Adaptive Noise Reduction of the Frequency Domain using the MDFT in the Biomedical Signal

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Abstract

This paper presents the high speed noise reduction processing system using the MDFT on the frequency domain. The proposed system use the linear prediction coefficients of the AR method based on the SLMS(sign least mean square). The signals with a random noise tracking per-formance are examined through computer simu-lations. It is confirmed that the high speed adaptive noise reduction processing system is realized by the SLMS algorithms with rapid convergence on the FD(frequency domain).

1. Introduction.

It is well known that the convergence speed of a time domain adaptive filter (TDAF) is degraded when an input signal is colored since the eigenvalue spread become large. To accelerate the convergence speed, a frequency domain adaptive filter(FDAF) in which the input autocorrelation matrix is approximately diagonalized by using the discrete Fourier transform(DFT) and normalized by the time-variable step size algorithm has been proposed[1-2]. In case of the FFT method, guarantees stable convergence, but a continues output signal can not be obtained for block-processing.

The frequency sampling filter(FSF) method[3] is able to process sample by sample, but the repeated structure bring an unstable convergence and accumulated error.[2] To obtain the continued output signal to preserve stable convergence property, we have proposed the adaptive filter using MDFT on the frequency domain. In adding to improve its convergence performance proposed the spectral error method using the MDFT[8]. This method is increased the convergence speed.

In this paper, we proposed the high speed adaptive noise reduction algorithm on the frequency domain using the SLMS. It is know that the proposed system is to evaluate linear prediction coefficient using the AR(Auto-regressive) method. In order to increase the convergence speed, the noise reduction algorithm is adapted. By computing the existed algorithm, the proposed system is identified the fast convergence speed on frequency domain.

II. The properties of MDFT and SLMS.

We are proposed a block diagram to reduce the noise as figure 1.

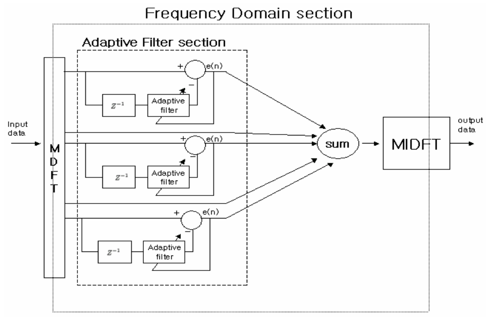


Fig. 1 The SLMS structure

The proposed structure using the modified DFT(MDFT) has the minimum quantity of operations to enable nonblock processing keeping stable convergence.

To improve the convergence speed is applied to FDAF(SLMS) algorithm that the input auto-correlation matrix is approximately diagonalized by using the discrete Fourier transform(DFT) and normalized by the time-variable step size algorithm. In Generally, the normalizing by spectral power effect to improve the convergence speed[2].

When the input signal in DFT is real, the modified DFT(MDFT) is as follows[2],

$$X_{k,i} = \sum_{n=0}^{N-1} x_{i-n} \cos \frac{2\pi nk}{N} \qquad (1)$$

$$x_i = \frac{X_{0,i}}{N} + \frac{2}{N} \sum_{k=1}^{\frac{N}{2}-1} X_{k,i} \qquad (2)$$

Where N is the number of samples and assumed to be even in the following. The notes n, i and k are used as a time, another time and frequency index, respectively.

If we calculate the operational number. The multiplication and addition of the MDFT pair is as follows[2].

$$4(\frac{N}{2})\log N-\sum_{r=3}^{\log N}2^{r-3}(r-2))-N \quad (3)$$

$$2N\log N-2\sum_{r=2}^{\log N}2^{r-2}(r-1)+2-\frac{N}{2} \quad (4)$$

As a result, it is shown a few operations against DFT's [6].

If we apply an equation (1) to an analysis algorithm, a coefficient vector is as follows[4],

$$H(n+1)=H(n)+\mu X(n)e(n) \quad (5)$$

Where H(n) is the vector of coefficients with a time n index. X(n) is the primary input vector. μ is a time-variable convergence parameter, e(n) is the error for tracking of reference input d(n) using the X(n). We assume that an input correlation matrix is diagonalized approximately. To decrease a number of operations used the sign method to avoid multiplications instead of an error signal or data value of signal. Before starting the analysis, Let H_{opt} denote the optimal filter coefficient vector given by,

$$H_{OPT}=R^{-1}{}_{xx}R_{xd} \quad (6)$$

Also, define the misalignment vector as[4],

$$V(n)=H(n)-H_{OPT} \quad (7)$$

The SLMS is defined by the adapted LMS for the misalignment vector[4],

$$H(n+1)=H(n)+\mu X(n)sign(e(n)) \quad (8)$$

$$E\{V(n+1)\}=(I-\frac{\mu}{\sigma e(n)}\sqrt{\frac{2}{\pi}}R_{xx})E\{V(n)\} \quad (9)$$

$$R_{xx}=E\{X(n)X^T(n)\}=\sigma^2{}_\tau I \quad (10)$$

$$R_{xd}=E\{X(n)d(n)\} \quad (11)$$

The filter's properties doesn't changed from the filter output and the error calculation, but it degraded steeply the multiplication operations in the adjustable part of coefficients by calculating to only get the symbol of input signal and error signal in that. If the μ is very small, make the result of real properties. The $\sigma_{e(n)}$ as LMS error in time-variable n is[4],

$$\sigma_{e(n)}>\frac{\mu\lambda\max}{\sqrt{2\pi}} \quad (12)$$

$$\mu_s=\mu_L\sqrt{\frac{2}{\pi}}\sqrt{\xi_{\min}} \quad (13)$$

$$\xi\min=E\{d^2(n)\}-R^T{}_{xd}H_{opt} \quad (14)$$

The μ is chosen μ_s to get the mean square error in stable state between the LMS and the SLMS.

$$\mu=\mu_s=\mu_L\sqrt{\frac{2}{\pi}}\sqrt{\xi_{\min}} \quad (15)$$

$$E\{V(n+1)\}=(I-\frac{2}{\pi}\frac{\sqrt{\xi_{\min}}}{\sigma e(n)}\mu_L R_{xx})E\{V(n)\} \quad (16)$$

Where μ_L is a convergence constant of LMS.

III. Experimental results

Figure 2 shows the input signal. The input signals are generated the spectrum by magnitude of output, and the normalized step size algorithms using its magnitude pass through the next state. As a result, that makes fast corrections in procedure.

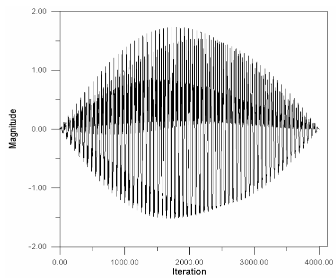
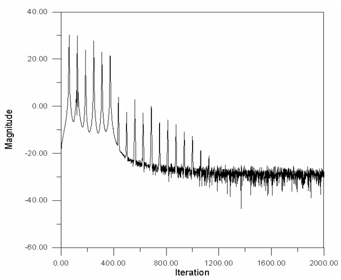
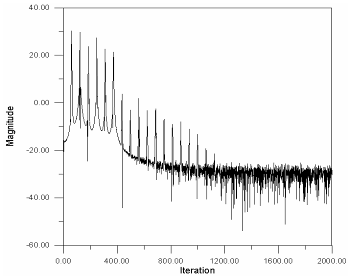


Fig. 2 The input signal waveform.

Figure 3 shows the result of conversion.
The results of graphics were confirmed a few differ greatly between DFT and MDFT.



(a)The DFT



(b)The MDFT

Fig. 3 The results of conversion.

Figure 4 shows the convergence speed between LMS and SLMS.

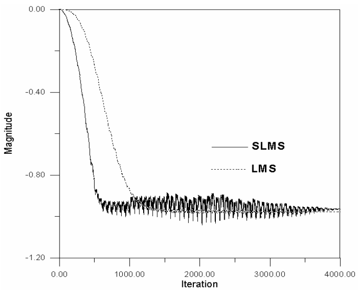


Fig. 4 The comparisons of the convergence speeds.

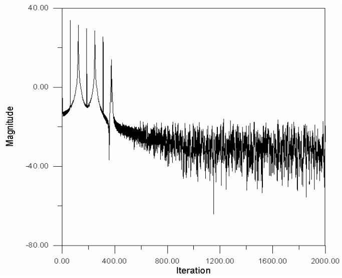
The result is shown the SLMS's convergence speed. Also, if the μ is very small, there isn't a wide difference between LMS and SLMS in error of the stable state.

The performances of the proposed system are confirmed through computer simulation. The generated signals were presented figure 1, and following as[2],

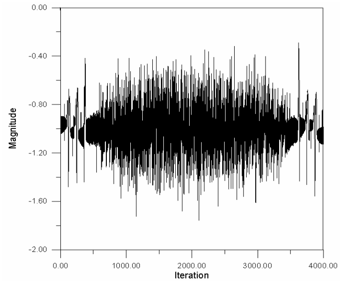
$$\begin{aligned}&\sin(2\pi i/8000)\{(1.2-0.2i/4000)\sin(2\pi i/64)\\&+(0.7+0.1i/2000)\cos(4\pi i/64)\\&+(0.3-0.1i/4000)\sin(6\pi i/64)\\&+(0.7-0.1i/1000)\cos(8\pi i/64)\\&+0.2\sin(10\pi i/64)\\&+(0.5-0.2i/1000)\sin(12\pi i/64)\}\end{aligned}$$

The signals that used experiment was added to the noise that had the white Gaussian noise of variance 1 for confirming the noise reduction performance.

The number of samples N was 64, and the data point was 4000. The coefficient of filter degree was 1, and the μ set 0.005.



(a)The input signal with noise.



(b) Adaptive coefficient signal.

Fig. 5 The waveforms.

Figure 5 shows the input signal waveform with the white Gaussian noise and the adaptive signal waveform of the applied SLMS in order to remove the noise signals.

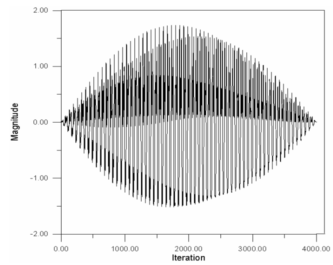


Fig. 6 The output signal waveform.

The proposed system is regenerated approxim-ately.

V. Conclusion.

In this paper, we are proposed the high speed adaptive noise reduction on the frequency domain using the SLMS, and its performances were confirmed through the simulations. The system using SLMS is much better former research[3]. To the high speed processing, the input autocorrelation matrix is assumed approx-imately diagonalizing. Also, it's ignored the fine error. It is necessary to method of correc-tion for the error in real states.

References

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