

# We are IntechOpen, the world's leading publisher of Open Access books Built by scientists, for scientists

5,000

Open access books available

125,000

International authors and editors

140M

Downloads

Our authors are among the

154

Countries delivered to

TOP 1%

most cited scientists

12.2%

Contributors from top 500 universities



WEB OF SCIENCE™

Selection of our books indexed in the Book Citation Index  
in Web of Science™ Core Collection (BKCI)

Interested in publishing with us?  
Contact [book.department@intechopen.com](mailto:book.department@intechopen.com)

Numbers displayed above are based on latest data collected.  
For more information visit [www.intechopen.com](http://www.intechopen.com)



# Speech Enhancement based on Iterative Wiener Filter using Complex LPC Speech Analysis

Keiichi Funaki  
*University of the Ryukyus  
Japan*

## 1. Introduction

In these days, the speech enhancement plays an important role to improve the performance of the speech coding or speech recognition since cellular phone or the car navigation system are being widely used more and more. These systems are often used in noisy environment. Therefore, the quality of speech coding or the performance of speech recognition is deteriorated due to the surrounding noise. In order to avoid the deterioration, technology that removes noise from the noisy speech viz., speech enhancement is strongly desired. Especially, speech enhancement is an important factor for speech coding to keep the quality even under noisy environment. 3GPP (The 3rd Generation Partnership Project) thus provides the minimum performance requirement and the evaluation procedure for AMR-NB [1]. Several speech enhancement methods such as [2] have already satisfied the requirement. Moreover, speech enhancement is being sincerely demanded for wide band speech coding such as [3] since the additive noise in wide band speech can be percept by human auditory system. Traditional approaches for speech enhancement have been proposed from the end of 1970's to 1980's [4][5][6]. Spectrum subtraction (SS) method [4] is widely adopted since it can be implemented easily and it can offer some degree of effect. However, the SS generates unpleasant artificial sound called musical noise so that it is not suitable for speech coding. In MMSE-STSA (Minimizing Mean Squared Error-Short Term Spectral Amplitude) method [5], under an assumption of Gaussian distribution of Fourier coefficient for speech, speech enhancement is realized by minimizing the mean squared error for Short Term Spectral Amplitude (STSA) spectrum. On the other hand, MAP (Maximum a Posterior) method [7] has been proposed, in which the parametric function that differs from that for the MMSE-STSA, is adopted as a criterion. Wiener filter method has been proposed by J.S.Lim [6], and the method designs the optimal filter minimizing the mean squared error (MSE) in the frequency domain. The musical noise is reduced by the Wiener filter method than the SS method. If accurate power spectrum for clean speech and accurate power spectrum of additive noise can be estimated, the Wiener filter can be designed accurately. However, the power spectrum of clean speech cannot be observed directly. Therefore, the iterative Wiener filter (IWF) method is adopted to estimate the power spectrum more accurately. First, the power spectrum for noise is estimated in silent segment of speech and the speech power spectrum is estimated by LPC analysis for noisy

speech. Next, the Wiener filter is designed by using the estimated two spectra and speech enhancement is carried out by filtering the noisy speech with the Wiener filter to obtain the enhanced speech. Next, LPC analysis is operated for the enhanced speech and the Wiener filter is designed again and the filter is operated for the noisy speech to obtain enhanced speech. These procedures are repeated to obtain more accurate speech power spectrum and to design more optimal Wiener filter. However, it is known that the spectrum of the enhanced speech is distorted after several iterations and the optimal number of iteration cannot be determined [8][9].

On the other hand, the complex LPC speech analysis methods have already been proposed for an analytic signal [10][11][12]. An analytic signal is a complex signal having an observed signal in real part and a Hilbert transformed signal for the observed signal in imaginary part. Since the analytic signal provides the spectrum only on positive frequencies, the signals can be decimated by a factor of 2 with no degradation. As a result, the complex speech analysis offers attractive features, for example, more accurate spectral estimation in low frequencies. The remarkable feature is feasible to design more appropriate Wiener filter in the IWF and it is expected that it can lead to higher performance of speech enhancement especially for the additive noise whose energy is concentrated in low frequencies, for example, babble noise or car internal noise.

In this paper, we propose an improved IWF method by adopting the MMSE based time-varying complex AR (TV-CAR) speech analysis [12] instead of LPC analysis. The TV-CAR speech analysis introduces the TV-CAR speech model, in which the AR model parameters are represented by complex basis expansion.

The remainder of this paper is organized as follows. We will explain the TV-CAR speech analysis in Section 2 and we will explain the iterative Wiener filter method and the proposed algorithm in Section 3. The benefit of complex speech analysis will be explained in Section 4. We will explain the experiments evaluating the performance for additive white Gaussian, pink, babble, or car internal noise in Section 5.

## 2. TV-CAR Speech Analysis

### 2.1 Analytic speech signal

Target signal of the time-varying complex AR (TV-CAR) method is an analytic signal that is complex-valued signal defined by

$$y^c(t) = \frac{y(2t) + j \cdot y_H(2t)}{\sqrt{2}} \quad (1)$$

where  $j = \sqrt{-1}$  and  $y^c(t)$ ,  $y(t)$ , and  $y_H(t)$  denote an analytic signal at time  $t$ , an observed signal at time  $t$ , and a Hilbert transformed signal for the observed signal, respectively. Since analytic signals provide the spectra only over the range of  $(0, \pi)$ , analytic signals can be decimated by a factor of two. The term of  $1/\sqrt{2}$  is multiplied in order to adjust the power of an analytic signal with that of the observed one. Note that superscript **c** denotes complex value in this paper.

## 2. 2 Time-Varying Complex AR (TV-CAR) model

Conventional LPC model is defined as

$$Y_{LPC}(z^{-1}) = \frac{1}{1 + \sum_{i=1}^I a_i z^{-i}} \quad (2)$$

where  $\{a_i\}$  and  $I$  are  $i$ -th order LPC coefficient and LPC order, respectively. Since the conventional LPC model cannot express the time-varying spectrum, LPC analysis cannot extract the time-varying spectral features from speech signal. In order to represent the time-varying features, the TV-CAR model employs a complex basis expansion shown as

$$a_i^c(t) = \sum_{l=0}^{L-1} g_{i,l}^c f_l^c(t) \quad (3)$$

where  $\{a_i^c(t)\}$ ,  $I$ ,  $L$ ,  $\{g_{i,l}^c\}$  and  $f_l^c(t)$  are taken to be  $i$ -th complex AR coefficient at time  $t$ , AR order, finite order of complex basis expansion, complex parameter, and a complex-valued basis function, respectively. By substituting Eq.(3) into Eq.(2), one can obtain the following transfer function.

$$Y_{TVCAR}(z^{-1}) = \frac{1}{1 + \sum_{i=1}^I \sum_{l=0}^{L-1} g_{i,l}^c f_l^c(t) z^{-i}} \quad (4)$$

The input-output relation is defined as

$$y^c(t) = - \sum_{i=1}^I a_i^c(t) y^c(t-i) + u^c(t) = - \sum_{i=1}^I \sum_{l=0}^{L-1} g_{i,l}^c f_l^c(t) y^c(t-i) + u^c(t) \quad (5)$$

where  $u^c(t)$  and  $y^c(t)$  are taken to be complex-valued input and analytic speech signal, respectively. In the TV-CAR model, the complex AR coefficient is modelled by a finite number of arbitrary complex basis expansion. Note that Eq.(3) parameterizes the AR coefficient trajectories that continuously change as a function of time so that the time-varying analysis is feasible to estimate continuous time-varying speech spectrum. In addition, as mentioned above, the complex-valued analysis facilitates accurate spectral estimation in the low frequencies, as a result, the TV-CAR analysis allows for more accurate spectral estimation in low Frequencies. Since more optimal Wiener filter can be designed, it assigns better performance on speech enhancement.

Eq.(5) can be represented by vector-matrix notation as

$$\begin{aligned}
 \bar{y}_f &= -\bar{\Phi}_f \bar{\theta} + \bar{u}_f \\
 \bar{\theta} &= [\bar{g}_0, \bar{g}_1, \dots, \bar{g}_l, \dots, \bar{g}_{L-1}] \\
 \bar{g}_l &= [g_{1,l}^c, g_{2,l}^c, \dots, g_{i,l}^c, \dots, g_{l,l}^c] \\
 \bar{y}_f &= [y^c(I), y^c(I+1), y^c(I+2), \dots, y^c(N-1)] \\
 \bar{u}_f &= [u^c(I), u^c(I+1), u^c(I+2), \dots, u^c(N-1)] \\
 \bar{\Phi}_f &= [\bar{D}_0^f, \bar{D}_1^f, \dots, \bar{D}_l^f, \dots, \bar{D}_{L-1}^f] \\
 \bar{D}_l^f &= [\bar{d}_{1,l}^f, \dots, \bar{d}_{i,l}^f, \dots, \bar{d}_{l,l}^f] \\
 \bar{d}_{i,l}^f &= [y^c(I-i)f_l^c(I), y^c(I+1-i)f_l^c(I+1), \dots, y^c(N-1-i)f_l^c(N-1)]^T
 \end{aligned} \tag{6}$$

where  $N$  is analysis interval,  $\bar{y}_f$  is  $(N-1,1)$  column vector containing analytic speech signal,  $\bar{\theta}$  is  $(L,1)$  column vector containing complex parameters,  $\bar{\Phi}_f$  is  $(N-1, L)$  matrix containing weighted analytic speech signal by the complex basis. Superscript  $T$  denotes transposition.

### 2.3 MMSE-based algorithm [12]

Fig.1 shows the block diagram of MMSE estimation. In the estimation, parameters are estimated so as to minimize the mean-square-error of equation error, or residual. MSE criterion is defined as

$$\bar{r}_f = [r^c(I), r^c(I+1), \dots, r^c(N-1)]^T = \bar{y}_f + \bar{\Phi}_f \bar{\theta} \tag{7}$$

$$r^c(t) = y^c(t) + \sum_{i=1}^l \sum_{l=0}^{L-1} \hat{g}_{i,l}^c f_l^c(t) y^c(t-i) \tag{8}$$

$$E = \bar{r}_f^H \bar{r}_f = (\bar{y}_f + \bar{\Phi}_f \bar{\theta})^H (\bar{y}_f + \bar{\Phi}_f \bar{\theta}) \tag{9}$$

where  $\{\hat{g}_{i,l}^c\}$  is the estimated complex parameter,  $r^c(t)$  is an equation error, or complex AR residual and  $E$  is Mean Squared Error (MSE) for the equation error. To obtain optimal complex AR coefficients, we minimize the MSE criterion. Minimizing the MSE criterion of Eq.(9) with respect to the complex parameter leads to the following MMSE algorithm.

$$(\bar{\Phi}_f^H \bar{\Phi}_f) \hat{\theta} = -\bar{\Phi}_f^H \bar{y}_f \tag{10}$$

Superscript  $H$  denotes Hermitian transposition. After solving the linear equation of Eq.(10), we can get the complex AR parameter at time  $t$ ,  $\hat{a}^c(t)$ , by calculating the Eq.(3) with the estimated complex parameter,  $\{\hat{g}_{i,l}^c\}$ .

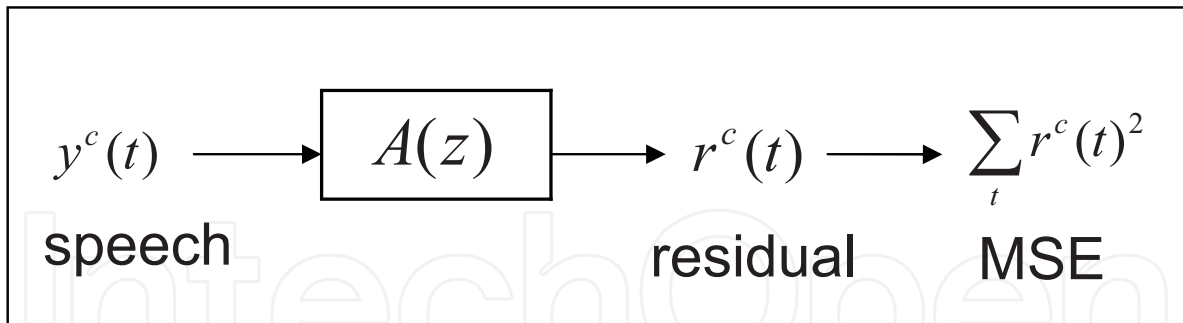


Fig. 1. Block diagram of MMSE estimation

### 3. Wiener Filter Algorithm

#### 3.1 Wiener filter

Assuming that the clean speech,  $s(t)$ , degraded by an additive noise,  $w(t)$ , the noisy speech,  $x(t)$ , is defined by

$$x(t) = s(t) + w(t) \quad (11)$$

Wiener filter is an optimal filter that minimizes the Mean Squared Error (MSE) criterion. In the case of Eq.(11), the filter can be defined by

$$S(\omega) = H(\omega)X(\omega) \quad (12)$$

where  $\omega$  is the frequency index,  $S(\omega), X(\omega), H(\omega)$  are the discrete Fourier transform of the clean speech, that of noisy speech and that of Wiener filter, respectively. The MSE can be defined as follows. The error is defined as

$$E(\omega) = S(\omega) - \hat{S}(\omega) = S(\omega) - H(\omega)X(\omega) \quad (13)$$

The Mean-Square-Error of Eq(11) is defined by

$$E[|E(\omega)|^2] = E[|S(\omega) - H(\omega)X(\omega)|^2] \quad (14)$$

where  $E[\bullet]$  stands for an expectation operator. By minimizing the MSE, the Wiener filter  $H(\omega)$  can be estimated

$$\frac{\partial E[|E(\omega)|^2]}{\partial H(\omega)} = 2H(\omega)E[|X(\omega)|^2] - 2E[X(\omega)S^*(\omega)] = 2H(\omega)P_{XX}(\omega) - 2P_{XS}(\omega) = 0 \quad (15)$$

where  $P_{XX}(\omega), P_{XS}(\omega)$  are the power spectrum of noisy speech and cross power spectrum between noisy speech and clean speech, respectively. If there is no correlation between the speech signal  $s(t)$  and additive noise  $w(t)$ , the power spectrum of the noisy speech and the cross power spectrum can be transformed as follows.

$$\begin{aligned} P_{XX}(\omega) &= E[|X(\omega)|^2] = E[|S(\omega)|^2] + E[|2S(\omega)W(\omega)|] + E[|W(\omega)|^2] \\ &= E[|S(\omega)|^2] + E[|W(\omega)|^2] = P_{SS}(\omega) + P_{WW}(\omega) \end{aligned} \quad (16)$$

$$P_{XS}(\omega) = E[(S(\omega) + W(\omega))S^*(\omega)] = E[|S(\omega)|^2] = P_{SS}(\omega)$$

Consequently, the Wiener filter can be derived as follows.

$$H(\omega) = \frac{P_{ss}(\omega)}{P_{ss}(\omega) + P_{ww}(\omega)} \quad (17)$$

From Eq.(12) and (15), the enhanced speech is estimated in the frequency domain by

$$S(\omega) = \frac{P_{ss}(\omega)}{P_{ss}(\omega) + P_{ww}(\omega)} X(\omega) \quad (18)$$

and then inverse FFT is operated to obtain enhanced speech as:

$$s(t) = IFFT(S(\omega)) \quad (19)$$

Finally, the OLA (OverLap Add) procedure is carried out in the time domain between adjacent frames to avoid click sound.

### 3.2 Iterative Wiener Filter (IWF) algorithm [8][9]

The performance of the Wiener filter depends on the accuracy of speech power spectral estimation,  $P_{ss}(\omega)$ . It is possible to make the estimated spectrum close to the true one by repeating the Wiener filter processing. Fig.2 shows the block diagram of the iterative Wiener filter algorithm. The two kinds of power spectra can be estimated by LPC analysis as follows. Noise power spectrum,  $P_{ww}(\omega)$ , are estimated in the first non-speech segment. Speech power spectrum,  $P_{ss}(\omega)$ , is estimated by LPC analysis for input noisy speech,  $x(t)$ . By the Wiener filtering in the frequency domain and Inverse FFT operation, enhanced speech is estimated and then it is analyzed in order to estimate more accurate speech power spectrum,  $P_{ss}(\omega)$ , by means of LPC analysis and the Wiener filter is operated again. The iterative procedure is repeated to obtain more clean speech.

### 3.3 Proposed Method

The block diagram of the proposed method is shown in Fig.3. The proposed method employs the estimated two spectra,  $P_{ss}(\omega)$  and  $P_{ww}(\omega)$ , estimated by the TV-CAR speech analysis [12] instead of LPC analysis. The two spectra can be estimated as

$$P_{ss}(\omega) = \frac{G_s^2}{|1 + \sum_{i=1}^I \sum_{l=0}^{L-1} \hat{g}_{si,l}^c f_l^c(t) e^{-ji\omega}|^2}$$

$$P_{ww}(\omega) = \frac{G_w^2}{|1 + \sum_{i=1}^I \sum_{l=0}^{L-1} \hat{g}_{wi,l}^c f_l^c(t) e^{-ji\omega}|^2} \quad (20)$$

$\{\hat{g}_{si,l}^c\}$  is estimated by Eq.(10) from analytic speech for the enhanced speech at previous iteration (input speech at first iteration) and  $G_s$  is energy of the corresponding residual.

$\{\hat{g}_{wi,l}^c\}$  is estimated by Eq.(10) from analytic speech for the input speech in first silent

segment and  $G_w$  is energy of the corresponding residual. Note that these two power spectra provide only one side of spectrum, thus, mirroring is operated to apply to Eq.(17) .

As mentioned above, complex speech analysis can estimate more accurate speech spectrum in low frequencies. It is expected that the feature leads to higher performance of the IWF algorithm. In this paper, time-invariant complex speech analysis (L=1), is equivalent to complex LPC analysis, is adopted.

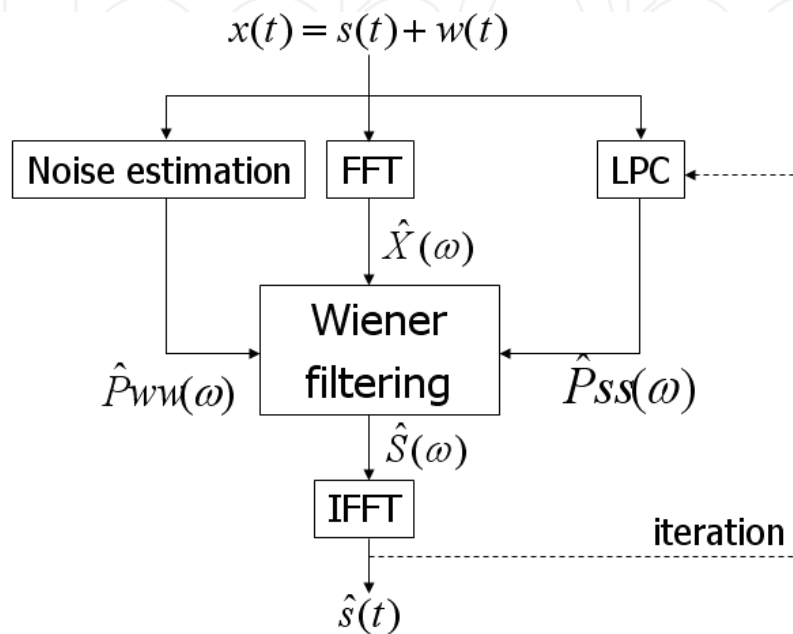


Fig. 2. Block diagram of the IWF algorithm

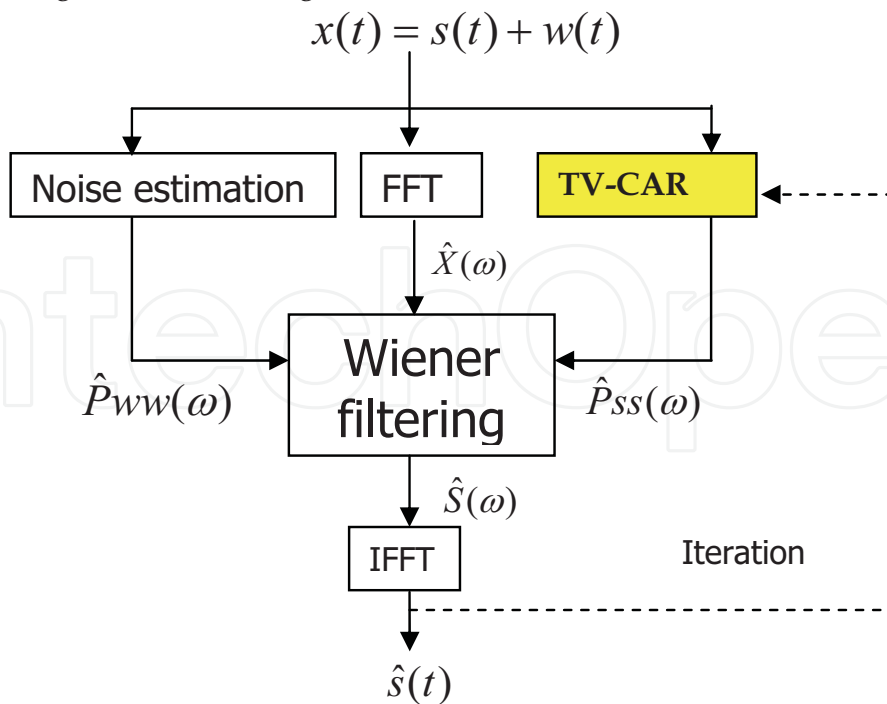


Fig. 3. Block diagram of the proposed IWF algorithm



#### 4. Benefit of Complex Speech Analysis

Fig.4 shows example of the estimated speech spectra of natural Japanese vowel /o/ for analytic signal by complex LPC [11] and conventional LPC analysis for speech signal.

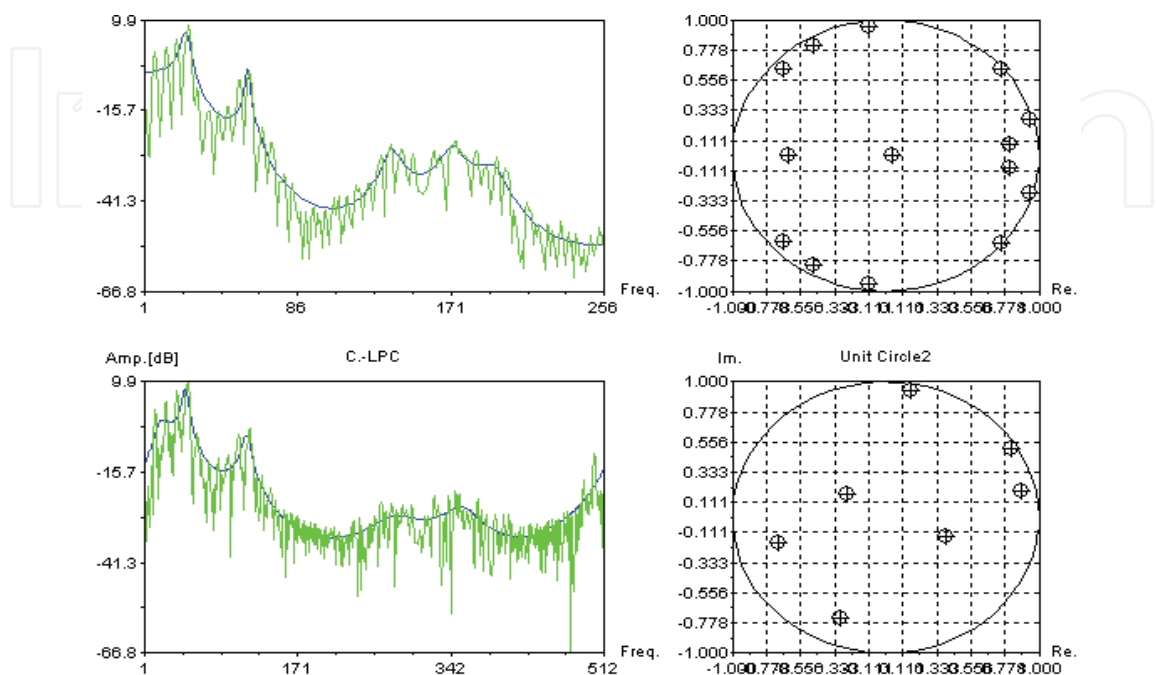


Fig. 4. Estimated Spectra of vowel /o/ with complex and conventional LPC analysis

In Fig.4, left side denote the estimated spectra. Upper is for real-valued LPC analysis. Lower is for complex-valued LPC analysis. Blue line means estimated spectrum by LPC analysis and green line means estimated DFT spectrum. Right side means estimated poles from the estimated AR filter. Fig.5 and 6 show the estimated running spectrum for clean natural speech /arayu/ and for the speech corrupted by white Gaussian (10[dB]), respectively. In Fig.5 and 6, (1) means speech waveform, (2),(3),(4),(5) and (6) mean the estimated spectrum by auto-correlation LPC speech analysis, by time-varying complex AR (TV-CAR) speech analysis ( $L=2$ ), by time-invariant complex AR (CAR) speech analysis ( $L=1$ ), by time-varying real AR (TV-RAR) speech analysis ( $L=2$ ), and by time-invariant real AR (RAR) speech analysis ( $L=1$ ), respectively. Analysis order  $I$  is 14 for real analysis and 7 for complex analysis. Basis function is 1<sup>st</sup> order polynomial function (1,t).

One can observe that the complex analysis can estimate more accurate spectrum in low frequencies whereas the estimation accuracy is down in high frequencies. Since speech spectrum provides much energy in low frequencies, it is expected that the high spectral estimation accuracy in low frequencies makes it possible to improve the performance on the IWF.

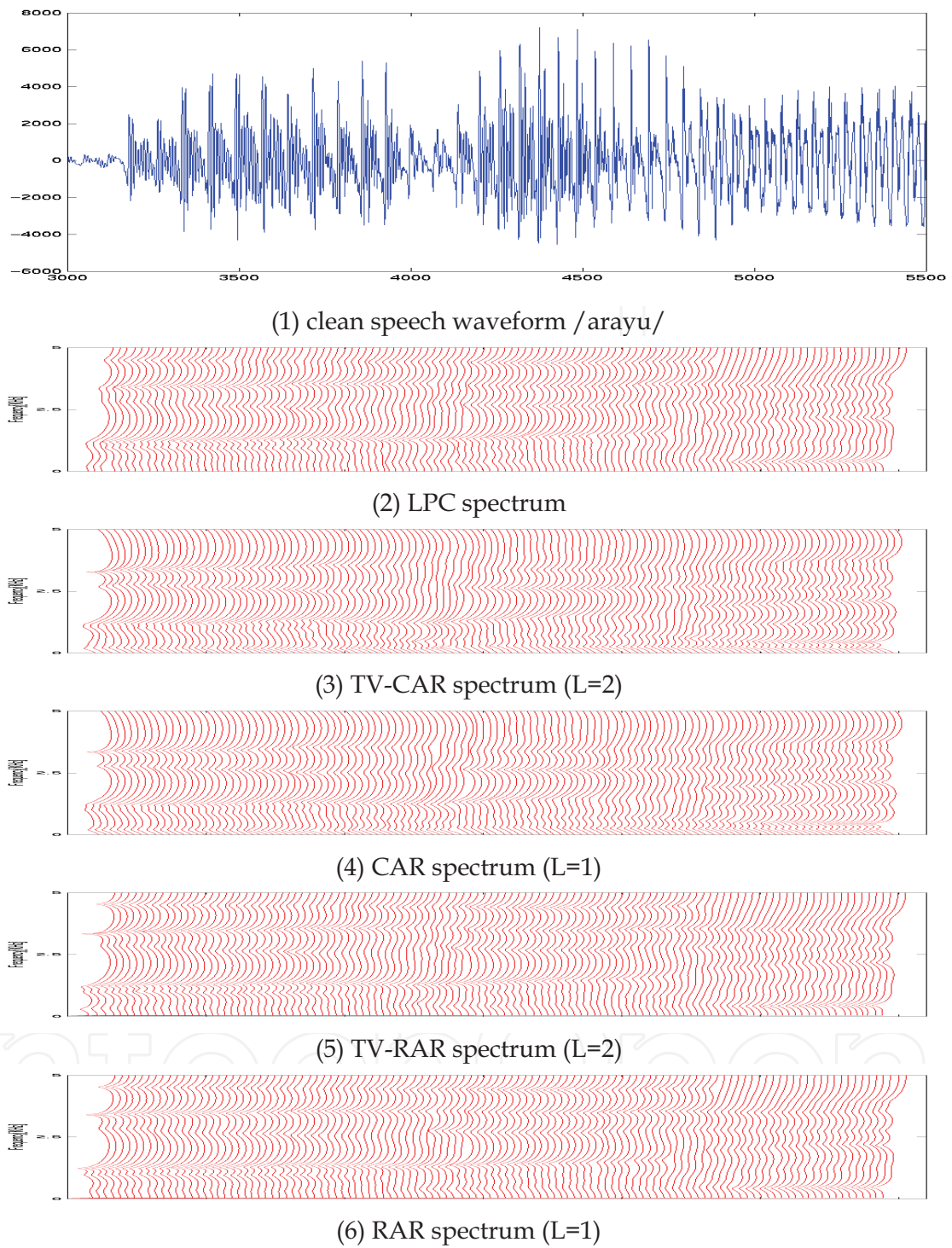
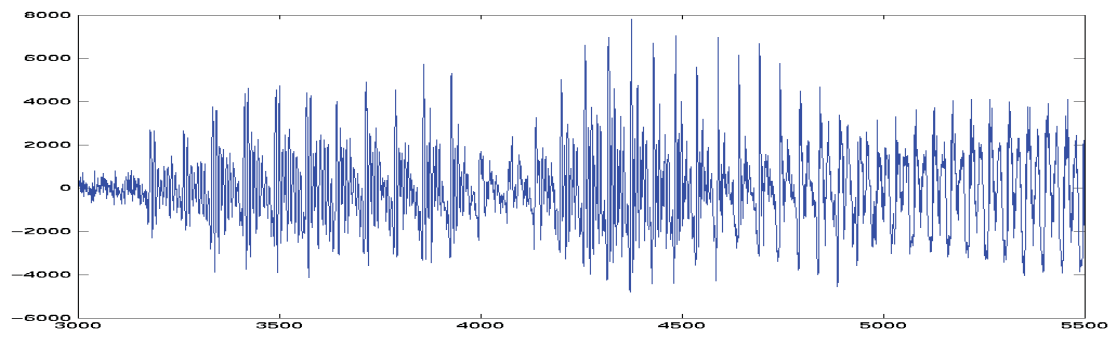
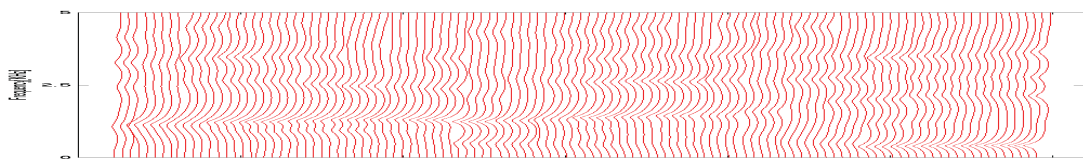


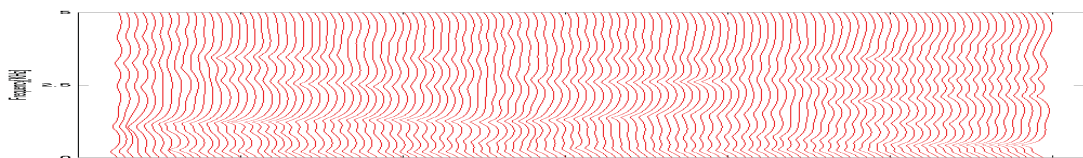
Fig. 5. Estimated spectrum for clean speech /aryu/



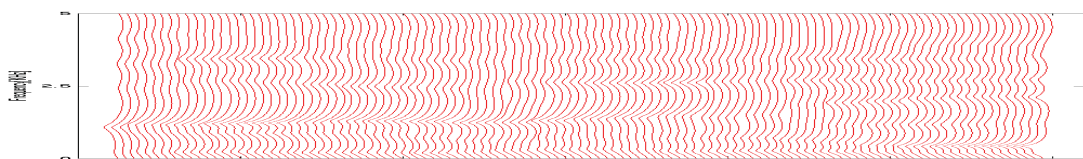
(1) clean speech waveform /arayu/



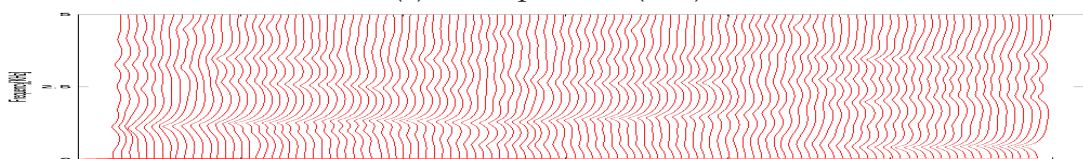
(2) LPC spectrum



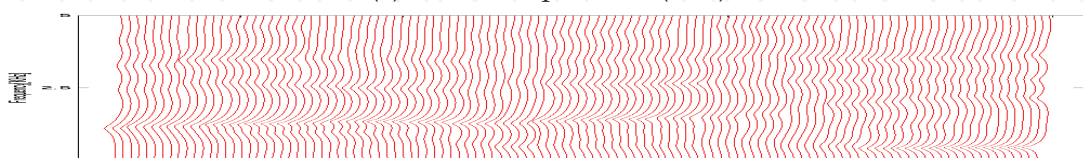
(3) TV-CAR spectrum (L=2)



(4) CAR spectrum (L=1)



(5) TV-RAR spectrum (L=2)



(6) RAR spectrum (L=1)

Fig. 6. Estimated spectrum for noise corrupted speech /arayu/ (10[dB])

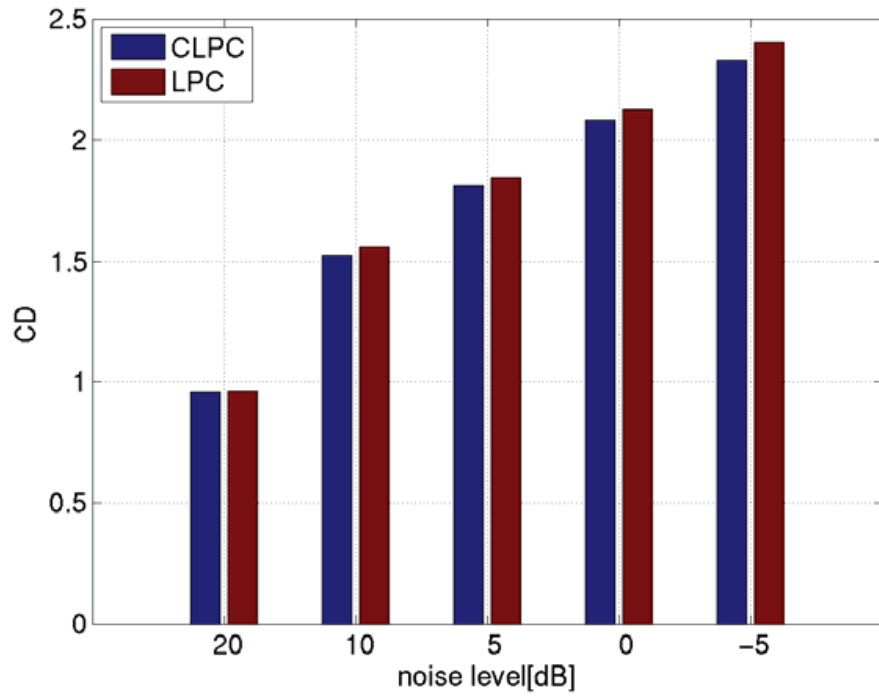
## 5. Experiments

We have already carried out the experiments to compare the performance of the proposed method (TV-CAR) for analytic speech with that for the conventional one (LPC method) for observed speech by means of objective evaluation of LPC Cepstral distance (CD). Since the IWF is based on filtering in the frequency domain, spectral distance such as LPC cepstral distance is appropriate measure for objective evaluation. Table 1 shows the experimental conditions. Sampling rates were 16KHz or 8KHz. Additive noises were white Gauss noise, pink noise, babble noise or car internal noise [13]. Noise levels were -5, 0, 5, 10 or 20[dB]. In the TV-CAR speech analysis,  $L$  is set to be one, thus the TV-CAR speech analysis is equivalent to non-time varying, complex LPC analysis. Figures 7 and 8 show the experimental results. Fig.7 means the results for 8 KHz of speech. Fig.8 means the results for 16 KHz of speech. In these figures, (1),(2),(3) and (4) means CDs for additive white Gauss noise, those for additive pink noise, those for additive babble noise, and those for additive car internal noise, respectively.

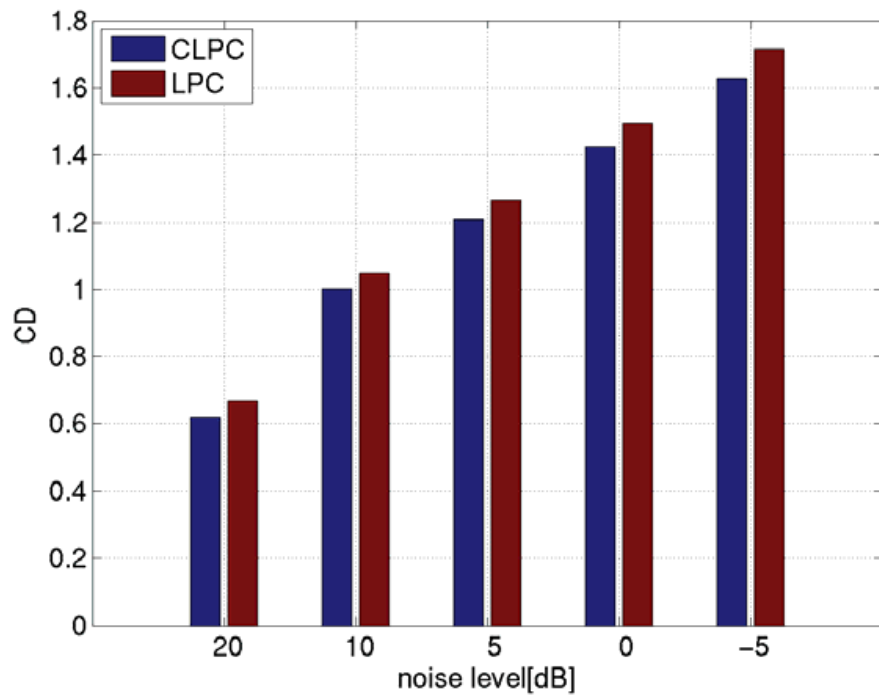
In these figures, X-axis means noise level (20, 10, 5, 0, -5 [dB]) and Y-axis means CD. **LPC** denotes the CDs by means of the conventional method based on LPC analysis. **CLPC** denotes the CDs by means of the proposed method based on complex LPC analysis. The results demonstrate that the proposed method can perform better than the conventional one for additive pink, babble or car internal noise whereas the proposed method does not perform better for additive white Gauss noise. The reason why the proposed method can perform better for additive pink, babble or car internal noise is as follows. The complex speech analysis can estimate more accurate speech spectrum in low frequencies for these noises whose energy is concentrated in low frequencies.

Speech data	Male 10 sentences Female 10 sentences ATR database set B
Sampling	8KHz/16bit 16KHz/16bit
Window Length/ Shift Length	20ms/10ms
FFT	1024 samples
LPC analysis	I=14, L=1(time-invariant)
Pre-emphasis	None
Complex LPC analysis	I=7, L=1(time-invariant)
Noise	(1) White Gauss noise (2) Pink noise [13] (3) Babble noise [13] (4) Car internal noise [13]
Noise Level	20,10,5,0,-5[dB]
Cepstral Distance (CD) Window Length/ Shift Length LPC order Cepstral order	LPC Cepstral Distance 20[msec]/ 20[msec] 16 for 8KHz, 32 for 16KHz 16 for 8KHz, 32 for 16KHz

Table 1. Experimental Conditions

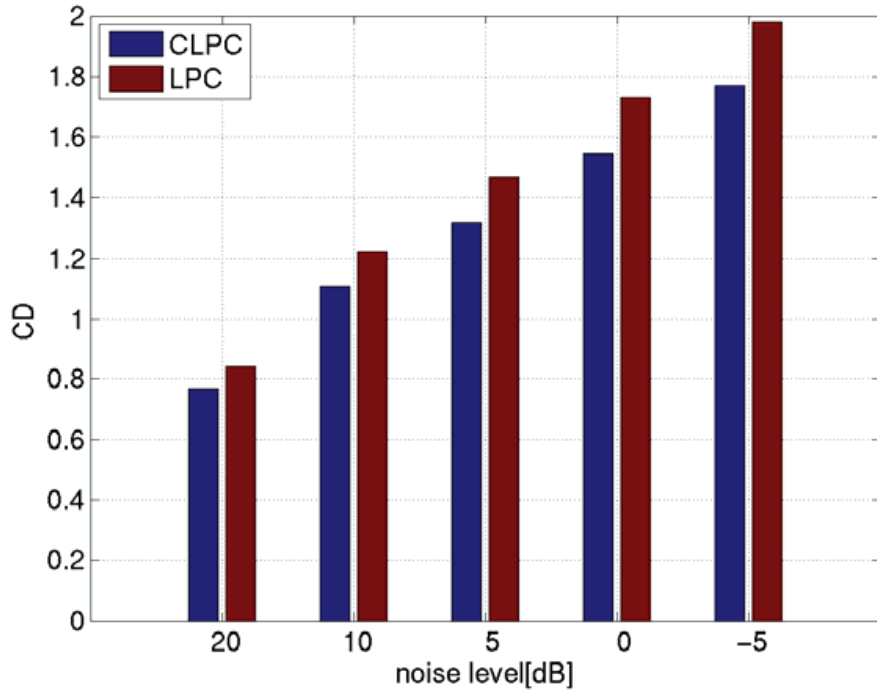


(1) CDs for additive white Gauss noise (8KHz)

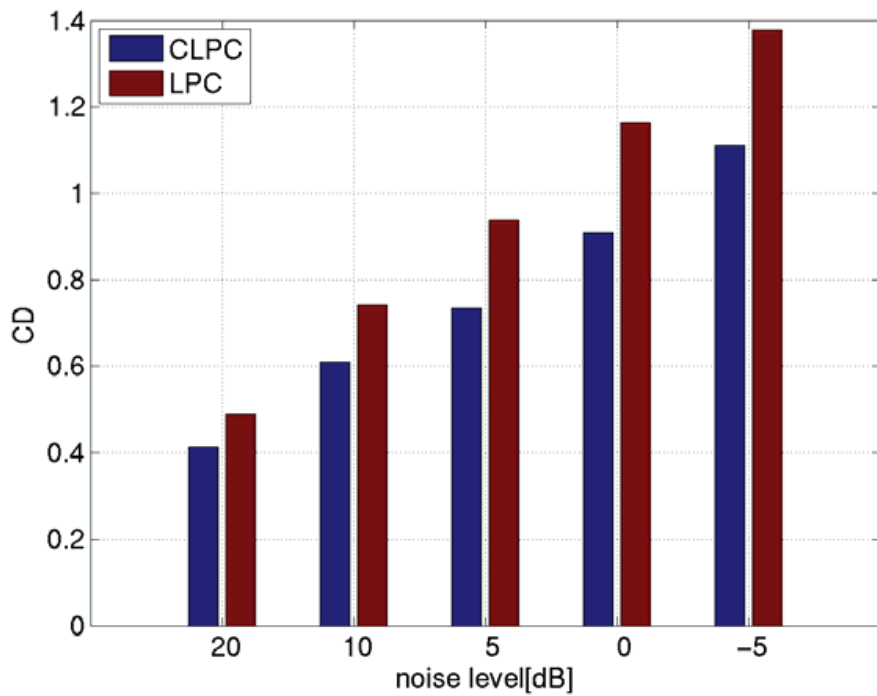


(2) CDs for additive Pink noise (8KHz)

Fig. 7. CDs for 8KHz speech

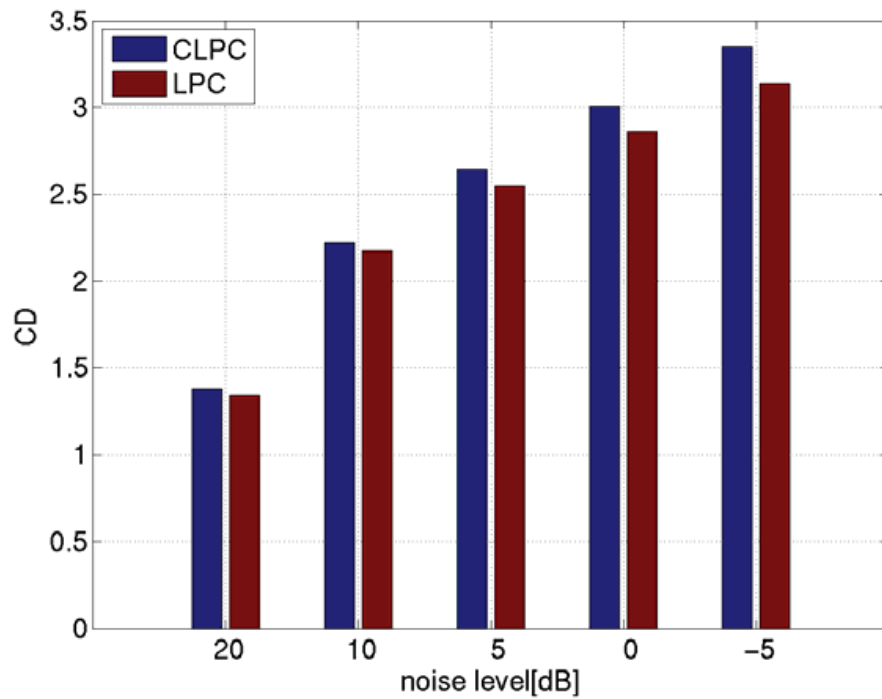


(3) CDs for additive Babble noise (8KHz)

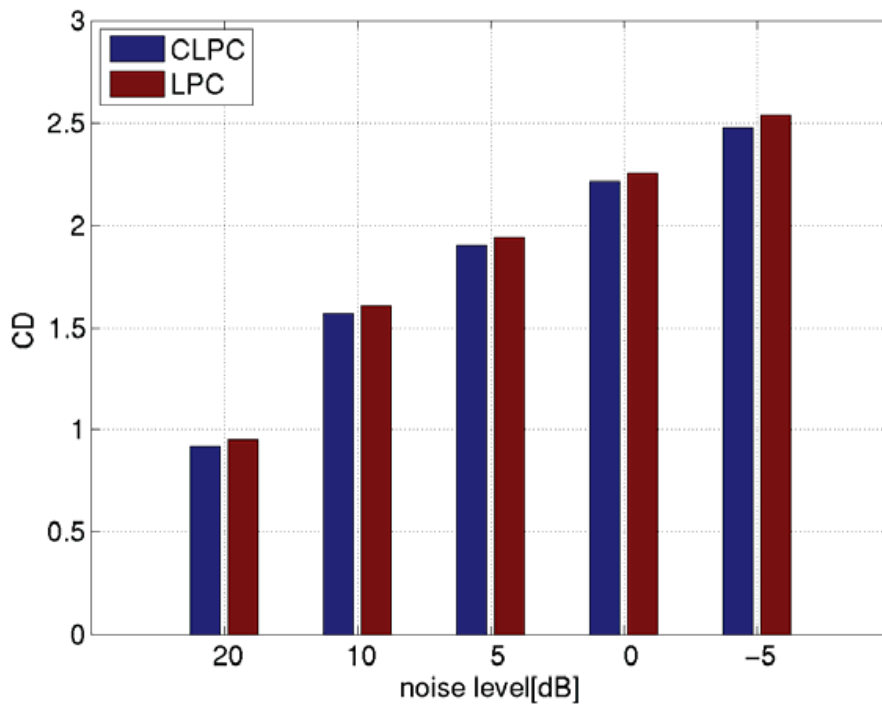


(4) CDs for additive Car Internal noise (8KHz)

Fig. 7. CDs for 8KHz speech

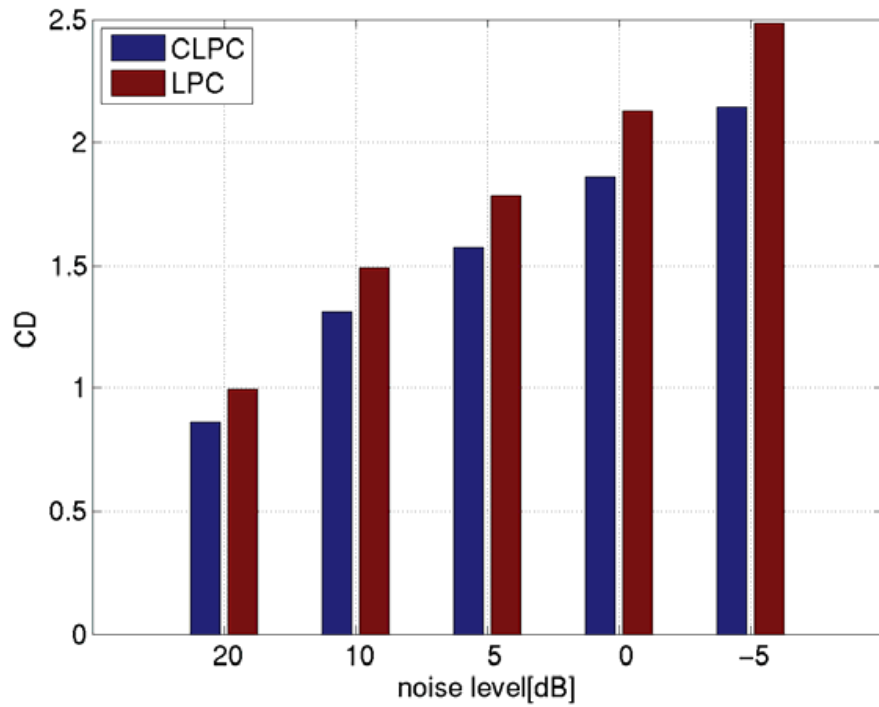


(1) CDs for additive white Gauss noise (16KHz)

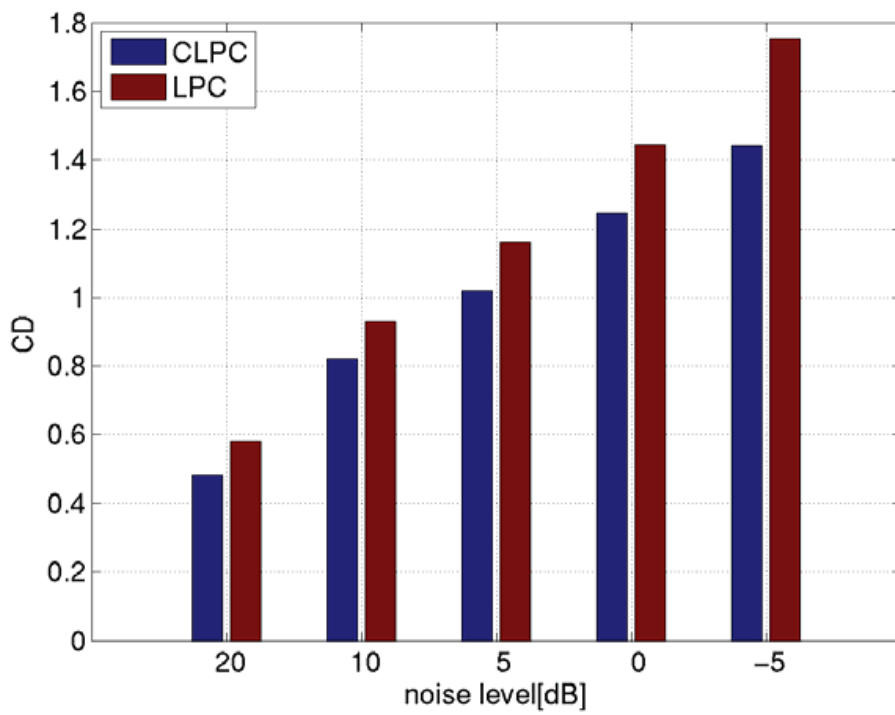


(2) CDs for additive Pink noise (16KHz)

Fig. 8. CDs for 16KHz speech



(3) CDs for additive Babble noise (16KHz)



(4) CDs for additive Car Internal noise (16KHz)

Fig. 8. CDs for 16KHz speech



## 6. Conclusions

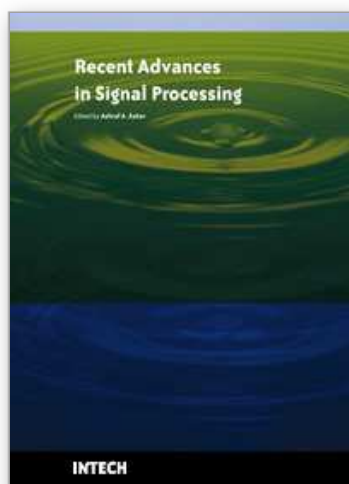
In this paper, we have proposed the improved iterative Wiener filter (IWF) algorithm based on the TV-CAR speech analysis in a single channel system. The performance has already been evaluated by means of LPC cepstral distance (CD) not only for 8KHz but also for 16KHz sampled speech signal corrupted by additive white Gauss, pink, babble or car internal noise. According to an informal listening test and objective evaluation of CD, the proposed method outperforms conventional IWF for additive pink, babble or car internal noise that contains much energy in low frequencies.

Future study is as follows.

- (1) Improve the noise estimation
- (2) Introduce robust TV-CAR speech analysis based on ELS method [14]
- (3) Introduce the time-varying speech analysis ( $L=2$ ).
- (4) Introduce complex-valued Wiener filter.

## 7. References

- [1] "Minimum Performance Requirements for Noise Suppressor Application to the AMR Speech Encoder," 3GPP TS 06.77 V8.1.1, Apr. 2001.
- [2] M.Kato, et.al., "Noise Suppression with High Speech Quality Based on Weighted Noise Estimation and MMSE STSA," IEICE Trans. Vol.E85-A. No.7, July 2002.
- [3] ITU-T Recommendation G.722.2, "Wideband coding of speech at around 16 kbit/s using Adaptive Multi-Rate Wideband (AMR-WB)," Jul., 2003.
- [4] S.F.Boll, "Suppression of acoustic noise in speech using spectral subtraction," IEEE Trans., ASSP-27, pp.113-120, 1979.
- [5] Y.Ephraim and D.Malah, "Speech enhancement using minimum mean-square error log-spectral amplitude estimator," IEEE Trans., ASSP-33, pp.443-445, 1985.
- [6] J.S.Lim and A.V.Oppenheim, "All-pole modeling of degraded speech," IEEE Trans., ASSP-26, pp.197-210, 1978.
- [7] T.Lotter, et.al., "Speech enhancement by MAP spectral amplitude estimation using a super-gaussian speech model," EURASIP Journal on Applied Signal Processing, pp.1110-1126, Jul. 2005.
- [8] H.L.Hansen and M.A.Clements, "Constrained iterative speech enhancement with application to speech recognition," IEEE Trans. Signal Processing, vol.39, pp.795-805, April 1991.
- [9] P.C.Loizou, "Speech Enhancement, Theory and Practice," CRC Press, 2007.
- [10] S.M.Kay, "Maximum entropy spectral estimation using the analytic signal," IEEE Trans. ASSP-26, pp.467-469, 1980.
- [11] T.Shimamura and S.Takahashi, "Complex linear prediction method based on positive frequency domain," IEICE Trans., Vol.J72-A, pp.1755-1763, 1989. (in Japanese)
- [12] K.Funaki, et.al., "On a time-varying complex speech analysis," Proc. EUSIPCO-98, Rhodes, Greece, Sep. 1998.
- [13] NOISE-X92, [http://spib.rice.edu/spib/select\\_noise.html](http://spib.rice.edu/spib/select_noise.html)
- [14] K.Funaki, "A time-varying complex AR speech analysis based on GLS and ELS method," Proc. EUROSPEECH-2001, Alborg, Denmark, Sep. 2001.



## **Recent Advances in Signal Processing**

Edited by Ashraf A Zaher

ISBN 978-953-307-002-5

Hard cover, 544 pages

**Publisher** InTech

**Published online** 01, November, 2009

**Published in print edition** November, 2009

The signal processing task is a very critical issue in the majority of new technological inventions and challenges in a variety of applications in both science and engineering fields. Classical signal processing techniques have largely worked with mathematical models that are linear, local, stationary, and Gaussian. They have always favored closed-form tractability over real-world accuracy. These constraints were imposed by the lack of powerful computing tools. During the last few decades, signal processing theories, developments, and applications have matured rapidly and now include tools from many areas of mathematics, computer science, physics, and engineering. This book is targeted primarily toward both students and researchers who want to be exposed to a wide variety of signal processing techniques and algorithms. It includes 27 chapters that can be categorized into five different areas depending on the application at hand. These five categories are ordered to address image processing, speech processing, communication systems, time-series analysis, and educational packages respectively. The book has the advantage of providing a collection of applications that are completely independent and self-contained; thus, the interested reader can choose any chapter and skip to another without losing continuity.

### **How to reference**

In order to correctly reference this scholarly work, feel free to copy and paste the following:

Keiichi Funaki (2009). Speech Enhancement Based on Iterative Wiener Filter Using Complex LPC Speech Analysis, *Recent Advances in Signal Processing*, Ashraf A Zaher (Ed.), ISBN: 978-953-307-002-5, InTech, Available from: <http://www.intechopen.com/books/recent-advances-in-signal-processing/speech-enhancement-based-on-iterative-wiener-filter-using-complex-lpc-speech-analysis>

**INTECH**  
open science | open minds

### **InTech Europe**

University Campus STeP Ri  
Slavka Krautzeka 83/A  
51000 Rijeka, Croatia  
Phone: +385 (51) 770 447  
Fax: +385 (51) 686 166  
[www.intechopen.com](http://www.intechopen.com)

### **InTech China**

Unit 405, Office Block, Hotel Equatorial Shanghai  
No.65, Yan An Road (West), Shanghai, 200040, China  
中国上海市延安西路65号上海国际贵都大饭店办公楼405单元  
Phone: +86-21-62489820  
Fax: +86-21-62489821

© 2009 The Author(s). Licensee IntechOpen. This chapter is distributed under the terms of the [Creative Commons Attribution-NonCommercial-ShareAlike-3.0 License](https://creativecommons.org/licenses/by-nc-sa/3.0/), which permits use, distribution and reproduction for non-commercial purposes, provided the original is properly cited and derivative works building on this content are distributed under the same license.

IntechOpen

IntechOpen