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

P. 1

Topic: Human-Machine Interfaces in Rehabilitation
ABSTRACT
Myocntrol based upon machine learning (ML) relies on the stability and repeatability of signals related to muscular activity. However, ML algorithms typically employed in myocntrol 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 telemedicence. These issues can become dramatic whenever, e.g., muscular activity is present not only when the user is trying to move, but also for more 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 Digeritorum Superficialis, and a substantial part of this instability is to be attributed to the inherent heteroscedasticity of the eSEMG signal. In this study we introduce and characterize an adaptive filter for eSEMG 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 contractisons or co-contractisons 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:

$$F_c = \exp(G2 \cdot |x(t)| + G1 \cdot |\dot{x}(t)|, B1 + B2)$$

with cutoff frequency $F_c$, and input signal $x$

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

$$y_t = \alpha x_t + (1 - \alpha)y_{t-1} \quad y_t \text{ being the time-discretized signal } y$$

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 $8$ eSEMG envelopes ($F_c = 200\text{Hz}$, 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 ($2\text{kg}$ and $10\text{kg}$).

RESULTS
Figure 2: Left: empirically measured signal delay values over the corresponding $G1$ and $G2$ coefficient values for the isometric contractison 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 contractison 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 $G1 = 7.5; G2 = 4; B1 = 1; B2 = 0.3$.

<table>
<thead>
<tr>
<th>Metric [Unit]</th>
<th>Adaptive filter</th>
<th>Low-pass filter</th>
<th>Significant effects and notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Delay [s]</td>
<td>0.0067 (0.0133)</td>
<td>0.1602 (0.0627)</td>
<td>(t(23) = 12.2254, p &lt; 0.005, \text{ all tasks})</td>
</tr>
<tr>
<td>5D [Nm]</td>
<td>0.5168 (0.1520)</td>
<td>0.5801 (0.1991)</td>
<td>(t(11) = 2.6123, p &lt; 0.05, \text{ weightlifting task})</td>
</tr>
<tr>
<td>5D [Nm]</td>
<td>0.2280 (0.0927)</td>
<td>0.2682 (0.1260)</td>
<td>(t(11) = 3.6589, p &lt; 0.05 \text{ isometric contractison})</td>
</tr>
<tr>
<td>RMSE [Nm]</td>
<td>0.2945 (0.0503)</td>
<td>0.3369 (0.0904)</td>
<td>(t(11) = 2.9429, p &lt; 0.05 \text{ isometric contractison})</td>
</tr>
</tbody>
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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 contractison 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 contractisons.
- The lower standard deviation of the adaptive filter output during the isometric task indicates a more constant signal in spite of the inherent eSEMG noise during contractison (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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