EMG Based Decoding of Object Motion in Dexterous, In-Hand Manipulation Tasks

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***Abstract*— Brain Machine Interfaces (BMI) are used to establish a communication pathway between the human brain and machines. Using BMI, signals from the brain are transmitted to an external processing unit where they are decoded into meaningful actions (e.g., browsing the internet using a PC or grasping an object with a prosthetic hand). BMIs are used to increase intuitiveness of the control of technical devices that can help individuals with motor or sensory impairments to regain their lost dexterity or able-bodied people to augment their capabilities. In this work, we present an Electromyography (EMG) based method for decoding object motion in dexterous, in-hand manipulation tasks. To do that, we use EMG signals derived from specific muscles of the human hand and forearm, and an optical motion capture system that records the object motion. The decoding is formulated as a regression problem using the Random Forests methodology that is based on a combination of decision trees. The model was trained using time-domain features, namely: root mean square, waveform length and zero crossings. A 5-fold cross validation procedure is used for model assessment purposes. This preliminary study achieves significantly high estimation accuracies, proving that object motion can be directly decoded from myoelectric activations of the muscles of the human hand and forearm. This work can support the formulation of EMG based telemanipulation schemes for advanced robotic and prosthetic hands.**

I. Introduction

Surface electromyography (sEMG) has been used for the development of Brain Machine Interfaces (BMI) and Brain Computer Interfaces (BCI) for a variety of applications. It is a relatively cheap, non-invasive method that can measure muscle activations from the surface of the human skin. These activations can be extracted, translated and decoded into human motion or intention. Most EMG based interfaces have been proposed for the control of technical devices such as prosthetic arms and hands. In prosthetics, EMG control is the most common solution and it typically facilitates the execution of simple motions in unconstrained space.

But the role of prosthetic devices is to help amputees regain their lost dexterity and this dexterity concerns not only simple motions but also dexterous manipulation tasks and complicated interactions with the environment. In the case of prosthetic hands, previous studies have focused on the EMG based control of individual finger movements [1], [2] and the execution of grasping tasks of low complexity [3]. The EMG based decoding of human motion and the EMG based control of robot hands in dexterous manipulation tasks are topics that are still unexplored and this is to the best of our knowledge the first study that focuses on them.

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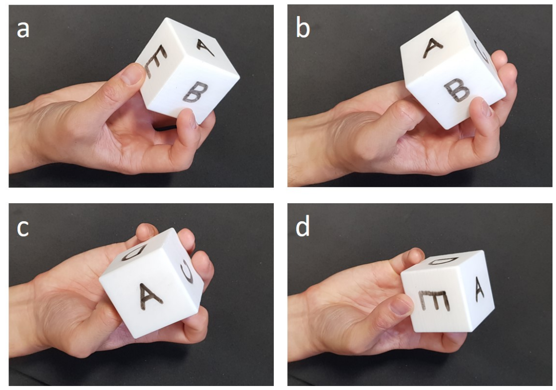

Fig. 1. Execution of a dexterous, in-hand manipulation task with a 3D printed cube. This equilibrium point manipulation imposes a twirling motion to the object. The figure shows a sequence of the object motion during manipulation (from subfigure a to d).

Regarding in-hand manipulation, there are many types of tasks that can be performed depending on the intended object motion. One of the main types is Equilibrium Point Manipulation (EPM). During EPM, the finger contact points remain relatively stationary[1] on the object surface, while the object is manipulated (see Fig. 1 for details). EPM is commonly used for object inspection or for in-hand repositioning and\or reorientation. Although there are robot hands that have been designed to achieve EPM [4], development of an EMG based control scheme that achieves the execution of EPM tasks with a robot or prosthetic hand is yet to be achieved.

The traditional approach to mapping muscle activity to object motion involves a three-step process where first the finger kinematics (i.e., joint angles or velocities) are estimated from the myoelectric activations of the muscles of the human forearm and hand, then the finger kinematics are used to compute the fingertip velocities and finally the fingertip velocities are mapped to the equivalent object velocities using the grasp matrix, as described in [5]. However, some drawbacks of this approach are: i) it requires an accurate EMG based estimation of the finger kinematics that could be hard to derive (e.g., due to the high dimensionality of the problem), ii) it relies on the accurate calculation of the aforementioned parameters (e.g., forward kinematics and Grasp matrices), and iii) it requires an a-priori knowledge regarding the human hand anatomy and kinematics (e.g., digit sizes) for able-bodied people and on the existence of a prosthesis model for amputees.

[1] Involve only some infinitesimal, local rolling and slipping.

In this paper, we propose a machine learning scheme that maps the myoelectric activations of the muscles of the human forearm and hand, directly to the examined object motion. To do so, we formulate decoding as a regression problem and we use the Random Forests (RF) regression technique. RF is an ensemble regression method that is based on a combination of multiple decision trees. The rest of the paper is organized as follows: Section II discusses the related work, Section III describes the equipment used in this study and the experiments conducted, Section IV reports the methods that were used to train the Random Forests model as well as the model assessment procedures, Section V presents the results, while Section VI concludes the paper.

II. Related Work

The human musculoskeletal system is primarily responsible for providing the motions and forces required to perform complex everyday activities. Bioengineers and neurophysiologists have been trying to model the human musculoskeletal system for decades. In 1938, Hill [6] developed a model that simulates the behavior of human muscles, which is known as the Hill-Type muscle model. However, this model is quite complex as it has a lot of internal parameters such as the muscle fibre length and muscle contraction velocity that vary for different muscle types and different subjects. Thus, a complex calibration procedure is required to make the model subject and muscle specific. To overcome these problems, researchers have focused on machine learning based approaches [7], [8], [9].

Regarding EMG based decoding using Machine Learning, the two most common approaches involve either classification or regression methods. Classification methods result to a discrete decision on the user's intention (i.e., identifying the task to be executed), while regression methods result to a continuous estimation of the human motion (i.e., derive specific trajectories). The non-linear relationship between the EMG signals and the human motion is one of the biggest issues researchers face when trying to decode the human motion or intention from EMG activity [10]. Due to this, most studies have avoided the decoding of continuous arm or hand trajectories, focusing on the discrete control of robotic devices, such as the bidirectional control of a robotic wrist [11] or the gestures based control of a robot or prosthetic hand [12], [13]. Several machine learning schemes based on classification methods have been used to identify user intention using the myoelectric activations of her\his muscles and trigger an appropriate control strategy (e.g., the execution of a particular grasp with a prosthetic hand). However, a drawback of this approach is that it uses a fixed, predetermined set of movement strategies that in the case of in-hand manipulation tasks does not offer the versatility in controlling the object motion in a fine and precise manner.

The EMG feature variables can be classified into three different categories, Time Domain (TD) features, Frequency Domain (FD) features or Time-Frequency Domain (TFD) features [14]. TD features contain information that concerns the amplitude of the EMG signals, while FD features contain the information about the Power Spectral Density (PSD) of the EMG signals. TFD features are a combination of amplitudes and the PSD of the signal. Previous studies [15], [16] have compared TD features with FD features and reveal that TD features provide a more consistent performance over time than FD. Moreover, several studies have focused on the TD features because of the lower computational complexity required when deriving these features compared to FD or TFD features.

Regarding the selection of feature variables, in [17], Hudgins et al. employed four TD features, namely, Mean Absolute Value (MAV), Slope Sign Changes (SSC), Zero Crossing (ZC) and Waveform Length (WL) for the EMG based control of a prosthesis. ZC and SSC provide insight on FD aspects that require complex computations. According to [18], ZC is also an important indicator of muscle fatigue. WL is a measure of the complexity of the EMG signal, and is used, along with ZC and SSC, as a quantitative measure for electrode positions selection (higher WL values lead to better electrode positions). MAV represents the area under the rectified EMG signal and quantifies the effort of the examined muscles. Another TD feature that quantifies this effort is the Root Mean Square (RMS) that represents the average power of a signal for a given period of time [19].

In [1], Anam et al. achieved classification of individual finger movements using myoelectric activations of the muscles of the forearm and TD features. Spectral Regression Discriminant Analysis (i.e, a modified version of Linear Discriminant Analysis) was used to reduce the dimensionality of the problem and an Extreme Learning Machine was applied to classify the finger movements quickly and accurately. In [20], Park et al. proposed a methodology for movement intention decoding using myoelectric activations. The methodology is based on a Convolutional Neural Network that performs deep feature learning. The proposed methodology enables them to have robust movement intention decoding even for inter-user variability and achieves classification accuracies that range from 60% to 90%.

In [21], Liarokapis et al. proposed a task-specific framework for the EMG based decoding of human reach to grasp motions and compared the performance of RF with Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), kNN, Artificial Neural Network (ANN) and Support Vector Machine (SVM). To do that, they used the myoelectric activations of 16 human upperarm and forearm muscles and they combined classification and regression techniques in a synergistic manner. They showed that: i) task-specific models outperform general models trained for the entire problem space and ii) RF outperform other learning techniques in terms of classification and motion estimation accuracy.

III. Apparatus and Experiments

The experiments were performed by two healthy subjects who are both male and aged 24. The study has received the approval of the University of Auckland Human Participants Ethics Committee (UAHPEC) with the reference number

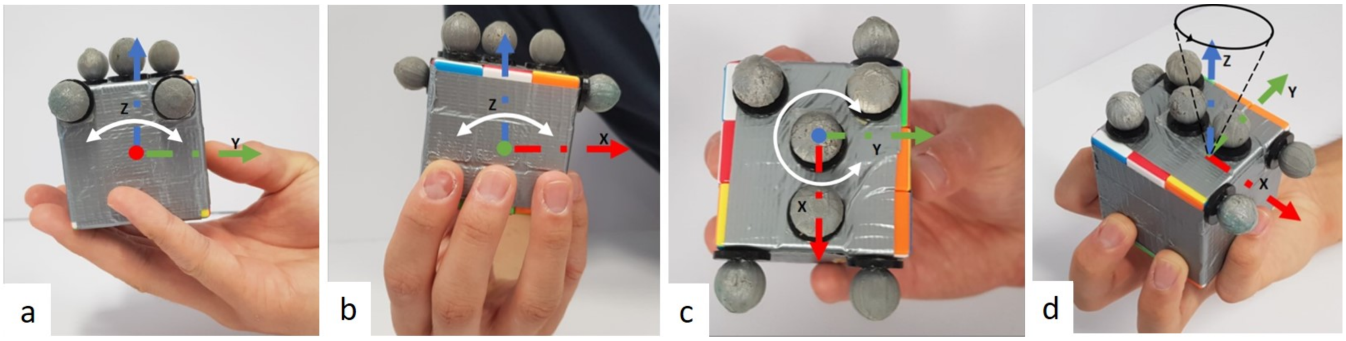

Fig. 2. Manipulation tasks performed. Subfigure a) shows a pitch motion, subfigure b) shows a roll motion, subfigure c) shows a yaw motion and subfigure d) shows a twirl motion. Axes are color coded and the colored dots at the origin indicate that the axis is orthogonal to the page. The white colored arrows in subfigures a), b) and c) show the direction of the movement, while the black arrow in subfigure d) shows the movement of the z-axis that is bounded by the dashed lines.

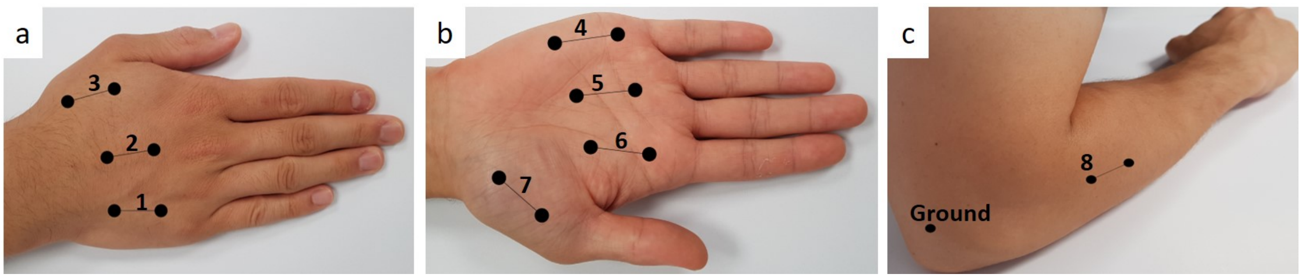

Fig. 3. Electrode placement positions for EMG data collection on the right arm hand system. The double dot with the connected line represents a double-differential EMG electrode. Electrodes 1, 2 and 3 are placed at the back of the palm measuring the interossei muscles myoelectric activations. Electrodes 4, 5, and 6 are placed at the front of the palm measuring the lumbrical muscles myoelectric activations. Electrode 7 is placed at the base of the thumb measuring the flexor pollicis brevis muscle myoelectric activations. Finally, electrode 8 is placed near the elbow measuring the extensor digitorum superficialis muscle myoelectric activations. Ground is represented with a single dot and is placed at the elbow where muscular activity becomes minimal.

#019043. Prior to the study all subjects provided written and informed consent to the experimental procedures. The experiments were performed by each subject with their dominant hand. One subject was left hand dominant while the other was right hand dominant.

A. Experimental Tasks

Each subject was given verbal and visual instructions on how to perform 3-dimensional equilibrium point manipulation tasks using the Rubik's cube of the Yale-CMU-Berkeley grasping object set [22]. For all the manipulation tasks, each subject was to sit upright with their forearm rested on a custom-made stand. Each manipulation task session was executed with a sequence starting with a 5 s rest period (where the hand holds the object in a stationary pose), followed by 10 repetitions of the manipulation motion for each trial. There were 10 of these trials per session. Adequate resting time between every trial (approximately 30 s) was used to reduce muscle fatigue for all subjects. Fig. 2 shows visualizations of each manipulation task. It must be noted that all motions are expressed relatively to the global planes of movement (global reference frame of the Vicon system). The different types of manipulation tasks performed during the experiments, are as follows:

- Pitch: a coordinated movement of the fingers that creates a pitch rotation of the cube
- Roll: a coordinated movement of the fingers that creates a roll rotation of the cube
- Yaw: a coordinated movement of the fingers that creates a yaw rotation of the cube
- Twirl: a coordinated movement of the fingers that creates a spiral motion similar to wine glass twirling

B. Experimental Setup

EMG snap cables attached to stickers were used to record the EMG signals, and these signals that were acquired and preprocessed by a g.Tec g.USBamp bioamplifier. A sampling rate of 1200 Hz was used, along with a Butterworth bandpass filter (5 Hz-500 Hz) and a 50 Hz notch filter (used to reduce the electric noise). To record the motion of the Rubik's cube, a Vicon optical motion capture system that consists of 8 Vicon T-series cameras connected to the Giganet system and appropriate reflective markers were used. The Vicon Tracker software captures the trajectories of the reflective markers and extracts the corresponding transformation matrices. The markers on the cube were placed in a way that they do not affect the natural hand postures during the grasp, as the contact points do not change significantly during EPM. The sampling rate of the Vicon system was 100 Hz. A trigger

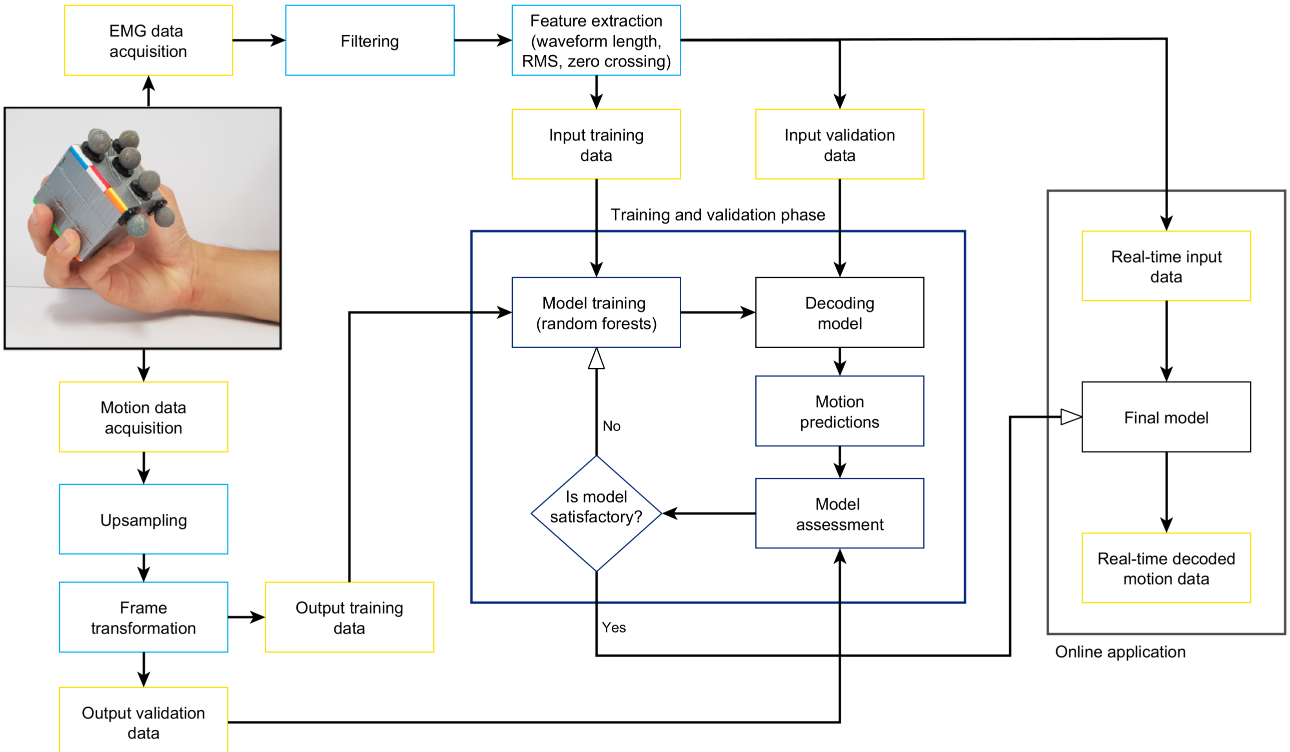

Fig. 4. A block diagram of the proposed EMG-based learning scheme. EMG data containing the measurements of the myoelectric activations of the examined muscles were filtered and time domain features were extracted. These features were then used as input training data and input validation data during the training and validation phase of the decoding model. The object motion data is recorded, upsampled and transformed to the object reference frame. The training and validation phase guarantee that if the predicted object motions closely follow the actual recorded motions of the object, then the model is accepted as the final model that will be used for online EMG-based control. If the model assessment is not satisfactory, the model is retrained with different Random Forests parameters until it can accurately predict the object motion.

cable was used to connect to the g.Tec bioamplifier in order to facilitate data synchronization. Due to the differences in sampling rates, the object motion data was upsampled to match the sampling frequency of the EMG data.

C. *Muscle Selection*

For all experiments, myoelectric activations were measured from seven muscles of the hand and one muscle of the forearm using double-differential EMG electrodes (please see Fig. 3). Three of the hand electrodes were placed at the back of the hand measuring the myoelectric activations of the interossei muscles, while three electrodes were placed on the front of the palm measuring the myoelectric activations of the lumbrical muscles. The last electrode of the hand was placed on the base of the thumb in order to measure the myoelectric activations of the flexor pollicis brevis muscle. The forearm electrode was placed near the elbow to measure the myoelectric activations of the extensor digitorum superficialis muscle. The selection of the electrode positions was inspired by existing literature [23], [24] as well as by the Innerbody website [25]. The Innerbody website provides an accurate 3D muscle anatomy atlas of the human hand and arm, as well as an outline of the contributions of each muscle to the motion of the human joints.

IV. Methods

A. *Feature Extraction*

The EMG signals that were acquired and filtered by the bioamplifier were segmented using a sliding window of 200 ms with an increment of 10 ms for the extraction of the time domain features. The size of the window and the increment value are hyperparameters that were optimized to improve the estimation accuracy. The window length should not be too long, due to real-time constraints, but it should be adequately large to avoid large variances of the features that can degrade the performance of the trained model [14]. The following three TD features were extracted from each EMG channel: Root Mean Square Value (RMS) [19], Waveform Length (WL) and Zero Crossings (ZC) [17], [26].

1) Root Mean Square Value: The RMS value is one of the most commonly used values in the TD. It represents the square root of the average power of the signal for the given time period. The RMS value is defined as:

$$RMS = \sqrt{\frac{1}{N}\left(\sum_{k=1}^{N}(x_k)^2\right)}, \tag{1}$$

where N is the size of the window applied to the data.

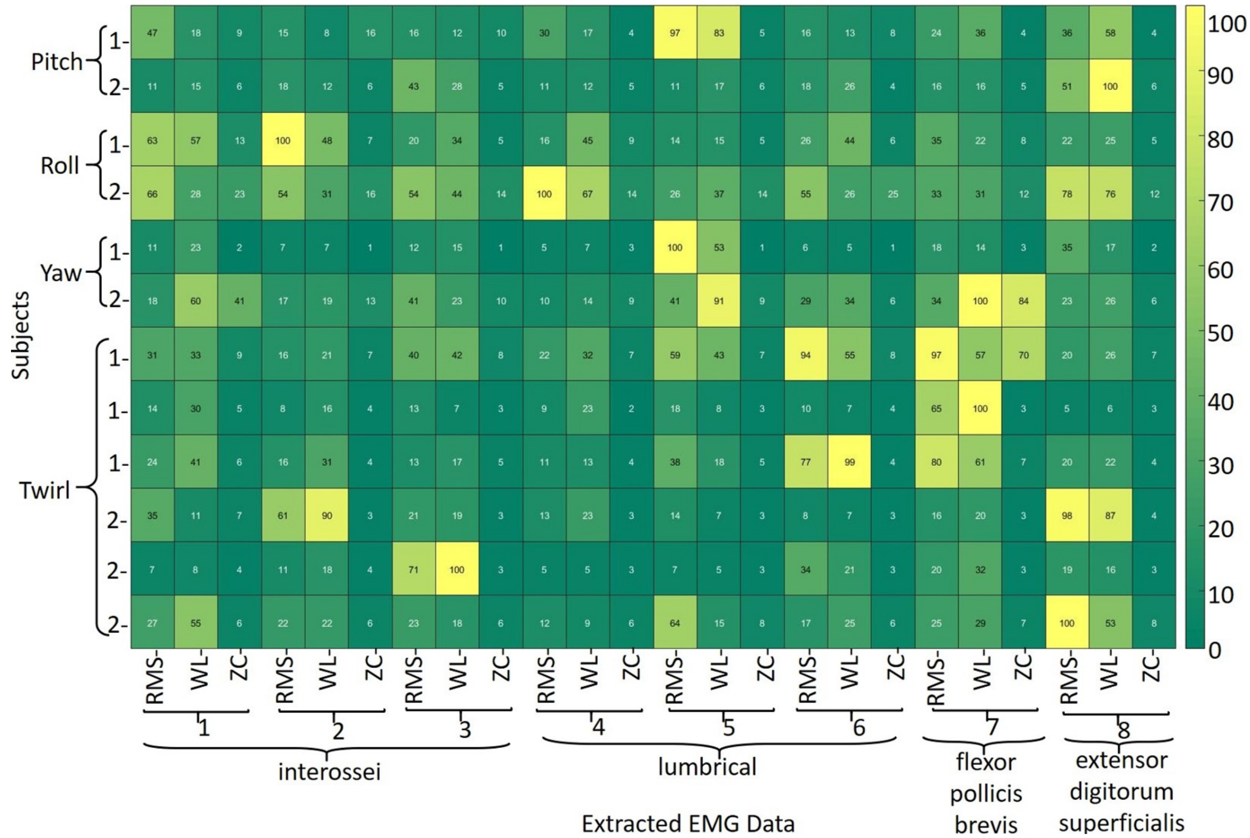

Fig. 5. Comparison of the feature variable importances for each subject. The importance scores have been derived using the inherent RF feature variables importance calculation procedure. The results have been normalized over the 5-fold cross-validation method.

2) Waveform Length: WL is the measure of the complexity of the EMG signal. It represents the measure of the waveform amplitude, frequency, and duration all in a single parameter and is defined as:

$$WL = \sum_{k=1}^{N} |\Delta x_k|, \tag{2}$$

where $\Delta x_k = x_k - x_{k-1}$.

3) Zero Crossings: ZC is the number of times the signal crosses the zero value in a given time period. This feature can be used to get a rough measure of muscle fatigue [18]. The count of ZC is incremented when:

$$\begin{gathered} x_k < 0 \quad \&\& \quad x_{k+1} > 0 \\ |||| \\ x_k > 0 \quad \&\& \quad x_{k+1} < 0 \\ \&\& \\ |x_k - x_{k+1}| > V_t \end{gathered} \tag{3}$$

where V_t is a voltage threshold selected according to the signal noise. This algorithm does not increment the ZC if it falls in the deadzone as it tries to eliminate the effect of noise on the zero crossings.

The input dimension of the data for the learning algorithm is 3 EMG features per channel $*$ 8 channels $=$ 24 input features. The output dimensionality is determined by the rotation of the object along the axes of interest (which are 1 axis for roll, pitch and yaw motions and 3 axes of for the twirl motion).

B. Random Forests Based Object Motion Decoding

For object motion decoding we solve a mapping problem between the EMG space and the object motion, using the Random Forests regression methodology that was originally proposed by Tin Kam Ho of Bell Labs [27] and Leo Breiman [28]. RF is an ensemble learning method that can be used for both classification and regression. RF consists of multiple decision trees and the output of the forest is the most popular class among the decisions of the individual trees for the classification case or the average of the estimations of the individual trees in the regression case. Some of the main advantages of RF are: i) they run efficiently on large databases, ii) are able to handle thousands of input variables without variable deletion, iii) are extremely fast, iv) can handle multi-dimensional spaces and multi-class problems and v) offer excellent predictive performance.

Decision trees are built top-down from a root node, and involve partitioning the data into subsets that contain instances with homogeneous values. In a RF-based learning scheme, N such trees are grown. For each tree the RF uses a different bootstrap sample set from the original data. One-third of the samples are left out of this set (they are called out-of-bag

TABLE I
CORRELATION AND ACCURACY RESULTS FOR EACH SUBJECT

Motion	Pitch		Roll		Yaw		Twirl					
Subjects	1	2	1	2	1	2	1			2		
Correlation (%)	88.2	82.5	80.2	77.3	95.4	92.7	85.6	81.8	87.2	92.0	91.3	79.9
Standard Deviation (%)	4.0	5.1	4.8	1.7	1.3	2.0	3.6	9.8	4.0	2.8	3.1	3.1
Accuracy (%)	74.4	65.6	63.4	55.8	88.1	84.9	69.1	67.1	69.6	84.0	80.9	59.6
Standard Deviation (%)	9.0	9.7	7.1	2.5	3.4	3.4	6.0	15.2	14.3	5.3	7.8	8.3

samples) and are not used in the construction of the N^{th} tree. In the classification case, the number of votes casted are counted for the correct class for every tree in the forest. Then the values of the feature variable 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 RF. In the case of regression, RF work essentially the same way as in the classification case, but instead of counting the number of votes, they compute the average of the individual tree estimations.

In this study, we use the RF regression technique to perform an EMG based estimation of the object motion during the execution of dexterous manipulation tasks. To do that, the TD feature data is divided into two sets, one for training and the other for validation. If the performance of the model during the training and validation phases is unsatisfactory, it is retrained by tuning the RF parameters. More details regarding the proposed EMG based learning scheme can be found in Fig. 4. The results presented in Section V are the average values of the 5-fold cross validation procedure.

V. RESULTS AND DISCUSSION

In this section, we present and discuss the experimental results that validate the efficiency of the proposed methodology. In particular, we focus on the feature variable importances, the correlation between the actual and the predicted object motions and the estimation accuracies.

In Fig. 5, we present the importance plots for each feature variable for both subjects, as derived by the RF inherent feature variables calculation procedure [29]. From this figure, it is evident that for subject 1, the lumbrical muscles are important for the execution of pitch, yaw and twirl motions, the interossei muscles are important for the execution of roll motions, the flexor pollicis brevis muscle is important for the execution of twirl motion and the extensor digitorum superficialis does not contribute significantly in the execution of the examined tasks. For subject 2, the lumbrical muscles are important for the execution of yaw motions, the interossei muscles are important for the execution of twirl motions, the flexor pollicis brevis muscle is important for the execution of yaw motion and the extensor digitorum superficialis is important for the execution of pitch, roll and

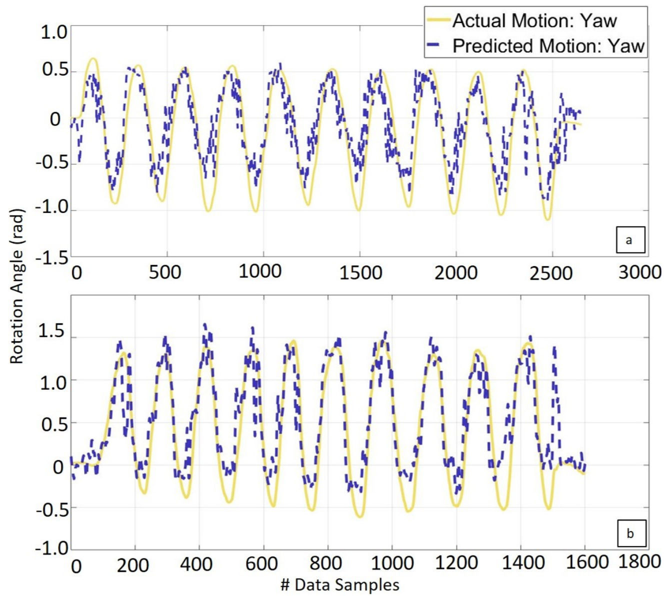

Fig. 6. Plots of actual yaw motion vs estimated yaw motion from the Random Forests regressor model for both subjects. A shows the plots for Subject 1, while B shows the plots for Subject 2.

twirl motions. The above preliminary results indicate that the muscle selection for the EMG based decoding of object motions in dexterous manipulation tasks should be done in a subject-specific manner and that the inter-subject variability of the myoelectric activations is very significant.

Fig. 6 shows the plots of the predicted and actual yaw motion for each subject. For both subjects, it can be seen that the predicted motion data follows the trends of the actual motion data with the direction of movement being synchronized. In this study, we assess the efficiency of the trained models by using the Pearson correlation coefficient and the percentage of the NMSE for accuracy, comparing the predicted and the actual object motion. For the NMSE percentage, 100% means that the two trajectories are identical.

Table I shows the means and the standard deviations of both metrics over the 5-fold cross validation procedure that was used for model assessment. The correlations between the predicted and the actual values is very high and this shows that the model is able to closely predict the trend of the object motion. In terms of accuracies, the predicted values were high and the model is able to track quite efficiently the actual object motion. It must be noted that a perfect EMG based estimation of the object motion (100% accuracy), is not possible due to dynamic phenomena such as uncontrolled slipping and rolling. These phenomena are common during the execution of dexterous, in-hand manipulation tasks.

VI. Conclusions

In this work, we presented an EMG-based methodology for decoding object motion in dexterous, in-hand manipulation tasks. To do that, we used EMG signals derived from specific muscles of the human hand and forearm, and an optical motion capture system that records the object motion. Time-domain features were extracted from the recorded EMG signals. The decoding was formulated as a regression problem using the Random Forests methodology that is based on decision trees. The estimation results are significantly high, proving that EMG-based decoding of object motion is actually feasible.

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