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Real-Time Noise Cancelling Approach on Innovations-Based Whitening Application to Adaptive FIR RLS in Beamforming Structure

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1. Introduction

The techniques for noise cancellation have been developed with applications in signal processing, such as homomorphic signal processing, sensor array signal processing and statistical signal processing. Some exemplar applications may be found from kepstrum (also known as complex ceptstrum) method, beamforming and ANC (adaptive noise cancelling) respectively as shown in Fig. 1.
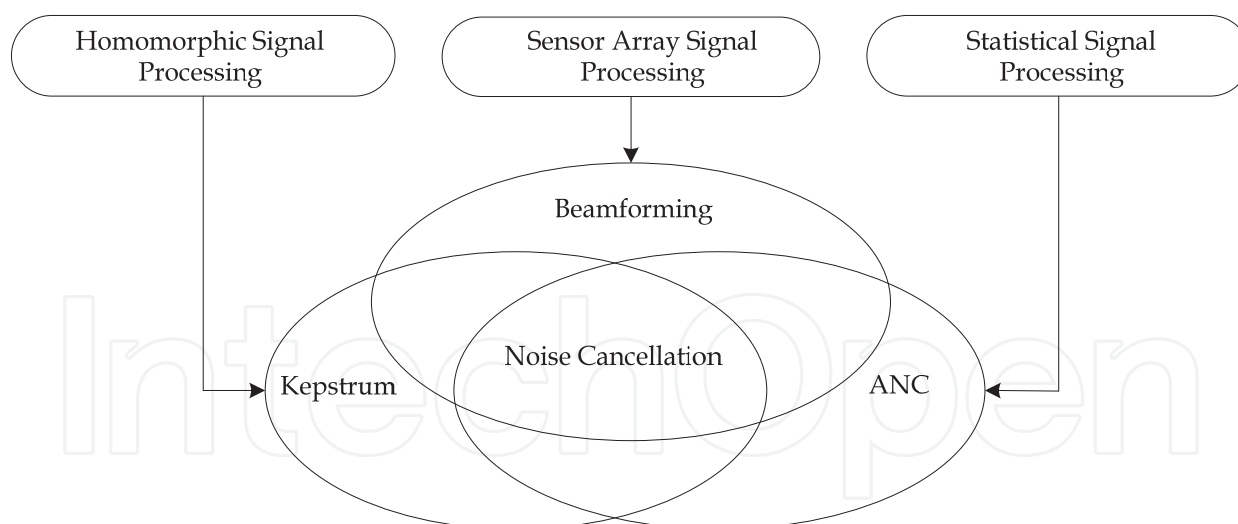

Fig. 1. Signal processing techniques and the application of methods for noise cancellation

Based on the two-microphone approach, the applications are characterized as three methods, which are based on identification of unknown system in acoustic channels, adaptive speech beamforming and adaptive noise cancellation. It can be described as generalized three sub-block diagram as shown in Fig. 2, where it is shown as three processing stages of (1) kepstrum (complex cepstrum), (2) beamforming and (3) ANC and also two structures of beamforming and ANC.
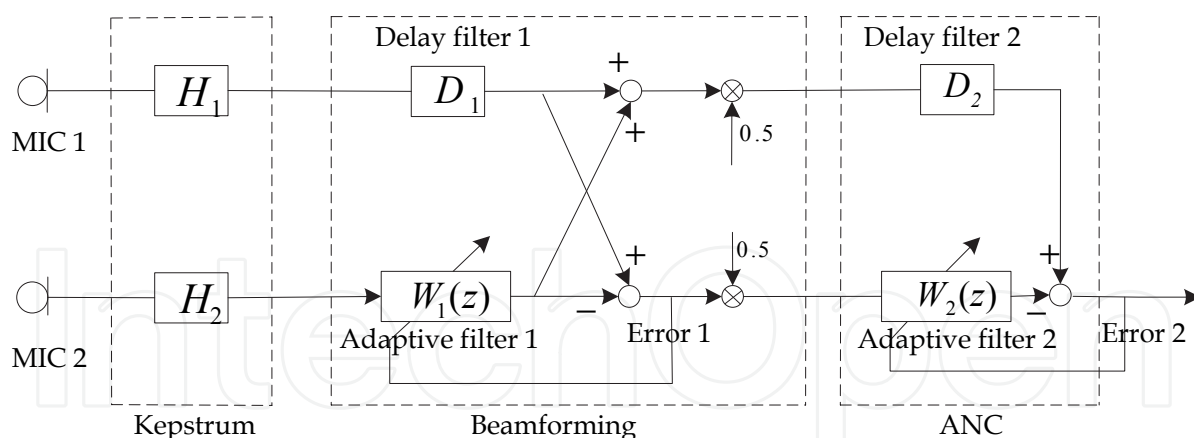
Fig. 2. Generalized diagram for the typical two-microphone approach

1.   Kepstrum - estimation of acoustic path transfer functions (H_1 and H_2)

From the output of sensor array, the acoustic transfer functions (H_1 and H_2) are estimated from the acoustic channels as noise statistics during the noise period and it is applied to speech and noise period for noise cancellation. It can be applied as preprocessor to second processing stage, beamforming or directly to third processing stage, ANC. The application can be found from (Moir & Barrett, 2003; Jeong & Moir, 2008), where the unknown system has been estimated as the ratio (H_1 / H_2) of two acoustic transfer functions between each microphones and noise source. Kepstrum filter is used as estimate of unknown system and it is applied in front of SS (sum and subtract) functions in beamforming structure (Jeong & Moir, 2008).

2.   Beamforming - adaptive filter (W_1) , delay filter (D_1) and SS functions

The beamforming structure contains SS functions, where it is used as signal separator and enhancer by summing and subtracting the signals of the each microphones input (Griffiths & Jim, 1982). An adaptive filter 1 is placed in front of SS functions and used as speech beamforming filter (Compernolle, 1990). It is used as a beam steering input and hence DS (delay and sum) beamformer in primary input during speech period using VAD (voice activity detector) and its output is then applied to third stage, ANC as an enhanced primary input. Both output signals from the SS functions are divided by a number of microphones used (in the case of two microphone, it should be 0.5). Alternatively, adaptive filter 1 can be used as a first adaptive noise canceller. For this application, its output is a noise reference input to next cascading adaptive filter 2 during noise period in VAD (Wallace & Goubran, 1992). Based on a same structure, two-stage adaptive filtering scheme is introduced (Berghe and Wouters, 1998). As a speech directivity function, GCC (genenalized cross-correlation) based TDOA (time difference of arrival) function may alternatively be used instead of adaptive filter 1 in beamforming structure (Knapp & Carter, 1976).

3.   ANC - adaptive filter (W_2) and delay filter (D_2)

The last part of block diagram shows ANC method (Widrow et al., 1975), where it consists of adaptive filter 2 and delay filter 2. The adaptive filter generally uses FIR (finite impulse response) LMS (least mean square) algorithm in signal processing or IIR (infinite impulse response) RLS (recursive least square) algorithm in adaptive control for the noise cancellation in MMSE (minimize mean square error) sense. According to the application, both algorithms show compromised effects between performance and computational complexity. It shows that RLS gives, on average, two-tenths of a decibel SNR (signal to

noise ratio) improvement over the LMS algorithm (Harrison et al., 1986) but it requires a high demand of computational complexity for the processing. Delay filter 2 is used as noncausality filter to maintain a causality.

As desribed above, the techniques have been developed on the basis of above described methods and the structures. From the above analysis, kepstrum noise cancelling technique has been studied, where the kepstrum has been used for the identification of acoustic transfer functions between two microphones and the kepstrum coefficients from the ratio of two acoustic transfer functions have been applied in front of adaptive beamforming structure for noise cancellation and speech enhancement (Jeong & Moir, 2008). Furthermore, by using the fact that the random signal plus noise may be represented as output of normalized minimum phase spectral factor from the innovations white-noise input (Kalman & Bucy, 1961), the application of an innovations-based whitened form (here we call it as inverse kepstrum) has been investigated in a simulation test, where front-end inverse kepstrum has been analyzed with application of cascaded FIR LMS algorithm (Jeong, 2009) and also FIR RLS algorithm (Jeong, 2010a; 2010b), both in ANC structure for noise cancellation.

In this paper, for a practical real-time processing using RLS algorithm, analysis of innovations-based whitening filter (inverse kepstrum) has been extended to beamforming structure and it has been tested for the application in a realistic environment. From the simulation test, it will be shown that overall estimate from front-end inverse kepstrum processing with cascaded FIR RLS approximates with estimate of IIR RLS algorithm in ANC structure. This provides alternative solution from computational complexity on ANC application using pole-zero IIR RLS filter, which is mostly not acceptable to practical applications. For the application in realistic environment, it has been applied to beamforming structure for an effective noise cancelling application and it will be shown that the front-end kepstrum application with zero-model FIR RLS provides even better performance than pole-zero model IIR RLS algorithm in ANC structure.

2. Analysis of optimum IIR Wiener filtering and the application to two-microphone noise cancelling approach

For the IIR Wiener filtering approach, the z- transform of optimum LS (least squares) filter is constrained to be causal but is potentially of infinite duration, hence it has been defined by (Kailath, 1968) as

$$H_{opt} = \frac{1}{H^+(z)} \left[\frac{\Phi_{xd}(z)}{H^-(z)} \right]_+ = A(z)B(z) \tag{1}$$

From the equation (1), it may be regarded as a cascaded form of transfer functions $A(z)$ and $B(z)$, where $\Phi_{xd}(z)$ is the double-sided z-transform of the cross-correlation function between the desired signal and the reference signal. $H^+(z)$ and $H^-(z)$ are the spectral factors of the double-sided z-transform, $\Phi_{xx}(z)$ from the auto-correlation of reference signal. These spectral factors have the property that the inverse z-transform of $H^+(z)$ is entirely causal and minimum phase, on the other hand, the inverse z- transform of $H^-(z)$ is non causal. The notation of + in outside bracket indicates that the z- transform of the causal part of the inverse z- transform of $B(z)$ is being taken.

From the optimum Wiener filtering structure, the innovations process ε_n can be obtained by the inverse of spectral factor $A(z)$ from the input signal of desired signal plus noise as shown in Fig. 3. Therefore, the optimal Wiener filter can be regarded as combination of two cascaded filters, a front-end whitening filter $A(z)$, which generates the white innovations process and a cascaded shaping filter $B(z)$, which provides a spectral shaping function for the input signal.
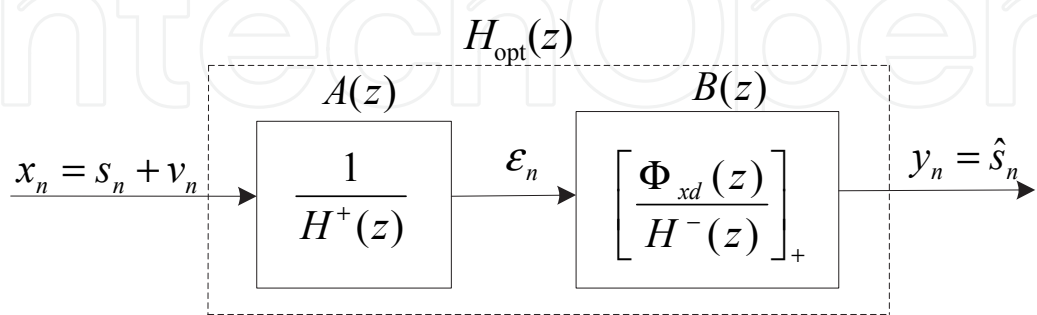

Fig. 3. Analysis of innovations-based optimal Wiener filter: $A(z)$: whitening filter and $B(z)$: spectral shaping filter

It can be applied to two-microphone noise cancelling structure as optimum IIR Wiener filtering approach as shown in Fig. 4.
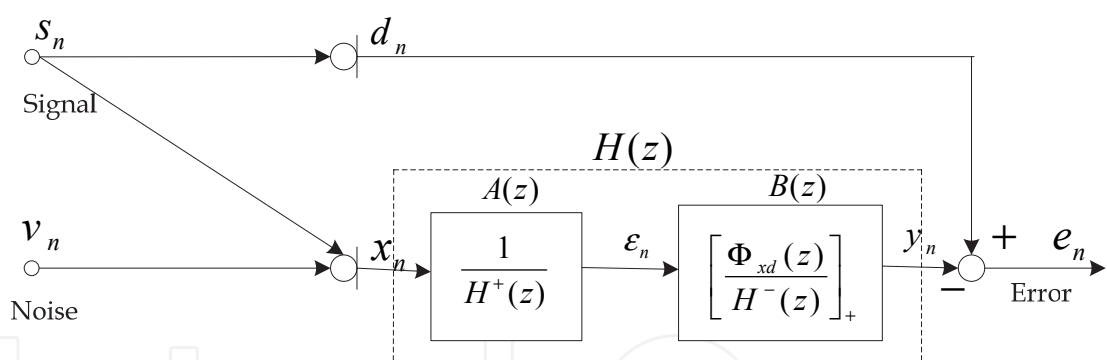

Fig. 4. Optimum IIR Wiener filtering application to two-microphone noise cancelling approach

3. Front-end whitening filter and cascaded adaptive FIR RLS filter

To obtain the innovations-based whitened sequence, inverse kepstrum filter is used as whitening filter. This section describes a whitening procedure by kepstrum processing as front-end application and overview of FIR RLS filter as rear-end application to beamforming structure (Jeong, 2010b).

3.1 The innovations-based whitening filter
Fig. 5 shows that the generating input model may be whitened as innovations white-noise by the inverse of minimum phase spectral factor from input signal of signal plus noise.
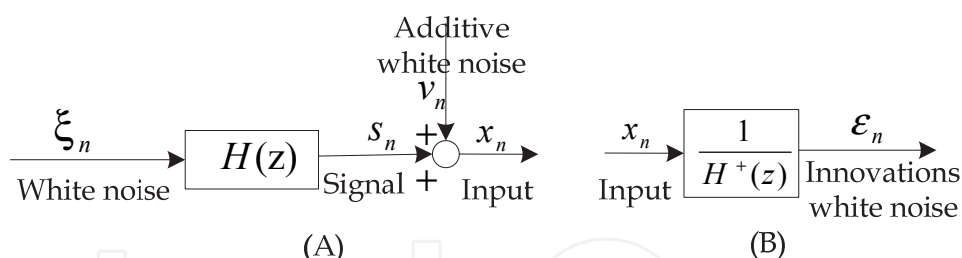
Fig. 5. (A): The generating input model for signal plus noise (x_n) (B): whitening model for innovations-based white noise input (ε_n)

To obtain the innovations white noise, the processing procedure is described as:
Step 1. Take periodogram (P) from FFTs (fast Fourier transforms) of the input signal x_n.

$$P = \frac{1}{N}|X_i|^2 \tag{2}$$

where N is frame size and $i = 0, 1, 2, \ldots, N\text{-}1$.
Step 2. Get the kepstrum coefficients from the inverse FFT (IFFT) of the logarithm of the periodogram.

$$k_n = \{IFFT \ (\log P + \gamma)\} \tag{3}$$

where $K(z) = \log P + \gamma$ (γ is Euler constant, 0.577215 is added to be unbiased).

Step 3. Negate it from the obtained kepstrum coefficients because the logarithmic function of inverse minimum phase transfer function can be obtained by a negated sign from the kepstrum coefficients.

$$\log \frac{1}{H^+(z)} \leftrightarrow -K^+(z) \tag{4}$$

Step 4. Normalize the negated kepstrum coefficients.
Step 5. Truncate it less than half frame size and then make first zeroth coefficient to half from their previous value.
Step 6. Convert it to impulse response by the recursive formula (Silvia & Robinson, 1978) as:

$$(n+1)h_{n+1} = \sum_{m=0}^{n}(n+1-m)h_m(k_{n+1-m}), \quad 0 \le n \le l-1 \tag{5}$$

Step 7. Finally, convolve the impulse response (5) with input signal x_n to obtain the innovations whitened sequence.

3.2 The FIR RLS algorithm
The RLS algorithm is to estimate the inverse of the autocorrelation matrix of the input vector and it requires information from all the previous input data used (Haykins, 1996).
The recursive method of least squares is to minimize the residual sum of squares of the error signal (e_n) and find immediate search for the minimum of cost function, such as:

$$\nabla_h(J_n) = \nabla_h(\sum_{k=1}^{n} \beta^{n-k} e_k^2) = 0 \tag{6}$$

where $e_k = d_k - y_k$ β is exponentially weighted forgetting factor, $0 < \beta \le 1$.

The resulting equation for the optimum filter weights at time n is described as normal equation:

$$w_n \mathbf{R}_n = \mathbf{p}_n \tag{7}$$

where autocorrelation matrix, $\mathbf{R}_n = \sum_{k=1}^{n} \beta^{n-k} \mathbf{x}_k \mathbf{x}_k^T = \mathbf{X}^T \mathbf{\Lambda} \mathbf{X}$, cross-correlation vector,

$\mathbf{p}_n = \sum_{k=1}^{n} \beta^{n-k} d_k \mathbf{x}_k^T = \mathbf{X}^T \mathbf{\Lambda} \mathbf{d}$ with $\mathbf{\Lambda} = \text{diag}[\beta^{n-1} \ \beta^{n-2} ....1]$

Both $\mathbf{R}_n$ and $\mathbf{p}_n$ can be computed recursively:

$$\mathbf{R}_n = \beta \mathbf{R}_{n-1} + \mathbf{x}_n \mathbf{x}_n^H, \ \mathbf{p}_n = \beta \mathbf{p}_{n-1} + d_n \mathbf{x}_n \tag{8}$$

To find the weight vector w_n from (7), we need the inverse matrix $\mathbf{R}_n^{-1}$ from $\mathbf{R}_n$. Using a matrix inversion lemma (Haykins, 1996), a recursive update equation for $\mathbf{R}_n^{-1}$ is found as:

$$\mathbf{R}_n^{-1} = \beta^{-1} \mathbf{R}_{n-1}^{-1} - \beta^{-1} \mu_n' \mathbf{x}_n^T \mathbf{R}_{n-1}^{-1} \tag{9}$$

where gain vector, $\mu_n' = \dfrac{\beta^{-1} \mathbf{R}_{n-1}^{-1} \mathbf{x}_n}{1 + \beta^{-1} \mathbf{x}_n^T \mathbf{R}_{n-1}^{-1} \mathbf{x}_n}$

The equation (9) is known as ordinary RLS algorithm and it is valid for FIR filters because no assumption is made about the input data $\mathbf{x}_n$. We can then find the weights update equation as:

$$\mathrm{w}_n = \mathrm{w}_{n-1} + \mu_n'(\mathrm{d}_n - \mathrm{x}_n \mathrm{w}_{n-1}) \tag{10}$$

4. Application to noise cancelling

Adaptive filter, such as FIR LMS filter (Widrow & Hoff, 1960) or IIR RLS filter (Ljung & Sodestrom, 1987) is used to estimate two acoustic path transfer functions ($H_1(z)$ and $H_2(z)$) between each mirophone input and noise source. It is represented as the ratio of $H_1(z)/H_2(z)$ in the two-microphone ANC approach as shown in Fig. 6 (A). Front-end whitening application is used to estimate the inverse of acoustic path transfer function $H_2(z)$ in the reference input shown in Fig. 6 (B), where the cascaded adaptive filter is used to estimate acoustic path transfer function, $H_1(z)$ in the primary microphone input.

In this paper, the inverse kepstrum filter is used to estimate $1/H_2(z)$ as whitening filter in front of SS functions and FIR RLS algorithm is used as rear-end spectral shaping adaptive filter in two-microphone beamforming structure as shown in Fig. 7. As an alternative approach, the system identification based kepstrum method has been studied in beamforming structure (Jeong & Moir, 2008).
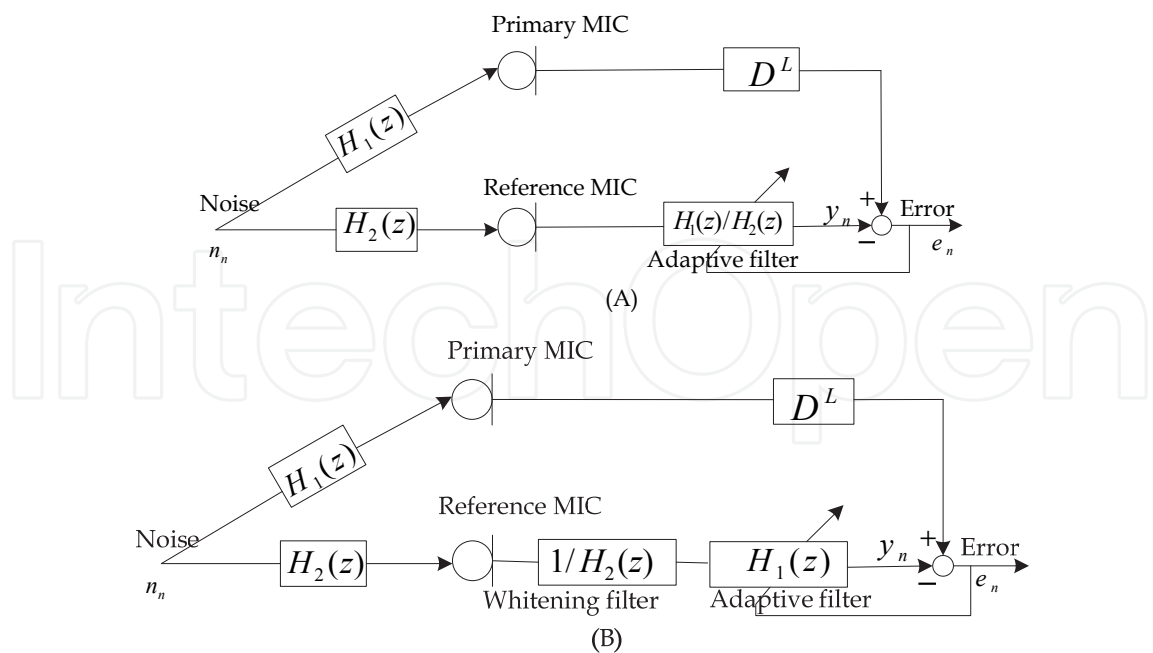
Fig. 6. (A) typical ANC method (B) front-end innovations based inverse kepstrum method, where both are applied to ANC structure
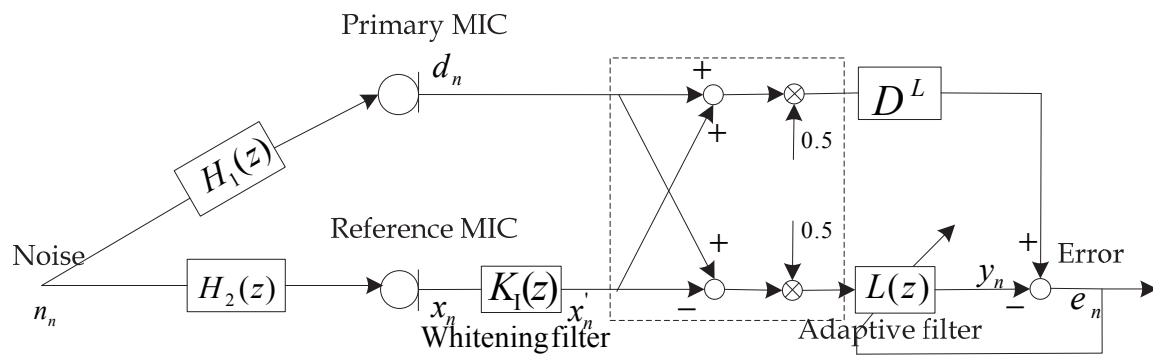

Fig. 7. Whitening application to beamforming structure: application of inverse kepstrum method

5. Experiment

The objective is to analyze the operation of the front-end innovations based whitening method and the rear-end FIR RLS filter between ANC and beamforming structure. For the simulation test, 2 kepsturm coefficients and first order of zero model RLS have been used, which will be compared with pole-zero model IIR RLS with first order of numerator polynomial and first order of denominator polynomial in ANC structure. Based on this, it will be tested in beamforming structrue for real-time processing in a realistic room environment, where noise cancelling performance will be compared with typical IIR RLS method in ANC structure. For the application of signal plus noise, a simple sine waveform (consisting of 500Hz, 550Hz and 700Hz) has been selected as a desired signal, which considered as a desired signal of speech signal with real data in noise signal. For the processing, two FFT points (2048 in simulation

test and 4096 in real test) frame sizes have been used, and sampling frequency of 22050Hz and Nyquist frequency of around 11000Hz have been chosen.   For the precise test, programmed operation is made to stop the estimate to freeze both kepstrum coefficients and adaptive (FIR and IIR RLS) filter weights when the signal is applied as desired speech signal (Jeong, 2010a; 2010b). The frozen coefficients and weights are then applied to desired signal and noise periods.   For the test in a real environment, two unidirectional microphones (5cm distance apart) with broadside configuration have been set up and tested in a corner of room (3.8m(d)x3m(w)x2.8m(h)) with moderate reverberant status.

5.1 Simulation test in ANC structure

The noise characteristic between two microphones is estimated as the ratio of two acoustic path transfer functions, where the front-end innovations kepstrum estimates minimum phase term of a denominator polynomial and also zero-model FIR RLS algorithm of the cascaded adaptive filter estimates the remaining numerator polynomial as shown in Fig. 8. Both coefficients and weights are continously updated during the noise periods only and frozen during the signal plus noise periods.
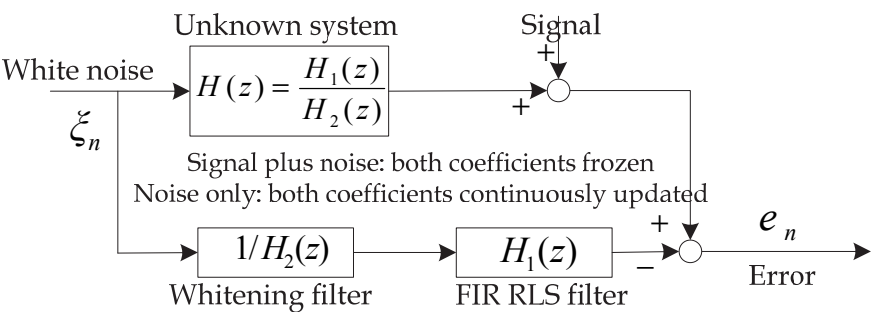

Fig. 8. Identification of unknown system in ANC structure based on estimates of innovations-based inverse kepstrum whitening filter and cascaded FIR RLS filter

5.2 Operation of innovations-based whitening filter and cascaded zero-model FIR RLS filter in ANC structure

To verify the operation of inverse kepstrum whitening filter with a nonminimum phase term from numerator polynomial and a minimum phase term from denominator polynomial, $H(z) = H_1(z) / H_2(z)$ has been used as a simple example of unknown system, where each acoustic transfer functions are

$$H_1(z) = 1 + 1.5z^{-1} \quad H_2(z) = 1 + 0.4z^{-1} \tag{11}$$

Hence $H(z) = (1 + 1.5z^{-1}) / (1 + 0.4z^{-1})$, which is illustrated as zero $(z = -1.5)$ and pole $(p = -0.4)$ in Fig. 9 (A).

Therefore, it can be described as a polynomial of:

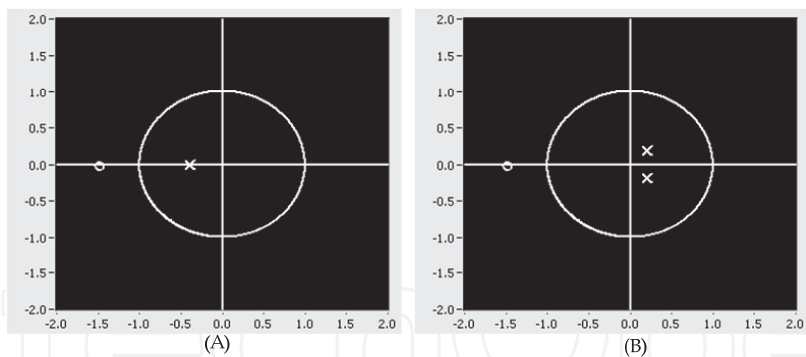$$H(z) = 1 + 1.1z^{-1} - 0.44z^{-2} + ... \tag{12}$$

Fig. 9. Comparison of pole-zero placement: (A): ordinary IIR RLS (B): front-end inverse kepstrum method and cascaded FIR RLS

As shown in Fig. 9 (B), the front-end inverse kepstrum estimates minimum phase term (13) in denominator polynomial and cascaded zero-model RLS estimates remaining nonminimum phase term (14) in numerator polynomial,

$$K_I(z) = 1 / (1 + 0.4z^{-1}) \qquad (13)$$

$$L(z) = (1 + 1.5z^{-1}) \qquad (14)$$

It is also compared in terms of overall estimate, where overall estimate (III) from (C) is obtained from the convolution of estimate (I) and estimate (II). Table 1 shows that (A) is the ordinary IIR RLS with one pole $(p = -0.4)$ and one zero $(z = -1.5)$ model , (B) is its estimates, and (C) is estimates of front-end inverse kepstrum and cascaded FIR RLS as listed in Table 1. From the observation, it can be found that innovations based inverse kepstrum gives approximation to the ordinary IIR RLS, where it is also be verified in Fig. 9.

(A)	I: IIR RLS Numerator (weights)				
	1	1 . 5	–	–	–
	II: IIR RLS Denominator (weights)				
	1	0 . 4	–	–	–
	III: Overall estimate (weights)				
	1	1 . 1	− 0 . 44	0 . 176	− 0 . 070
(B)	I: IIR RLS Numerator (weights)				
	1	1 . 499	–	–	–
	II: IIR RLS Denominator (weights)				
	1	0 . 4	–	–	–
	III: Overall estimate (weights)				
	1	1 . 099	− 0 . 439	0 . 175	− 0 . 070
(C)	I: Innovations kepstrum estimate of impulse response (coefficients)				
	1	- 0 . 397	0 . 078	–	–
	II: Cascaded FIR RLS estimate (weights)				
	1	1 . 501	–	–	–
	III: Overall estimate (weights)				
	1	1 . 096	-0 . 525	0 . 122	0 . 000

Table 1. Comparison of overall estimate in vector weights: (A) IIR RLS in theory (B) IIR RLS in estimate (C) front-end innovations based inverse kepstrum and cascaded FIR RLS in estimate

5.3 Simulation test in beamforming structure

Based on the analysis in Fig. 2, whitening filter is applied to beamforming structure as front-end application as shown in Fig. 7, where it comprised of three parts, such as (1) whitening filter, (2) SS functions in beamforming structure and (3) adaptive filter in ANC structure as shown in Fig. 10.
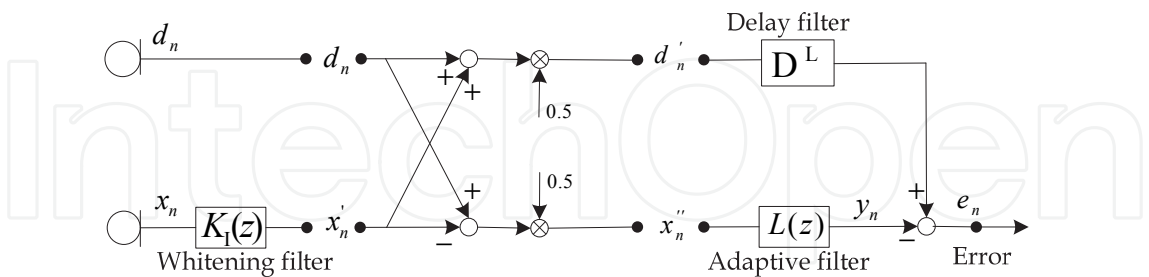

Fig. 10. Application of front-end whitening filter and rear-end adaptive filter to beamforming structure

Without application of whitening filter, acoustic path transfer function is estimated by adaptive filter $L(z)$ as the ratio of combined transfer functions, $\mathrm{H}(z) = (\mathrm{H}_1(z) + \mathrm{H}_2(z)) / (\mathrm{H}_1(z) - \mathrm{H}_2(z))$ in beamforming structure. With application of whitening filter $1 / \mathrm{H}_2(z)$, the rear end adaptive filter estimates $\mathrm{L}(z) = (\mathrm{H}_1(z) + 1) / (\mathrm{H}_1(z) - 1)$ in beamforming structure as shown in Fig. 11 (A), where it is shown that adpative filter is only related with estimates of $\mathrm{H}_1(z)$. From the analysis on the last ANC structure, adaptive filter now estimates only numerator polynomial part $(\mathrm{H}_1(z) + 1)$ with one sample delay filter D^{-1} as shown in Fig. 11 (B). Both whitening coefficients and adaptive filter weights are continuously updated during the noise period only, and then stopped and frozen during the signal plus noise period.
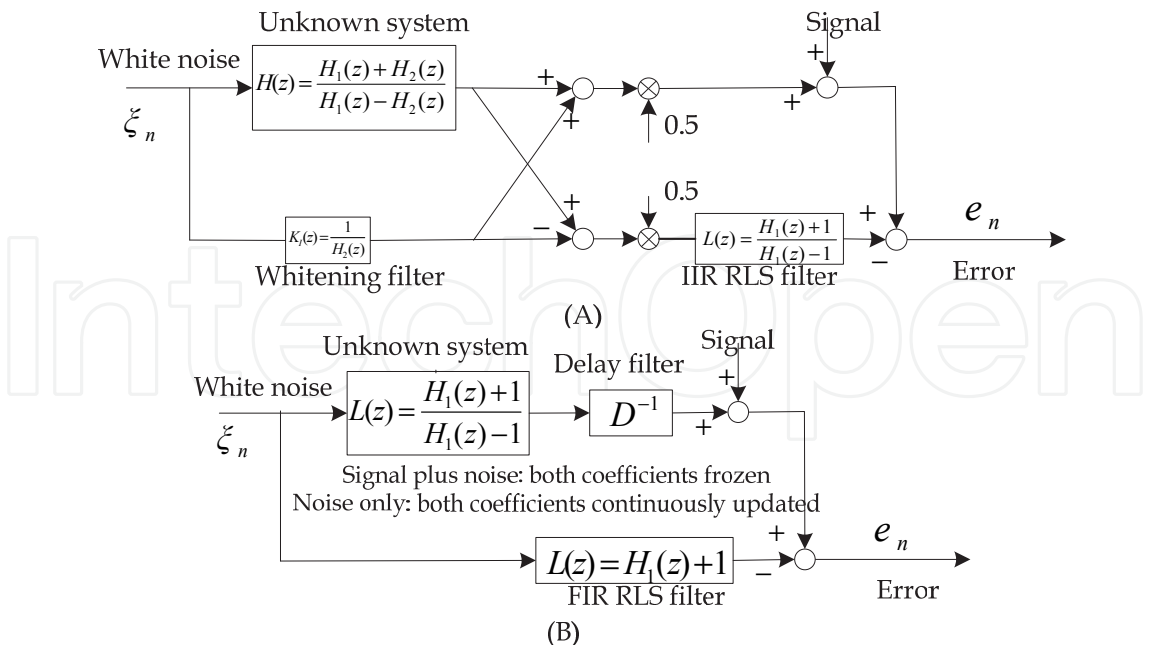

(A)

(B)

Fig. 11. Identification of unknown system in Beamforming structure of (A) estimates of innovations-based inverse kepstrum whitening filter and IIR RLS filter in front and rear of SS functions (B) estimate for adaptive FIR RLS filter with delay filter (one sample delayed) in the last ANC structure

5.4 Operation of front-end innovations-based whitening filter and rear-end zero-model FIR RLS filter in beamforming structure

With the use of same unknown system (11) as in ANC structure, the operation of inverse kepstrum whitening filter in front of SS functions in beamforming structure is same as one (13) in ANC structure.
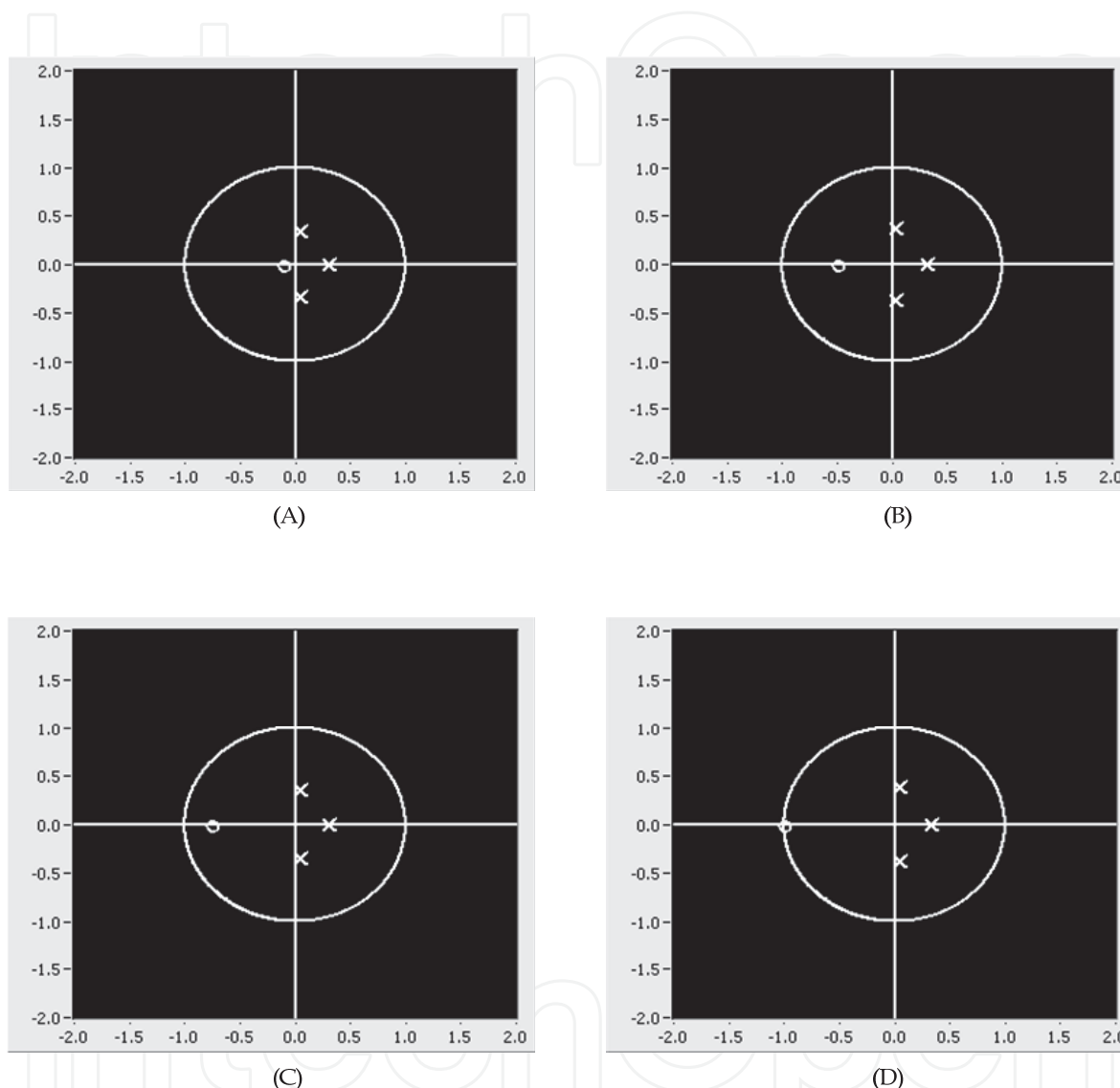

(A)

(B)

(C)

(D)

Fig. 12. Locations of pole-zero placement: (A) $H_1(z) = 1 + 0.2z^{-1}$ (B) $H_1(z) = 1 + 1z^{-1}$ (C) $H_1(z) = 1 + 1.5z^{-1}$ (D) $H_1(z) = 1 + 2z^{-1}$: $H_2(z)$ is commonly applied as $H_2(z) = 1 + 0.4z^{-1}$

The FIR RLS filter is then estimated on $(H_1(z) + 1)$, which gives that $L(z) = 1 + 0.75z^{-1}$, where $a_0 = 0.75$. It shows that weight value is half in size from the orignal weight value, 1.5 in $H_1(z)$. Fig. 12 shows pole-zero locations according to different weight value in $H_1(z)$, where a_0 values are (A) 0.2 (B) 1 (C) 1.5 and (D) 2. With the use of three inverse kepstrum coefficients as shown in Fig. 12, it shows that adaptive FIR RLS is approximated to the half values, which are (A) 0.1 (B) 0.5 (C) 0.75 and (D) 1, respectively.
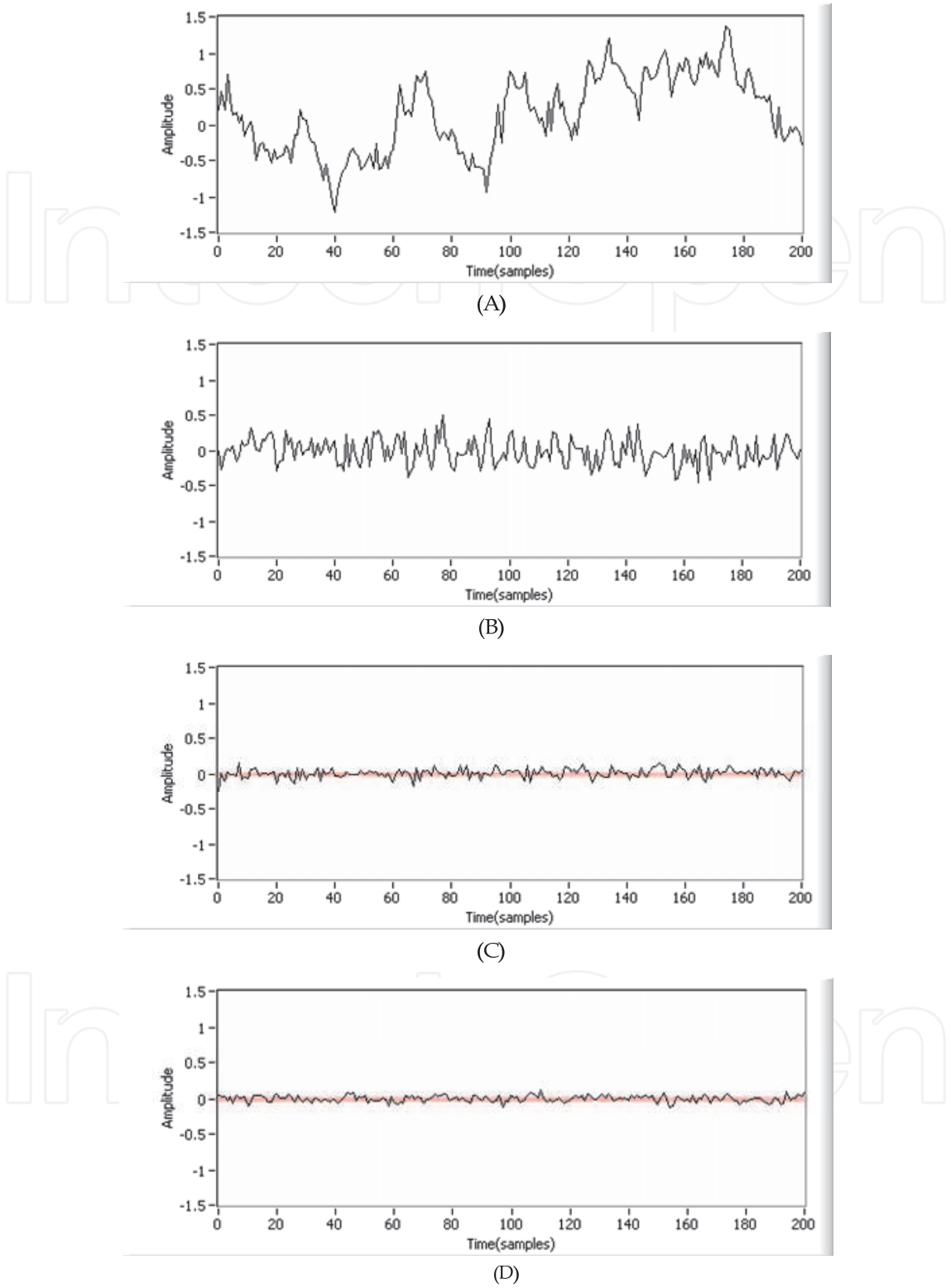
(A)

(B)

(C)

(D)

Fig. 13. Noise cancelling performance comparison in beamforming structure on (A) microphone ouput at x_n (B) whitening output $x_n^{'}$ (C) overall output e_n with inverse kepstrum filter only (wthout FIR RLS flter) and (D) overall output e_n with inverse kepstrum filter and FIR RLS filter

5.5 Test of noise cancellation on signal plus noise for real-time processing in a realistic environment

For real-time processing in a realistic room environment, it has been tested for the comparison of 1) the noise cancelling performance at each step in beamforming structure, and 2) the performance on front-end whitening application between ANC structure and beamforming structure, and finally 3) the noise cancelling performance in noise and signal plus noise between ordinary ANC approach using IIR RLS in ANC structure and front-end whitening approach with FIR RLS in beamforming structure.

Firstly, as shown in Fig. 13, the noise cancelling perfomance has been found from each processing stage, of 1) microphone output x_n , 2) inverse kepstrum filter output x'_n 3) overall output e_n with application of inverse kepstrum filter only and 4) overall output e_n with application of inverse kepstrum filter and FIR RLS filter from the each points in Fig. 10. For this test, 32 inverse kepstrum coefficients have been processed with FFT frame size 4096.

Based on this, it is found that inverse kepstrum filter works well in beamforming structrure. Secondly, with the sole application by inverse kepstrum filter only, its noise cancelling performance has been tested in (A) ANC structure and it has been compared in (B) beamforming structure as shown in Fig. 14. From the test, it has been found that inverse kepsrum is more effective in beamforming structure than its application in ANC structure.

Thirdly, it has also been compared in average power spectrum between IIR RLS in ANC structure and inverse kepstrum filter in front with rear-end FIR RLS in beamforming structure. From the test result, it shows that inverse kepstrum provides better noise cancelling performance in frequency range over 1000 Hz for noise alone period as well as signal plus noise period as shown in Fig. 15.
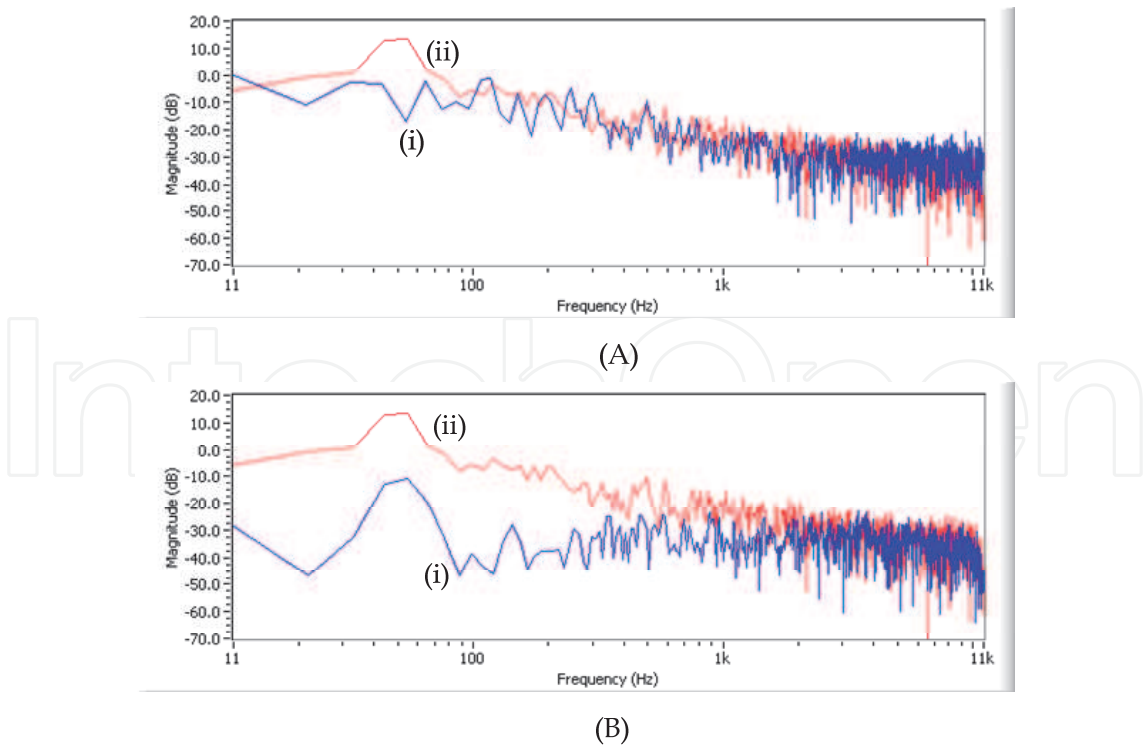

(A)

(B)

Fig. 14. (A) Comparison in ANC structure: between (i) whitening filter application only and (ii) no-processing, (B) comparison in beamforming structure: between (i) whitening filter application only and (ii) no-processing
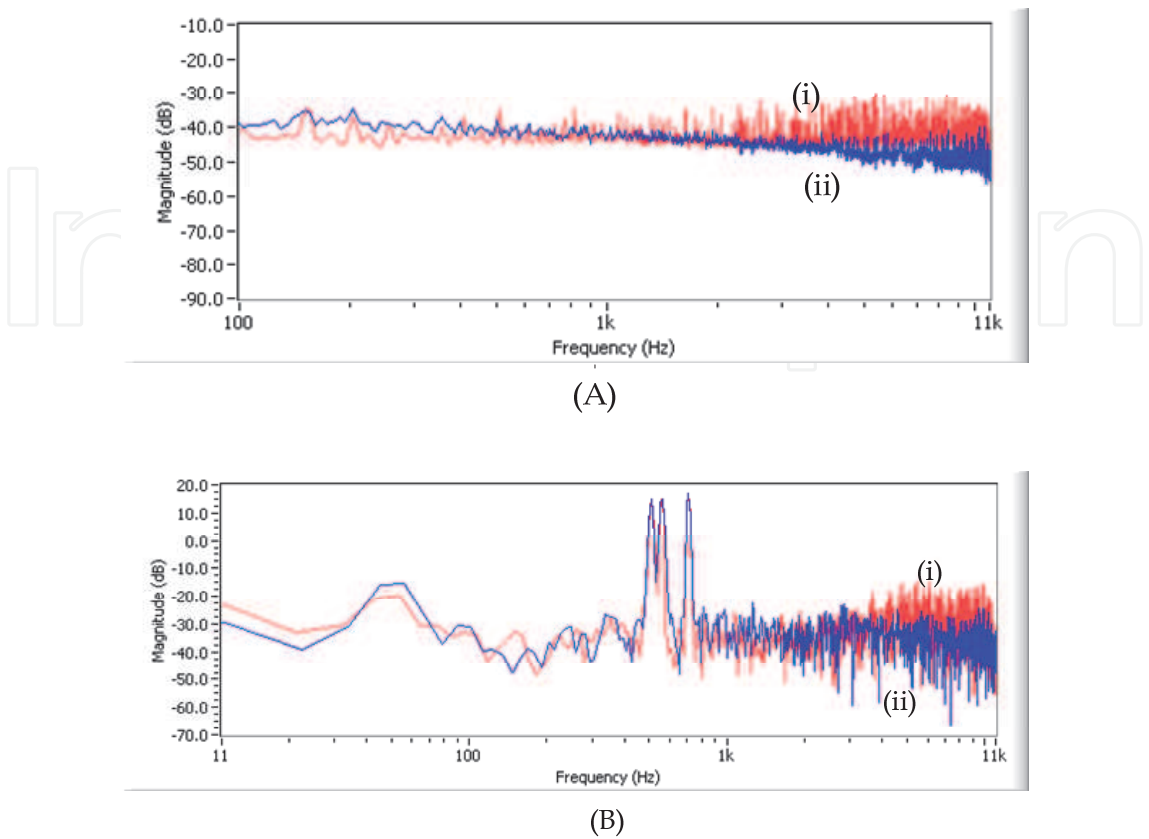
(A)

(B)

Fig. 15. Average power spectrum showing noise cancelling performance: comparison between (i) IIR RLS in ANC structure and (ii) whitening filter with FIR RLS in beamforming structure during the period of (A) noise and (B) signal and noise

6. Conclusion

It has been shown in simulation test that the application of front-end innovations-based whitening application (inverse kepstrum method) to cascaded zero model FIR RLS algorithm in ANC structure could perform almost same performance on convergence compared with pole-zero model IIR RLS in ANC structure. For the more effective performance in realistic environment, the front-end whitening application with rear-end FIR RLS to beamforming structure has shown better noise cancelling performance than the ordinary approach using pole-zero model IIR RLS in ANC structure. Therefore, when it is processed in real-time, it is claimed that the front-end whitening application could provide an effective solution due to a reduced computational complexity in inverse kepstrum processing using FFT/IFFT, which could be a benefit over sole application of IIR RLS algorithm.

7. Acknowledgment

8. References

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Adaptive Filtering

Edited by Dr Lino Garcia

Adaptive filtering is useful in any application where the signals or the modeled system vary over time. The configuration of the system and, in particular, the position where the adaptive processor is placed generate different areas or application fields such as prediction, system identification and modeling, equalization, cancellation of interference, etc., which are very important in many disciplines such as control systems, communications, signal processing, acoustics, voice, sound and image, etc. The book consists of noise and echo cancellation, medical applications, communications systems and others hardly joined by their heterogeneity. Each application is a case study with rigor that shows weakness/strength of the method used, assesses its suitability and suggests new forms and areas of use. The problems are becoming increasingly complex and applications must be adapted to solve them. The adaptive filters have proven to be useful in these environments of multiple input/output, variant-time behaviors, and long and complex transfer functions effectively, but fundamentally they still have to evolve. This book is a demonstration of this and a small illustration of everything that is to come.

How to reference

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Jinsoo Jeong (2011). Real-Time Noise Cancelling Approach on Innovations-Based Whitening Application to Adaptive FIR RLS in Beamforming Structure, Adaptive Filtering, Dr Lino Garcia (Ed.), ISBN: 978-953-307-158-9, InTech, Available from: http://www.intechopen.com/books/adaptive-filtering/real-time-noise-cancelling-approach-on-innovations-based-whitening-application-to-adaptive-fir-rls-i

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