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Stimulus Artifact Suppression Using the Stimulation Synchronous Adaptive Impulse Correlated Filter for Surface EMG Application

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Abstract – The voluntary EMG (vEMG) signal from electrically stimulated muscle is very useful for feedback control in functional electrical stimulation. However, the recorded EMG signal from surface electrodes has unwanted stimulation artifact and M-wave as well as vEMG. Here, we propose an event-synchronous adaptive digital filter for the suppression of stimulation artifact and M-wave in this application. The proposed method requires a simple experimental setup that does not require extra hardware connections to obtain the reference signals of adaptive digital filter. For evaluating the efficiency of this proposed method, the filter was tested and compared with a least square (LS) algorithm using previously measured data. We conclude that the cancellation of both primary and residual stimulation artifacts is enhanced with an event-synchronous adaptive digital filter and shows promise for clinical application to rehabilitate paretic limbs. Moreover because this algorithm is far simpler than the LS algorithm, it is portable and ready for real-time application.

Keywords: Stimulus artifact, Electrical stimulation, Electromyography, Event-synchronous adaptive digital filter

1. Introduction

Spinal cord injury (SCI) and stroke patients frequently are left with a partially paralyzed, or paretic arm. Rehabilitation of these survivors can be enhanced with functional electrical stimulation (FES).The goal of FES is to restore functional movement and requires that the FES system be under the individual's control and reliable enough to improve the subject's function during normal daily activities [1]. Some studies have demonstrated value of adding EMG feedback [2]. These therapies should encourage patient use outside of the rehabilitation center and reduce the need for frequent intervention by medical personnel. Non-invasive, reversible rehabilitative systems like surface electrical stimulation of muscles are especially well suited due to their easy application and utilization in therapeutic applications [3]. Therefore, a biofeedback signal like EMG for FES control is a critical component. Extensive research has been done using FES to improve the lives of persons with weak or paralyzed muscles following neurological insult. Use of natural signals to control FES has been performed in at least three ways. First, EMG-triggered FES detects a threshold EMG signal to trigger onset of a predetermined stimulation sequence with no further EMG measurements made during stimulation [4]. Secondly, EMG-controlled FES continuously measures EMG from one muscle to proportionally stimulate another muscle [5]. Finally, autogenic EMG-controlled FES (aEMGcFES) specifically refers to measuring the voluntary EMG (vEMG) from the stimulated muscle, allowing more physiologically appropriate closed loop control [6, 7].

This method would be one that is able to sense the volitional intent to activate a paretic muscle and then translate that intent into an appropriate muscular activation and functional movement. This would provide the most natural way to reinforce the normal physiological pathways for activating and controlling functional movements. A fundamental challenge preventing the realization of such a natural closed loop FES system is the inability to measure a vEMG continuously and accurately from the stimulated muscle. Therefore, because the stimulation intensity is modulated in proportion to vEMG amplitude at each stimulus and the characteristic of the M-wave varies, the key problem lies in being able to sense the vEMG while ignoring the much larger amplitude stimulation artifacts that can create a problematic positive feedback loop [8].

The pulse amplitudes of the FES signal can be 1k-10k times greater than the vEMG signals from the muscle of interest [9]. These much greater signal amplitudes will saturate a conventional EMG amplifier in attempting to measure vEMG from sensor electrodes placed adjacent to stimulation electrodes. This poses a significant problem for an autogenic EMG-controlled FES (aEMGcFES) device

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due to positive feedback errors. The saturation of FES, which means that the electrical stimulation voltage would go up to the maximum, comes from the presence of positive feedback error.

An EMG amplifier shutdown control can eliminate most, but not all, of the saturation effect [10]. This problem is solved by using a low impedance node [11], which is much less susceptible to high-amplitude transient spikes as are often seen with an analog switch.

The remainder of the stimulation artifact can be removed with a blanking circuit, but the muscle response wave produced by stimulation (M-wave) still remains as a significant barrier to measuring vEMG for aEMGcFES. Because the M-wave varies based on factors such as stimulation intensity, fatigue, and activation level of the muscle, an adaptive filter is required to eliminate the M-wave [9]. The power spectrum of M-wave signals does not differ greatly from that of vEMG with some small but significant exceptions. The origin of interference due to stimulation is clear; the tissues and muscle cells of the subject are excited by stimulation potential by the EMG-controlled FES system. The voltages induced by the stimulation of muscles during electrically evoked contractions produce artifacts that are added to the EMG signal. These residual stimulation artifacts (RSA) generated during electrically evoked contractions is the sum of contributions from synchronously firing motor units. The impulse response, $h_x(t)$, of each motor units is due to instantaneous stimulation voltage source. It is quasi-deterministic and periodic, with a repetition rate equal to the stimulation rate. However the vEMG signal is the sum of contributions from asynchronously firing motor units, and is stochastic with near-Gaussian amplitude distribution.

M-wave signals do exhibit regularity in the variations of their amplitude and shape due to the simultaneous activation of many motor units. These variations can be accurately estimated using linear adaptive filters [12]. Fortunately, due to their stochastic nature, vEMG signals are hardly affected by these filters. A linear adaptive filter based on a least square (LS) algorithm can effectively filter the M-wave signal to a level comparable to the vEMG [13]. Some research groups have attempted to eliminate the stimulation artifact and M-wave in off-line mode since these computationally demanding methods can be done off-line [14, 15]. But the linear LS filter requires an explicit estimation of the autocorrelation matrix and its inverse, which is computationally demanding and complex (e.g., QR decomposition), rendering this approach less than ideal for a real-time filter [16]. For this reason real time systems which need to minimize an error signal power use gradient descent based adaptive filters such as the least mean squares (LMS), normalized least mean square (NLMS) or recursive least squares (RLS) type algorithms. These methods are more effective than LS filter. In addition, the Gram-Schmidt Prediction Error Filter (GS-PEF) filter used by Yeom and Chang (2010) is a modified version of a LS filter. This filter also used gradient descent based adaptive filters. They showed that a 6th-order GS-PEF was capable of reducing the M-wave to the level of the pure voluntary EMG in on-line system. However these methods still require a higher computational load than the presently proposed filter. Details of computational complexity for the proposed and upper methods are described in section 4.4.

For real-time application, the most recent advances in digital signal processing have attempted to reduce the M-wave using a comb filter [7] that predicts the filtered EMG output, y, for the nth sample of the raw EMG, x, by subtracting $x(n-N_{Tstim})$, the value of the raw EMG from the same point in time from the previous stimulation cycle (Eq. (1)).

$$y(n)=\frac{x(n)-x(n-N_{Tstim})}{\sqrt{2}} \tag{1}$$

In this application, the comb filter is a finite impulse response (FIR) filter and assumes that the M-wave to be filtered out is a deterministic signal. The M-wave, however, has been shown to be non-stationary in nature [9] and use of a comb filter to predict artifacts that vary in time from cycle to cycle leads to an unstable closed loop system.

M-wave removal is a major issue when skin surface stimulation and detection techniques are used. This issue is particularly relevant if the stimulation and detection electrodes are relatively close. Even though the blanking circuit method eliminates the majority of the stimulation artifact, the long-latency residual stimulation artifacts including the M-wave remain [6].

The RSA and vEMG consists of similar frequency components. Therefore, good performance cannot be expected with linear time-domain and frequency-domain fixed filters for suppression of RSA. The approach of the adaptive filtering techniques permits to remove RSA by time varying stimulation because the RSA during the previous stimulation period is strongly correlated with that of the current stimulation period because they are quasi-deterministic and periodic.

In the study, we proposed an adaptive algorithm for the suppression of M-wave signals. The proposed algorithm uses a stimulation-synchronous adaptive impulse correlated filter (SSAICF) whose reference signal is synchronous to the peaks of stimulation signals. The advantage of this proposed method is that it uses the impulse signal as the reference signal. So, its adaptation needs to be performed only once during the sampling period of the stimulation pulses, which greatly simplifies the algorithm for implementation.

2. Methodology

2.1 SSAICF for suppression of RSA signal

If the stimulation by the EMG system is applied to muscles, the M-wave induced in EMG signal ($g(n)$) can be expressed as

$$g(n) \cong h(n) \otimes \delta(n) \quad (2)$$

Here, $h(n)$ denotes an impulse response of the possible paths between the stimulation source and the EMG sensor.

Thus, given a stimulation source $\delta(n)$, $h(n)$ can be estimated using the model in Eq. (2). However, a priori information about $\delta(n)$ is generally available because $\delta(n)$ is directly detected and produced from the EMG-controlled FES hardware system. Therefore, we have to develop a method of estimating the impulse response $h(n)$.

The contaminated EMG signal contains both the vEMG signal and RSA signal. The output of the EMG channel can be expressed as

$$l(n) = c(n) + g(n) \quad (3)$$

where $c(n)$ and $g(n)$ are the sampled versions of the pure EMG signal and the RSA signal in the EMG channel. To estimate the RSA signal in the EMG channel, the minimum mean-square error (MMSE) criterion can be applied to the models in Eq. (2).Using Eq. (2), the M-wave in the EMG channel can also be modeled as

$$\hat{g}(n) = \mathbf{h}^T \mathbf{s}(n) \quad (4)$$

where $\hat{g}(n)$ is the M-wave estimated by proposed model, $\mathbf{h}_j$ is the (M × 1) weight vector $[h_0, h_1, \cdots h_{M-1}]^T$ and $\mathbf{s}(n)$ is the reference input vector $[s(n), s(n-1), \cdots, s(n-M+1)]^T$ composed of the stimulation source signal $\delta(n)$. Now, the RSA signal is calculated using a single-channel filter whose weight vector is determined according to the MMSE criterion as

$$\mathbf{h}^o = \mathbf{\Phi}^{-1}\mathbf{\theta} \quad (5)$$

where $\mathbf{\Phi} = E\left\{\mathbf{s}(n)\mathbf{s}^T(n)\right\}$ and $\mathbf{\theta} = E\left\{l(n)\mathbf{s}(n)\right\}$ denote the (M ×M) autocorrelation matrix and (M × 1) cross-correlation vector, respectively.

If we knew $\mathbf{\Phi}$ and $\mathbf{\theta}$, we could directly compute the optimum weight vector. But in general, we do not have access to $\mathbf{\Phi}$ and $\mathbf{\theta}$. Therefore, we use adaptive estimation method as one approach to find the optimum weight in Eq. (5).To address the time-varying feature of RSA signal in EMG channel, the adaptive estimation of RSA signal is necessary. For the updating process, the filter weights the adaptive algorithms.

For comparison, we use a computationally efficient adaptive algorithm based on the least mean square (LMS) adaptive filter proposed by J. R. Laguna [17]. The LMS is an adaptive noise canceller for deterministic component of event-related signals that are time-locked to a stimulus, in which a pulse related to the stimulus was used as a reference input. The method estimates the deterministic component of the signal and removes the noise uncorrelated with the stimulus, even if this noise is colored, as in the case of evoked potentials and reflects transient changes in the deterministic signal better than an ensemble average method. In the method, the filter uses two inputs: the desired signal (primary input) and a pulse correlated with the deterministic component (reference input). Since the pulse is composed of one sample, they refer to this approach as “adaptive impulse correlated filter (AICF)”. The adaptive filter used in this study is a specific form of the previous AICF, in which the impulse train synchronized by the stimulation voltage is used as a reference input. The proposed algorithm is referred to as the stimulation synchronous adaptive impulse correlated filter (SSAICF). Fig. 1 shows the block diagram of the SSAICF.

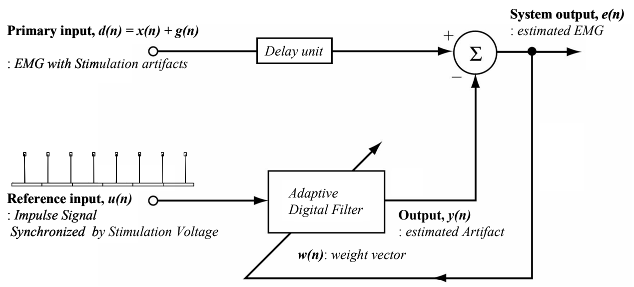

Fig. 1. Block diagram of the SSAICF.

The primary input of the SSAICF is a delayed version of RSA contaminated EMG signal in Eq. (2).The reference input, *u(n)*, is not correlated with the background EMG but synchronized with stimulation voltage in the EMG channel. The reference input consists of an impulse train.

$$u(n) = \begin{cases} 1, & n = q_m \\ 0, & otherwise \end{cases} \quad (6)$$

where q_m represent a location of the occurrence each stimulation frame.

Considering an Nth order conventional adaptive filter (N : the adaptive filter length), the filter output and the error signal are computed as

$$\begin{aligned} y(n) &= \sum_{i=0}^{N-1} w_i(n)u(n-i) \\ e(n) &= x(n-\Delta) - y(n) \end{aligned} \quad (7)$$

where $w_i(n), 0 \le i \le N-1$ are the weights of the filter.

The filter weights can be updated using one of adaptive algorithms such as recursive least square (RLS), affine projection (AP), and least mean square (LMS). The LMS algorithm is very simple and straightforward to implement in real time and adapt to a neighborhood of the Wiener-Hopf least mean square solution. If the LMS algorithm is used, the weight update is accomplished as

$$w_i(n+1) = \begin{cases} w_i(n) + \mu e(n), & n - q_m - 1 \le i \le n - q_m, \ \text{for all } q_m \in [n-N+1, n-1] \\ w_i(n) & , \mathit{otherwise} \end{cases} \tag{8}$$

where μ is the convergence parameter.

2.2 Implementation of SSAICF for suppression of RSA signal

The main steps in the SSAICF implementation for suppression of RSA signal are as follows:

Step1: Generation and transfer of the blanking event information.

Step 2: Generation of impulse train based on the blanking event information.

Step 3: Estimation of RSA and vEMG.

Step 4: Update of impulse response vector.

Fig. 2 shows the main steps in the SSAICF implementation for suppression of RSA signal. The blanking event information in initial state of stimulation voltage is applied to the SSAICF. And then the impulse train is generated synchronously to the blanking event information. The RSA is estimated and then vEMG signal is estimated as doing subtraction the estimated RSA from RSA contaminated vEMG. And weight vector update of SSAICF is processed.

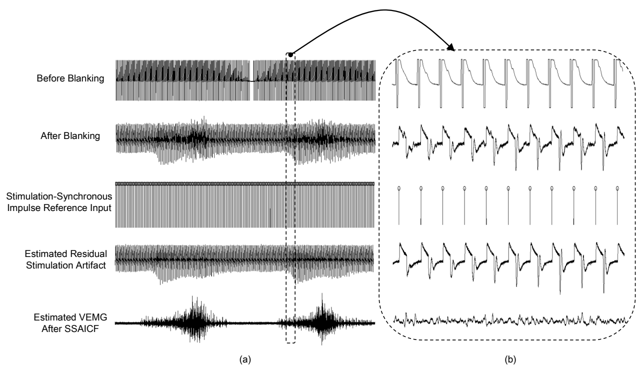

Fig. 2. The main steps in the SSAICF implementation for suppression of RSA signal: (a) Process scheme of the proposed method; (b) enlarged figure of dashed area in (a).

The SSAICF updates the weight vector only when the reference input is one. Since the square pulses in the reference input are sparse, the filtering and update process is executed over only small portion of the reference input. In fact, the filtering process in Eq. (7) requires *K* multiply-and-accumulate (MAC) operations, where *K* is the number of RSA-peaks within the time period covered by the N-length reference input vector. The LMS update in Eq. (8) also requires *K*MAC's. Therefore, the computational cost of the proposed SSAICF is much simpler than that of the conventional adaptive digital filter of order N. In the end, the proposed scheme has a huge advantage according to other adaptive algorithms because the computational simplicity is very important in the embedded system such as the aEMGcFES system. Nevertheless simplicity, performance of the proposed method is good and robust because of it is less sensitive to the reference input of adaptive filter

3. Experimental Setup

A male subject (36 yrs old, 83.9 kg) gave informed consent to participate in this study approved by the Georgia Institute of Technology IRB (protocol #H10018). The raw EMG signal was recorded using pre-gelled disposable bipolar pellet surface electrodes (Ag–AgCl, 10mm diameter, Noraxon, OH) which were placed with an inter electrode distance of 2 cm along the extensor carpi ulnaris muscle and the ground electrode was positioned over the bony protuberance on the elbow. We verified accurate placement of the recording electrodes with a qualitative check of the recorded EMG signal during voluntary wrist extension. We placed self-adhesive stimulating surface electrodes (2.54cmX2.54cm, Medical Supplies Shop, NY) with an inter electrode distance of 5cm. The raw EMG signal and force transducer data were sampled at 16kHz using data acquisition hardware (National Instruments, PCI-6289DAQcard) and software (Mr. Kick, Sensory Motor Institute, Aalborg University, Fig. 3).We set the stimulation frequency to be 25Hz.The evaluation of the system performance, the subjects were asked to control their wrist extension torque using a target-force paradigm. Following the recording of the maximum voluntary contraction (MVC), the subjects were asked to follow, as best as they could, a sinusoidal trace with maximal amplitude of 50% of their MVC. The tracking test is based on a visual feedback of the produced force compared to a reference target trajectory using a computer monitor. The outcome measure to determine the system efficacy would be the accuracy of the tracking.

A simulation study was carried out to test the performance of the proposed method. In the case of vEMG corrupted by the RSA, the EMG signal comprises the RSA and background vEMG signal. Exact form of them has been unidentified so that it is hard to conduct a quantitative evaluation of the performance of the RSA estimation and elimination by the proposed method.

First, we applied a series of open-loop submaximal sinusoidal electrical stimulations without any voluntary contraction to collect the RSA (Fig. 4(a) first raw signal). Second, we asked the subject to contract his muscle without any electrical stimulation according to same

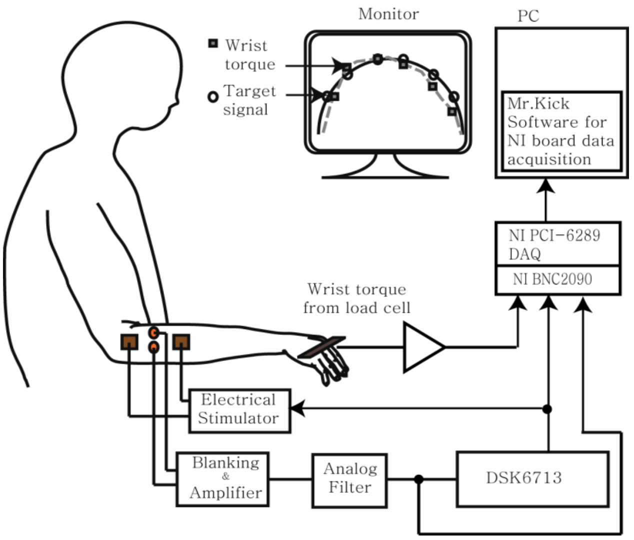

Fig. 3. Block diagram of the measurement system

sinusoidal reference and we collected the vEMG (Fig. 4(a) second raw signal. Finally, we added two signals for making the RSA signal with vEMG (Fig. 4(a) third raw signal). The M-wave can be more than a magnitude lager than the vEMG. However when we collect the RSA from EMG amplifier with a blanking circuit, the amplitudes of RSA and vEMG are almost same [6].

The proposed method was tested on the simulated signal and applied to actual signal thereafter. In order to assess the performance of the vEMG estimation and RSA elimination using the proposed method, the LS algorithm is compared with the SSAICF.

4. Results

4.1 Analysis of results on the simulated synthetic vEMG data with the RSA

Fig. 4 shows a simulated data set and results of analysis using the simulated data set. The filter coefficients of the SSAICF were chosen for the order of the filter to be 600 and a learning rate (μ) was set to 0.05 on an empirical basis. The simulated data set as shown in Fig. 4(a) and blanking circuit event synchronous impulse as shown in Fig. 4(b) were applied to a primary input and a reference input of the SSAICF respectively so as to estimate the simulated RSA signal. To maximize performance of the SSAICF, the order of filter must be determined based on the duty cycle of the control signal of blanking circuit. We found the impulse response for a cycle by deciding the filter order as pointed above.

The estimated RSA signal using the SSAICF, the estimated vEMG signal using the SSAICF and the estimated vEMG signal using the LS algorithm are shown in Fig. 4(c), Fig. 4(d) and Fig. 4(e).The result shown in Fig. 4(c), (d) and (e) illustrate that the signal estimation and elimination works well without reducing the information in the vEMG signal. However, a detailed morphology of the estimated vEMG can't be observed in Fig. 4(d) and (e). For analysis of the detailed morphology of the estimated vEMG using the SSAICF and the LS algorithm, as shown in Fig. 4(f) and (g) we plotted the enlarged figures of dashed area in Fig. 4(d) and (e). It makes certain that both the SSAICF and the LS algorithm estimate well vEMG included in simulation input signal.

As shown in Fig. 4, there appears to be little difference between the qualities of the different filters, but there needs to be some quantitative evaluation of how the different methods perform. Therefore, we used two parameters of correlation coefficients (between the simulated vEMG and the estimated vEMG) and MSE (mean square error) for quantitative evaluation of two methods. As correlation coefficients of two methods was each 0.8179 and 0.8225, the result of LS method shows slightly higher correlation than SSAICF. MSE of SSAICF and LS filter was each 0.0316 and 0.0291. Consequently, LS filter showed slightly higher performance than SSAICF. However, unlike the SSAICF, the LS method requires more complex calculation than the SSAICF to estimate vEMG.

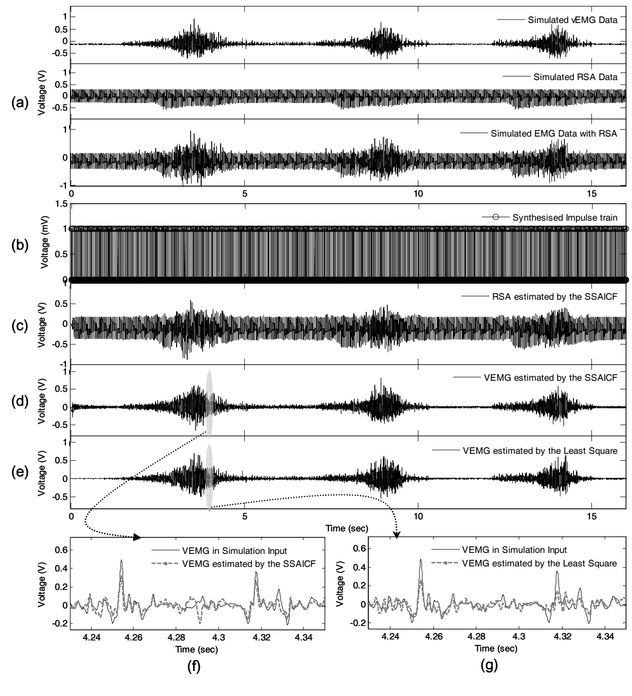

Fig. 4. The simulated data set and results of analysis using the simulated data set: (a) a simulated data set through linear summation of pure RSA and pure vEMG signal; (b) an impulse train synchronized by events of the blanking circuit; (c) the estimated RSA signal using the SSAICF; (d) the estimated vEMG signal using the SSAICF; (e) the estimated vEMG signal using the LS algorithm; (f) enlarged figure of dashed area in (d); (g) an enlarged figure of dashed area in (e).

4.2 Estimation performance using actual RSA contaminated EMG

In the case when the RSA corrupts actual EMG, the LS method and the proposed method were compared. Fig. 5. shows the result of analysis using a real data set. The patient's actual RSA contaminated vEMG that is controlled by feedback signal that is shown in Fig. 5(a) is shown in Fig. 5(b). The vEMG signal estimated by eliminating RSA signal using the above 2 methods are shown in Fig. 5(c) and Fig. 5(d). And the force signal estimated by the above 2 methods are shown in Fig. 5(e) and Fig. 5(f). The result illustrates that above both methods well estimate the information of the vEMG signal. As seen in Fig. 5(c)~(f), the result by the SSAICF is similar to that of the LS method. For more quantitative evaluation of filter performance, we used correlation coefficients and MSE between filter response and the force signal measured by a force sense. After that, values of two indexes are compared. Correlation coefficients of the SSAICF and LS method are each 0.9545 and 0.9510. Also MSE of the SSAICF and LS method are each 0.0063 and 0.0065. In spite of lower calculation cost, the result of SSAICF shows slightly higher correlation than LS method. Consequently SSAICF estimate the vEMG based force signal a little better than LS method. This result is very significant result.

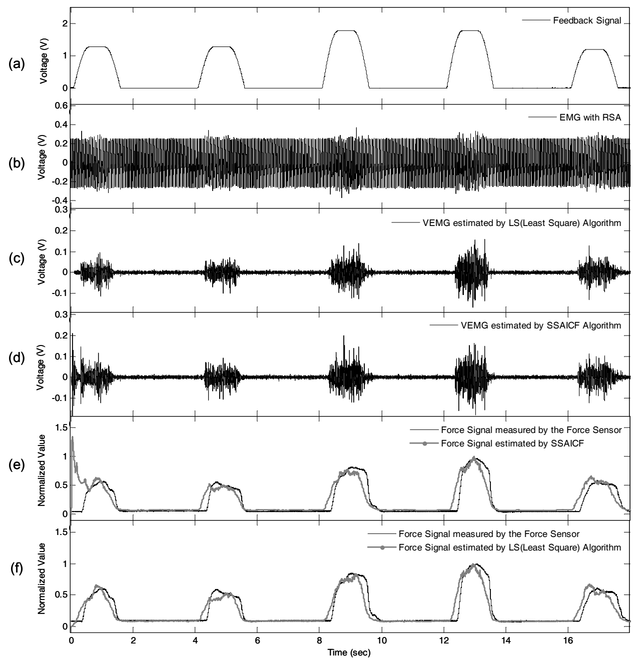

Fig. 5. The result of analysis using a real data set: (a) feedback signal to induce Vemg; (b) a real data set of RSA corrupted vEMG signal; (c) the estimated vEMG signal using the SSAICF; (d) the estimated vEMG signal using the LS algorithm; (e) the estimated force signal using the SSAICF; (f) the estimated force signal using the LS algorithm

4.3 Power spectral density analysis

Computer simulations and power spectra analysis were performed to measure the RSA cancellation performance of the Comb filter, 6th order GS PEF and SSAICF. For simulations, we used a simulation model presented in [14].

The raw data was comprised of the RSA and vEMG. As we can see at Fig. 6, the Comb filter was not able to satisfactorily filter out the RSA and resulted in false positive vEMG signals. It is seen that the 6th-order GS PEF and SSAICF are capable of reducing the RSA power to that of vEMG at most frequency bandwidth.

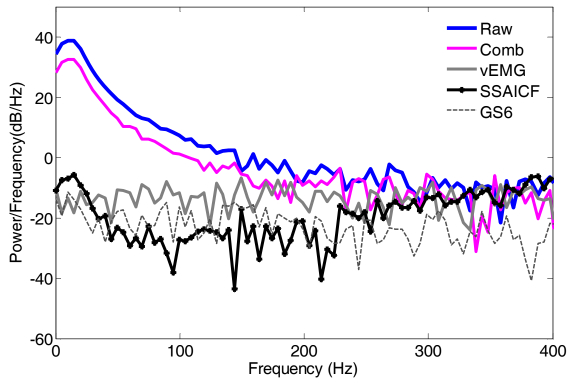

Fig. 6. Power spectral density analysis of the input and output signals of the Comb filter, GS-PEF and SSAICF. The logarithmic power spectrum densities of TA vEMG data from Figure 4using Welch's method shows that the power spectrum of the volitional EMG signal is hardly changed by the real-time GS-PEF. The vEMG is nearly identical to results of 6^{th} order GS-PEF and SSAICF.

4.4 Analysis of computational complexity in the SSAICF

The computational complexity of the SSAICF has been determined in this section. The SSAICF updates the weight vector only during the period corresponding to the width of the square pulses. Conventional adaptive filter perform calculations to the filtering and update processes for each of the all-time points in the frame. On the contrary, SSAICF perform over only small portion in the frame because of the square pulses in the reference input are sparse. Therefore, this scheme has advantage in simplicity of computational complexity. Because of the zeros between the square pulses, the adaptive filter attempts to estimate only the components synchronized to the impulse.

The filtering process described in Eq. (4) requires K additions, where K is the number of event peaks within the time period covered by the M-sample reference input. The LMS update procedure described in Eq. (5) also requires K multiply-and-accumulate (MAC) operations. Therefore, the computational cost of the proposed algorithm is much lower than that of conventional Adaptive digital filtering methods with the same order. Table 1 shows computational complexity in various adaptive algorithms. Index of complexity calculation has been defined as multiplication count during one iteration period. In case of LS filter calculation of auto-correlation and cross-correlation matrix requires approximately $2*M*N$ multiply and accumulate MAC operations. The inversion of auto-correlation matrix requires around 'N^3' MACs, and the matrix-vector multiplication, 'N^2' MACs. Therefore the total number of computations in performing this one step algorithm is '$2*M*N+N^3+N^2$'MACs. The computation load is therefore very high and real time operation is computationally expensive. The LMS based conventional adaptive filter is only requires 'N' MACs to perform the FIR filtering, and 'N' MACs to implement the LMS equation. On the contrary, the SSAICF only requires 'C' MACs to perform the FIR filtering, and 'C' MACs to implement the LMS equation. [18].

Table 1. Computational complexity in various adaptive algorithms

Algorithm	Complexity
Least Square	$2*M*N+N^3+N^2$
Least Mean Square	2N
Normalized Least Mean Square	5N
Recursive Least Square	$4N^2$
GS PEF	$4(N^2 + N)$
The SSAICF	2C

'M' is the number of samples in a "suitably" representative data sequence, 'N' is the adaptive filter length and 'C' is the number of sample points of impulse signal that is the reference input of the SSAICF

5. Conclusion

The test subject was able to proportionally control the stimulated muscle smoothly in real-time, over a continuous force range and able to voluntarily stop the stimulation. Usage of the LS method is limited in real-time application. If vEMG estimation performance of two methods is similar, we can judge that the SSAICF is more efficient than the LS algorithm in practical application due to advantages that the SSAICF requires only simple calculation.

In the application that has been presented in this paper, the similarity in the performances of the SSAICF and the LS method is evident. However, computational complexity can be reduced with the SSAICF, because it uses an impulse train that is synchronized by the RSA signal. The SSAICF is a potentially powerful method for real-time RSA elimination and vEMG estimation

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References

[1] D. N. Rushton, "Functional electrical stimulation," *Physiological Measurement,* vol. 18, pp. 241-275, Nov 1997.

[2] S. L. Wolf, "Electromyographic biofeedback applications to stroke patients - A critical review," *Physical Therapy,* vol. 63, pp. 1448-1459, 1983.

[3] P. H. Peckham and J. S. Knutson, "Functional electrical stimulation for neuromuscular applications," *Annual Review of Biomedical Engineering,* vol. 7, pp. 327-360, 2005.

[4] J. Cauraugh, K. Light, S. Kim, M. Thigpen, and A. Behrman, "Chronic motor dysfunction after stroke - Recovering wrist and finger extension by electromyography-triggered neuromuscular stimulation," *Stroke,* vol. 31, pp. 1360-1364, 2000.

[5] T. Keller, A. Curt, M. R. Popovic, A. Signer, and V. Dietz, "Grasping in high lesioned tetraplegic subjects using the EMG controlled neuroprosthesis," *Neurorehabilitation,* vol. 10, pp. 251-255, Apr 1998.

[6] H. Yeom and Y. H. Chang, "Autogenic EMG-controlled functional electrical stimulation for ankle dorsiflexion control," *Journal of Neuroscience Methods,* vol. 193, pp. 118-125, Oct 2010.

[7] C. Frigo, M. Ferrarin, W. Frasson, E. Pavan, and R. Thorsen, "EMG signals detection and processing for on-line control of functional electrical stimulation," *Journal of Electromyography and Kinesiology,* vol. 10, pp. 351-360, Oct 2000.

[8] R. Thorsen, M. Ferrarin, and P. Veltink, "Enhancement of isometric ankle dorsiflexion by automyoelectrically controlled functional electrical stimulation on subjects with upper motor neuron lesions," *Neuromodulation,* vol. 5, pp. 256-263, Oct 2002.

[9] R. Merletti, M. Knaflitz, and C. J. Deluca, "Electrically evoked myoelectric signals," *Critical Reviews in Biomedical Engineering,* vol. 19, pp. 293-340, 1992.

[10] J. M. J. Minzly, N. Hakim, and A. Liberson, "Stimulus artifact suppressor for EMG recording during FES by a constant-current stimulator," *Med. Biol. Eng. Comput,* vol. 31, pp. 72-75, 1993.

[11] E. B. a. E. U. Haxthausen, "Current conveyor based EMG amplifier with shutdown control," *Electron. Lett,* vol. 27, pp. 2172–2174, Nov. 1991 1991.

[12] S. Haykin, *Adaptive Filter Theory*. Englewood Cliffs: Prentice-Hall, 2002.

[13] F. B.-S. Sennels, O.T. Andersen, and S.D. Hansen, "Functional neuromuscular stimulation controlled by surface electromyographic signals produced by volitional activation of the same muscle," *IEEE Trans. Rehabil. Eng,* vol. 5, pp. 195-206, June 1997 1997.
[14] B. S. F. Sennels S., Andersen O.T, Hansen S.D., "Functional neuromuscular stimulation controlled by surface electromyographic signals produced by volitional activation of the same muscle: adaptive removal of the muscle response from the recorded EMG-signal," *IEEE transactions on rehabilitation engineering,* vol. 5 pp. 195-206 Jun 1997.
[15] H. J. Yeom, Y. C. Park, and Y. H. Chang, "Eigen filter to detect volitional EMG signals in autogenic EMG-controlled FES," *Electronics Letters,* vol. 43, pp. 1410-1411, Dec 2007.
[16] J. Z. H. Z. Q. Wu, and J.M. Bowman, "Inverse perturbation via singular value decomposition: Application to correction of potential surface for HCN," *J. Chem. Phys.,* vol. 107, pp. 3602-3610, 1997.
[17] J. R. Laguna P, Meste O, Poon PW, Caminal P, Rix H, Thakor NV., "Adaptive filter for event-related bioelectric signals using an impulse correlated reference input: comparison with signal averaging techniques," *IEEE Trans Biomed Eng.,* vol. 39, pp. 1032-44, 1992.
[18] N. Kim, "A Least Squares Approach to Escalator Algorithms for Adaptive Filtering," *ETRI,* vol. 28, pp. 155-161, April 2006.

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