Artifact Elimination using Fuzzy Rule Based Adaptive Nonlinear Filter

Tohru Kiryu, Hidekazu Kaneko**, and Yoshiaki Saitoh**

*Department of Information Engineering, Faculty of Engineering, Niigata University
**National Institute of Bioscience and Human-Technology, Agency of Industrial Science and Technology
*8050 Ikarashi-2nocho, Niigata, 950-21, JAPAN
kiryu@info.eng.niigata-u.ac.jp

ABSTRACT

Myoelectric (ME) signals during dynamic movement suffers from artifact noise caused by mechanical friction between electrodes and the skin. The frequency components of artifact noise is similar to those of ME signals. Thus it is difficult to reject artifact noise using linear filters. We have proposed a nonlinear artifact elimination method that consists of an inverse autoregressive (AR) filter, a nonlinear filter, and the AR filter. To improve the performance we installed adaptive filters so as to track time-varying signals. Moreover, fuzzy rules was employed for fine control of the nonlinear parameter. As a result, we achieved a better artifact elimination performance. The fuzzy rule based adaptive nonlinear filter will be useful in sport science and rehabilitation.

1. INTRODUCTION

Artifact noise is caused by a sudden change in the dc contact at the electrodes-skin interface. In biomedical signal recordings during movement, artifact noise is inevitable. Several methods have been proposed to solve this problem including active electrodes, improvement of an analog electronic circuits, and signal processing. The signal processing approach is a better choice because many researchers can access to the artifact elimination method by the computer network.

Artifact elimination corresponds to estimating the time-varying electronic base-line change from an observed signal. A linear moving average filter is a popular signal processing approach in this field. Alsté and Schilder [1] used an FIR filter to remove the base-line wander and power-line interference from electrocardiographic recordings, because almost all the artifacts consisted of low frequency components. However, a linear filter does not perform well for artifact noise when the same frequency components are also contained in the target biomedical signals. Impulsive noises like abrupt artifacts could be removed by the median filter [2] and its related methods which have been developed in the fields of speech signal processing and image processing.

It seems useful to employ a nonlinear filter, whose coefficients depend on the local features of an observed signal. Abramatic and Netravali [3] used the Winner filter based adaptive noise smoothing filter to restore noisy images, depending on the local variance of images. Moore and Parker [4] proposed the E-filter, which changed its frequency characteristics by referring to the amplitude of the observed signal. Arakawa *et al.* [5] proposed the ε-separating nonlinear digital filter to separate abrupt changes in waveform from the electroencephalogram, using the $\pm\varepsilon$ threshold functions. Kaneko *et al.* [6] developed a method of rejection artifacts from surface myoelectric (ME) signals with a series of filters: the structure was a linear-nonlinear-linear filter.

In this paper, we propose a fuzzy rule based adaptive nonlinear filter based on Kaneko's artifact rejection method. We study an artifact elimination performance of our method by computer simulation

2. METHOD

Kaneko *et al.* [6] proposed a nonlinear artifact elimination filter. It consisted of a filter for selectively whitening ME signals, a nonlinear filter that eliminates ME-related components from the filtered observed signals, and a restoring filter that recovers only artifact-related components. The whitening and the restoring (inverse whitening) filters are both autoregressive (AR) filters and they have the same coefficients. Subtracting the restored artifacts from the observed signal leads to desirable artifact elimination.

Let us assume that a digitized observed signal, $y(n)$, can be expressed as the sum of a biomedical signal, $x(n)$, and artifact noise, $a(n)$, as follows:

$$y(n) = x(n) + a(n) \tag{1}$$

where n denotes the time index. Using the AR coefficients estimated from a biomedical signal, we design the whitening and the inverse whitening filters. The signal after whitening filter is given by

0-7803-1775-0/94 $3.00 © 1994 IEEE

$$\psi(n) = \xi(n) + \alpha(n) \qquad (2)$$

where $\xi(n)$ is white noise, if the AR filter at the first stage is suitably designed for the biomedical signal. On the other hand, an artifact is partly filtered and its amplitude is higher than that of a filtered biomedical signal. The nonlinear filter in the middle stage separates the filtered biomedical signal and the filtered artifact by the difference in their amplitudes. As a nonlinear filter, we employed a nonlinear LMS smoothing filter [7] defined by:

$$\zeta(n) = \gamma(n)\{\psi(n) - E[\psi(n)]\} + E[\psi(n)] \qquad (3)$$

where $\gamma(n)$ is a time-varying coefficient of the adaptive LMS smoothing filter. The frequency characteristic is

$$G(\omega) = \gamma(n) + [1 - \gamma(n)]\, sinc(\frac{\omega M}{2f_s}) \qquad (4)$$

where M is the number of samples in each analyzing interval and f_s is the sampling rate. Since $G(\omega)$ contains the *sinc* function, $G(\omega)$ changes from a low-pass filter to an all-pass filter depending on $\gamma(n)$. Assuming the locally stationarity and ergotic process, $\gamma(n)$ was determined in each interval as follows:

$$\text{if } \sigma_\xi^2(n) << \sigma_\psi^2(n), \text{then } \gamma(n) \approx 1 \text{ and } \zeta(n) \approx \psi(n); \qquad (5.1)$$

$$\text{if } \sigma_\xi^2(n) < \sigma_\psi^2(n), \text{then } \gamma(n) = \frac{\sigma_\psi^2(n) - \sigma_\xi^2(n)}{\sigma_\psi^2(n)}; \qquad (5.2)$$

$$\text{if } \sigma_\xi^2(n) \geq \sigma_\psi^2(n), \text{then } \gamma(n) = 0 \text{ and } \zeta(n) = E[\psi(n)]. \qquad (5.3)$$

where σ_ξ^2 and σ_ψ^2 are the variances of $\xi(n)$ and $\psi(n)$ in each interval, respectively. Equation (5.1) denotes the all-pass filter for $\xi(n)$ whereas equation (5.3) expresses the low-pass filter for $\alpha(n)$. After estimation of the artifacts, subtraction of the restored artifacts form the observed signal leads to desirable artifact rejection.

We use an adaptive strategy for Kaneko's filter to track the time-varying behavior of the filter coefficients, $[c_i^{(p)}]$, using the Lee's algorithm [8]. For the nonlinear filter coefficient, the initial value of $\sigma_\xi^2(n)$ can be estimated in an artifact-free interval. Then we update $\sigma_\xi^2(n)$ in each overlapping interval as follows:

$$\text{if } \sigma_\xi^2(n-1) \approx \sigma_\psi^2(n), \text{then } \sigma_\xi^2(n) = \sigma_\psi^2(n-1), \qquad (6.1)$$

$$\text{if } \sigma_\xi^2(n-1) << \sigma_\psi^2(n), \text{then } \sigma_\xi^2(n) = \sigma_\xi^2(n-1). \qquad (6.2)$$

The characteristics of the nonlinear LMS smoothing filter were insufficient when $\sigma_\xi^2(n)$ and $\sigma_\psi^2(n)$ came close

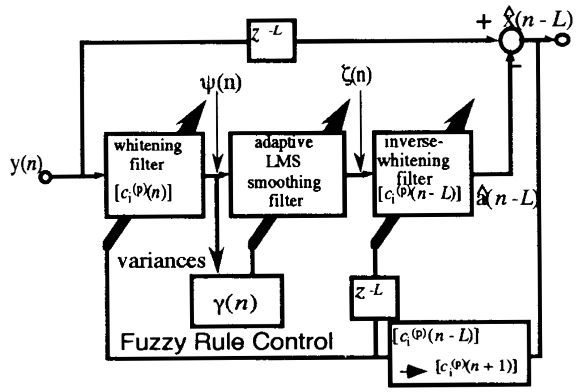

Fig. 1. Fuzzy Rule based adptive nonlinear artifact elimination filter. Whitening and inverse whitening filters are AR filters. AR coefficients, $[c_i^{(p)}]$, are estimated by the adaptive procedure (Lee's algorithm). The nonlinear filter parameter, $\gamma(n)$, is time-updated by the fuzzy rules.

to each other. Hence, we introduce the fuzzy associated rules [9] in order to effectively adjust $\gamma(n)$ to the local features of an observed signal (**Fig. 1**).

Figure 2 demonstrates the fuzzy membership functions, $m_A(B)$. The number $m_A(B)$ indicates the degree to which object B belongs to fuzzy set A. We use triangular shaped membership functions. The fuzzy sets are S (small), RS (rather small), RL (rather large), and L (large) for the variances, σ_ξ^2 and σ_ψ^2, that are used as input associants. Fuzzy sets of output associants are F (filtering), PF (partial filtering), PP (partial passing), and P (passing) for $\gamma(n)$. Therefore, the fuzzy bank matrix contains 16 rules, as showed in **Fig. 3**. For example, if $\sigma_\xi^2(n)$ is S and $\sigma_\psi^2(n)$ is L, then $\gamma(n)$ is P. That is, if the variance of the filtered ME signal is smaller than the variance of the observed signal, then the nonlinear filter functions as an all-pass filter: artifact noise is highly expected. The fuzzy set F occupies more than half of the fuzzy bank matrix. In particular, if $\sigma_\xi^2(n)$ and $\sigma_\psi^2(n)$ have the same range, we designed that $\gamma(n)$ should be "F." As a defuzzification method, we used the correlation-minimum (the correlation-minimum encoding with the max-min composition) inference procedure with the centroid defuzzification method.

3. RESULTS AND DISCUSSION

We confirmed the performance of our artifact elimination filters by computer simulation (**Figure 4**). The types of artifacts tested were sinusoidal, exponential, triangular, and

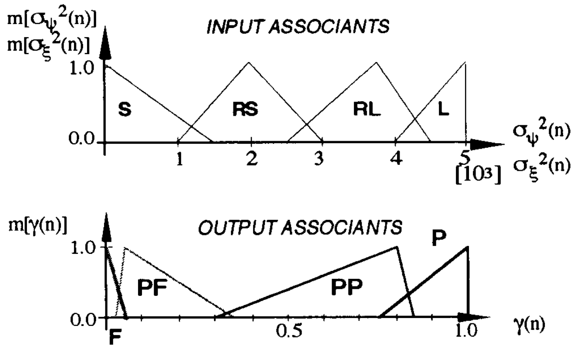

Fig. 2. Fuzzy membership functions.

(a) / (b)	S	RS	RL	L
S	F	F	F	F
RS	PF	F	F	F
RL	PP	PF	F	F
L	P	PP	PF	F

Fig. 3. Fuzzy bank matrix for the nonlinear artifact elimination filter: (a) variance of a filtered ME signal; (b) variance of an observed signal.

impulsive waveforms (Fig. 4(a)). A simulation signal (Fig. 4(b)) was composed of several types of artifacts superimposed on the ME signal measured during a sustained contraction. The ME signals were sampled at 5 kHz. The order of the AR filters at the first and last stages was 10. The forgetting factor of Lee's algorithm was 0.998. The adaptive procedure was carried out every 0.2 ms (one sample). The initial variance of $\sigma_\xi^2(n)$ was estimated at an early interval of 35 ms, in which the ME signal of a sustained contraction was locally stationary and did not contain artifact noise. The variance of the observed signal, $\sigma_\psi^2(n)$, was estimated every 0.2 ms in each overlapping interval of 35 ms, then $\sigma_\xi^2(n)$ at time instant n was time-updated

The result of Fig. 4(c) demonstrates that the fuzzy rule based adaptive nonlinear artifact elimination filter achieved better performance for individual artifacts than the adaptive nonlinear artifact elimination filter (adding the adaptive procedure in Kaneko's filter). Introduction of fuzzy rules made the performance of the adaptive nonlinear artifact elimination filter better than ever. It was, however, difficult to eliminate abrupt changes in artifacts.

The variance of the filtered observed signal, $\sigma_\psi^2(n)$ and the time-updated $\sigma_\xi^2(n)$ are indicated in Fig. 4(d). Except for the abrupt changes in the observed signal, $\sigma_\psi^2(n)$ appears white noise. Note that $\sigma_\xi^2(n)$ was updated by equations (6.1) and (6.2) to proceed with the adaptive procedure. Figure 4(e) shows the performance of the nonlinear filter parameter $\gamma(n)$ for the adaptive nonlinear artifact elimination filters with and

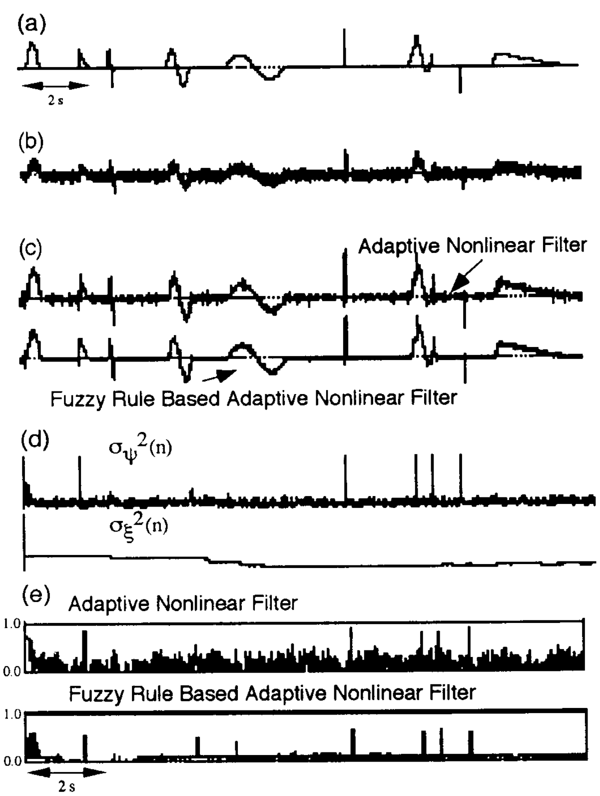

Fig. 4. Result: (a) given artifacts; (b) observed signal contaminated by artifacts; (c) estimated artifacts; (d) variances of filtered signals; (e) performance of the nonlinear filter parameter $\gamma(n)$.

without fuzzy rules. Comparing the time-series of $\gamma(n)$, the performance of the adaptive nonlinear artifact elimination filter was worse when $\sigma_\psi^2(n)$ came close to $\sigma_\xi^2(n)$, in which $\gamma(n)$ varied frequently from 0 to around 0.5; on the other hand, the fuzzy rule based adaptive nonlinear artifact elimination filter remained steady around 0.2 almost everywhere. The nonlinear filter parameter $\gamma(n)$ is strictly determined by the characteristics of the employed function (5.2) in the adaptive nonlinear artifact elimination filter. On the other hand, the fuzzy rule based adaptive nonlinear artifact elimination filter can adjust the performance of $\gamma(n)$, depending on the local features. As a result, the frequency characteristic of the fuzzy rule based method became more low-pass filtering around small value of $\sigma_\psi^2(n)$ and $\sigma_\xi^2(n)$ than that of the adaptive nonlinear method.

Fine control of the frequency characteristic around the small value of $\sigma_\psi^2(n)$ was useful for ME signals during a sustained contraction. The flexible control of the frequency characteristic by customizing the fuzzy rules will possibly benefit the artifact elimination for ME signals during dynamic movement. Further study will be required to balance the membership functions and fuzzy rules for practical ME signals.

4. CONCLUSION

We proposed the fuzzy rule based adaptive artifact elimination filter composed of inverse AR filter, nonlinear LMS smoothing filter, and AR filter. The inverse AR filter adaptively makes surface ME signals random and small amplitude white noises. The nonlinear LMS smoothing filter selectively averages small amplitude signals at each time, depending on the local standard deviations of an observed signal. We applied the fuzzy rules for the adjustment of the nonlinear filter coefficient. The last AR filter, which has the same coefficients as those of the AR inverse filter, finally provides the estimated artifact. Subtraction of the estimated artifact from observed signals leads to artifact elimination.

The computer simulation demonstrated that our method achieved better than ever for several types of artifacts. It will be applicable to the measurement of surface ME signals during dynamic movement in sports science and rehabilitation.

ACKNOWLEDGEMENT

The authors wish to thank Takao Kobayashi, a student at Niigata University, who carried out the implementation of fuzzy rules. This research is supported by the TEPCO Research Foundation and the experimental part is supported by the Desant Sports Foundation.

REFERENCES

[1] J. Alsté and T. Schilder, "Removal of base-line wander and power-line interference from the ECG by an efficient FIR filter with a reduced number of taps," *IEEE Trans. Biomed. Eng.*, vol. BME-32, pp.1052-1060, 1986.

[2] N. C. Gallagher and G. L. Wise, "A theoretical analysis of the properties of median filters," *IEEE Trans. Acoust., Speech & Signal Processing*, vol. ASSP-29, pp. 1136-1141, 1981.

[3] J. Abramatic and A. Netravali, "Nonlinear restoration of noisy images," *IEEE Trans. Pattern Anal. & Mach. Intell.*, vol. PAMI-4, pp. 141-149, March 1982.

[4] D. Moore and Parker, "On non-linear filters involving transformation of the time variable," *IEEE Trans. Inf. Theory*, vol. IT-19, pp. 415-422, July 1973.

[5] K. Arakawa, D. H. Fender, H. Harashima, H. Miyakawa, and Y. Saitoh, "Separation of nonstationary component from the EEG by a nonlinear digital filter," *IEEE Trans. Biomed. Eng.*, vol. BME-33, pp. 724-726, 1986.

[6] H. Kaneko, T. Kiryu, H. Makino, and Y. Saitoh, "An elimination method of artifacts added in surface myoelectric signals (in Japanese)," *Trans. of IEICE*, vol. J71-D, pp. 1832-1838, 1988.

[7] S. Kawata and S. Minami, "Adaptive smoothing of spectroscopic data by a linear mean-square estimation," *Appl. Spectrosc.*, 38, 1, pp. 49-58, 1984.

[8] D. Lee, M. Morf and B. Friedlander, "Recursive least squares ladder estimation algorithm," *IEEE Trans. Acoust., Speech & Signal Processing*, vol. ASSP-29, pp. 627-641, 1981

[9] B. Kosko, *Neural networks and fuzzy systems*. London: Prentice-Hall, 1992.