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Motion Artifact Elimination Using Fuzzy Rule Based Adaptive Nonlinear Filter

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SUMMARY Myoelectric (ME) signals during dynamic movement suffer from motion artifact noise caused by mechanical friction between electrodes and the skin. It is difficult to reject artifact noises using linear filters, because the frequency components of the artifact noise include those of ME signals. This paper describes a nonlinear method of eliminating artifacts. It consists of an inverse autoregressive (AR) filter, a nonlinear filter, and an AR filter. To deal with ME signals during dynamic movement, we introduce an adaptive procedure and fuzzy rules that improve the performance of the nonlinear filter for local features. The result is the best ever reported elimination performance. This fuzzy rule based adaptive nonlinear artifact elimination filter will be useful in measurement of ME signals during dynamic movement.

key words: *nonlinear filter, fuzzy, adaptive filter, artifact elimination, separation of superimposed signals*

1. Introduction

Motion artifact noise is caused by a sudden change in the dc contact at the interface between electrodes and the skin. In biomedical signal recordings during movement, artifact noise is unavoidable. Several methods have been proposed to solve this problem including active electrodes [1], improvement of analog electronic circuits [2], [3], and signal processing. The signal processing approach seems to be a better choice among them.

Artifact elimination corresponds to estimating the time-varying electronic base-line wander from an observed signal. A linear moving average filter is a popular signal processing approach in this field. Alstẽ and Schilder [4] 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.

A nonlinear filter, whose coefficients depend on the local features of an observed signal, looks promising. Abramatic and Netravali [5] used the Winner filter based adaptive noise smoothing filter to restore noisy images, depending on the local variance of images. Moore and Parker [6] proposed the E-filter, which changed its frequency characteristics by referring to the amplitude of the observed signal. Arakawa et al. [7] 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. [8] 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 describe a fuzzy rule based adaptive nonlinear filter based on Kaneko's artifact rejection method. By introducing an adaptive procedure and adjusting fuzzy parameters empirically, we obtained better artifact elimination for time-varying ME signals during dynamic contractions.

2. Method

2.1 Adaptive Nonlinear Artifact Elimination Filter

Kaneko et al. [8] 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. Artifact noise is presumed to include the same frequency components that are also contained in the target biomedical signals. AR coefficients are estimated from a biomedical signal for the whitening and the inverse whitening filters. The signal after whitening filter is given by

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$$\psi(n)=\xi(n)+\alpha(n). \quad (2)$$

The filtered biomedical signal $\xi(n)$ is white noise if the whitening filter at the first stage is suitably designed for the biomedical signal. On the other hand, artifact noise is partly filtered and its amplitude is rather higher than that of the filtered biomedical signal. Thus, the nonlinear filter in the middle stage separates the filtered biomedical signal $\xi(n)$ from the filtered artifact $\alpha(n)$ by the difference in their amplitudes. As a nonlinear filter, we employed a nonlinear LMS smoothing filter [9] defined by:

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

where $\gamma(n)$ is a nonlinear parameter of the nonlinear LMS smoothing filter and $E[\cdot]$ is the expectation procedure in an analytical interval. The z transform of the nonlinear LMS smoothing filter is given by

$$G(z, n)=\frac{Z(z, n)}{\Psi(z, n)}$$

$$=\gamma(n)+[1-\gamma(n)]\frac{1}{M+1}\sum_{m=-M/2}^{M/2} z^{-m}, \quad (4)$$

where M is the number of samples in each interval. The analog representation of the frequency characteristic is

$$G(\omega, t)=\gamma(t)+[1-\gamma(t)]\mathrm{sinc}\left(\frac{\omega M}{2f_s}\right), \quad (5)$$

where f_s is the sampling rate and t indicates the analog time. Since $G(\omega, t)$ contains the sinc function, $G(\omega, t)$ changes from a low-pass filter to an all-pass filter depending on $\gamma(t)$. The nonlinear filter parameter, $\gamma(n)$, is determined as follows:

if $\sigma_\xi^2(n) \ll \sigma_\psi^2(n)$,

then $\gamma(n)\approx 1$ and $\zeta(n)\approx\psi(n)$; (6a)

if $\sigma_\xi^2(n)<\sigma_\psi^2(n)$, then $\gamma(n)=\dfrac{\sigma_\psi^2(n)-\sigma_\xi^2(n)}{\sigma_\psi^2(n)}$; (6b)

if $\sigma_\xi^2(n)\geqq\sigma_\psi^2(n)$,

then $\gamma(n)=0$ and $\zeta(n)=E[\psi(n)]$. (6c)

where $\sigma_\xi^2(n)$ and $\sigma_\psi^2(n)$ are the variances of $\xi(n)$ and $\psi(n)$ in each interval, respectively. As a result, the nonlinear filter acts as an all-pass filter to separate $\alpha(n)$ form $\psi(n)$ (Eq. (6a)) and as a low-pass filter to separate $\xi(n)$ form $\psi(n)$ (Eq. (6c)), depending on the local features in the variances.

We use an adaptive procedure for Kaneko's filter to treat ME signals during dynamic movement. Figure 1 shows an adaptive nonlinear artifact elimination filter. The time-varying AR filter coefficients, $[c_i^{(p)}]$, are estimated by Lee's algorithm [10]. Lee's algorithm adaptively estimates the time-varying AR coefficients

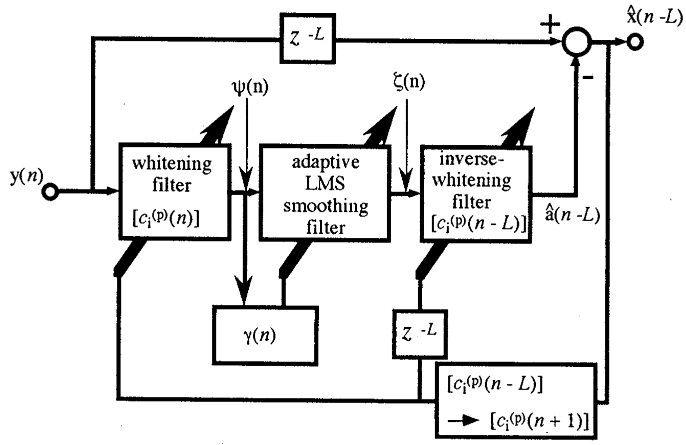


Fig. 1 Adaptive nonlinear artifact elimination filter. Whitening and inverse whitening filters are AR filters. AR coefficients, $[c_i^{(p)}]$, are estimated by the adaptive procedure (Lee's algorithm). The nonlinear filter parameter, $\gamma(n)$, is time-updated by Eqs. (6) and (7).

by introducing the forgetting factor and a recursive procedure. The AR coefficients are time-updated for the estimate of the ME signal, $\hat{x}(n)$, after eliminating the estimated artifact noise, $\hat{a}(n)$, from the observed signal, $y(n)$. Thus, the sufficient artifact elimination improves the performance of the whitening and the restoring filters. For the nonlinear filter, we introduce a simple time-update procedure, because the variance of the filtered biomedical signal, $\sigma_\xi^2(n)$, cannot be calculated in an arbitrary interval theoretically. The initial value of $\sigma_\xi^2(n)$ can be estimated in an arbitrary early interval, in which artifact noise does not exist. Then, using the variance of the filtered observed signal, $\sigma_\psi^2(n)$, estimated in each overlapping interval, $\sigma_\xi^2(n)$ is time-updated as follows:

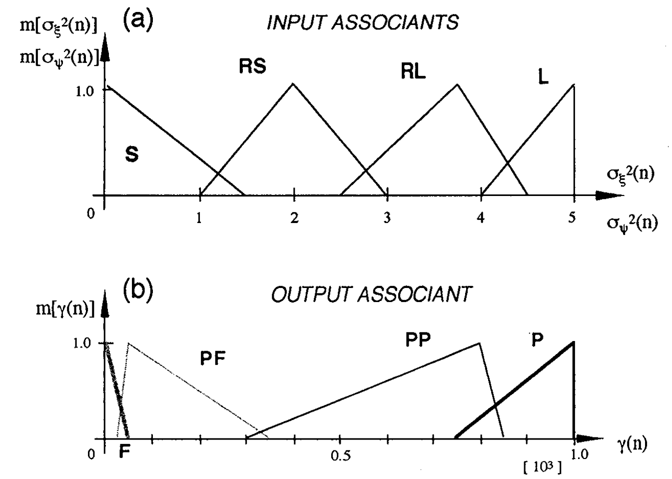
if $\sigma_\xi^2(n-1)\approx\sigma_\psi^2(n)$, then $\sigma_\xi^2(n)=\sigma_\psi^2(n)$, (7a)

if $\sigma_\xi^2(n-1)\ll\sigma_\psi^2(n)$, then $\sigma_\xi^2(n)=\sigma_\xi^2(n-1)$. (7b)

2.2 Fuzzy Rule Based Adaptive Nonlinear Artifact Elimination Filter

Although the time-update procedure of $\sigma_\xi^2(n)$ is sufficient for ME signals during a sustained contraction, the time-updated $\sigma_\xi^2(n)$ sometimes includes a large bias during dynamic movement. It is difficult to control $\gamma(n)$ for such a bias by the Eq. (6b). Consequently, the insufficient artifact elimination enlarges the bias of the time-updated AR coefficients and in turn the bias of the time-updated $\sigma_\xi^2(n)$. In order to compensate the behavior of the time-updated $\sigma_\xi^2(n)$, we introduce the fuzzy associated rules [11] and then effectively adjust $\gamma(n)$ to the local features even during dynamic movement.

Figure 2 demonstrates the fuzzy membership func-



(c)

$\sigma_\psi^2(n)$ ↓ \ $\sigma_\xi^2(n)$ →	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. 2 Fuzzy membership functions and the fuzzy bank matrix for ME signals during a sustained contraction: (a) input associants as a function of variances; (b) output associant as a function of $\gamma(n)$; (c) fuzzy bank matrix representing the rules between the variances and $\gamma(n)$.

tions and the fuzzy bank matrix for ME signals during a sustained contraction. The fuzzy membership function $m_A(B)$ 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, $\sigma_\xi^2(n)$ and $\sigma_\psi^2(n)$, 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. The fuzzy set "F" means that the observed signal $y(n)$ is mainly dominated by the ME signal $x(n)$. On the other hand, the fuzzy set "P" means that $y(n)$ is mainly dominated by artifact noise $a(n)$. Other fuzzy sets of output associants are prepared for the ME signal contaminated with artifact noise. The fuzzy membership functions of "F" and "PF" are narrower than "PP" in order to obtain fine control for the ME signal (Fig. 2(b)). As a defuzzification method, we use the correlation-minimum (the correlation-minimum encoding with the max-min composition) inference procedure with the centroid defuzzification method.

The time-updated $\sigma_\xi^2(n)$ has a small bias and only $\sigma_\psi^2(n)$ increases around artifact noise for ME signals during a sustained contraction. Thus, we design that $\gamma(n)$ should be "F" if $\sigma_\psi^2(n)$ is under the time-updated

$\sigma_\psi^2(n)$ ↓ \ $\sigma_\xi^2(n)$ →	S	RS	RL	L
S	F	PF	PF	F
RS	PF	F	PF	F
RL	PF	PF	F	F
L	PP	PF	F	F

Fig. 3 Fuzzy bank matrix for ME signals during dynamic movement.

$\sigma_\xi^2(n)$ (Fig. 2(c)) and should be "P" if $\sigma_\psi^2(n)$ is "L" and $\sigma_\xi^2(n)$ is "S." The bias in the time-updated $\sigma_\xi^2(n)$ is inevitable for the ME signal during dynamic movement, because the time-varying ME signal is superimposed on the base-line wander artifact. Thus, we design an alternative fuzzy bank matrix (Fig. 3) with the same membership functions in Figs. 2(a) and (b). That is, we consider that artifact noise possibly appears around the parts where $\sigma_\psi^2(n)$ and $\sigma_\xi^2(n)$ are "RS" or $\sigma_\psi^2(n)$ is significantly larger than $\sigma_\xi^2(n)$.

3. Experimental Procedure

Working with the tibialis anterior muscle, we measured ME signals during sustained and dynamic movement. The dynamic movement was an ergocycle exercise. An active four-bar electrode was pasted on the skin parallel to the muscle fibers, with each bar perpendicular to the muscle fibers. The distance between each bar was 1 cm. The raw surface ME signals were bandpass filtered, 53–1000 Hz, to eliminate power-line interference and low frequency artifact noise. The gain of the amplifiers was 60 dB. The ME signals were sampled at 5 kHz with a 14-bit digital data recorder (TEAC, DR-F1).

The order of the AR filters at the first and last stages was 10. The forgetting factor of Lee's algorithm [10] was 0.998. The adaptive procedure was carried out every 0.2 ms (one sample). These values were suitable for ME signals during dynamic movement in our experiment. The initial variance of $\sigma_\xi^2(n)$ was estimated at an early interval of 35 ms ($M=175$ samples), 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 according to Eqs. (7a) and (7b).

4. Results

First of all, we confirmed the performance of our artifact elimination filters by computer simulation (Fig. 4), using the membership functions and the fuzzy

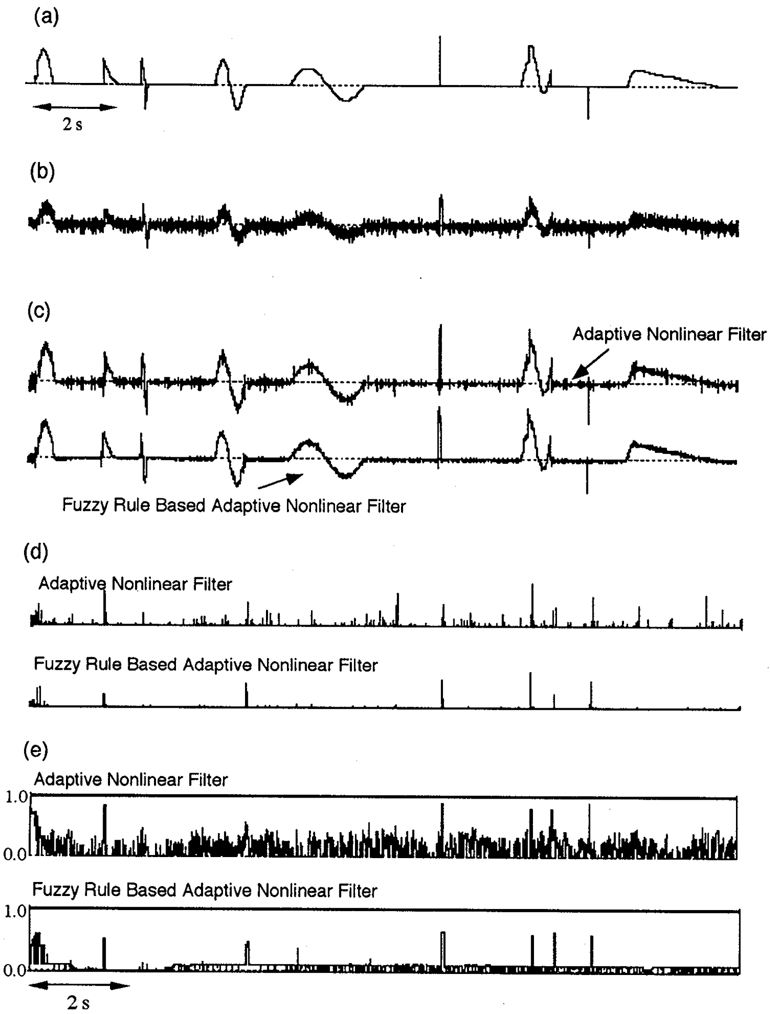


Fig. 4 Estimation of some types of artifacts by the adaptive nonlinear artifact elimination filter and the fuzzy rule based adaptive nonlinear artifact elimination filter: (a) given artifacts; (b) observed signal contaminated by artifacts; (c) estimated artifacts; (d) mean square error of estimated artifacts; (e) performance of the nonlinear filter parameter $\gamma(n)$.

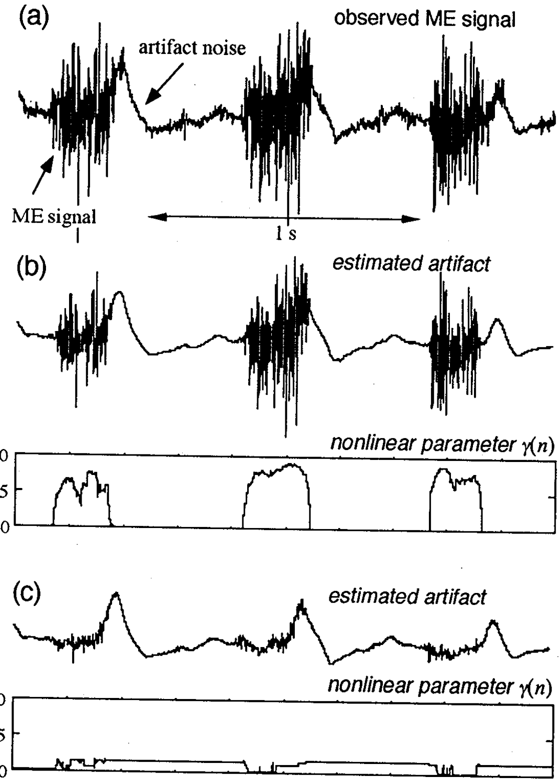


Fig. 5 Result of artifact elimination for the ME signal during an ergocycle exercise: (a) observed signal contaminated by artifacts; (b) estimated artifact and the nonlinear parameter $\gamma(n)$ with the adaptive nonlinear artifact elimination filter; (c) estimated artifact and the nonlinear parameter $\gamma(n)$ with the fuzzy membership functions of Figs. 2(a) and (b), and the bank matrix showed in Fig. 3.

bank matrix in Fig. 2. The types of artifacts tested were sinusoidal, exponential, triangular, and 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. According to the result of Fig. 4(c), ME signals still remained on the artifacts restored by the adaptive nonlinear artifact elimination filter (adding the adaptive procedure in Kaneko's filter). On the other hand, the fuzzy rule based adaptive nonlinear artifact elimination filter achieved better performance for individual artifacts. This was also confirmed by the mean squared error evaluation (Fig. 4(d)). Employment of the 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. Figure 4(e) shows the performance of the nonlinear filter parameter $\gamma(n)$ for the adaptive nonlinear artifact elimination filters with and without fuzzy rules. Fine control of $\gamma(n)$ around a small value was effective for the ME signal during a sustained contraction. That is, comparing the time-series of $\gamma(n)$, the performance of the adaptive nonlinear artifact elimination filter was worse when $\sigma_\varphi^2(n)$ came close to $\sigma_\xi^2(n)$, in which $\gamma(n)$ varied frequently from 0.0 to around 0.5; on the other hand, $\gamma(n)$ remained steady around 0.2 almost everywhere in the fuzzy rule based adaptive nonlinear artifact elimination filter.

Figure 5 demonstrates the result for the actual ME signal during an ergocycle exercise. The surface ME signal was contaminated by the complex base-line wander associated with cyclic movement. The execution time of the fuzzy rule based adaptive nonlinear artifact elimination filter was around 70 s for the ME signal of about 20 s by using a SPARC station 10, model 30 (86.1 MIPS). It seems small enough to proceed with the practical experiments in the field.

Using the adaptive nonlinear artifact elimination filter, the ME signal was not removed from the estimated artifact and the artifact-dominant parts were unexpectedly low-pass filtered (Fig. 5(b)); in which $\gamma(n)$ varied from 0.0 to about 0.8. The incorrect behavior of $\gamma(n)$ was caused by the insufficiently time-updated $\sigma_\xi^2(n)$ and AR coefficients of the whitening and the restoring filters. This defect was overcome by the fuzzy rule based adaptive nonlinear artifact elimination filter with the suitable fuzzy bank matrix designed in Fig. 3; in which $\gamma(n)$ was finely adjusted around 0.0, whereas $\gamma(n)$ varied from 0.1 to 0.2 around artifact noise (Fig. 5(c)).

5. Discussion

5.1 Employment of Fuzzy Rules in Motion Artifact Elimination

The benefits of Kaneko's filter have already been published [9]. It showed better performance than a Bessel linear filter and an ε-separating filter [7]. Kaneko's filter is, unfortunately, effective only if ME signals are stationary. Locally stationary ME signals could be measured during a sustained contraction in a basic physiological research. ME signals of current interested are, nevertheless, nonstationary during dynamic movement.

Time-varying properties of ME signals can be tracked by introducing an adaptive procedure. As an adaptive procedure, we used the time-update procedure designed for tracking ME signals sample by sample. The adaptive filter designed for the ME signal, however, did not separate artifact noise effectively, because artifact noise was temporary and contained the same frequency components as the ME signal. Another problem was the inevitable bias in the time-updated $\sigma_\xi^2(n)$. Accordingly, effective separation in the variances between the filtered time-varying ME signal and the filtered artifact was not always obtained after the time-varying whitening procedure. In order to compensate the above defects in a practical situation, fuzzy rule based determination of $\gamma(n)$ was incorporated, instead of the $\gamma(n)$ functionally defined by the Eq. (6b).

5.2 Customizing the Performance of $\gamma(n)$

The nonlinear filter parameter $\gamma(n)$ is strictly determined by the characteristics of the employed function (6b) 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. Fine control of the frequency characteristic around the small value of $\sigma_\psi^2(n)$ was useful for ME signals during a sustained contraction (Fig. 4). It was, however, difficult to eliminate abrupt parts of artifacts probably due to the insufficiency of time-varying procedure. The flexible control of the frequency characteristic by changing the fuzzy rules benefitted the time-varying ME signal superimposed on the base-line wander artifact noise (Fig. 5(c)). That is, we expected that the base-line wander artifact noise would appear around the rather small values in $\sigma_\psi^2(n)$ and $\sigma_\xi^2(n)$.

Further study will be required to balance the membership functions and fuzzy rules for practical ME signals. Moreover, the time-update procedure of $\sigma_\xi^2(n)$ should be improved to reduce the bias. Impulsive noises like abrupt artifacts could be removed by the median filter [12] and its related methods [13], [14] which have been developed in the fields of speech signal processing and image processing. Hence, the application of the median filter should be examined as well.

6. Conclusion

We have developed a fuzzy rule based adaptive nonlinear artifact elimination filter composed of a whitening (inverse AR) filter, a nonlinear LMS smoothing filter, and an inverse whitening (AR) filter. The inverse AR filter adaptively makes surface ME signals into random and small amplitude white noises by Lee's algorithm. The nonlinear LMS smoothing filter selectively averages small amplitude signals at each time, depending on the local variances of the observed signal. We applied the fuzzy rules to adjust the performance of the nonlinear filter parameters to the local features more effectively. The AR filter at the last stage, which has the same coefficients as those of the AR inverse filter, finally provides the estimated artifact. Subtracting the estimated artifact from the observed signal results in artifact elimination.

Computer simulation and practical experiment showed that the fuzzy rule based adaptive nonlinear artifact elimination filter achieved better performance than ever before. As a result, it is applicable to the measurement of surface ME signals during dynamic movement in sports science and rehabilitation.

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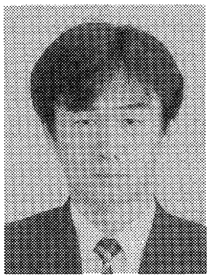

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