MLP and HMM Synergistic Use in an sEMG-Based Control Algorithm for a Bidirectional Prosthetic Hand

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HAND prostheses need an effective bidirectional control. In fact, achieving to couple a robust voluntary control of motion with feedback would result in an important feature that could increase the controllability of the prosthesis and enable a more intuitive functional experience, thus fostering the acceptability and daily usage of these devices [1].

In this work we focus on developing an effective control algorithm for decoding the intention of a user during grasping tasks conceived to exploit, down-the-line, the present potential of induced tactile sensation, elicited by the stimulation of the peripheral nerves [2]. A commercially available robotic hand [3] was programmed to respond to a multi-degree of freedom position control featuring palmar, radial, and ulnar grasps, hand opening and rest. The choice of hand motion patterns was driven by the previous finding that touch sensations elicited by neural stimulation can be reliably located independently at the ulnar and radial sides of the palm [2]. The estimation of hand motion intention (online decoding) is inferred from measurements of bipolar surface Electromyographic (sEMG) electrodes positioned at 5 muscle sites on the forearm.

Our approach was tested on robotic hand control by a participant with hand amputation. It combines 1) a Self-Organizing Map (SOM) to suppress the need for manual labeling during the initial supervised training of the classifier; 2), a Multi-Layer Perceptron (MLP) for classifying motion intention from sEMG signals; 3), Hidden Markov Model filtering (HMM) to increase robustness towards chattering of decoded output, due to signal quality variations.

1) The MLP network was trained each time the electrodes were placed on the arm, using a set of sEMG data that had been collected in a specific initial session of approximately 50s, featuring the whole variety of decoded states. To automatically label the recorded trained data, we used a SOM as a non-supervised network training approach. This procedure made manual labeling no longer necessary to obtain optimal accuracy, with 100% success in automatic labeling over 7 such sessions.

2) For the purpose of motion control decoding, sEMG data were acquired and binned at intervals of 100ms. Time and frequency domain features were extracted [4] and processed by a MLP that decoded the hand motion state. MLP decoding precision over 7 different datasets (assessed in a leave-one-out fashion over trial segments) was 90.2% (mean class accuracy).

3) During online classification, chattering of MLP output was smoothed using HMM filtering with fixed transition weights; this choice features virtually no delay in response to voluntary switches between motor commands. This approach improved the classification accuracy level by significantly reducing output fluctuations during each single grasp control, taking it to 93.5% over the 7 mentioned datasets. This strategy also significantly improves the performance of classifiers that are trained with suboptimal hyper-parameters. As an example, when training the MLP with 1/5 of the "optimal" number of iterations, which is estimated from a separate dataset, the HMM addition raises the accuracy level from 75.6% to 86.7%.

The final motor control output was transferred to the hand prosthesis within a soft real-time deadline set at 100ms, at the time that the next sEMG signal block was made available, resulting in an imperceptible delay for the user [5].

These results improved the quality of user experience in an intuitive grasping control, using a hand prosthesis whose tactile feedback could be enabled by a peripheral neural interface.

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