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The Effects of EMG-Based Classification and Robot Control Method on User's Neuromuscular Effort during Real-Time Assistive Hand Exoskeleton Operation

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***Abstract*— EMG-based intention recognition and assistive device control are often developed separately, which can lead to the unintended consequence of requiring excessive muscular effort and fatigue during operation. In this paper, we address two important aspects of the performance of an integrated EMG-based assistive system. Firstly, we investigate the effects of muscular effort on EMG-based classification and robot control. Secondly, we propose a robot control solution that reduces muscular effort required in assisted dynamic daily tasks compared to the state-of-the-art control methods.**

I. Introduction

Over the past few decades, electromyography (EMG)-based intention recognition for upper body movements has been widely studied with the goal of classification of intent [1]–[4]. Many feature combinations and learning methods have been explored to improve the accuracy of EMG-based classification including time features, frequency features, and time-frequency features, as well as supervised and unsupervised learning methods, ranging from support vector machines (SVM) to K-nearest neighbors (KNN), artificial neural networks, and deep neural networks. Often, the motivation for EMG-based hand pose classification is to help amputees and individuals with disabilities control prosthetic and assistive devices for grasping. Robotic hand devices have been separately developed to assist affected populations including those with a spinal cord injury (SCI), accomplish daily grasping tasks [5]–[7]. However, the effect of the integrated systems involving EMG-based classifiers and assistive device control on the muscular effort required to use the device has rarely been investigated. We postulate that separately developing EMG-based intention recognition methods from robot control strategies will have unintended consequences. For instance, operating the device in real-time can cause users to exert excessive muscular effort, which can lead to fatigue and device disuse.

In our previous studies [7], we implemented EMG-driven exoskeleton control strategies for SCI subjects in daily tasks to investigate and improve the performance of integrated system of classifiers and assistive devices. We demonstrated their efficacy in improving hand function and for robustly switching between intended hand poses [8]. In the present work, we investigate the integration of EMG-based classification and real-time assistive robot control and its effect on required muscular effort in a pilot study. First, we examine the effects of muscular effort level during training on the accuracy of EMG-based classification of hand pose. We demonstrate that higher muscular effort leads to higher EMG-based classification accuracy and is a more robust approach to control the movement of an assistive hand exoskeleton. However, despite its higher classification accuracy, using this approach in a real-time assistive device control may require excessive continued muscular effort. Thus, in the second part of this study, we evaluate the muscular effort required during real-time exoskeleton control for daily tasks and propose a robust assistive control method to reduce the overall muscular effort. Finally, we validate that our proposed approach helps to significantly reduce the muscular effort levels compared to a simpler, intention-based robot control approach that is commonly used.

II. Methods

A. EMG-Based Classification of Hand Pose

In this section, we detail the methods to perform intention recognition based on EMG signals for hand pose classification.

1) EMG Data Acquisition and Pre-Processing: The Delsys Trigno wireless EMG system is used to measure activation from task-related muscles at three locations: anterior forearm to target the extensor digitorum (ED) muscle, posterior forearm to target the flexor digitorum superficialis (FDS), and palm to measure activity from the abductor pollicis (AP) and flexor pollicis brevis (FPB).

EMG signals are sampled at 2 kHz. The offset is calculated as the mean value at the relaxed state and is subtracted from the EMG signal. The signal is then rectified and filtered using a third order Butterworth low-pass filter with a cutoff frequency of 4 Hz and normalized to its maximum voluntary contraction (MVC) value.

2) Hand Pose Classes: We select three of the most essential grasping poses [9], namely transverse volar grip (TVG), lateral pinch (LP), and extended grip (EG), as well as extension (E) and relaxed (R) poses as the output classes for the classification (Fig. 1).

3) Classification Algorithm: An artificial neural network (ANN) algorithm is used to relate the EMG signals from the three sensors to the intended hand pose. Specifically,

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Fig. 1: Five classes of hand poses used in the study: relaxed (R), transverse volar grip (TVG), lateral pinch (LP), extended grip (EG), and extension (E).

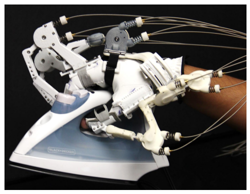


Fig. 2: Maestro hand exoskeleton assisting a subject in holding an iron.

a two-layer, feed-forward network with a sigmoid hidden layer and softmax output neurons is implemented using MATLAB. The network model is trained via scaled-conjugate-gradient backpropagation. Multiple data sets are used to train and test the ANN as detailed in Section III-A. The performance of the classification algorithm is measured based on the confusion matrix for the classes and the overall classification accuracy.

B. EMG-Based Robot-Assisted Performance in Daily Activities

1) Assistive Hand Exoskeleton, Maestro: The Maestro exoskeleton [7], which is used in this study, has three finger modules for the thumb, index, and middle fingers [10], [11]. Series elastic actuation (SEA) implemented in eight degrees of freedom (DOF) within these three fingers enables compliant control of the robot to perform multiple hand poses required in interactions with daily objects. Previously, we demonstrated that SCI subjects were able to grasp a set of 15 objects representative of activities of daily living (ADL) [8], [9] by using only four target hand poses (TVG, LP, EG, and E) and taking advantage of the compliant design of the robot.

2) Robot Control Method: We compare the effects of two different robot control modes on the assistive performance and muscular effort required during real-time grasping and manipulation tasks (Table I).

We refer to the first control mode as "online responsive control" (ORC), wherein there are five target hand poses performed by the robot (TVG, LP, EG, E, and R). We implement a polling mechanism that considers a window of 200 samples and takes the ANN output class based on muscle activations. Once the probability of one specific pose surpasses a threshold (60%), the robot moves to the target hand pose consistent with the ANN output. Therefore, for the successful completion of a task, it is important that the user maintain the correct muscle activation such that the intended hand pose is selected as the ANN classification output.

We propose a second robot control method, called "robust assistive control" (RAC), wherein two strategies are implemented to increase the robustness and decrease the effort required to complete the tasks. Firstly, we limit the robot hand pose outputs to four classes (TVG, LP, EG, and E) and take advantage of the relaxed (R) class to more robustly maintain a pose. Once a grasping pose is selected based on the polling mechanism taking into account the last 200 samples of the ANN classification output, the user can relax their muscles (R class) while the robot maintains the previous grasping pose. Secondly, to increase robustness and safety and to minimize the possibility of object drops, we implement an additional requirement for moving between hand poses: the user must first activate the extension pose before switching between two grasping poses.

3) EMG Post-Processing and Muscular Effort Evaluation: A measure of total integrated muscle activity (TIMA) [12] is used to estimate the muscular effort exerted during each task. Raw EMG signals from three sensors are first smoothed using a mean absolute value (MAV) function with a window size of 200 samples. The smoothed signals are then integrated over the duration of the task and summed to calculate an estimate of total muscular effort.

III. EXPERIMENTS

Two experiments are performed, with approval of the institutional review board, to test the performance of the classification algorithm and the robot control methods.

A. EMG-Based Classification with Different Effort Levels

We investigated the effect of effort level exerted during the training of an EMG-based ANN classification algorithm on its classification accuracy. The location of the surface EMG sensors for the targeted muscles (FDS, ED, and AP+ FPB) were determined on the forearm and palm using palpation. The MVC value and the resting offset for each muscle were recorded. In order to train the classification algorithm, the subject was asked to perform each target hand pose for 10 s and then relax for 10 s. Real objects were held during the grasping poses as seen in Fig. 1. We performed this experiment under two main conditions. For the low force condition, subjects were

TABLE I: List of daily tasks performed in the experiment

Task	Description
1	Pick up a 1 L milk carton and hold for 20 s.
2	Pick up a full 2 L jug and fill a cup of water, return the jug.
3	Pick up a mug, take to mouth and hold for 20 s.
4	Pick up an iron and hold for 20 s.
5	Pick up a cellphone, take to ear and hold for 20 s.
6	Pick up a textbook and hold for 20 s.
7	Pick up a plate and hold for 20 s.
8	Pick up a knife and cut a roll of play dough in half.
9	Turn key 90 degrees to the right and then back.
10	Open and close the zipper of a purse attached to a wall.

asked to exert minimal effort while performing the poses. For the high force condition, subjects were instructed to exert higher muscular effort while grasping the objects and during extension of the fingers. We hypothesized that the overall classification accuracy would be higher for the high force case since the differences between the EMG signals of different classes would be more pronounced. Two young healthy subjects were recruited to perform these experiments. The order of the experiments was pseudo-randomized to minimize potential effects of residual fatigue. The participants were instructed to be consistent in the level of the effort exerted in the hand poses within each condition. Five trials were performed, from which the first three data sets are used for training the ANN. The data collected from each hand pose were segmented, and the first and last 2 s of the data were cropped to eliminate dynamic effects during finger movements. An ANN was trained based on 70% of the data randomly selected from the first three collected data sets. From the remaining data in these data sets, 15% were used for validation, and 15% were used for testing the classification accuracy. In addition, we utilized two separate data sets for further testing of the trained classification algorithm.

B. Real-Time Performance of Daily Tasks with and without Robot

In a set of experiments, we examined the muscular effort exerted during 10 dynamic tasks (Table I) under three different conditions. We compare the performance using the two robot control modes, namely ORC and RAC, and a bare-hand (BH) condition without a robot.

The ANN classification algorithm trained based on the high force condition was used to detect the intention. Hand pose parameters for the robot movement were set for each class and adjusted to the hand size of the subjects. A time window of 20 s was allocated for completing each task, followed by 20 s of relaxation. Before each task, the relevant objects were placed in front of the subject by the researcher administering the experiment. The subject was allowed to relax and recover for at least 5 min between the two sets of experiments under each condition. The subjects were asked to relax if they finished the task sooner than the allotted 20 s. Raw EMG data collected from the three sensors during the 20 s of each task were separated and processed to estimate total muscular effort based on TIMA.

IV. Results and Discussion

A. Higher Effort Level in Training Results in Better Classification Accuracy

The overall classification accuracy, which is calculated based on the confusion matrices, is shown in Table II for each subject under the two loading conditions. Consistent with our hypothesis, the classification is more accurate in the high force case compared to the low force training condition. A Student's t-test showed significant improvement of the classification accuracy ($P = 0.013 < 0.05$). These results suggest that for a more reliable classification algorithm for real-time control of an assistive hand device, it may be better to train the classification algorithm with higher effort levels. We suspect that most of the classification results reported in the field are also results of training with higher than minimum muscle activity levels as the subject is instructed to intentionally hold a hand pose for data acquisition. However, maintaining this level of muscle activation during extended time periods to operate an assistive device may require excessive muscular effort and contradict the assistive purpose of the orthosis.

B. Muscular Effort during Real-time Daily Grasping Tasks

Analysis of the TIMA for the two subjects under the three conditions of RAC, ORC, and BH during 10 dynamic daily tasks is shown in Fig. 3. On average, our proposed RAC mode, which allows the subject to relax their muscles after switching to a hand pose, requires significantly lower muscular effort ($P = 0.007$) compared to ORC. This result supports the idea that implementing a suitable robot control mode for an assistive device could reduce muscular effort requirements, prevent fatigue, and as a result, increase the usability of the device. A closer look at the summed muscle activation in grasping tasks completed with the robot and the BH condition sheds light on the different requirements in muscle activation across tasks. For instance, during the tasks that require holding heavy objects, such as a milk carton in Task 1, and a ceramic plate in Task 7, the RAC mode using the exoskeleton results in lower muscle activation compared to the BH condition (Fig 4a). However, for the tasks that involve holding or manipulating light or small objects, such as zippers and keys in Tasks 9 and 10, respectively, the BH condition usually requires lower effort levels (Fig 4b). This difference stems from the higher effort required to initiate the grasping mode while controlling the robot and the longer time required to complete the task with the robot compared to the BH condition.

V. Conclusions and Future Work

In this research, we addressed the integrated development of EMG-based classification and real-time assistive robot control and proposed a control method to prevent excessive muscular effort, fatigue, and device disuse. First, we investigated the effects of muscular effort on the accuracy of EMG-based classification and demonstrated that higher forces during the training may result in better classification accuracy. Then, we proposed a robust assistive exoskeleton control method that helped to reduce the

TABLE II: Classification accuracy for the low force (white) and high force (shaded) conditions

Subject	Training Data Set	Test Data Set 1	Test Data Set 2
S1	82.9%	82.3%	77.2%
S2	91.5%	84.4%	92.4%
S1	97.2%	96.9%	94.3%
S2	93.8%	90.1%	96.9%

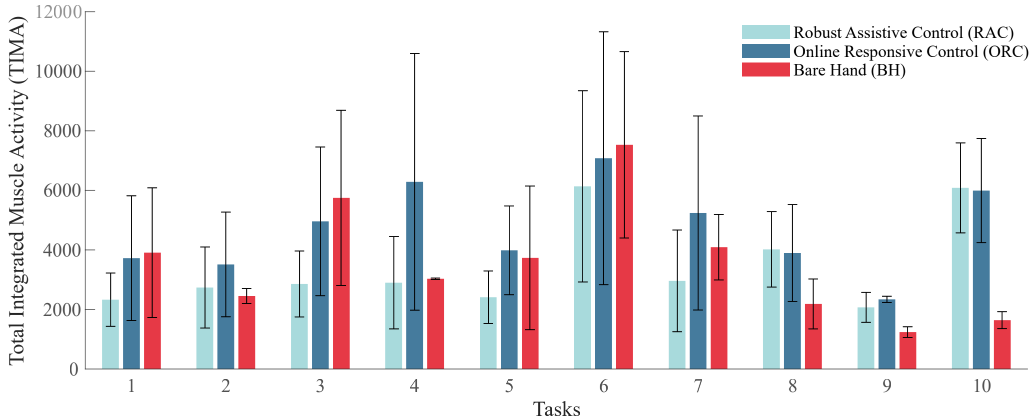
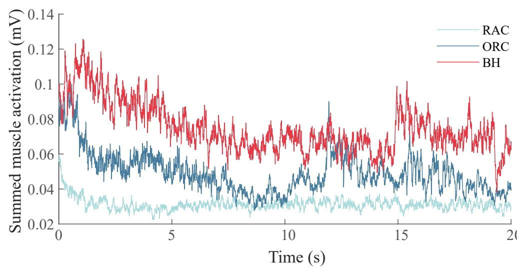
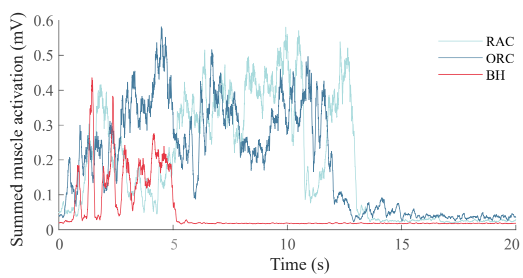


Fig. 3: Estimated total muscular effort (TIMA) calculated for different daily tasks (Table I) for two different exoskeleton control modes (RAC and ORC), and the bare hand (BH) condition. The values have been averaged for S1 and S2, and the error bars demonstrate the range of effort values for the two subjects.



(a) Muscle activation of S2 during the plate task



(b) Muscle activation of S1 during the zipper task

Fig. 4: Muscle activations shown for two example tasks for the robot control (RAC and ORC) and BH conditions. The robot assistance modes require less effort during manipulation of heavy objects. The BH condition is more efficient in manipulating small objects with low forces.

muscular effort required during the assisted performance of dynamic daily grasping tasks compared to state-of-the-art control methods.

In future studies, we plan to address the limitations of this work by testing the presented methods on a larger sample size and affected populations. In addition, we plan to implement an EMG-based exoskeleton control method to vary the grasping force as well as the hand pose based on the detected intention.

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