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Power-line Interference Removal of Bioelectric Signal Measurement by using Genetic Adaptive Filter

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Abstract—**In this study, we proposed a genetic adaptive filter to removing power-line interference. In previous work, the proposed structure, which extracts the interference component from the input biomedical signal to be a reference signal of the adaptive filter to estimate power-line interference, is effective for removing interference. Since this adaptive filter with least-mean square algorithm is sensitive to the eigenvalue spread of the autocorrelation matrix of the reference signals, and the selection of its step-size. Thus, we employ the genetic parallel search technique to improve the least-mean square algorithm. Through simulations, it shows that the adaptive filter with genetic algorithm provides better performance with any step-size.**

Keywords—**power-line interference, adaptive filter, least-mean square algorithm, genetic algorithm**

I. INTRODUCTION

Power-line interference is a major low-frequency interference source in bioelectric signal measurement. This interference is coupled into the measurement system from a variety of path [1]. The performance of the traditional hardware circuits used to solve this issue is limited. Nowadays, adaptive filtering technique is proposed to solve this problem. The power-line interference can be assumed to be a sinusoidal wave. However, in practice, this power-line interference signal is non-stationary. To solve this, we proposed an effective adaptive structure with least mean square (LMS) algorithm for removing power-line interference [2], [3]. In this structure, we extract the interference component from the input biomedical signal to be a reference signal of the adaptive filter to estimate power-line interference. In previous work, it showed the effective performance for removing interference. However, it is well-known that the least-mean square algorithm is sensitive to the eigenvalue spread of the autocorrelation matrix of the reference signals, and the selection of its step-size and apt to trap local minimum depending on initial conditions. To improve this shortcoming, we propose the genetic adaptive filter in this study. The genetic algorithm is a parallel search technique which uses the principles of genetics and evolution to perform a directed random search from a population of controllers to select the best to implement at a specific sampling time period [4], [5], [6]. It is suitable to solve eigenvalue disparity and local minimum issues due to its property of global optimization in control and signal processing area. Through some simulations, we found that it is more satisfactory and acceptable than least-mean square algorithm for removing power-line interference.

II. METHODOLOGY

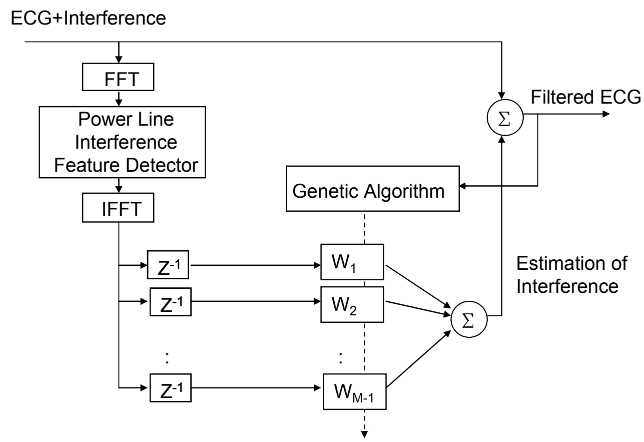

Fig. 1. The basic scheme of genetic adaptive filter for removing power-line interference

Fig.1 is the basic scheme of the genetic adaptive filter for removing power-line interference. The corrupted ECG is used as the primary input. In order to effectively estimate correlated interference, the reference signal is obtained by an interference detector. This interference detector consists of three parts. First, the FFT of the primary input is computed. Next, we find the significant peak from the spectrum of the primary signal in the range of interference bandwidth. Then the reference signal is obtained by recovering the significant peak of the spectrum from frequency domain to time domain via IFFT. In this study, the genetic algorithm is modified from the least-mean-square algorithm. In this algorithm, the generation and evaluation of its step-size are invoked regularly every period of T.

At the beginning of the k-th interval, the generation part of the algorithm first was occurred. Let $\mu_{optimum}^{k-1}$ is the optimal step-size in the (k-1)-th period. Then we generate several offspring of step-sizes by randomly increasing and decreasing the parent step-size $\mu_{optimum}^{k-1}$. The generation function, random perturbation function is described as

$$\begin{cases} \mu_1^k = \mu_{optimum}^{k-1} \\ \mu_{2j}^k = (1-\rho_{2j})\alpha^{-j}\mu_{optimum}^{k-1} + \rho_{2j}\mu_{optimum}^{k-1} \qquad ,1 \le j \le \dfrac{R-1}{2} \\ \mu_{2j+1}^k = \rho_{2j+1}\alpha^{j}\mu_{optimum}^{k-1} + (1-\rho_{2j+1})\mu_{optimum}^{k-1} \end{cases} \tag{1}$$

where R is the number of offspring, α is a positive constant related to the perturbation of these new generated step-sizes, and $\rho_i, 1 < i \le R$ are random numbers distributed over (0,1). And these new generated step-sizes must fit the convergent condition $0 < \mu_i^k < 2$.

Next, the tap-weight vectors corresponding to these new generated step-sizes are adapted and the filtered outputs $y_i^k(n)$ in the iteration n are computed.

$$y_i^k(n) = \mathbf{w}_i^k(n)^T \mathbf{u}(n) \quad ,1 \le i \le R \tag{2}$$

$$e_i^k(n) = d(n) - \mathbf{w}_i^k(n)^T \mathbf{u}(n) \quad ,1 \le i \le R \tag{3}$$

$$\mathbf{w}_i^k(n+1) = \mathbf{w}_i^k(n) + \frac{\mu_i^k}{a + P_u}\mathbf{u}(n)e_i^k(n) \quad ,1 \le i \le R \tag{4}$$

where $\mathbf{w}_i^k(n)$ and $e_i^k(n)$ denote the tap-weight vector and the priori estimation error corresponding μ_i^k to at time n.

To calculate the convergence criteria for evaluation, we define the posteriori estimation error and the convergence criteria as follows.

$$\eta_i^k(n) = d(n) - \mathbf{w}_i^k(n+1)^T \mathbf{u}(n), 1 \le i \le R \tag{5}$$

$$J_i = \sum_{n=0}^{T-1}\left[(1-\beta)e_i^k(n)^2 + \beta\eta_i^k(n)^2\right] \Big/ T = (1-\beta)J_i^e + \beta J_i^\eta \tag{6}$$

where β is a parameter in (0,1), and J_i^e and J_i^η denote the estimations of the mean-squared priori and posteriori error. The basic principle for adjusting parameter β is written as

$$\beta = \frac{J_0^e}{J^{e,\max}(k)} \tag{7}$$

where $J^{e,\max}(k)$ is the estimation of the mean-squared priori error using maximum μ in the k-th interval. The optimal step-size $\mu_{optimum}^k$ which gives the minimum convergence criteria in the k-th interval will survive and be selected as the optimal parent step-size for next interval. And the tap-weights vector and the adaptive filtering output corresponding to the new optimal step-size $\mu_{optimum}^k$ are kept.

III. RESULTS AND DISCUSSIONS

A. *Comparison of LMS and genetic algorithm*

In order to compare the performance of adaptive filter with LMS and genetic algorithm for removing power-line interference, first an original clear ECG pattern is corrupted intentionally to behave like a non-stationary signal resembling the non-stationary power-line interference ECG. The variation of the frequency of the simulated interference is in the range from 55 Hz to 65 Hz. Fig.2 (a) and Fig.2 (b) respectively show signal waves and their power spectrums of the clear ECG pattern and the corrupted ECG. In this simulation, the length of FFT in the interference detector is set to 256 points, and the filter taps of both are identically 16. Fig.2 (c) and Fig.2 (d) are respectively the filtered output and its power spectrum by LMS and genetic algorithm in the SNR 0f -5 dB. In this simulation, the step-sizes of both are set to 0.1. The effects of the above methods seem similar. In order to compare closely, we determine the normalized mean-squared error (MSE) of both methods corresponding to different step-sizes, shown in Fig.3. From the result, we found that the adaptive filter with genetic algorithm is insensitive to the selection of its step-size. This is due to that the genetic algorithm can easily adjust its step-size to optimum via evolution.

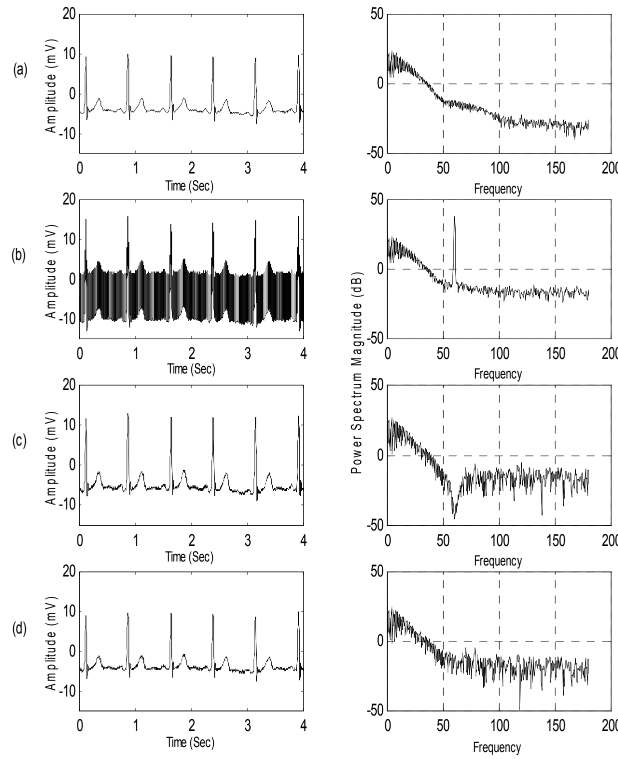

Fig. 2. The wave of signal and its power spectrum of (a) ECG pattern (b) simulated corrupted ECG (c) filtered output of the adaptive filter with LMS algorithm (d) filtered output of the adaptive filter with genetic algorithm, in the SNR of -5 dB.

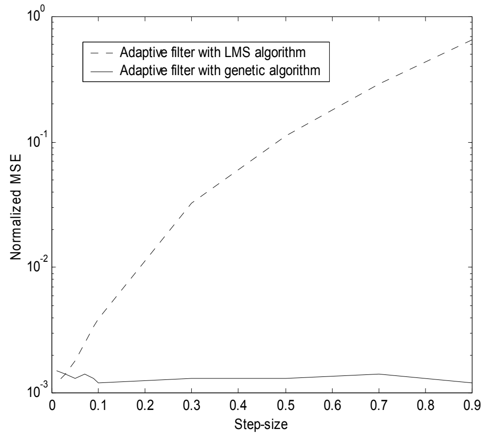

Fig. 3. The normalized mean squared error of the LMS and genetic algorithm corresponding to different step-size in the SNR of -5 dB

B. *Comparison in different noise level*

In this section, the performance of the LMS and genetic algorithm in different noise level are compared. The SNR range of the simulated corrupted ECG is set from -2.5 dB to -15 dB. The length of FFT in the interference feature detector is set to 256 points. In all simulations, the step-sizes are both identically 0.1. The filter taps of both are set to 16. The result was shown in Fig.4. From Fig.4, we found that the genetic algorithm provides a better performance in different noise level. However, the effects of both methods are limited when the SNR is very poor. This is due to that both the LMS and genetic algorithm are based on second statistics, and they are sensitive to the eigenvalue spread of the autocorrelation matrix of the reference signals. Thus, the SNR of the reference signal is an important factor for improving the performance.

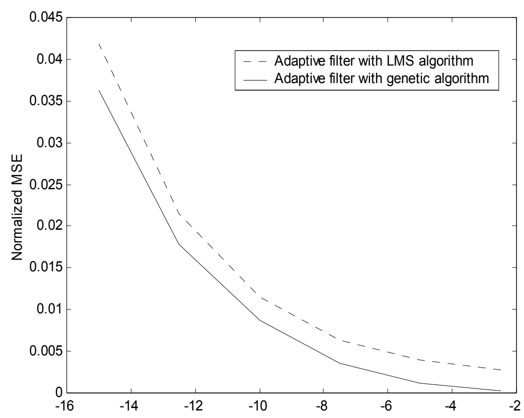

Fig. 4. The normalized mean squared error of the LMS and genetic algorithm in different noise levels

IV. CONCLUSION

Finally, this result clearly showed that the adaptive filter with genetic algorithm is insensitive to the changing of filter step size since it can rapidly adjust its step-size to approach the optimum via generation and evaluation. By randomly generating new offspring of step-sizes cover a large range, it is efficient to search the optimal step-size without expensively computation in the different noise level of input signals. It is useful for removing power-line interference of bioelectrical signals in the unknown condition.

REFERENCES

[1] Yue-Der Lin, “Interference Removal and Noise Analysis for Bioelectric Signal Measurement”, Doctorate thesis of Institute of E.E.,NTU, Taiwan R.O.C.,1998.

[2] Chin-Chia Chang, Bor-Shyh Lin, Jen-Chien Chien, Yue-Der Lin, and Fok-Ching Chong, “A Feature Enhancement Adaptive structure for Removing Residual Power-line Interference”, 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2001.

[3] Bor-Shyh Lin,Nor-Shing Lin, Wan-Chi Lee,Fok-Ching Chong, and Yue-Der Lin, "Removing residual power-line interference using WHT adaptive filter", 24rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2002.

[4] S.C. Ng, C.Y. Chung, S.H. Leung, and A. Luk, “A variable step size algorithm using evolution strategies for adaptive filtering”, Proceedings of the 1999 Congress on Evolutionary Computation,vol.1 , pp.542-545, 1999.

[5] S.C. Ng, S.H. Leung, C.Y. Chung, A. Luk, and W.H. Lau, “The genetic search approach. A new learning algorithm for adaptive IIR filtering”, IEEE Signal Processing Magazine, vol.13, Issue: 6, pp.38-46, 1996.

[6] K. H. Yim, J. B. Kim, T. P. Lee, and D. S. Ahn, “Genetic adaptive IIR filtering algorithm for active noise control”, Proceedings of the1999 IEEE International Fuzzy Systems Conference, vol.3 , pp.22-25, 1999.