On Muscle Selection for EMG Based Decoding of Dexterous, In-Hand Manipulation Motions

Yongje Kwon, Anany Dwivedi, Andrew J. McDaid, and Minas Liarokapis

***Abstract*— The field of Brain Machine Interfaces (BMI) has attracted an increased interest due to its multiple applications in the health and entertainment domains. A BMI enables a direct interface between the brain and machines and is capable of translating neuronal information into meaningful actions (e.g., Electromyography based control of a prosthetic hand). One of the biggest challenges in developing a surface Electromyography (sEMG) based interface is the selection of the right muscles for the execution of a desired task. In this work, we investigate optimal muscle selections for sEMG based decoding of dexterous in-hand manipulation motions. To do that, we use EMG signals derived from 14 muscle sites of interest (7 on the hand and 7 on the forearm) and an optical motion capture system that records the object motion. The regression problem is formulated using the Random Forests methodology that is based on decision trees. Regarding features selection, we use the following time-domain features: root mean square, waveform length and zero crossings. A 5-fold cross validation procedure is used for model assessment purposes and the importance values are calculated for each feature. This pilot study shows that the muscles of the hand contribute more than the muscles of the forearm to the execution of in-hand manipulation tasks and that the myoelectric activations of the hand muscles provide better estimation accuracies for the decoding of manipulation motions. These outcomes suggest that the loss of the hand muscles in certain amputations limits the amputees′ ability to perform a dexterous, EMG based control of a prosthesis in manipulation tasks. The results discussed can also be used for improving the efficiency and intuitiveness of EMG based interfaces for healthy subjects.**

I. Introduction

Over the past few decades, surface electromyography (sEMG) has been the most popular choice for the development of practical muscle computer interfaces (muCI). Such non-invasive BMIs involve the detection, recording and interpretation of the myoelectric activity of groups of muscles in static (rest) and dynamic actions [1]. In fact, it has become one of the most popular sensing methods for many Human Machine Interfaces (HMI) in general [2], as it is able to decode muscular activity and effort [3] that can be translated into appropriate motions for the control of wheelchairs, prostheses, and orthoses [4]. One of the most popular and common applications is the EMG based control of prosthetic devices that typically leads to the execution of robust grasping and dexterous manipulation tasks.

A lot of work has been done on development of EMG based interfaces for decoding human motions. In [5], Liarokapis et al. presented a Random Forests (RF) based learning scheme that discriminates between different reach to grasp strategies and triggers a task specific motion decoding model. To do that, they used the myoelectric activations of 16 muscles of the upper-arm and the forearm and they employed a combination of classification and regression RF models. In [6], Tenore et al. presented a framework for dexterous EMG based control of the fingers of a prosthetic hand. For this framework they used the myoelectric activations of 32 muscles of the forearm and they employed a Neural Networks (NN) based classifier that used time-domain features. The proposed methodology managed to decode 12 individuated flexion and extension movements of the fingers.

Vogel et al. [7], presented a complete framework for the EMG based teleoperation and telemanipulation with a robot arm-hand system. To do that, they used a Support Vector Machines (SVM) based leaning scheme and the myoelectric activations of 9 muscles of the forearm so as to decode the human hand motion and grasping force. The proposed methodology did not require precise placement of the EMG electrodes and no model of the human arm hand system was employed, making the system essentially subject independent. In [8], Khushaba et al. proposed an EMG based recognition system that facilitates the execution of individual and group finger movements by combining a Bayesian data fusion postprocessing approach, an SVM classifier and a k-Nearest Neighbours (kNN) classifier. This methodology utilizes only two EMG electrodes placed on the human forearm. In [9], Castellini et al. applied and compared NN based regression, SVM based regression, and Locally Weighted Projection regression to the EMG based estimation of the exerted human grasp forces. The particular methods can also be used for the online force control of a robot or prosthetic hand. In [10], Artemiadis et al. proposed a methodology that "maps" the human myoelectric activations to human arm motion. To do that, the particular methodology uses a state space model and the low dimensional embeddings of the EMG signals (input) and the human kinematics (output). The proposed methodology has been used for the EMG based teleoperation of a robot arm. In [11], Adewuyi et al. examined the contributions of the intrinsic and extrinsic muscles of the hand in classification of hand grasps. More precisely, they used a Linear Discriminant Analysis (LDA) classifier to discriminate between different grasps. They also showed that a model trained with the myoelectric activations of only the extrinsic muscles achieved an efficiency of 73% for partial hand amputees and 88% for non-amputees, while a model trained with the myoelectric activations of both the extrinsic and intrinsic muscles achieved an efficiency of 96% for partial hand amputees and 100% for non amputees.

The authors are with the Department of Mechanical Engineering, University of Auckland, NZ. Emails: {adwi592,ykwo675}@aucklanduni.ac.nz, {andrew.mcdaid,m.liarokapis}@auckland.ac.nz.

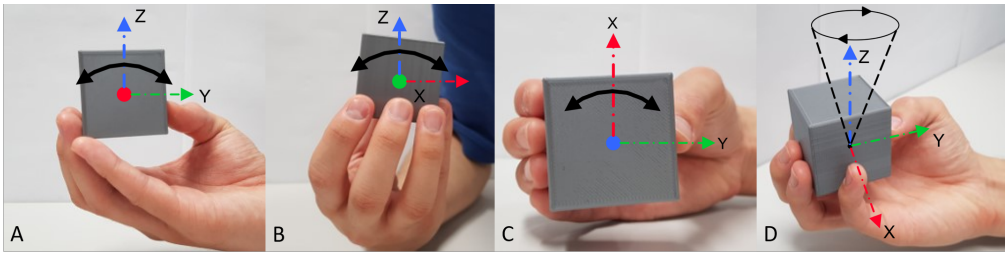

Fig. 1. Instances of the manipulation tasks performed. Fig. A shows Pitch, Fig. B shows Roll, Fig. C shows Yaw and Fig. D shows Twirl motion. Axes are color coded and the colored dots at the origin indicate that the axis is orthogonal to the page. The thick black colored arrows show the direction of the movement. In Fig. D the black arrows and dashed lines depict the twirl motion.

All the aforementioned studies, addressed the need for EMG based continuous decoding of human motion and EMG based control of prosthetic and robotic devices in grasping tasks, but none of them focused on the execution of dexterous, in-hand manipulation tasks. In this work, we address the problem of optimal muscle selection for the EMG based decoding of in-hand manipulation motions. The rest of the paper is organized as follows: Section II describes the equipment used and the experiments conducted, Section III reports the methods used to train the RF model and the verification procedures, Section IV presents all the experimental results and finally Section V concludes the paper.

II. Apparatus and Experiments

Experiments were performed by two healthy subjects, both aged 24. The study got the approval of the University of Auckland Human Participants Ethics Committee (UAHPEC) with the reference number #019043. Prior to the study all subjects provided written and informed consent to the experimental procedures. The experiments were performed by each subject with the dominant hand. One subject was left arm dominant while the other was right arm dominant.

A. Experiment tasks

For the experiments, each subject was instructed to perform 3D equilibrium point manipulation tasks with the Rubik's cube of the Yale-CMU-Berkeley Grasping Object Set [12]. Each subject was sat upright on a chair and the forearm was rested on an appropriately designed support structure. The sequence for each manipulation task session was executed with an initial rest period of 5s (where the object is held in a stationary pose by the hand), followed by 10 manipulation motion repetitions for each trial. Adequate resting time between every trial (approximately 30s) was used to reduce fatigue. There were ten trials for each session. The manipulation tasks are visualized in Figure 1 and are classified as follows (all motions are relative to the global planes of movement):

- Pitch: finger motions create a pitch rotation of the cube
- Roll: finger motions create a roll rotation of the cube
- Yaw: finger motions create a yaw rotation of the cube
- Twirl: finger motions create a spiral motion similar to wine glass twirling

B. Experimental setup

The signals were recorded using surface EMG electrodes (DIN EMG snap cables attached to EMG stickers) with signals acquired and preprocessed by an EMG bioamplifier (g.Tec g.USBamp). The sampling rate was 1200Hz. A Butterworth bandpass filter was applied to each channel (5Hz high-pass, 500Hz low-pass) with a 50Hz notch filter to reduce the line noise. In order to capture the motion of the Rubik's cube, a Vicon optical motion capture system was used. The Vicon system consists of 8 Vicon T-series cameras connected to the Giganet camera. The trajectories of the reflective markers were captured using the Vicon Tracker software. The sampling rate of the system was set at 100Hz with a trigger cable connected to the g.Tec bioamplifier to facilitate data synchronization. The object motion data was upsampled to match the sampling frequency of the EMG data.

C. Muscle selection

For all experiments, the myoelectric activations of 14 muscles of the hand and the forearm were recorded using double-differential electrodes. More precisely, for the hand, 3 electrodes were placed at the back of the hand focusing on the interossei muscles, 3 electrodes on the palm focusing on the lumbrical muscles, and 1 electrode was placed on the thumb to capture the activity of the flexor pollicis brevis muscle. On the forearm, 3 electrodes were placed at the extensor digitorums site, 3 electrodes were placed where the flexor digitorums are located, and the final electrode was positioned on the extensor pollicis brevis muscle site. The selection of the muscles and electrode placement was based on the directions provided in [13] and the Innerbody website [14] that features a muscle anatomy map.

III. Methods

A. Feature extraction

The raw EMG signals were filtered and segmented using a sliding window of 200 ms with an increment of 10 ms for extraction of the time domain features. The size of the window and the increment value are parameters that were optimized to improve the estimation results. Due to real-time constraints the window length should not be too long. Furthermore, a segment length should be adequately large, as the bias and variance of the features rise with a

TABLE I

NAMES AND LOCATION OF MUSCLES USED IN THIS STUDY

Muscle Name	interossei (x3)	lumbrical (x3)	flexor pollicis brevis	extensor digitorum superficialis (x3)	flexor digitorum superficialis (x3)	extensor pollicis brevis
Muscle Location	Hand			Forearm		

TABLE II

CORRELATION AND ACCURACY RESULTS FOR THE 3 SETS OF MUSCLES EXAMINED

Motion		Pitch		Roll		Yaw		Twirl					
Subjects		1	2	1	2	1	2	1			2		
Set 1[1]	Correlation (%)	89.5	82.7	85.7	85.0	94.2	93.3	86.9	82.6	88.7	92.6	92.0	83.6
	Standard Deviation (%)	3.71	5.34	4.24	3.02	3.22	1.93	2.76	10.78	3.32	3.00	2.77	5.41
	Accuracy (%)	77.6	65.2	72.0	68.2	84.7	85.9	71.5	66.5	72.5	85.2	81.8	65.5
	Standard Deviation (%)	7.79	10.31	7.00	2.91	8.08	3.45	6.18	18.95	12.81	5.54	7.30	11.99
Set 2[2]	Correlation (%)	87.9	80.3	80.4	72.6	95.2	92.0	85.1	81.8	86.4	89.4	90.8	79.0
	Standard Deviation (%)	2.88	3.81	4.50	0.63	1.38	2.08	3.92	9.95	4.25	3.82	3.30	3.37
	Accuracy (%)	73.4	60.2	63.9	48.4	88.4	83.8	68.5	65.2	68.2	79.1	80.5	57.9
	Standard Deviation (%)	7.01	11.97	6.62	3.36	3.21	3.56	6.70	17.58	14.68	6.72	7.65	8.30
Set 3[3]	Correlation (%)	85.3	74.2	76.7	68.2	85.3	81.3	55.9	38.7	75.6	84.3	77.4	77.9
	Standard Deviation (%)	4.20	1.98	4.62	6.32	8.81	3.36	9.17	6.41	5.33	2.46	4.14	7.26
	Accuracy (%)	68.7	52.1	50.0	44.3	70.4	64.5	22.3	9.6	49.3	63.8	57.3	56.4
	Standard Deviation (%)	9.70	4.32	8.39	7.74	16.53	4.61	13.76	8.95	11.50	10.04	7.15	10.12

[1]Set 1 consists of all 14 muscles. [2]Set 2 consists of the hand muscles. [3]Set 3 consists of the forearm muscles.

decreasing segment length [15]. From each of the EMG channels 3 different features were extracted, namely: Root Mean Square Value (RMS) [16], Waveform Length (WL) and Zero Crossings (ZC) [17], [18].

B. Object motion decoding

For object motion decoding we solve a regression problem using the Random Forest (RF) learning methodology. RF is an ensemble learning method that can be used for both classification and regression. The output of RF is the most commonly voted class among the individual trees for the classification case or the mean value of the outputs of the individual trees for the regression case. For each tree Random Forests use a different bootstrap sample set from the original data. One-third of the samples are left out of this set (out-of-bag samples) and they are not used in the construction of the n-th tree. For every tree in the forest the number of votes cast are counted for the correct class. Then the values of the variable m (training feature m) are randomly permuted in the out-of-bag samples and the votes are recomputed and recounted. Subtracting the number of votes casted for the correct class in the permuted out-of-bag data from the number of votes casted for the correct class in the untouched out-of-bag data, we get the importance score of a feature variable m, for each tree. The raw importance score for each feature variable is computed as the average importance score of all trees of the random forest.

IV. RESULTS

In this section we present the results for three different sets of muscles focusing on the EMG based decoding of the motion of in-hand manipulation tasks. The first set consists of muscles from both the hand and the forearm (selected muscles are discussed in Section II-C). The second set consists only of the hand muscles and the third set consists only of the forearm muscles. Table I summarizes the muscles sets used and the locations of the muscles in each set. In this study, we assess the efficiency of the trained models by using the Pearson correlation coefficient and the percentage of the NMSE, comparing the predicted object motion and the actual object motion. Table II shows the means and the standard deviations of both metrics over the 5-fold cross validation procedure that was used for model assessment. The results depicted concern also all three muscles group sets. From these results we observe that the estimations of Set 1 and Set 2 are almost comparable, even though the features used for Set 2 (21 features) are half the number of the features used for Set 1 (42 features). It is also evident that the results of Set 3 are worse that the results of Set 1 and Set 2. This suggests that the hand muscles are more important for performing in-hand manipulation tasks. This is also supported by Figure 2 that shows the importance plots of the features for all the examined muscles. These importance plots were derived from the RF inherent feature variable importance calculation procedure [5]. From this figure, it is clear that the first 10 muscle sites (7 of the hand and 3 of the forearm) are the most important for the EMG based decoding of in-hand manipulation motions in the object space.

V. CONCLUSION

In this study, we focused on muscle selection for the EMG based decoding of in-hand manipulation motions in the object space. To do so, we captured the myoelectric activations of 14 muscles of the hand and the forearm along with the object manipulation motion. A Random Forest based learning scheme was used to predict the object motion

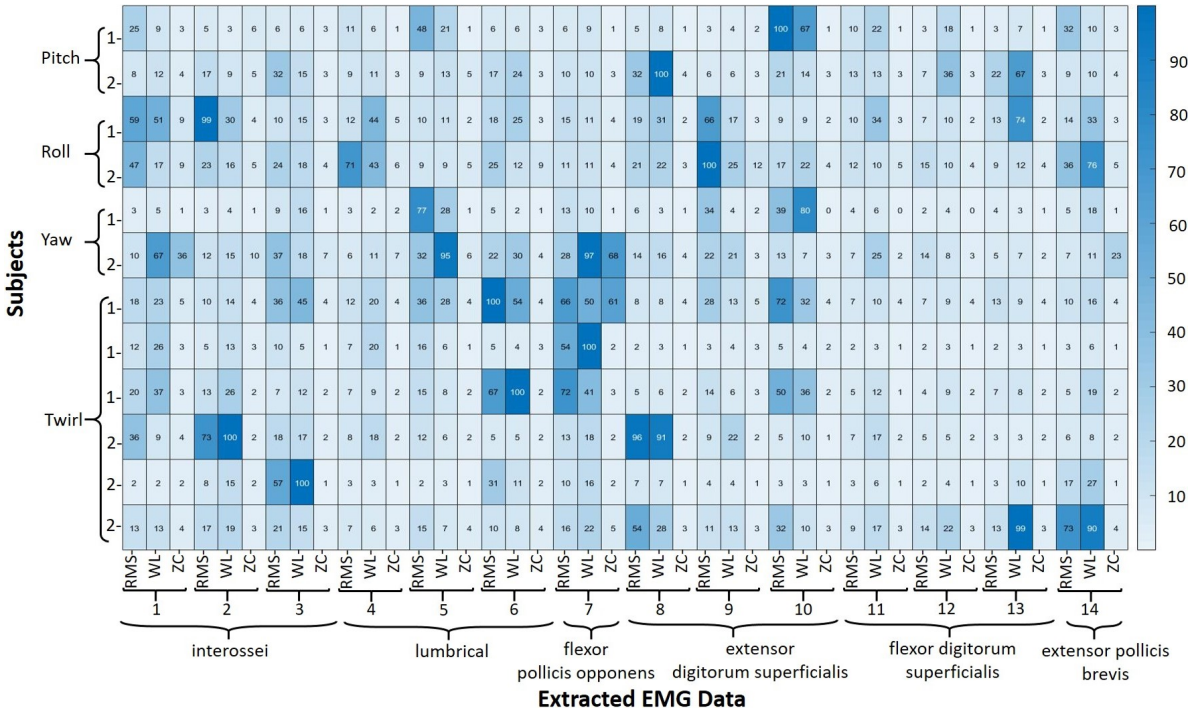

Fig. 2. Comparison of the importance plots of all features for each subject for all 14 muscles examined. RMS stands for Root Mean Square, WL stands for Waveform Length, and ZC stands for Zero Crossings.

from the extracted Time-Domain features of the myoelectric activations. Three different sets of muscles were tested for the prediction accuracies. The results obtained show that hand muscles are much more important than the forearm muscles for the EMG based decoding of in-hand manipulation motions. This finding suggests that the loss of the hand muscles in certain amputations limits the amputees′ ability to perform a dexterous, EMG based control of a prosthesis. The examined hand muscles can be used to improve the control of prosthetic devices for partial hand amputees or the efficiency of EMG based interfaces for healthy subjects.

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