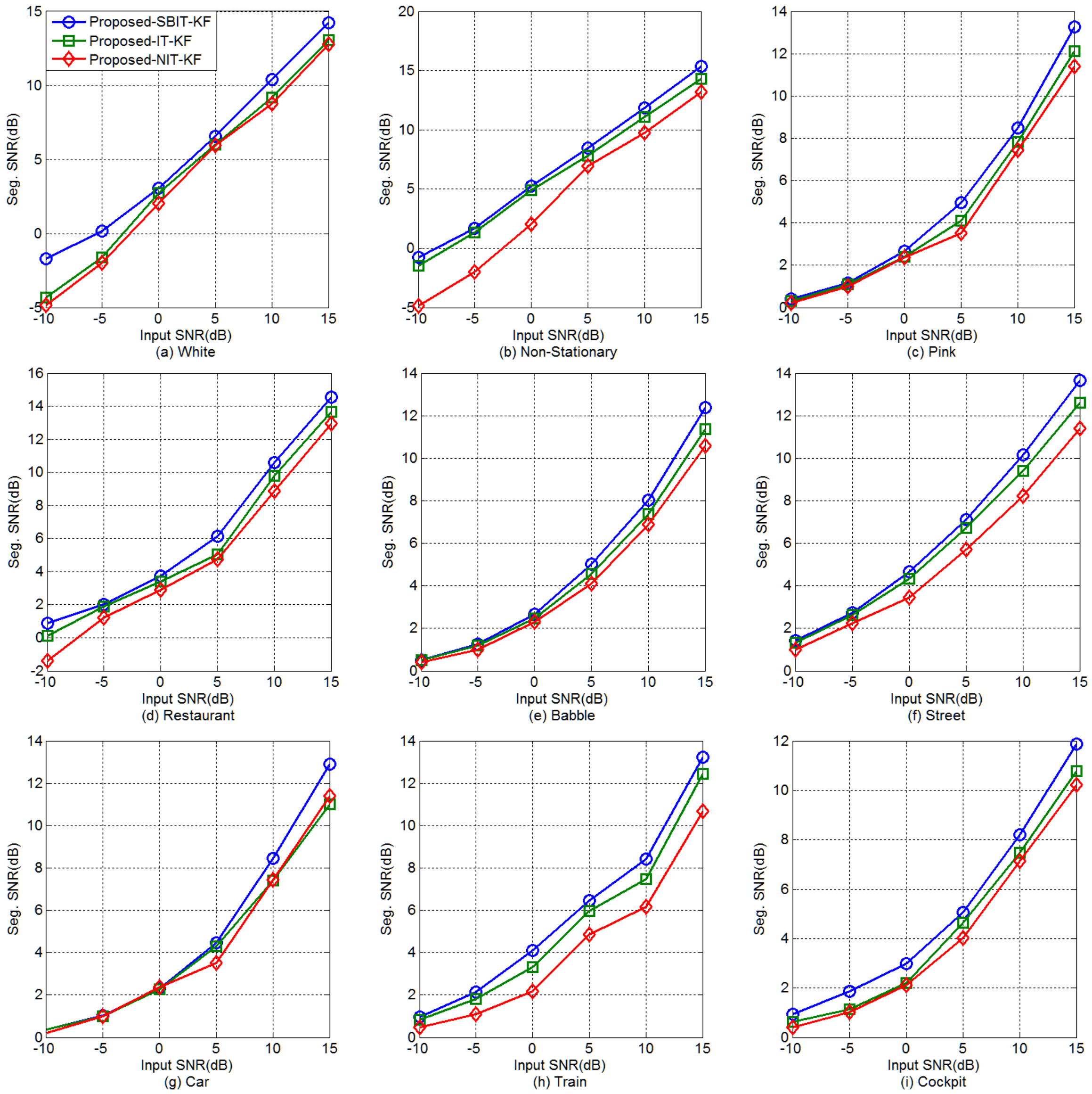
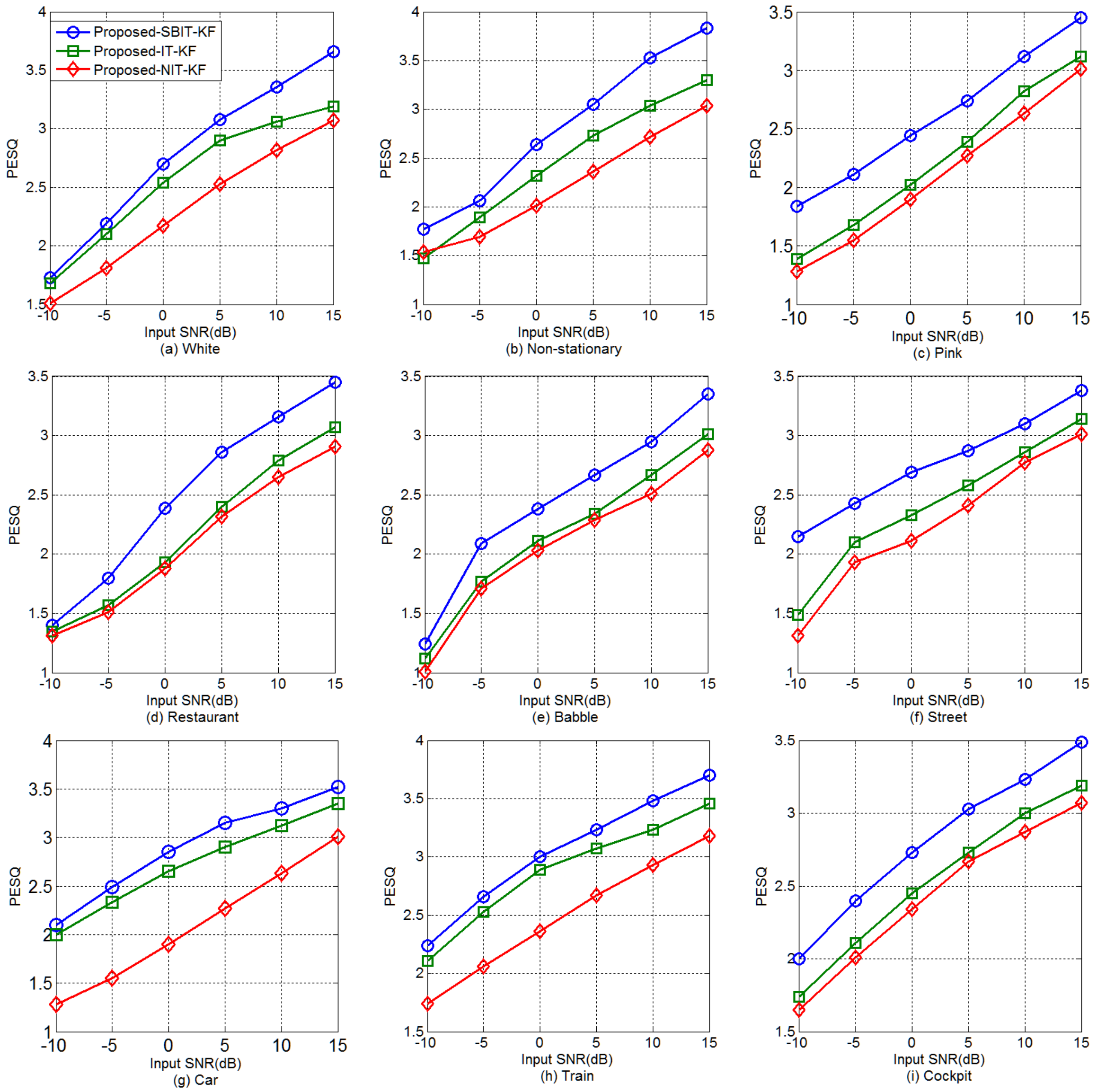


Figure 4.8: Performance comparison between the proposed methods in terms of segmental SNR (dB) for a wide range of input SNRs (-10dB to 15dB) in the presence of 9 types of noises.



(a) White

(b) Non-stationary

(c) Pink

(d) Restaurant

(e) Babble

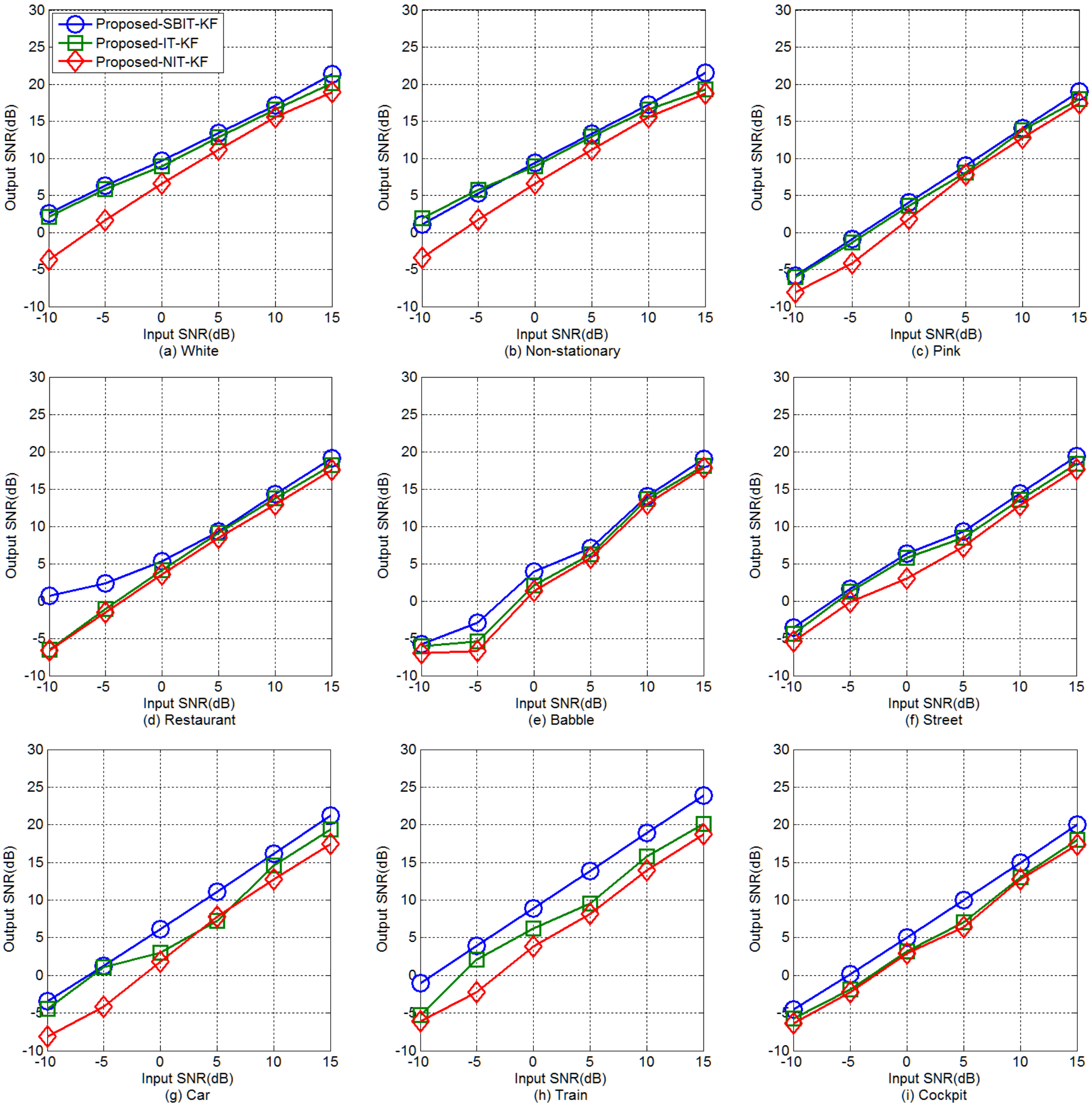
(f) Street

(g) Car

(h) Train

(i) Cockpit

Figure 4.9: Performance comparison between the proposed methods in terms of PESQ for a wide range of input SNRs (-10dB to 15dB) in the presence of 9 types of noises.



(a) White

(b) Non-stationary

(c) Pink

(d) Restaurant

(e) Babble

(f) Street

(g) Car

(h) Train

(i) Cockpit

Figure 4.10: Performance comparison between the proposed methods in terms of output SNR (dB) for a wide range of input SNRs (-10dB to 15dB) in the presence of 9 types of noises.

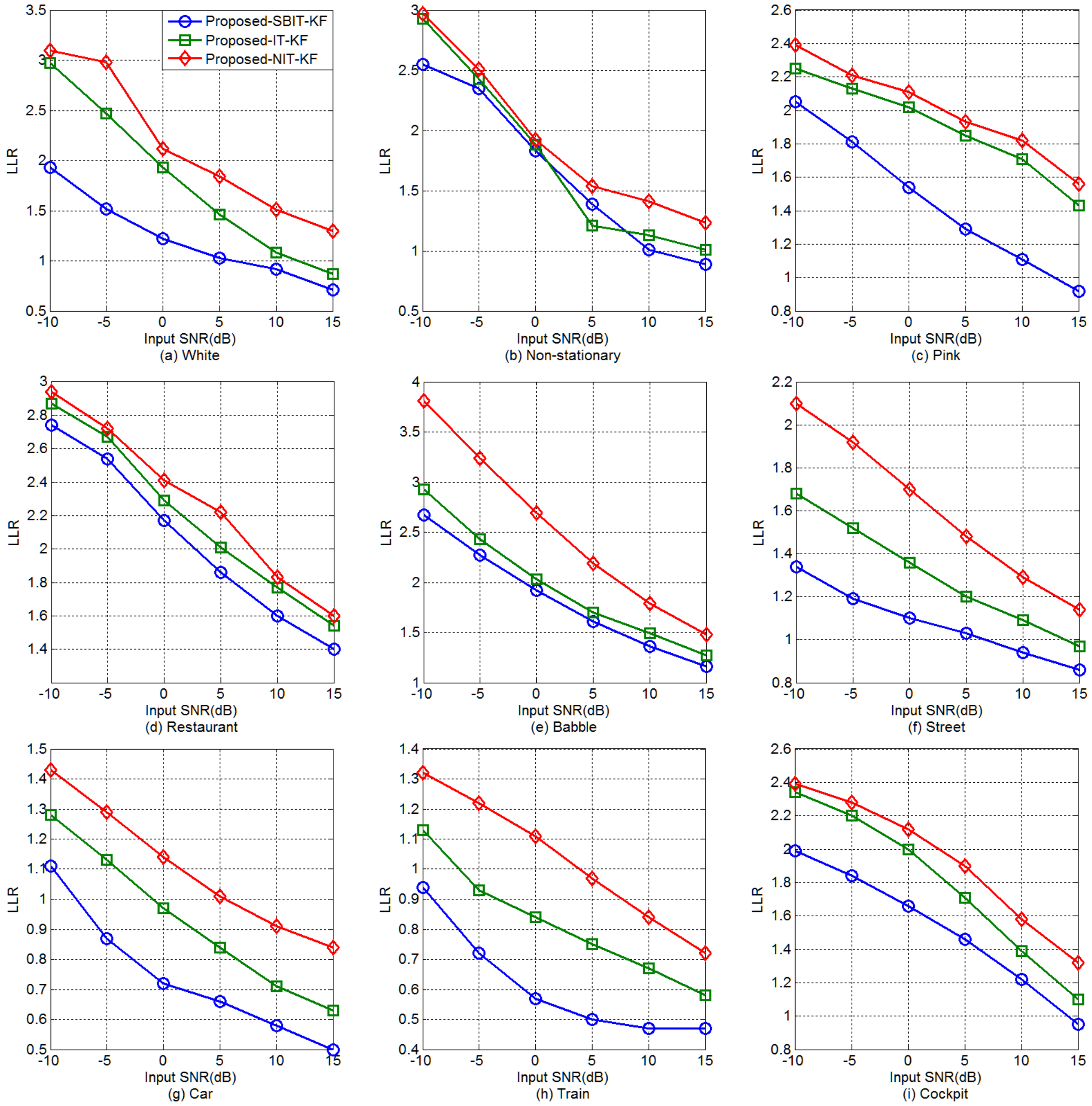


Figure 4.11: Performance comparison between the proposed methods in terms of LLR for a wide range of input SNRs (-10dB to 15dB) in the presence of 9 types of noises.

input SNR, the average PESQ for the sub-band iterative KF is greater than 3.5 for all experiments, while at -10dB input SNR, it is still greater than 2, which ensures a good quality of the enhanced speech. Although, the iterative KF provides better performance than non-iterative KF, it introduces a little bit residual noise in the enhanced speech. Therefore, the PESQ score of the iterative KF is relatively lower than the sub-band iterative KF. The non-iterative KF, on the other hand, provides relatively lower PESQ than the other two proposed methods, but it still performs well across all the 9 types of noises.

The output SNR (dB) comparison results among the proposed methods are presented in Figure 4.10, where as usual, the sub-band iterative KF provides better output SNR in the enhanced speech as compared to other two proposed methods. For example, at 15dB input SNR, the output SNR (dB) provided by the sub-band iterative KF is around 20dB, which is regarded as better competitive performance in terms of output SNR (dB) improvement. At low input SNR, say at -10dB, there we have also found noticeable output SNR(dB) improvement. The iterative KF also performs well across all input SNRs and of course not as good as the sub-band iterative KF. The output SNR (dB) results for the non-iterative KF is relatively lower than the other two proposed methods. However, it still works well across all noise experiments.

The LLR performance comparisons between the proposed methods are shown in Figure 4.11. It also measures the amount of distortion in the enhanced speech. As mentioned earlier, a lower LLR value indicates a lower speech distortion level, which ultimately preserves good quality in the enhanced speech. Again, the sub-band iterative KF provides the lowest LLR for all the experiments even at a low input SNR, which is followed by the iterative and non-iterative KF.

4.5 Computational Complexity

The computational complexity of the proposed algorithms depends on a couple of things, namely, the LPC order to be used, the number of iterations for the itarative Kalman filter to be converged and the level of input SNRs. Through extensive simulations, it is observed that the proposed iterative Kalman filter normally convereges after 3 iterations, while the sub-band iterative Kalman filter converges at the second iteration. The existing iterative Kalman filter methods, on the other hand, converges after 4-5 iterations. In order to fix the LPC order, an experiment is performed for different LPC order versus the CPU computational times and the PESQ results for each LPC order. For this experiment, 30 speech utterances are taken from TIMIT database. The experiment is performed in the presence of restaurant noise with 10dB input SNR. The simulation is conducted on a computer with Windows 7 (64-bit), 6GB RAM, Intel corei 7 processor having CPU speed of 2.40 GHz. The experimental results are shown in Figure 4.12.

From Figure 4.12, it is observed that, as the LPC order increases, a minor increase of PESQ results is found for the three proposed methods but the CPU computational time (sec) increases dramatically. Since the iterative KF converges after 3 iterations, the computational time for iterative KF is logically three times larger than the non-iterative KF as shown in Figure 4.12. For the same reason, the computational time for sub-band iterative KF is two times larger than non-iterative KF. However, considering the *trade off* between computational complexity and speech enhancement performance, we set the LPC order 8 in the overall simulation study.

It is important to note that, the computational time of the proposed methods for different levels of input SNR (-10dB to 15dB) varies slightly. In general, it is observed that the non-iterative KF takes less computational time followed by the sub-band iterative KF and then the iterative KF, respectively. However, the sub-band iterative KF performs better than the iterative and non-iterative KF based methods.

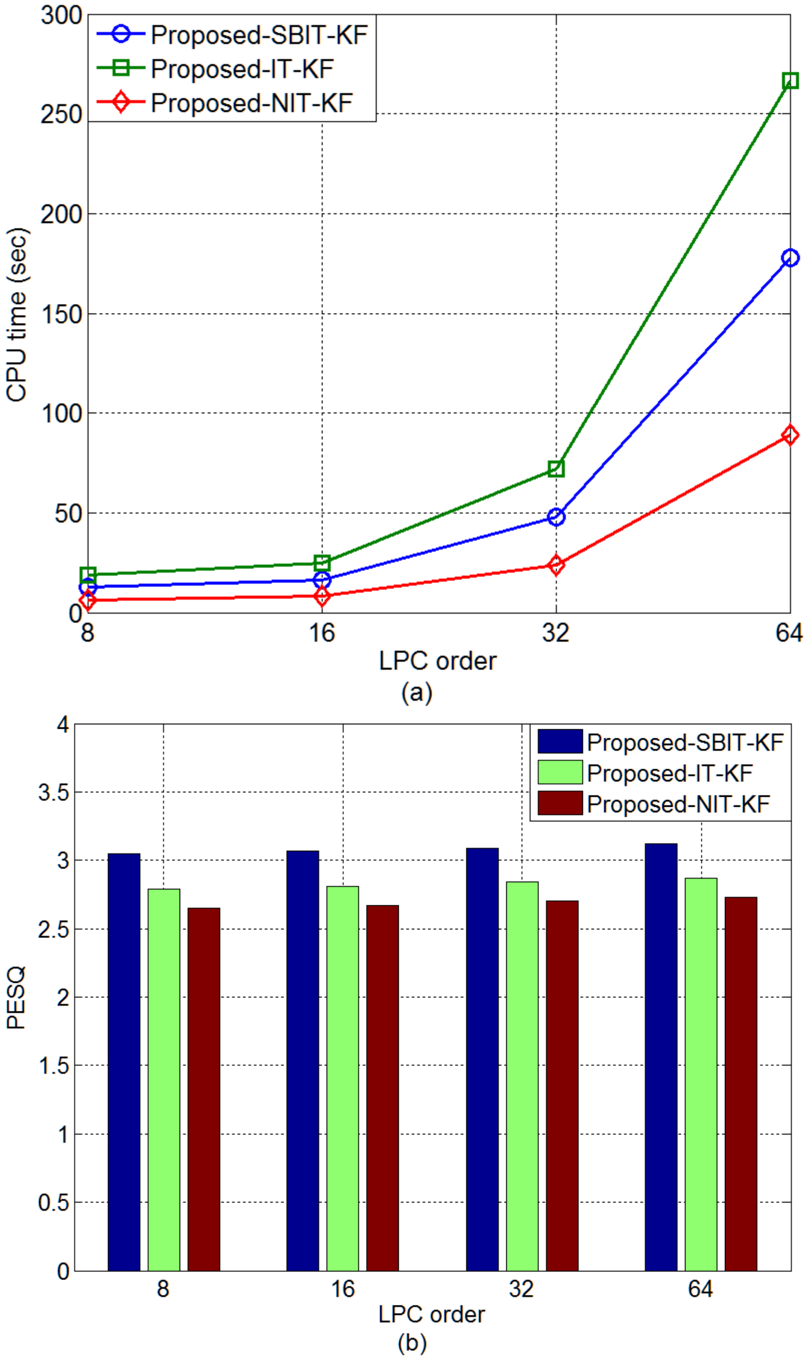


Figure 4.12: Computational complexity comparison of the proposed methods, (a): CPU time (sec) versus LPC order and (b): PESQ versus LPC order in the presence of restaurant noise (input SNR=10dB).

4.6 Conclusion

In this chapter, an extensive simulation study has been conducted for the evaluation of the proposed methods in the presence of 9 different types of noises for a wide range of input SNRs. The performances have been evaluated and compared with some of the existing methods in terms of four evaluation metrics. The experimental results reveal that the proposed methods provide very good performance in terms of all the performance metrics with the consumption of a resonable amount of CPU computational time. Through the extensive experimental results, it is also shown that the proposed methods perform much better for different environmental noises than the other existing competitive methods whose performances are limited to particular types of noises as mentioned in the literature. In addition, among the proposed methods, the sub-band iterative Kalman filter performs the best, followed by the iterative and non-iterative Kalman filter based methods, respectively, for all the noisy cases in terms of all the evaluation metrics.

Chapter 5

Conclusion

5.1 Summary of the Work

In this thesis, Kalman filter based single channel speech enhancement algorithms that are capable of dealing with adverse environmental noises have been investigated. The proposed algorithms have been implemented in non ideal cases, where the state-space model parameters of the Kalman filter, namely, the LPC and noise variance are estimated in noisy conditions without considering any *a priori* knowledge of the clean speech and the additive noise. In most of the existing Kalman filter based methods, however, the clean speech and noise information are assumed to be available for these parameter estimation. These prior assumptions make these algorithms impractical in the sense that in real speech enhancement scenarios, we can access only the noisy speech. In order to resolve these issues, new methods for LPC and noise variance estimation in noisy conditions have been proposed. Depending on these parameter estimation techniques, three Kalman filter based speech enhancement methods operating on a frame-by-frame basis have been developed.

First, in the non-iterative Kalman filter based method, the state-space model parameters, namely, LPCs and noise variance are estimated in noisy conditions. A combined speech smoothing and autocorrelation method has been proposed for LPC estimation. A new method based on a truncated Taylor series expansion of the noisy speech along with a difference operation serving as high-pass filtering is introduced for the noise variance estimation. It has been shown that the proposed non-iterative Kalman filter is implemented effectively with these estimated parameters.

Although the non-iterative Kalman filter performs relatively well, yet it introduces some residual noises and small distortions in the enhanced speech. In order to improve the speech enhancement performance as well as parameter estimation accuracy in noisy conditions, an iterative Kalman filter based method has been presented as the second approach. For each frame, at first, the state-space model parameters of the Kalman filter are estimated from the noisy speech. When the Kalman filtering iteration has gone through the entire frame, the LPCs and other state-space model parameters are re-estimated from the processed speech frame and the Kalman filter is applied again to the same processed frame for further enhancement. The iteration stops when the Kalman filter converges or when the preset maximum number of iterations is exhausted, giving further enhanced speech frame corresponding to the input noisy speech frame. The same procedure will repeat for the following frames until the end of all noisy frames being processed.

Although the enhanced speech provided by the iterative Kalman filter is free from residual noise that appear in the proposed non-iterative Kalman filter based method, some *musical-like* artifacts do remain in the enhanced speech. For further improving the speech enhancement results, a sub-band iterative Kalman filter has been proposed as the third approach. A wavelet filter-bank is first used to decompose the noisy speech into a number of sub-bands. To achieve the best trade-off among the noise reduction, speech intelligibility and computational complexity, a partial reconstruction scheme based on consecutive mean squared error (CMSE) is proposed to synthesize the LF and HF sub-bands such that the iterative Kalman filter is employed only to the partially reconstructed HF sub-band speech. Finally, the enhanced HF sub-band speech is combined with the partially reconstructed LF sub-band speech to reconstruct the full-band enhanced speech.

The proposed methods have been tested with two widely used speech databases, namely, TIMIT and NOIZEUS corpus, respectively. The experiments have been conducted in the presence of 9 types of noises for a wide range of input SNRs, where real-life speech conversations often take place. The performances are evaluated and compared against some state-of-the art speech enhancement methods. Through extensive simulations, it is clearly observed that the proposed methods are effective in noise reduction, while preserving a good quality in the enhanced speech than existing competitive methods. The computational time for the proposed methods is also resonable. In addition, the proposed methods can perform well in the presence of different environmental noises, while the performances of some existing methods are limited to specific types of noise. Among the proposed methods, the sub-band iterative Kalman filter performs the best, followed by the iterative and non-iterative Kalman filter in terms of the reported evaluation metrics.

5.2 Suggestions for Future Work

The proposed methods have been implemented for single channel speech enhancement, where one noisy mixture gives the overall spectral information of the degraded speech since there is only one microphone/channel available. In addition, the proposed thesis considers only the noise reduction, where the room dereverberation, and acoustic echo cancellation are not yet considered, which are also treated as the important environmental disturbance in the original acoustic environments. In order to capture the noisy mixtures including the reverberation, and acoustic echo more precisely, which exhibit some advantages in incorporating both the spatial and the spectral information, the multi microphone/channel experimental environment plays an important role. Therefore, the future direction of this research is to extend the proposed Kalman filter based methods such that they are capable of working in the multi channel/microphone environments, which is expected to reduce the additive noise, the room reverberation, and acoustic echo efficiently.

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