A Soft Exoglove Equipped With a Wearable Muscle-Machine Interface Based on Forcemyography and Electromyography

Anany Dwivedi, Lucas Gerez, Waris Hasan, Chi-Hung Yang, and Minas Liarokapis

***Abstract*—Soft, lightweight, underactuated assistive gloves (exogloves) can be useful for enhancing the capabilities of a healthy individual or to assist the rehabilitation of patients who suffer from conditions that limit the mobility of their fingers. However, most solutions found in the literature do not offer individual control of the fingers, hindering the execution of different types of grasps. In this letter, we focus on the development of a soft, underactuated, tendon-driven exo-glove that is equipped with a muscle-machine interface combining Electromyography and Forcemyography sensors to decode the user intent and allow the execution of specific grasp types. The device is experimentally tested and evaluated using different types of experiments: first, grasp experiments to assess the capability of the proposed muscle machine interface to discriminate between different grasp types and second, force exertion capability experiments, which evaluate the maximum forces that can be applied for different grasp types. The proposed device weighs 1150 g and costs $\sim$ 1000 USD (in parts). The exoglove is capable of considerably improving the grasping capabilities of the user, facilitating the execution of different types of grasps and exerting forces up to 20 N.**

***Index Terms*—Physically assistive devices, prosthetics and exoskeletons, human performance augmentation.**

I. Introduction

According to the World Health Organization (WHO), in many countries, less than 15% of people who require assistive devices and technologies have access to them [1]. Impairment of hand function is one of the most common consequences of neurological and musculoskeletal diseases such as arthritis, Cerebral Palsy, Parkinsons Disease, and stroke [2]. In order to accelerate the rehabilitation process of impaired people, it is important to execute repetitive movements and to try to perform daily tasks [3]. Many robotic devices have been developed to assist patients with limited mobility of the hand during physical therapy or to augment the capabilities of able bodied users [4].

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Although soft, underactuated, robotic exogloves have become very popular over the last years, they still have several limitations. One of these limitations is their inability to execute different types of grasps without requiring mechanical interaction between the user and the device (e.g., pressing buttons or activating differential mechanisms). Many studies describe the use of surface electromyography (EMG) sensors, flex sensors, or other mechanical methods to control the motion of each finger of an exo-glove in a simplified and intuitive manner [2]. In [5], the authors propose a cable-driven, portable, exoskeleton glove that uses an infrared and a flex sensor to actuate the system. Although the device can exert up to 16 N during a pinch grasp, it cannot execute different grasping postures and gestures. In [6], the authors propose a tendon-driven, soft robotic glove made out of silicone which can exert up to 20 N of pinch force using an analog switch to trigger the device. In [7], the authors describe a soft assistive glove that can exert more than 14 N of force during power grasps by employing hydraulic actuators. The device uses EMG signals to control the closing motion of the device, but the user has to select the grasp type by pressing mechanical buttons on a control box. In [8], the authors propose a soft robotic glove with integrated EMG sensing for disabled people. The EMG signals are used to discriminate between the actions of opening, closing, and holding an object. In [9], the authors propose a fabric-regulated, soft, robotic glove that uses EMG sensors combined with RFID (Radio-Frequency Identification) tags in order to control the hand motion. RFID tags are attached on objects to help the glove to identify the type of grasp that must be executed, while the EMG signals are used to control the motion of the device. In previous works [10], we have proposed an underactuated, lightweight, assistive exo-glove that is capable of exerting more than 16 N of force using a single actuator and a differential mechanism. Although the device can be efficiently controlled with EMG signals, it does not allow the execution of multiple grasping postures and gestures.

Regarding muscle-computer interfaces and muscle-machine interfaces, many studies have used EMG signals to decode reach to grasp motions [11], the object motion during the execution of dexterous, in-hand manipulation tasks [12], and the motion of each finger independently. Such approaches can be used for the EMG based control of prosthetic, orthotic, and assistive mechanisms. In [13], the authors describe an offline process for classification of finger movements for hand prosthesis using EMG

signals. They obtained an accuracy of more than 90% for 12 classes of individual finger movements using 11 EMG channels. In [14], the authors propose an online method for predicting individual finger movements for the control of a prosthetic hand, using EMG signals. The data was recorded using 16 EMG channels and the accuracy was $\sim$ 80%. In [15], the authors discriminate between six different hand postures using signals from 5 EMG channels by employing a Support Vector Machines classifier. The classification accuracy ranged between 83-99% for the different hand postures.

In [16], the authors proposed a forcemyography (FMG) based approach for decoding the finger motions during the execution of different grasping tasks. More precisely, they developed a wearable wrist band that consists of an array of 8 Force Sensitive Resistors (FSRs). In [17], authors compared FSR based FMG sensors with commercially available EMG sensors. They concluded that FMG sensors performed better in decoding the grasp motion (accuracy of 91.2%) as compared to the EMG sensors (accuracy of 84.6%). In [18], the authors developed two different mechanical sensors to detect the muscle movements of the forearm for four different hand postures. The first sensor used two FSR sensors to detect the muscle movements, whereas the second sensor used a conductive force sensing fabric that was wrapped around the forearm for the same purpose. In [19], the authors conducted experiments using eight FSR sensors embedded into a flexible strap. The data was processed using non-kernel based extreme learning machine and the method was able to successfully detect several grasp gestures with 92.33% real-time classification accuracy. A similar strap with eight FSR sensors was used by [20] to detect eleven different hand gestures using Linear Discriminant Analysis (LDA). The authors reported a classification accuracy of 89% and that the number and positions of FSR sensors have a considerable effect on the accuracy of the system. In [21], the authors use an array of tactile sensors to detect five different grasping motions with 98.9% classification accuracy.

In this letter, we propose an assistive glove that is equipped with a muscle-machine interface, which combines EMG and FSR sensors to decode the user's intentions and discriminate between different grasp types (see Fig. 1). The device is experimentally tested and its performance is validated through two different experiments: i) classification experiments to validate the capability of the proposed muscle-machine interface to discriminate between five different grasp types and ii) force exertion capability tests, which focus on the maximum forces that the exoglove can apply for different types of grasps.

The rest of the letter is organized as follows: Section II presents the designs of the device and the classification methods, Section III details the experimental setup used and presents the results, while Section IV concludes the letter and discusses future directions.

II. Designs and Methods

In this section, the designs of the assistive exoglove and its components are described and the classification methods used are presented.

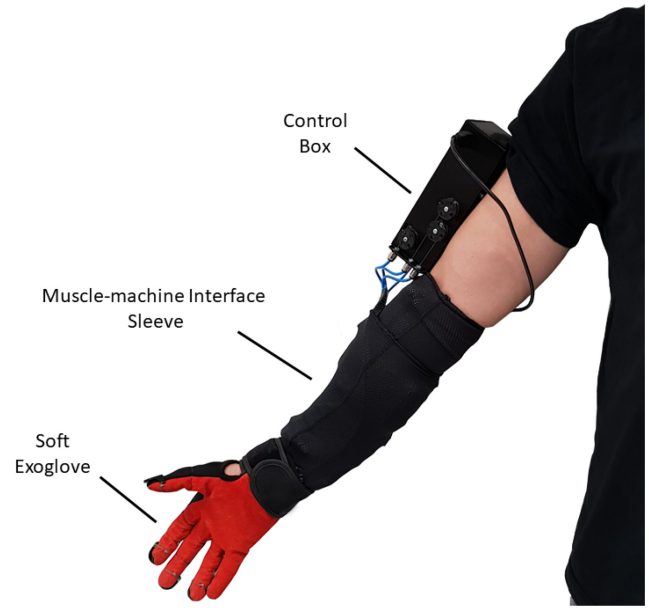

Fig. 1. The muscle-machine interface consists of a soft, wearable sleeve that accommodates multiple Forcemyography (FMG) and Electromyography (EMG) sensors. The muscle computer interface is connected to the control box that houses the four actuators which control the motion of the soft, robotic exoglove.

A. Exoglove

The exoglove was designed to increase the capabilities or to restore the lost dexterity of the human hand and it is composed of three main parts: a soft glove, a control box and a muscle-machine interface based on a sensorized sleeve. The soft glove weighs 49 g. The control box is composed of four motors (Dynamixel XM430-W350), a microcontroller (ATmega328P), a Raspberry Pi Zero, a U2D2 converter (a USB communication converter that enables to control and operate the Dynamixel motors through the Raspberry Pi) and a Li-Po battery. The control box can actuate four digits (index, middle, ring, and thumb) as the fifth digit (pinky) plays a supplementary role while grasping objects [22]. The sleeve based muscle-machine interface is used to decode the human intention based on EMG and FMG signals collected from the human forearm and will be discussed in detail in the following section. The entire robotic exoglove (see Fig. 2) weighs 1150 g (including the glove, the sensorized sleeve, and the control box), less than the devices analyzed in [6], [7], [23], [24]. The final prototype costs $\sim$ 1000 USD in parts to be manufactured.

The operation of the proposed assistive exo-glove is straightforward. When the user tries to execute a grasp, the muscle-machine interface detects and captures the activity of the muscles, three different EMG processing PCBs filter, rectify, and derive the envelopes of the EMG signals (by integrating them) and a microcontroller (ATmega328P) collects and sends the processed EMG and FMG data to a single board computer (Raspberry Pi Zero). Once the data have been collected by the single board computer, an appropriately trained classifier identifies the grasp type that is being executed and triggers the required motors. Artificial tendons made out of a low friction braided fiber

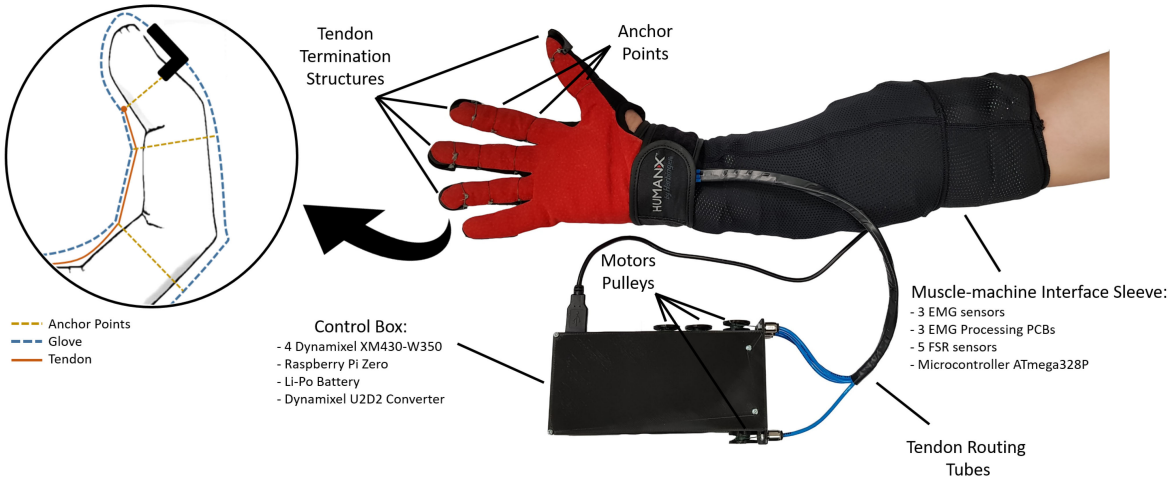

Fig. 2. Artificial tendons made out of a low friction braided fiber connect the motor pulleys to the tendon termination structures that are stitched at the fingertips of the soft, robotic exo-glove. Four polyurethane tubes offer a low friction tendon routing solution connecting the control box to the soft exo-glove. Soft anchor points are stitched onto the exoglove in order to implement rerouting at each finger.

of high-performance UHMWPE (Ultra-High Molecular Weight Polyethylene) connect the motor pulleys to tendon termination structures that are stitched onto the fingertips of the soft glove. Four Polyurethane tubes offer a low-friction tendon routing solution, connecting the control box to the soft glove. The tendons run inside these tubes and inside the glove not only to be rerouted but also to guarantee that their relative motions will not hurt the skin of the user. Soft anchor points are stitched onto the finger joints in order to reroute the tendon. The positions of the anchor points are chosen so as to maximize torque as described in [10]. When the motors are triggered the tendons are tensioned and the fingers are bent. The speed of execution of the grasping task can be set according to user's preference. For the experiments conducted for this work, we have selected a slow closing speed for the glove to guarantee safety of operation.

B. Sensorized Sleeve

The sensorized sleeve was designed to decode the user intention based on EMG and FMG signals collected from the user's forearm. The particular sensor positions correspond to the sites of the muscles that are responsible for moving the fingers. Several factors were taken into consideration while designing the sleeve, like cost, size, weight and intuitiveness of operation. The developed wearable prototype is equipped with 3 bipolar EMG channels and 5 FMG channels. All the sensors and electronics were integrated on the internal surface of the elastic sleeve. The sleeve was made out of a breathable and stretchable fabric and it can be easily worn using a zipper. The FMG sensors are implemented using Force Sensitive Resistors (FSR) and silicone based supporting pads, while the EMG sensors were developed using reusable wet silver electrodes supported by thick silicon blocks to maintain a tight contact with the human skin. The EMG electronics include four stages: i) the differential amplification, ii) band-pass filtering, iii) full-wave rectification and iv) calculation of the envelope of the signal. The inner surface of the sleeve is shown in Fig. 3. The FSR sensors used in this letter were the

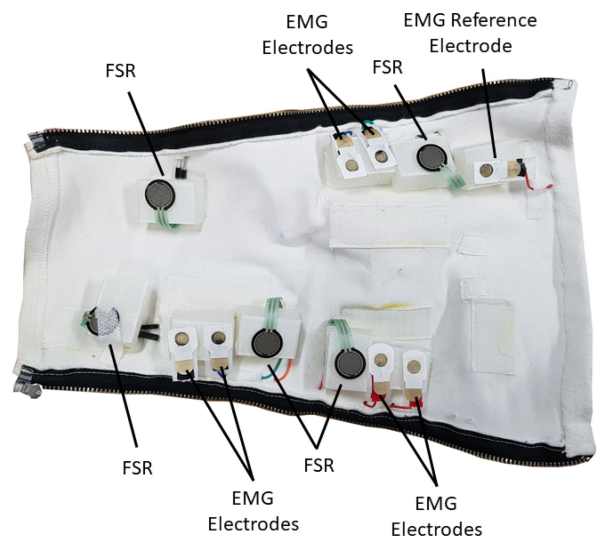

Fig. 3. The muscle-machine interface is composed of a sleeve made out of a stretchable fabric that can be easily worn by the user. The inner surface of the sleeve accommodates three Electromyography (EMG) sensors and five Force-myography (FMG) sensors based on Force Sensitive Resistors (FSR).The EMG sensors are connected to three different PCBs that were designed for signal amplification, filtering, rectification, and envelope calculation purposes.

402-Round sensors (Interlink Electronics, Camarillo, CA, USA) and have a force sensitivity range of 0.2 N-20 N which is enough to detect even the slightest muscle movements.

The reusable electrodes were manufactured by printing conductive silver ink on poly-ethylene terephthalate (PET) sheets using an inkjet printer. Previous studies describe the inkjet printing process for multiple applications, including EMG [25]–[27]. The advantage of using these electrodes over commonly used gel electrodes is that they do not need to be discarded after every use and can be developed in any shape and size to suit the requirements of the application and to improve the efficiency of the system. Reusable electrodes highly improve the practicality of the interface because the user does not have to go through the

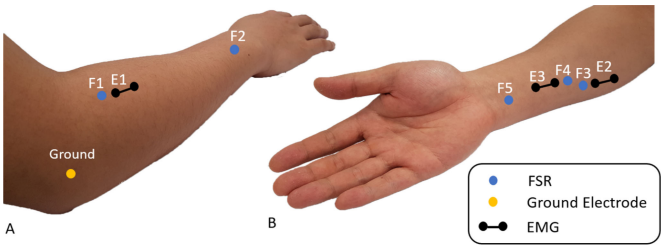

Fig. 4. Electrode placement positions for EMG data collection from the right human arm. The blue dots represent the FSR sensors, the single yellow dot represents the EMG ground electrode, while the black double dots represent the bipolar EMG electrodes. The letter 'E' refers to the EMG sensors and the letter 'F' to the FSR sensors. The number followed by each letter represents the channel number. E1 and F1 are placed at the extensor digitorum superficialis muscle site, F2 is placed at the extensor pollicis brevis muscle site, E2, E3, F3 and F4 are placed on the flexor digitorum superficialis muscle site, and F5 is placed at the flexor digitorum profundus musle site. The EMG ground electrode is placed near the elbow, where the myoelectric activity of the human muscles diminishes.

time consuming procedure of replacing the used electrodes and the sensors can be permanently attached to the interface. The main drawback of these electrodes is that in order to maintain the conductivity, conductive gel needs to be applied between the electrodes and the skin surface before every use. Fig. 4 shows the placement of the FMG and EMG sensors on the human forearm when the sleeve is worn. The sensors E1 and F1 were placed on the extensor digitorum superficialis muscle site to capture the finger extensions, sensor F2 was placed on extensor pollicis brevis muscle to capture the thumb extensions, sensor E2, E3, F3 and F4 were placed on the flexor digitorum superficialis muscle site to capture finger flexsions and sensor F5 was placed on flexor digitorum profundus muscle site to capture the flexion of the distal joints when a fist is made [28], [29]. The optimal sensor placement depends on the anatomical characteristics of each user but specific muscle groups are highly important across different people. These muscle sites are used for a proper positioning of the sensors. This has been studied in our previous work for a variety of tasks [30] and the findings of this study have been used for positioning the sensors of the proposed sleeve. The EMG recording requires amplification and filtering of the signals to obtain useful information. For this reason, custom printed circuit boards (PCB) were developed to acquire and process the raw data from the EMG electrodes. The collected EMG signal is filtered on board using a bandpass filter that has cut-off frequencies of 20 Hz and 480 Hz [31], [32]. The filtered signals are then rectified and enveloped before the classifier is trained.

C. Classification Methods

Three different classification algorithms were used to discriminate between the examined grasp types based on EMG and FMG data: i) a Linear Discriminant Analysis (LDA) classifier, ii) a Support Vector Machine (SVM) classifier and iii) a Random Forest (RF) classifier (a ensemble classifier based on decision trees). The output of the Random Forest classifier is the most popular class among the individual trees. Regarding features selection, the amplitudes of the EMG and FMG signals were used as input to the classification algorithms. The classifiers were trained and tested using the 5-fold cross validation method.

Fig. 5. The first experiment focuses on evaluating the accuracy of the muscle-machine interface in discriminating between five different types of grasps using both EMG and FMG sensors. The objects used during the experiments were: a cup, a card, a die, a baseball ball, and a bounce ball. The five grasps were: a power grasp (a), a key grasp (b), a pinch grasp (c), a spherical grasp (d), and a tripod grasp (e). All the objects used are contained in the Yale-CMU-Berkeley grasping object set [33].

III. Experiments and Results

The experiments that were conducted to assess the performance of the assistive exo-glove were divided into two parts. The first part focused on evaluating the ability of the muscle-machine interface to discriminate between different grasp types using FMG and EMG signals collected from the user's forearm. The second part focused on force exertion capability tests in order to measure the maximum forces that the exoglove can apply for different types of grasps. The study has received the approval of the University of Auckland Human Participants Ethics Committee (UAHPEC) with the reference number #019043. Prior to the study, the participating subjects provided written and informed consent to the experimental procedures.

A. Grasp Type Classification

The first experiment was executed to evaluate the ability of the muscle-machine interface to discriminate between the following actions: i) a spherical grasp, ii) a power grasp, iii) a pinch grasp, iv) a tripod grasp, v) a key grasp and vi) a rest state. According to [34], with these five different types of grasp it is possible to perform most of Activities of Daily Living (ADLs). For the experiments, the subjects were given verbal and visual instructions on how to perform the grasps. All the grasps were done using the objects from the Yale-CMU-Berkeley grasping object set [33]. The objects used for the spherical, power, key, tripod and pinch grasps were a baseball ball, a cup, a card, a bounce ball, and a die respectively (as shown in Fig. 5). For each grasp, 15 trials were recorded and every trial consisted of only one grasp. In each trial, the subject was instructed to start the experiment with a initial rest period of 5 s followed by a grasping action of 7 s.

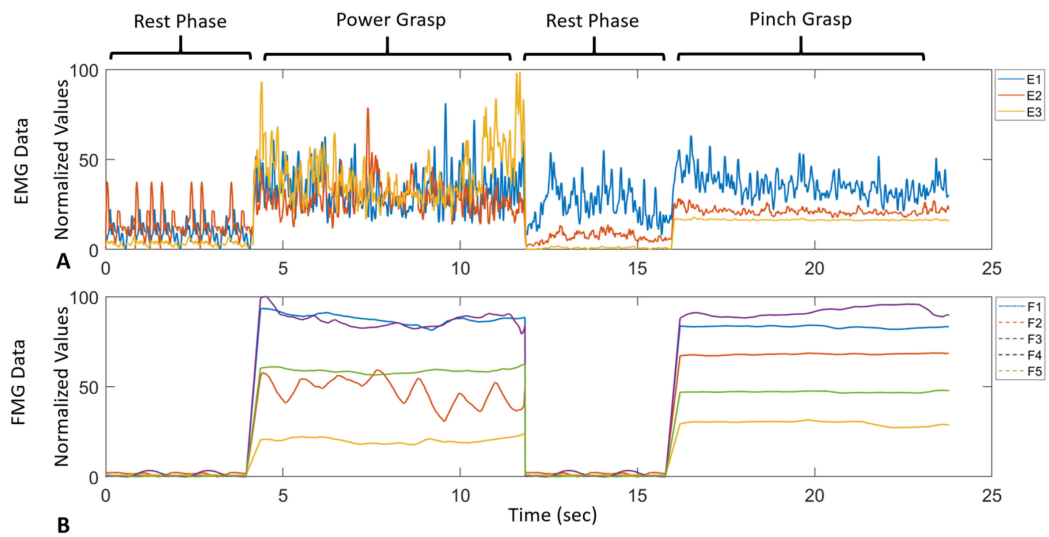

Fig. 6. EMG and FMG values during the rest phase, power grasp and pinch grasp.

To eliminate the reach to grasp phase at the beginning and relaxation phase (end of the trial), the first and the last second of each trial were omitted. Fig. 6 shows an example recording (values normalized to $0-100$) of the EMG and FMG data collection during the rest phase, a power grasp, and a pinch grasp.

For user intention classification the learning models use EMG and FMG data from eight different muscle sites collected using the sensorized sleeve. The data from the sleeve was acquired at 150 Hz. At a particular instance in time, the input data vector for training the learning model can be represented as:

$$X_t = (x_1^t, x_2^t, x_3^t, ..., x_8^t) \tag{1}$$

where x_1^t, x_2^t, x_3^t are values for the EMG sensors E_1, E_2, and E_3 at a time instance 't'. While $x_4^t, x_5^t, x_6^t, x_7^t$, and x_8^t represent values of the FMG sensors F_1, F_2, F_3, F_4, and F_5 at time 't'. The desired output of the learned model at time 't' can be represented as:

$$H_t \in \{SP, PO, PI, TP, K, R\} \tag{2}$$

where $H_t = SP$ corresponds to the spherical grasp, $H_t = PO$ corresponds to the power grasp, $H_t = PI$ corresponds to the pinch grasp, $H_t = TP$ corresponds to the tripod grasp, $H_t = K$ corresponds to the key grasp, while $H_t = R$ corresponds to the rest state of the hand at time 't'. For each of the intended grasp motion H_t, $\exists$ a pre-defined $M_t \in \mathbb{R}^4$ that correspond to the motor state for each of the grasp strategy. For each of the grasp types a specific M_t is triggered for the exo-glove to execute the corresponding grasping motion. For a robust classification outcome, we use the Majority Vote Criterion (MVC) [11]. To do this, we apply a sliding window, of size $W = 10$ on the data while performing predictions. The MVC classifies all the samples in the window as the class that received maximum number of votes in that window. With regards to the real-time experiments the same method of prediction was employed.

The final classification model was selected by considering the trade off between accuracy of classifying the grasps and the time taken to make the prediction. The three different techniques that were considered were Linear Discriminant Analysis (LDA), Random Forests (RF) and Support Vector Machines (SVM). The examined RF based models were trained with 100 trees and max depth of each tree as 10. For the SVM classifier we used a non-linear RBF kernel. Along with the type of classifier, the performance for the two types of data (EMG and FMG) was also evaluated. More precisely, the training data was divided into 3 different sets. In Set 1, only the data from the EMG sensors was used for training the classification model. In Set 2, only the data from the FMG sensors was used for training and in Set 3, data from both EMG and FMG sensors was used for training. The classification performance over the 5-fold cross validation method for the three different classifiers and the different sets of data is presented in Table I. The execution time to predict the grasp types for 10,000 data points (samples) for the three examined classifiers is shown in Table II.

TABLE I
RESULTS OF CLASSIFICATION ACCURACY (A) AND STANDARD DEVIATION (SD) OBTAINED FOR THREE DIFFERENT CLASSIFIERS AND THREE DIFFERENT DATA SOURCES

Data Source		EMG		FSR		EMG + FSR	
Efficiency		A (%)	SD (%)	A (%)	SD (%)	A (%)	SD (%)
Subject 1	LDA	74.83	7.10	95.15	5.97	96.19	5.31
	RF	84.49	5.56	98.70	2.28	98.82	2.20
	SVM	79.88	6.38	98.57	3.05	99.14	1.91
Subject 2	LDA	76.83	7.70	89.21	2.51	95.24	2.68
	RF	78.06	5.25	90.53	3.66	97.64	3.56
	SVM	77.85	4.13	90.88	4.56	97.88	4.23
Subject 3	LDA	78.57	7.27	88.02	5.77	96.41	5.25
	RF	80.46	7.17	90.43	2.51	98.65	5.08
	SVM	79.19	7.07	91.64	5.76	97.91	3.57

TABLE II
AVERAGE EXECUTION TIME FOR PROCESSING A DATASET (10,000 SAMPLES / 66 SEC) WITH THE CLASSIFIERS

Classifier	Execution Time (sec)
LDA	0.008
RF	0.033
SVM	0.12

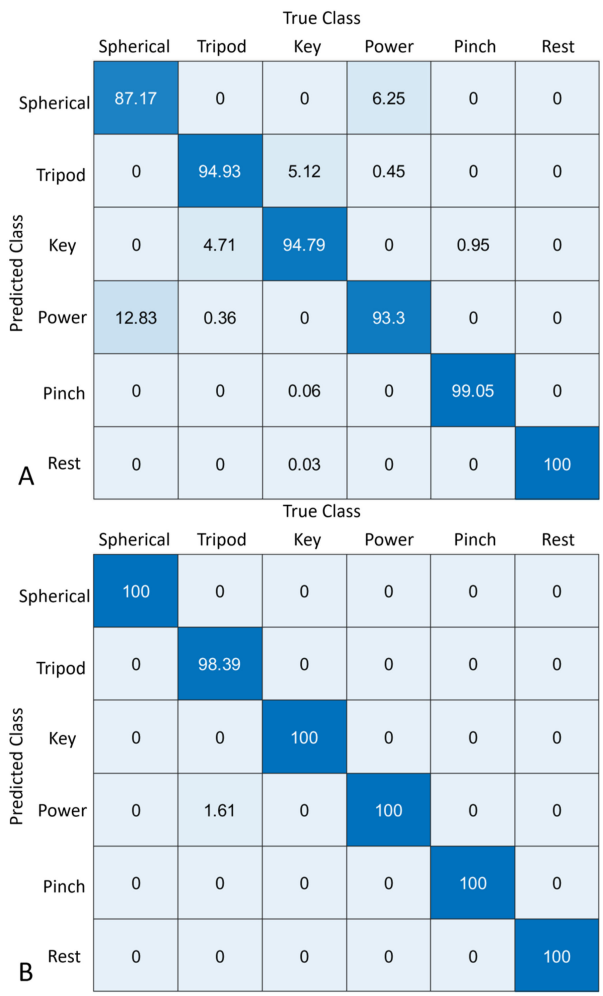

Fig. 7. Confusion matrices for the classification results of the LDA (a) and SVM (b) classifiers for combined EMG and FMG data (case 3, column 4 of Table I). The x-axis represents the ground truth and the y-axis the classifier's predictions. The diagonals represent the classification accuracies for each grasp.

Since the loss in accuracy when using LDA based models over RF or SVM based models is only $\sim 2-3\%$, for the final implementation the LDA was selected over the other classification methods, as it outperforms them in terms of speed of execution. Table II shows that LDA is ~ 15 times faster than SVM and ~ 3.6 times faster than RF. Fig. 7 presents the confusion matrices for the 5-fold cross validation method for the LDA and the SVM classifiers. The diagonal values represent the classification accuracies. It can be noticed that main misclassifications are between the spherical and the power grasps. The reason for this is that both these grasps are executed in a way which is very similar to each other.

TABLE III
SUMMARY OF MAXIMUM FORCES OBTAINED FOR FOUR DIFFERENT GRASP TYPES

Grasp Type	Force (N)
Pinch	11.3
Key	10.9
Tripod	11.5
Power	20.1

B. Force Exertion Experiment

The second experiment focused on measuring the amount of grasping force that can be exerted by the device. Four different grasping types were tested: pinch, key, tripod, and power grasp. Although the methodology can efficiently differentiate spherical grasps from power grasps, the motors motion necessary to execute the grasps are similar for both situations, so only one type of motion was implemented. The force measurements in each scenario were collected using a Biopac MP36 data acquisition unit (Biopac Systems, Inc., Goleta, California) equipped with the SS25LA dynamometer. The experiment was executed by gradually increasing the motors torque until a maximum predefined load was achieved.

Table III shows the maximum measured forces for four types of grasps. A total of five samples were collected for each type of grasp and the highest measured force was considered. The reported forces are the forces transmitted by the device only. The results demonstrate that the proposed exoglove can exert more than 20 N of force, which is enough to assist people in daily activities. According to [7], the forces required to perform most of the daily activities do not exceed 15 N. Moreover, the amount of pinch force required to execute most of ADLs is lower than 10.5 N [35].

Although the proposed device has multiple advantages in terms of weight, cost, execution of a variety of grasping postures, and force exertion capabilities, the exo-glove also has several limitations. One of the difficulties faced during the execution of experiments was to wear the sensorized sleeve and to keep the sensors in the right position for different subjects. Also, the EMG sensors require the application of a conductive gel between the electrodes and the skin surface before every use, in order to maintain the conductivity. Finally, the control box of the device is quite bulky due to the number of motors used and the battery dimensions. Extra effort should be put into optimizing its volume.

C. Devices Demonstration Video

A video containing the device description and the experiments can be found at the following URL: http://newdexterity.org/exogloves/

IV. Conclusions and Future Directions

In this letter, we presented a robotic exoglove equipped with a muscle-machine interface that can decode user intention using FMG and EMG signals from the human forearm. Two different experiments were performed to evaluate the proposed device. The first focused on assessing the classification accuracy of the system in discriminating different types of grasps and the second on the force exertion capabilities of the device. The results demonstrate that the robotic exoglove can assist the user in executing different types of grasps.

Regarding future directions, we plan to design a mechanism that can control the thumb opposition in the assistive glove. Such a mechanism will facilitate the execution of more grasp configurations. We also plan to include IMU sensors in order to establish a relation between the forearm inclination and possible gestures. This approach may increase the accuracy during the task execution.

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