Speech Enhancement Using Receding Horizon FIR Filtering

Pyung Soo Kim, Wook Hyun Kwon, and Oh-Kyu Kwon

Abstract : A new speech enhancement algorithm for speech corrupted by slowly varying additive colored noise is suggested based on a state-space signal model. Due to the FIR structure and the unimportance of long-term past information, the receding horizon (RH) FIR filter known to be a best linear unbiased estimation (BLUE) filter is utilized in order to obtain noise-suppressed speech signal. As a special case of the colored noise problem, the suggested approach is generalized to perform the single blind signal separation of two speech signals. It is shown that the exact speech signal is obtained when an incoming speech signal is noise-free.

Keywords : speech enhancement, RH FIR filter, BLUE, blind signal separation, deadbeat property

I. Introduction

Speech enhancement is the term used to describe algorithms or devices whose objective is to improve some perceptual aspects of speech when its clarity and intelligibility are greatly reduced due to either channel noise or noise present in the speaker's environment. During the last twenty years, development and widespread deployment of digital communication systems, i.e., cellular telephony and speech recognition systems have brought increased attention to the role of speech enhancement in speech processing problems.

The traditional speech enhancement literature has been largely dominated by the discrete Fourier transform(DFT) based spectral subtraction strategy in the frequency domain [1-4]. However, this spectral subtraction approach developed so far have been only approximative since no efficient exact approach is known. Moreover, many simplifying assumptions are used such as the independence of the noise signal spectrum from the speech signal spectrum and the mutual independence of their frequency components. In the time domain, the Wiener filtering approach[5] and the direct time-domain mapping approach[6] have been developed. However, in these approaches, it is assumed that the speech and noise signals are stationary. Therefore, if these signals are nonstationary, the result can be expected to be even worse.

In the recent years, due to the more compact representation and the efficient manner than above existing approaches, several attempts to use the Kalman filtering in speech enhancement approaches have been made by posing the estimation problem based on a state-space framework in the time domain [7-10]. The Kalman filtering approach makes use of models of the speech and noise signals and also works with nonstationary signals. However, due to its infinite impulse response (IIR) structure and recursive formulation, the Kalman filtering may be sensitive and show even divergence phenomenon for temporary modeling uncertainties and numerical errors [11-12]. Therefore, an efficient approach for better noise-suppressed speech signal would be to obtain the alternative filtering algorithm which can overcome disadvantages of the Kalman filtering while advantages of that are maintained.

It has been a general rule of thumb in signal processing areas that the finite impulse response(FIR) structure filter, which utilizes the information only on the finite interval, is more robust against temporary modeling uncertainties and numerical errors than the IIR structure filter, and guarantees the bounded input bounded output(BIBO) stability[13]. In addition, it is noted that long-term past information may be not important in speech signal analysis.

Therefore, in the current paper, an alternative approach for the speech enhancement is suggested using the receding horizon(RH) FIR filtering. The RH FIR filter is derived from the well known Kalman filter with the receding horizon strategy for the state estimation in discrete-time state-space models[14]. Recently, the RH FIR filter has been shown to be a best linear unbiased estimation (BLUE) filter with FIR structures, which processes the finite measurements on the most recent horizon linearly, doesn't require *a priori* statistics information of the horizon initial state and has the properties of unbiasedness, minimum variance and efficiency[15]. Due to its FIR structure, the RH FIR filtering has some good inherent properties. The suggested speech enhancement approach using RH FIR filtering also provides the compact representation and the efficient manner as the Kalman filtering approach, since a state-space signal model in the time domain is utilized to represent the noisy speech signal of an autoregressive(AR) model.

As a special case of the colored noise problem, the suggested approach is generalized to perform the blind signal separation of two or more speech signals from a single measurement. It is shown that the exact speech signal is obtained when there are no noises, which indicates the finite convergent time and the quick tracking ability of the RH FIR filtering. This property cannot be obtained from the IIR structure filteres such as the Kalman filtering in [7-10].

II. Problem statement and speech signal model

The main task of the speech enhancement is a filter design to provide a noise-suppressed estimate $\hat{z}_s(k)$ of a speech signal $z_s(k)$ without adverse effect given the actual incoming speech signal $z(k)$. This incoming speech signal is summed by a speech signal, a noise signal and a quantization noise, $z(k)=z_s(k)+z_n(k)+v(k)$. The basic concept of the speech enhancement is depicted in Fig. 1. A speech signal $z_s(k)$ is generally thought of as a realization of a stochastic process, where the underlying process must be assumed to have the quasiperiodic stationarity and ergodicity properties. The segments of a speech signal can be divided into two broad categories de-

Manuscipt received : Sep. 13, 1999., Accepted : Dec. 6, 1999.

Pyung Soo Kim, Wook Hyun Kwon : School of Electrical Engineering, Seoul National University

Oh-Kyu Kwon : School of Electrical and Computer Engineering, Inha University

pending on the manner of excitation : One is highly periodic voiced phonemes and the other is rather stochastic unvoiced ones. The voiced phonemes are generated form a quasiperiodic process. The unvoiced phonemes are generated from a random process produced by turbulent airflow. It has been known that an AR model is particularly suitable for modeling a speech signal. The AR model for a speech signal should be ideally driven by pulse train for voiced phonemes and by white noise for unvoiced ones. In a noisy environment, the quality of speech is degraded. Thus, the noise signal $z_n(k)$ has to be characterized in order to improve the clarity and intelligibility of the speech signal by a noise suppression approach. For most real-world speech applications, it is more realistic that a noise signal is assumed to be a colored noise and almost stationary for our application. Usually, a colored noise signal is also modeled white noise driven AR model for its simplicity. It can be assume safely that speech and noise signals are independent and uncorrelated due to physical constraints. The physiological phenomena of speech parameter changes induced by noise are too long-term to be influential. A quantization noise $v(k)$ may arise in an incoming speech signal which may be derived with the aid of a noisy sensor, i.e., one that contributes on a generally random basis some inaccuracy to the measured incoming speech signal. A quantization noise is a zero-mean Gaussian white noise with covariance r

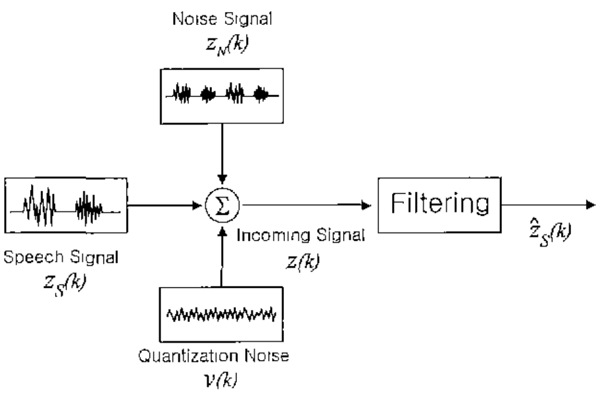


Fig. 1. Basic concept of the speech enhancement.

The corresponding AR models for a speech signal $z_s(k)$, a noise signal $z_N(k)$, and an actual incoming speech signal $z(k)$ are defined as

$$z_S(k)=\sum_{i=1}^{n} a_{S_i} z_S(k-i)+v_S(k), \tag{1}$$

$$z_N(k)=\sum_{i=1}^{m} a_{N_i} z_N(k-i)+v_N(k), \tag{2}$$

$$z(k)=z_S(k)+z_N(k)+v(k) \tag{3}$$

where excitation noises $v_s(k)$ and $v_N(k)$ are mutually uncorrelated zero-mean Gaussian white noises with covariances q_s and q_N, respectively. These noises are also mutually uncorrelated with a quantization noise $v(k)$.

In order to apply the RH FIR filtering which will be explained in the next section, the AR signal models (1)-(3) are represented in a state-space signal model. The state of a system at time k is the minimum set of internal variables that represents the effect of all past excitation and is fundamental in determining the future evolution of the system. The AR signal models are represented in the following state-space model :

$$x(k+1) = Ax(k) + G\,w(k), \tag{4}$$

$$z(k) = C\,x(k) + v(k) \tag{5}$$

where the state and system noise vectors are defined as

$$x(k)=\begin{bmatrix} x_S(k) \\ x_N(k)\end{bmatrix}=\begin{bmatrix}[z_S(k-n+1)\cdots z_S(k)]^T \\ [z_N(k-m+1)\ \cdots z_N(k)]^T\end{bmatrix}^T, \tag{6}$$

$$w(k)=\begin{bmatrix} v_S(k) \\ v_N(k)\end{bmatrix}$$

and the parameter matrices are defined as

$$A=\begin{bmatrix} 0 & & \uparrow & & 0 & 0 & 0 & 0 \\ \vdots & \leftarrow & I & \rightarrow & 0 & 0 & 0 & 0 \\ 0 & & \downarrow & & 0 & 0 & 0 & 0 \\ a_{S_n} & \cdots & a_{S_2} & a_{S_1} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & & \uparrow & \\ 0 & 0 & 0 & 0 & \vdots & \leftarrow & I & \rightarrow \\ 0 & 0 & 0 & 0 & 0 & & \downarrow & \\ 0 & 0 & 0 & 0 & a_{N_m} & \cdots & a_{N_2} & a_{N_1} \end{bmatrix},$$

$$G^T=\begin{bmatrix} \overbrace{0\cdots0\ 1}^{n} & \overbrace{0\cdots0\ 0}^{m} \\ 0\cdots0\ 0 & 0\cdots0\ 1 \end{bmatrix}, \quad C=\begin{bmatrix} \overbrace{0\cdots0\ 1}^{n} & \overbrace{0\cdots0\ 1}^{m} \end{bmatrix}.$$

The system noise $w(k)$ is now considered as excitation noises $v_S(k)$, $v_N(k)$ and the measurement noise $v(k)$ is considered as quantization noise. Noises $w(k)$ and $v(k)$ are zero-mean Gaussian white and mutually uncorrelated. The covariance of $w(k)$ is the diagonal matrix Q whose elements are q_S and q_N. Note that coefficient parameters a_{S_i} and a_{N_i} of the system matrix A are assumed to be given by the well known parameter estimation in [16] and remain constant during each frame as in [7-8].

III. Speech enhancement using RH FIR filtering

In this section, to obtain the noise-suppressed estimate of a speech signal, the RH FIR filtering algorithm developed recently in [14] is applied to the state-space signal model (4) and (5). The RH FIR filtering utilizes the only finite measurements on the most recent horizon and discards the past measurements outside the horizon for the estimate at the present time k. In order to determine the RH FIR filtering of the horizon length M, measurement information on the horizon $[k-M, k]$ is utilized, together with information about the state at the starting point $k-M$. This state, at time $k-M$, will be called the horizon initial state. In the RH FIR filtering, past measurements outside the horizon are discarded and it is assumed that the horizon initial state is unknown and can thus be anything at all. It follows from this fact that the horizon initial state must have an arbitrary mean and an infinite covariance. There are several reasons why this assumption about the horizon initial state must be taken. Firstly, for state estimation problems any state should be considered not measurable and thus unknown. Since the initial state is also a state, it is logical to assume that the horizon initial state is also not measurable and thus unknown. Secondly, *a priori* information is hard to obtain in some situations where the system is in an abrupt change or not asymptotically stable. Thirdly, an infinite covariance of the horizon initial state is a tool to obtain a BLUE with FIR structures and a deadbeat property which will be explained later. The RH FIR filter with unknown horizon initial state is time-invariant and defined by the following standard FIR form :

$$\hat{x}(k) = HZ(k) = \sum_{j=0}^{M} h(j)z(k-j) \qquad (7)$$

with the performance criterion

$$J = E[x(k) - \hat{x}(k)]^T [x(k) - \hat{x}(k)]$$

where M is the horizon length, the filter gain H and the measurements $Z(k)$ on the most recent horizon $[k-M,\ k]$ are defined respectively as

$$H \equiv [h(M)\ \ h(M-1) \cdots h(0)],$$
$$Z(k) \equiv [z(k-M)^T\ z(k-M+1)^T \cdots z(k)^T]^T.$$

When $\{A, C\}$ is observable, A is nonsingular and $M \geq n+m-1$, the elements of filter gain H can be determined by the following algorithm [14] :

$$h(j) = \frac{\Omega^{-1}(M)\Phi(j)C^T}{r}, \quad 0 \leq j \leq M \qquad (8)$$

where

$$\Phi(l+1) = \Phi(l)[I + A^{-T}\Omega(M-l-1)A^{-1}GQG^T]^{-1}A^{-T}, \qquad (9)$$

$$\Omega(l+1) = [I + A^{-T}\Omega(l)A^{-1}GQG^T]^{-1}A^{-T}\Omega(l)A^{-1} + C^TC/r, \qquad (10)$$

$$\Phi(0) = I,\ \ \Omega(0) = C^TC/r,\ \ 0 \leq l \leq M-1,$$

and $\Omega^{-1}(M)$ is known to be the estimation error covariance. Since each row of the filter gain is the filter gain for each individual state, the filter gains for speech and noise signals can be divided respectively by

$$H = \begin{bmatrix} H_S \\ H_N \end{bmatrix}, \qquad (11)$$

that is, H_S and H_N are given by the first n rows and the last m rows of the filter gain H. Given the measured incoming speech signals on the most recent horizon $[k-M,\ k]$, the noise-suppressed estimate $\hat{x}_S(k)$ for the state $x_S(k)$ is extracted by

$$\hat{x}_S(k) = \begin{bmatrix} \hat{z}_S(k-n+1) \\ \hat{z}_S(k-n+2) \\ \vdots \\ \hat{z}_S(k) \end{bmatrix} = H_S Z(k). \qquad (12)$$

Therefore, from equations (6) and (12), the ultimate noise-suppressed estimate $\hat{z}_S(k)$ for the speech signal $Z_S(k)$ is obtained from the following very simple formulation :

$$\hat{z}_S(k) = H_S^n Z(k) \qquad (13)$$

where H_S^n is the n th row of the H_S.

Unlike the Kalman filtering in [7-10], the RH FIR filtering in the current approach offers many practical advantages. Firstly, the RH FIR filter is a BLUE with an FIR structure, which processes the finite measurements on the most recent horizon linearly, doesn't require *a priori* statistics information of the horizon initial state and has the properties of unbiasedness, minimum variance and efficiency. Secondly, the filter gain H requires computation only on the interval $[0,M]$ once as shown in (8) and is time-invariant for all horizons, since $\Phi(l)$(9) and $\Omega(l)$(10) are determined uniquely on the interval $[0,M]$. This means that the filter gain H of the RH FIR filtering can be obtained from off-line computation. Moreover, as shown in (13), only one row H_S^n of the filter gain H is utilized and thus the simple formulation (13) is only needed in on-line computation. Thirdly, due to the FIR structure, the RH FIR filtering guarantees the BIBO stability, and may have the robustness to temporary modeling uncertainties and to numerical errors.

In the RH FIR filtering approach, both the horizon length M and the normalized noise covariance matrix Q/r are design parameters. They affect differently the noise suppression and the tracking properties of the RH FIR filtering. The RH FIR filtering has greater noise-suppressing ability and less tracking ability for the speech signal as the horizon length M increase. Since M is an integer, fine adjustment of the properties with M is difficult. Moreover, it is difficult to determine the horizon length is systematic ways Therefore, in the implementations, one way to determine M is to use a large enough value that can provides enough noise-suppressing ability. When the horizon length is fixed, the tracking ability for the speech signal increases and the noise suppressing ability decreases as Q/r increases. Q/r provides a continuous parameter to adjust the noise-suppressing and tracking properties. Moreover, the properties of the filtering can be selectively adjusted via elements of the Q matrix. Therefore, Q/r is a useful parameter in the adjustment of the noise-suppression and tracking properties of the RH FIR filtering for speech enhancement.

IV. Properties of suggested approach

In the previous section, a speech signal corrupted by a noise signal $Z_N(k)$ is considered. When the noise signal is colored and highly nonstationary, the distinction between what is speech signal and what is noise signal becomes somewhat ambiguous. In this case, this noise signal itself can be treated as an additional speech signal that must be estimated. In this case, the incoming speech signal, $z(k)=z_S(k)+z_N(k)+v(k)$, can be represented into a general form, the sum of two speech signals with a quantization noise, $z(k)=z_\alpha(k)+z_\beta(k)+v(k)$. This is a form of blind signal separation, i.e., when the signals result from the mixing of speakers. Single separation approach has primarily been based on harmonic selection and pitch tracking in the frequency domain[17]. In the literature[18], Γ signals are separated from Γ measurements by learning a fixed inverse weighting matrix. However, in the current approach, two or more speech signals are separated from only single measurement in the time domain. A state-space signal model is considered where two speech signals are represented as a state vector $x(k)=[x_\alpha^T(k)\ x_\beta^T(k)]^T$ assumed to be $x_\alpha(k)\in R^n$ and $x_\beta(k)\in R^m$. Then, given the measured incoming speech signals on the most recent horizon $[k-M, k]$, the RH FIR filtering provides best separated estimates $\hat{x}_\alpha(k)$ and $\hat{x}_\beta(k)$ as

$$\hat{x}_\alpha(k)=H_\alpha Z(k),\quad \hat{x}_\beta(k)=H_\beta Z(k)$$

where H_α and H_β are the filter gains for $\hat{x}_\alpha(k)$ and $\hat{x}_\beta(k)$ and given similarly to (11) by (8). Therefore, the ultimate noise-suppressed estimate $\hat{z}_\alpha(k)$ and $\hat{z}_\beta(k)$ for two speech signals $z_\alpha(k)$ and $z_\beta(k)$ are obtained from the following very simple formulation:

$$\hat{z}_\alpha(k)=H_\alpha^n Z(k),\quad \hat{z}_\beta(k)=H_\beta^m Z(k) \tag{14}$$

where H_α^n is the n th row of the H_α and H_β^m is the m th row of the H_β. It can be thus known from (14) that the RH FIR filtering for the speech enhancement is generalized to perform the blind signal separation of two speech signals from a single measurement $Z(k)$ when the distinction between two signals are somewhat arbitrary. Moreover, it can be seen that the blind signal separation in the current paper can be easily implemented to parallel processing since the corresponding filter gains H_α^n and H_β^m for each signal are structurally separated.

When the incoming speech signal nearly constant in the horizon, it can be assumed that $Q = 0$ from (4) and (5). Substituting $Q = 0$ into (8)-(10), the element of the filter gain, denoted by $\tilde{h}(j)$, is given by simpler algorithms as

$$\tilde{h}(j)=\tilde{\Omega}^{-1}(M)A^{-jT}C^T,\quad 0\le j\le M,$$
$$\tilde{\Omega}(M)=\frac{1}{r}\sum_{j=0}^{M}A^{-jT}C^TCA^{-j}.$$

Note that the Kalman filtering may diverge in this case, whereas the RH FIR filtering is still stable. This is an advantage of the RH FIR filtering approach.

It is noted that the actual incoming speech signal may be different from the model (4) and (5), although the RH FIR filtering is designed on the model. In the following, it will be shown that the RH FIR filtering provides the exact speech signal when the incoming speech signal is noise-free i.e., $v_s(k)=v_N(k)=v(k)=0$ in (1)-(3), although the excitation and quantization noise covariances q_S, q_N, r in the filter design are nonzero. From (4) and (5), a noise-free speech signal $z(k)$ is represented in the following state-space model :

$$x(k+1)=Ax(k),\quad z(k)=Cx(k).$$

From (9) and (10), $\Omega(M)$ can be written as

$$\Omega(M)=\frac{1}{r}\sum_{j=0}^{M}\Phi(j)C^TCA^{-j}.$$

Then the estimate $\hat{x}(k)$ using the deterministic measurement $z(k)$ becomes

$$\begin{aligned}\hat{x}(k)&=\sum_{j=0}^{M}h(j)z(k-j)\\&=\Omega^{-1}(M)\sum_{j=0}^{M}\frac{1}{r}\Phi(j)C^Tz(k-j)\\&=\Omega^{-1}(M)\left[\sum_{j=0}^{M}\frac{1}{r}\Phi(j)C^TCA^{-j}\right]x(k)\\&=x(k)\end{aligned}$$

and then $\hat{z}_S(k)=z_S(k)$.

Therefore, the suggested speech enhancement approach using the RH FIR filtering provides the exact speech signal for the noise-free speech signal. This exact estimation performance indicates the finite convergent time and the quick tracking ability of the filter. Moreover, this property cannot be obtained using the IIR structure filters such as the Kalman filtering [7-10].

V. Experiment

In this section, an experiment is performed in order to evaluate performance of the suggested speech enhancement algorithm when a noise signal due to a running drill is added to a speech signal inside a laboratory. The speech signal Fig. 2(a) is recorded by a male speaker using microphone mounted inside a laboratory when the drill is stationary. The noise signal Fig. 2(b) is recorded by the running drill when the speech signal is not present The recorded noise signal is artificially added to the speech signal to produce the actual incoming speech signal Fig. 2(c). The actual incoming speech signal is approximately 24,000 points. As mentioned previously, coefficient parameters a_{S_i} and a_{N_i} of the system matrix A are assumed to be given by the well known parameter estimation in [16] and remain constant during each frame as in [7-8]. The horizon length and noise covariances as design parameters are set by $M = 10$, $q_S= 0.5$, $q_N=0.1$ and $r = 0.05$. The last plot Fig. 2(d) is the noise-suppressed speech signal obtained by the suggested algorithm.

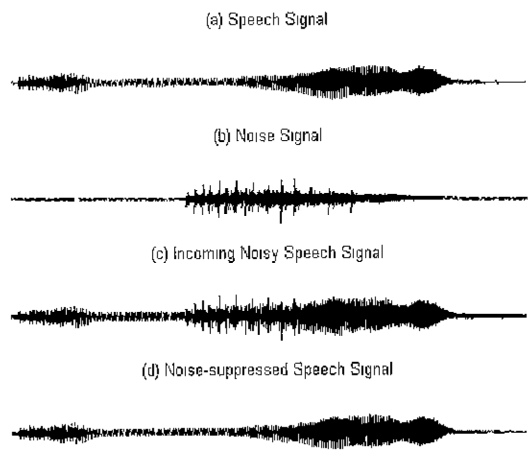


Fig. 2. Experiment result.

VI. Conclusions

A new speech enhancement algorithm for speech corrupted by slowly varying additive noise is suggested based on a state-space signal model. The RH FIR filter known to be a BLUE is utilized in order to obtain noise-suppressed speech signal due to its FIR structure and the unimportance of long-term past information in speech signal analysis. The suggested RH FIR filtering approach is generalized to perform the blind signal separation of two speech signals from a single measurement. It is shown that exact speech signal is given when an incoming speech signal is noise-free. Furthermore, due to the FIR structure, the RH FIR filtering approach guarantees the BIBO stability and may offer the robustness to temporary modeling uncertainties and to numerical errors, whereas in this case the Kalman filtering approach may be sensitive and show even divergence phenomenon for temporary modeling uncertainties and numerical errors

References

[1] S. Boll, "Suppression of acoustic noise in speech using spectral substraction," *IEEE Trans. Acous., Speech Signal Processing*, vol. 27, pp. 113-120, 1979.

[2] R. J. McAulay and M. L. Malpass, "Speech enhancement using a soft-decision noise suppression filter," *IEEE Trans Acous., Speech Signal Proc.* vol. 28, pp. 137-145, 1980.

[3] Y. Ephraim and D. Malah, "Speech enhancement using a minimum mean-square error," *IEEE Trans Acous, Speech Signal Proc* vol. 33, 1985.

[4] H. G. Hirsch, *Estimation of noise spectrum and its application to SNR estimation and speech enhancement*, Technical Report Tr-93-012, International Computer Science Institute, 1993.

[5] J. Lim and A. Oppenheim, "All-pole modeling of degrade speech," *IEEE Trans. Acous., Speech Signal Proc* vol. 26, no. 6, 1978.

[6] T. Le and J. Mason, "Artificial neural network for nonlinear time-domain filtering of speech," *IEE Proceeding*, vol. 143, pp. 149-154, 1996.

[7] K. Paliway and A. Basu, "A speech enhancement method based on Kalman filtering," *Proc. of the IEEE Int. Conf. Acoust., Speech, Signal Proc.* pp. 177-180, 1987.

[8] B. J. Kybic, *Kalman filtering and speech enhancement*, Diploma Thesis, Czech Technical University, 1998.

[9] S. Gannot, D. Burshtein, and E. Weinstein, "Iterative and sequential Kalman filter based speech enhancement algorithm," *IEEE Trans. Speech and Audio Proc.* vol. 6, no. 4, pp. 373-385, 1998.

[10] Z. Goh, K-C. Tan, and B. T G. Tan, "Kalman-filtering speech enhancement method based on a voiced-unvoiced speech model," *IEEE Trans Speech and Audio Proc* vol. 7, no. 5, pp. 510-524, 1999.

[11] R. J. Fitzgerald, "Divergence of the Kalman filter," *IEEE Trans Automat. Contr.*, vol. 16, pp. 736-747, 1971.

[12] L. Xie, Y. C. Soh, and C. E. de Souza, "Robust Kalman filtering for uncertain discrete-time systems," *IEEE Trans. Automat. Contr*, vol. 39, pp. 1310-1313, 1994.

[13] S. H. Park, W. H. Kwon, O. K. Kwon, and M. J. Kim, "Short-time Fourier analysis using optimal harmonic FIR filters," *IEEE Trans. Signal Proc* vol. 45, pp. 1535-1542, 1997.

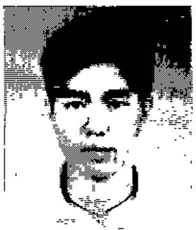
[14] W. H. Kwon, P. S. Kim, and P. Park, "A receding horizon Kalman FIR filter for discrete-time invariant systems," *IEEE Trans. Automat Contr*, vol. 44, pp. 1787-1791, 1999.

[15] W H. Kwon, P. S. Kim, and S. H. Han, "Best linear unbiased estimation filters with FIR structures for state space signal models," Submitted to *IEEE Trans. Automat. Contr.*, 1999.

[16] L. Ljung, *System identification, Theory for the user*, Englewood Cliffs, NJ : Prentice-Hall, 1999.

[17] P. N. Denbigh and J. Zhao, "Pitch extraction and separation of overlapping speech," *Speech Computation*, vol. 11, pp. 119-125, 1992.

[18] A Bell and T. Sejnowski, "An information-maximization approach to blind separation and blind deconvolution," *Neural Computation*, vol. 7, pp. 1129-1259, 1995.



Pyung Soo Kim

Pyung Soo Kim was born in Korea on February 5, 1972. He received the B.S. degree in electrical engineering from Inha University, Inchon, Korea in 1994 and the M.S. degree in control and instrumentation engineering from Seoul National University, Seoul, Korea in 1996. He is currently a Ph. D candidate in the School of Electrical Engineering, Seoul National University. His main research interests are in the areas of statistical signal processing, fault detection, identification and industrial application.

Wook Hyun Kwon

Wook Hyun Kwon was born in Korea on January 19, 1943. He received the B.S. and M.S. degrees in electrical engineering from Seoul National University, Seoul, Korea, in 1966 and 1972, respectively. He received the Ph.D. degree from Brown University, Providence, RI, in 1975. From 1976 to 1977, he was an adjunct assistant professor at University of Iowa, Iowa City. Since 1977, he has been with the School of Electrical Engineering, Seoul National University. From 1981 to 1982, he was a visiting assistant professor at Stanford University, Stanford, CA. Since 1991, he has been the Director of the Engineering Research Center for Advanced Control and Instrumentation. His main research interests are currently multivariable robust and predictive controls, statistical signal processing, discrete event systems and industrial networks

Oh-Kyu Kwon

Oh-Kyu Kwon was born in Seoul, Korea in 1952. He received the B.S. and M.S. degrees in electrical engineering and the Ph. D. degree in control and instrumentation engineering from Seoul National University, in 1978, 1980, and 1985, respectively. Since 1993, he has been a Professor at School of Electrical and Computer Engineering, Inha University, Inchon, Korea. He was also a visiting professor at Department of Electrical and Computer Engineering, the University of New Castle, New Castle, Australia, from August 1988 to August 1989. His research interests include robust control and estimation, signal processing, fault detection and diagnosis, and digital control applications.