Stimulation in Training Data to Improve Proportional Motor Control in a Dexterous Sensorimotor Task

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Why?

Between 30-50% of upper-limb amputees do not regularly use their prosthesis, in part because their prosthesis does not provide a sense of touch [1], [2]. Electrocutaneous stimulation is low-cost, and has a slim form factor that could be easily integrated into prostheses, making it a viable option for providing touch sensation. However, the high-voltage pulses used in electrocutaneous stimulation generate artifacts that corrupt sEMG signals and interfere with motor control. This can be especially problematic for proportional control algorithms capable of fine motor control. Given these challenges, this study investigates whether incorporating stimulation artifacts during training can mitigate their impact on sEMG decoding and improve motor control accuracy without adding computational burden.

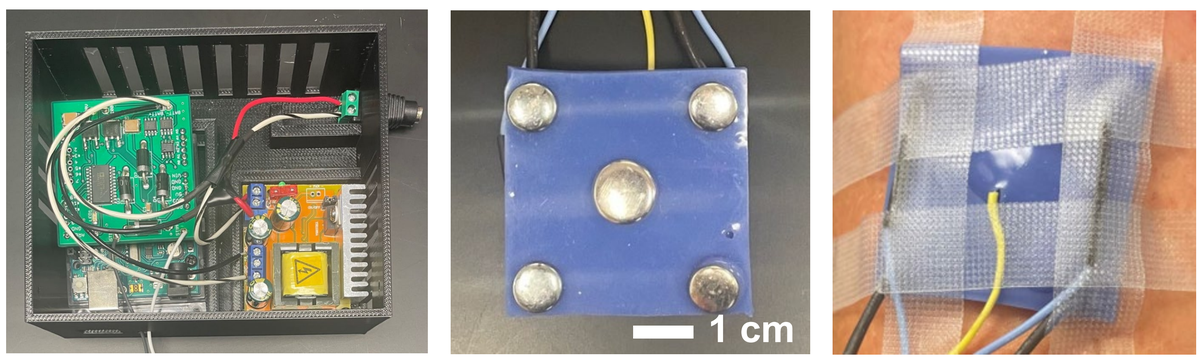


Figure 1: High-voltage (±150V) electrocutaneous stimulator (*left*) supplied constant current pulses through a 1cm-diameter active electrode (*center*) with four returns. Skin was first dampened, then the pad was placed on participants dominant, lateral upper arm (*right*).





Figure 2: Participants controlled a virtual arm (MuJoCo, DeepMind; *top*) using a 32-electrode surface EMG sleeve (*right*). During the experiment, the user pushed a block while feeling electrocutaneous stimulation proportional to the force experienced by the fingertip. Based on the sensory feedback, the user identified the block hardness (i.e., "hard" or "soft").

So What?

Training with stimulation artifacts improved compliance discrimination (Figure 3) for the soft blocks, increasing the median accuracy from 76% to 82% for the Kalman filter (KF) and from 72% to 85% for the Convolutional Neural Network (CNN). Improvements in correctly identifying the hard blocks were similar for the KF but less pronounced for the CNN: 71% to 76% (KF) and 67% to 68% (CNN). These differences were not significant; possibly a result of the limited power of non-parametric tests with small sample sizes (n = 8).

This suggests that artifact in training data may enhance motor control without additional computational complexity. This approach offers a practical way to mitigate artifact-related disruptions while enabling the dexterous control promised by proportional algorithms.

Further research with larger sample sizes and prosthesis users is needed to validate these findings. The observed improvements may be more pronounced for stimuli applied in a clinically relevant location, such as under the sEMG sleeve near the electrodes.

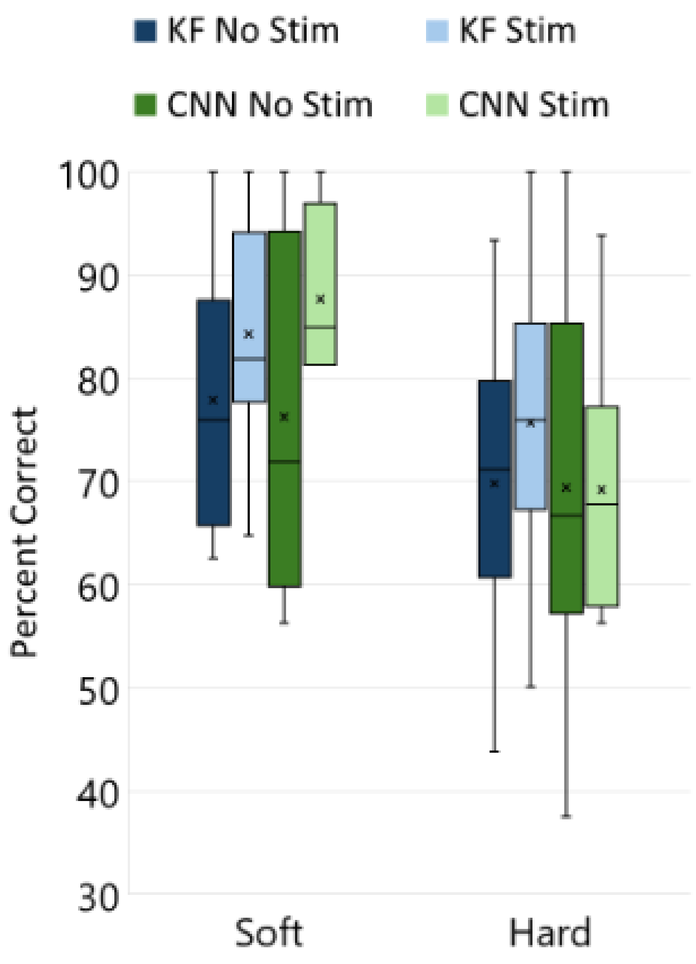


Figure 3: The percentage of trials that participants correctly identified as either "soft" or "hard" for the Kalman filter (KF) and the convolutional neural network (CNN), with and without stimulation in the training data. The box represents the interquartile range (IQR; 25th and 75th percentiles) and the line inside the box represents the median (x = mean). Effect of stimulation in the non-parametric data were insignificant ((Friedman's test: $p = 0.13$; $df = 1$; $\chi^2 = 2.26$; $n = 8$).

How?

Eight volunteers (aged 18-45) with intact limbs participated in the study. They trained a 5-degree-of-freedom (DOF) virtual hand using surface electromyography (sEMG; Figure 2) [3],[4]. SEMG signals were collected (at 2 kHz) using a 32-electrode sleeve placed on the forearm and then bandpass (15-375Hz) and notch filtered (60/120/180Hz). Participants mimicked flexion and extension of each DOF five times, holding full flexion and extension each for three seconds [5].

After filtering, differential EMG signals were calculated for all possible channel pairs, resulting in 496 differential recordings from 32 channels. Alongside 32 single-ended recordings, the Mean Absolute Value (MAV) was calculated at 30 Hz and smoothed using an overlapping 300-ms window. This process produced a final EMG feature set consisting of 528 channels (32 single-ended + 496 differential pairs). These features were then used as inputs to the KF and CNN algorithms for proportional control.

Participants completed training under two conditions: with electrocutaneus stimulation and without. For stimulation, bursts of pulsed (100-µs) biphasic stimuli (100 Hz) occurred randomly during each training movement with varying duration (0.95, 1.9, or 3.8 sec) and amplitude (2, 4, or 6 mA). Stimuli were delivered through a 0.8-cm² electrode on the upper arm (Figure 1).

Two proportional control algorithms were tested:

- Modified Kalman filter (KF): the 48 most unique and useful features of the full 528 were identified using Gram-Schmidt forward selection (Figure 3, also described in [5]).
- Convolutional Neural Network (CNN): all 528 features were applied with deep learning to extract motor intent from sEMG signals (Figure 3, also described in [5]).

During experimentation, pulsed (100-µs) biphasic stimuli were delivered at 100 Hz. Stimulation amplitude was proportional to the force experienced by the index fingertip while pressing a virtual block. For "soft" blocks the force was scaled by 0.75 and for "hard" blocks it was scaled by 1.5.

Participants performed a block-push experiment where they pressed on a virtual block and identified whether it was "soft" or "hard" based solely on sensory feedback. We examined how training with stimulation affected ability to discriminate object compliance.

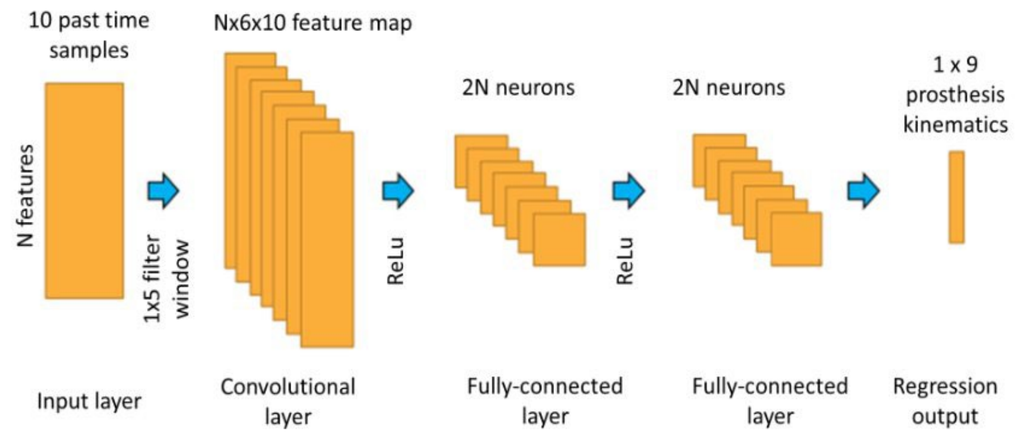


Figure 3: Convolutional neural network architecture. Trained using a Stochastic Gradient Descent with Momentum solver with an initial learning rate of 0.001

$$\hat{x}_{new} = \Gamma^* \hat{x}_{previous} + K^* z$$

Predicted Position · Physics Model · Previous Position · Kalman Gain · sEMG Features

Figure 4: Kalman filter update equation used to predict new finger position. The Kalman Gain matrix was trained using 48 unique and useful features.

Including stimulation artifact in training data could improve control of low-cost myoelectric prostheses equipped with electrocutaneous feedback

Acknowledgments
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References

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