TOPIC: Human-machine interfaces in rehabilitation

P-107

An Adaptive Filter for Low-Tolerance SEMG-Based Intention Prediction

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Myocontrol based upon machine learning (ML) relies on the stability and repeatability of signals related to muscular activity. However, ML algorithms typically employed in myocontrol are prone to several issues, which can make them non-viable in certain applications with low tolerances for delays and prediction instability, such as exoskeleton control or teleimpedance. These issues can become dramatic whenever, e.g., muscular activity is present not only when the user is trying to move, but also for mere gravity compensation, which is generally the case the more proximal a muscle is. The shoulder muscles, for instance, have to be activated to compensate for gravity in a far greater measure than, for example, the M. Flexor Digitorum Superficialis, and a substantial part of this instability is to be attributed to the inherent heteroscedasticity of the sEMG signal.

In this study we introduce and characterize an adaptive filter for sEMG-based motion intention prediction to be used in such situations, which automatically adjusts its own cutoff frequency to suit the current movement intention. This filter generally shows better behavior with regards to delay than a standard low-pass filter while providing much more stability during isometric contractions or co-contractions and less overshoot during, e.g., the lifting of a weight.

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An Adaptive Filter for Low-Tolerance sEMG-Based Intention Prediction

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Abstract

Myocontrol based upon machine learning (ML) relies on the stability and repeatability of signals related to muscular activity. However, ML algorithms typically employed in myocontrol are prone to several issues, which can make them non-viable in certain applications with low tolerances for delays and prediction instability, such as exoskeleton control or teleimpedance. These issues can become dramatic whenever, e.g., muscular activity is present not only when the user is trying to move, but also for mere gravity compensation, which is generally the case the more proximal a muscle is. The shoulder muscles, for instance, have to be activated to compensate for gravity in a far greater measure than, for example, the M. Flexor Digitorum Superficialis, and a substantial part of this instability is to be attributed to the inherent heteroscedasticity of the sEMG signal. In this study we introduce and characterize an adaptive filter for sEMG to be used in such situations, which automatically adjusts its own cutoff frequency to suit the current movement intention. This filter generally shows better behavior with regards to delay than a standard low-pass filter while providing much more stability during isometric contractions or co-contractions and less overshoot during, e.g., the lifting of a weight.

Keywords: sEMG, biosignals, heteroscedasticity, adaptive filtering.

Introduction

The adaptive filter consists of a single pole IIR discrete lowpass filter, which automatically sets its own cutoff frequency F_c based on the magnitude of the input signal $x(t)$ and of its first time derivative $\dot{x}(t)$, according to the following equations.

$$F_c = exp(G2 \cdot |x(t)| + G1 \cdot LP(|\dot{x}(t)|, B1) + B2) \qquad \text{with cutoff frequency } F_c \text{ and input signal } x$$

$$\alpha = \frac{2\pi F_c T_s}{1 + 2\pi F_c T_s} \qquad \alpha \text{ being the filter's decay coefficient, and } T_s \text{ being the sampling period}$$

$$y_i = \alpha x_i + (1-\alpha) y_{i-1} \qquad y_i \text{ being the time-discretized signal } y$$

In the above equations, $LP(x(t), F_c)$ indicates the output at time t of a lowpass filter with input $x(t)$ and cutoff frequency F_c. The filter was applied to the output of a ridge regression converting 8 sEMG envelopes ($F_s = 200\,\text{Hz}$, LP filter $F_c = 1\,\text{Hz}$ 2nd order Butterworth) using a *Myo* bracelet from *Thalmic Labs* to a prediction of the muscle torque along the elbow axis. Figure 1 shows the user training the ridge regression with a dumbbell. The training consisted in performing a 30 s isometric contraction and 10 repetitions raising the dumbbell. The procedure was repeated 6 times for two weights (2 kg and 10 kg).

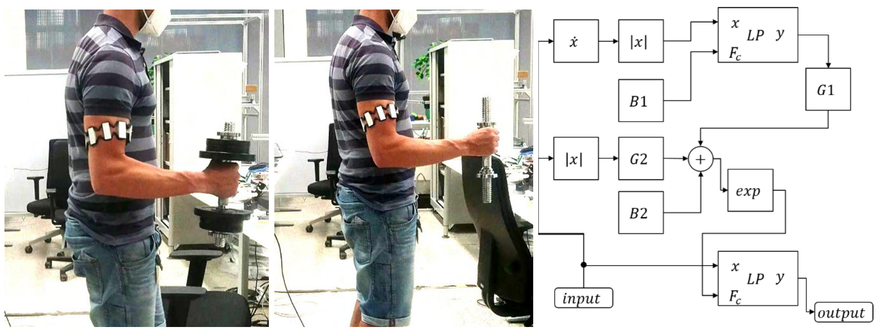

Figure 1: Left: User with sEMG sensor raising the heavy and the light weight. Right: Block diagram of the adaptive filter.

Results

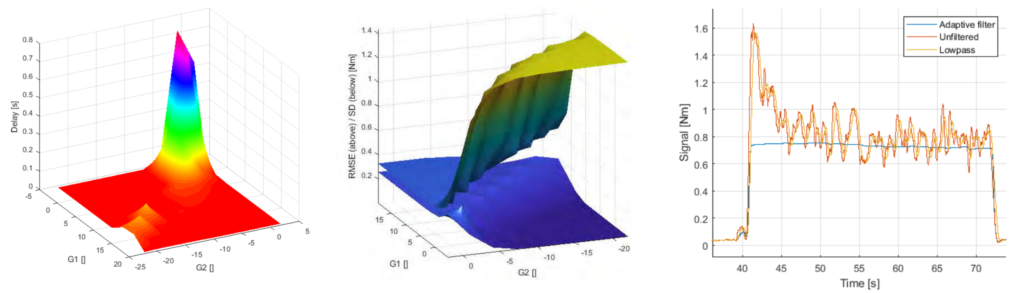

Figure 2: Left: empirically measured signal delay values over the corresponding G1 and G2 coefficient values for the isometric contraction task. **Center:** empirically measured RMSE (upper surface) and standard deviation (lower surface) of the adaptive filter output over the corresponding G1 and G2 coefficients for the isometric contraction task. **Right:** Representative comparison between the unfiltered signal, the adaptive filter output and a low-pass filter.

Table 1 shows the most significant results of the paired t-test on the experimental data ordered by experimental conditions. Unless otherwise specified, the adaptive filter's coefficients were tuned to $G1 = 7.5; G2 = -4; B1 = -1; B2 = 0.3$.

Metric [Unit]	Adaptive filter	Low-pass filter	Significant effects and notes
Delay [s]	0.0067 (0.0133)	0.1602 (0.0627)	$t(23) = 12.2254; p < 0.005$, all tasks
SD [Nm]	0.5168 (0.1520)	0.5801 (0.1991)	$t(11) = 2.6123; p < 0.05$, weightlifting task
SD [Nm]	0.2280 (0.0927)	0.2682 (0.1260)	$t(11) = 3.6589; p < 0.05$ isometric contraction
RMSE [Nm]	0.2945 (0.0503)	0.3365 (0.0904)	$t(11) = 2.9429; p < 0.05$, isometric contraction

Table 1: Result Overview: means and standard deviations (in parentheses) for all experimental conditions and significant effects.

Conclusions

- The adaptive filter shows a significantly lower delay compared to the low-pass filter (see Fig. 2 left).
- The fact that the adaptive filter output shows a lower standard deviation compared to the low-pass filter's indicates less overshoot overall during the weightlifting task.
- While a low root mean square error (RMSE) and a low standard deviation during a prolonged isometric contraction are a trade-off in the absence of feedback (see Fig. 2 center), the filter shows significantly lower RMSE and standard deviation than the low-pass filter during isometric contractions.
- The lower standard deviation of the adaptive filter output during the isometric task indicates a more constant signal in spite of the inherent sEMG noise during contraction (see Fig. 2 right).
- Furthermore, in the presence of feedback, the user should easily be able to reach a desired output level and then maintain it with very low noise, as shown in Figure 2 right.

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