Task Discrimination from Myoelectric Activity: A Learning Scheme for EMG-Based Interfaces.

Minas V. Liarokapis, Panagiotis K. Artemiadis and Kostas J. Kyriakopoulos

Abstract— **A learning scheme based on Random Forests is used to discriminate the task to be executed using only myoelectric activity from the upper limb. Three different task features can be discriminated: subspace to move towards, object to be grasped and task to be executed (with the object). The discrimination between the different reach to grasp movements is accomplished with a random forests classifier, which is able to perform efficient features selection, helping us to reduce the number of EMG channels required for task discrimination. The proposed scheme can take advantage of both a classifier and a regressor that cooperate advantageously to split the task space, providing better estimation accuracy with task-specific EMG-based motion decoding models, as reported in [1] and [2]. The whole learning scheme can be used by a series of EMG-based interfaces, that can be found in rehabilitation cases and neural prostheses.**

Index Terms: ElectroMyoGraphy (EMG), Learning Scheme, Task Specificity, Random Forests.

I. INTRODUCTION

EMG based interfaces have received increased attention during the last years due to their numerous applications, varying from EMG based teleoperation [3], [4] to EMG controlled prostheses [5], and from EMG controlled exoskeletons for rehabilitation [6] to muscle computer interfaces for human computer interaction [7]. Some well known issues of the EMG based interfaces are the high-dimensionality and complexity of human musculo-skeletal system, the non-stationarity of the EMG signals (e.g. fatigue), the noise caused by the electrode positioning, as well as the non-linear relationship between the human myoelectric activity and the human motion.

During the last decades the majority of researchers avoided to decode a continuous representation of human kinematics and chose to focus on the discrete control of robotic devices. Typical examples are the directional control of a robotic wrist [8] and the control of multifingered robotic hands to a series of discrete postures [9], [10] and [11], [12], [13]. Machine learning techniques and more specifically classification methods were used in [9] and [10] to discriminate using human myoelectric activity between independent human hand digit movements and different hand postures. Forearm surface EMG was used in [14] for the control of a hand prosthesis, discriminating three grip types (power grasp, index precision grip and middle-ring-pinky precision grip) in real-time. In [15] authors used the captured myoelectric activity from two adult macaque monkeys, while grasping 12 objects of different shapes, to distinguish between muscular co-activation patterns associated with different grasping postures while in [1] we discriminated using the myoelectric activity of 16 human arm hand muscles, between reach to grasp movements towards different positions and different objects in 3D space. A similar study was recently conducted in [16], where classification techniques were used to discriminate between different reach to grasp movements towards objects with different sizes and weights. It must be noted that in the last two studies the classification accuracy increases constantly as the reach to grasp movement evolves, providing an early decision of the task to be executed.

Regarding the continuous approach, Artemiadis et al. used a state-space model in [17] for the EMG based decoding of human arm kinematics, giving emphasis to the non-stationary characteristics of the EMG signals (i.e. muscle fatigue etc.) while in [3] a state space model was used to map muscular activations to human arm motion, using low dimensional embeddings of the myoelectric activity and the kinematics. Artificial neural networks (ANN) and sEMG have been used in [18] to estimate the continuous motion of the fingers, in [19] to control a one DoF robot arm and in [20] to decode human arm motion. A recent study, presented an interesting methodology to decode from sEMG the human arm hand system kinematics, using support vector machines (SVM) [4]. The position and orientation of the human wrist and the human grasp were decoded. Finally in [21] we used random forest regression to train task-specific models for the EMG-based estimation of the full human arm hand system motion (27 DoFs) for reach to grasp movements towards different positions and different objects.

In this paper we extend the learning scheme that we proposed in [1] and [21] in order to discriminate also the "task to be executed" for different reach to grasp movements, as well as to perform efficient features selection. The final scheme is able to decompose the task, discriminating three different task features: position to move towards, object to be grasped and task to be executed (with the identified object).

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Our scheme consists once again of a classifier combined with a regressor. The classifier uses sEMG to discriminate in the m-dimensional space (where m is the number of EMG channels) between different reach to grasp tasks. The regressor is used to train models for all possible tasks so as for the classification module to be able to trigger the appropriate task-specific EMG-based motion decoding model. The regression problem is formulated using the low-d spaces (extracted using Principal Components Analysis - PCA) of the human myoelectric activations (input) and the human motion (output). The proposed scheme is depicted for the example of EMG-based teleoperation of a robot arm hand system in Fig. 1, but it can also be used by other EMG based interfaces, like muscle computer interfaces, EMG controlled prostheses and rehabilitation devices.

The rest of the paper is organized as follows: Section II analyzes the apparatus and the experiments conducted, Section III focuses on the different methods used to formulate the proposed EMG-based learning scheme, results validating the efficiency of the proposed scheme are presented in Section IV, while Section V concludes the paper.

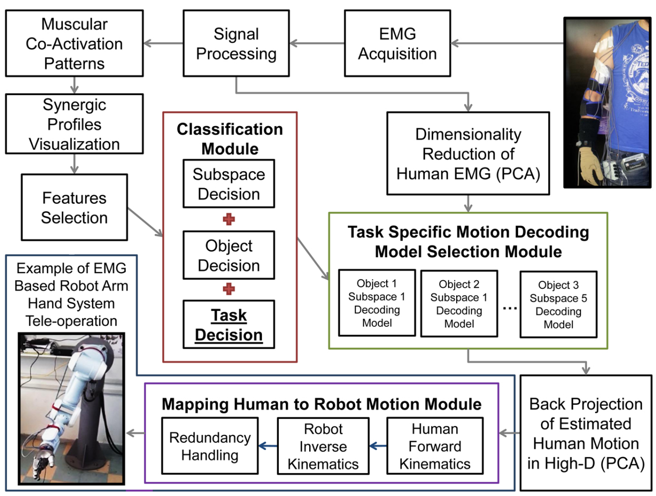

Fig. 1. Block diagram of the proposed learning scheme. Two main modules formulate the learning framework, the classification module and the task specific model selection module. Classification module provides decision for subspace to move towards, object to be grasped and task to be executed. Task specific model selection module examines classification decisions and triggers, subspace, object and task specific motion decoding models. The decoding model can efficiently estimate the human arm hand system motion using the human myoelectric activity. The EMG-based teleoperation of a robot arm hand system is presented as an EMG-based interface example.

II. Apparatus and Experiments

A. Experimental Protocol

Experiments were performed with five (4 male, 1 female) healthy subjects 21, 24, 27, 28 and 40 years old. All subjects gave informed consent for the experimental procedure and the experiments were approved by the Institutional Review Board of the National Technical University of Athens. All subjects performed the experiments with their dominant hand (right hand for all subjects involved).

During the experiments each subject was instructed to perform repeated reach to grasp movements in 3D space, in order to reach and grasp different objects placed at five different positions in 3D space, as depicted in Fig. 2. These experiments were used for the initial formulation of the learning framework proposed in [1] and are once again used in this paper to assess also feature variables importance for different positions and different objects. In order to discriminate between different tasks executed with the same object, new experiments were conducted using the same directions. A mug, a rectangle and a marker were used for the initial experiments, while a tall glass, a wine glass, a mug and a mug plate were used for the "task discrimination" experiments.

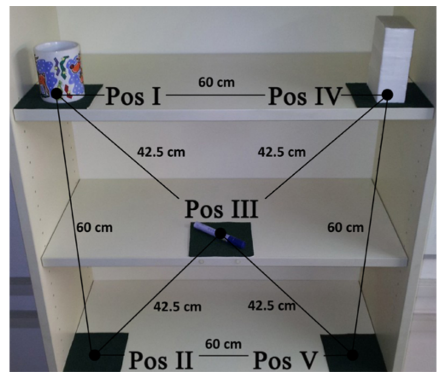

Fig. 2. Picture of the bookcase containing three different objects, a marker, a rectangular-shaped object and a mug, placed in five different positions, in three different shelves. The distances between the object positions are provided in terms of a superimposed diagram. The same positions were used for both types of experiments.

The different tasks that were executed (two tasks per object) for the second set of objects appear in Fig. 3. Adequate resting time (one min) was used between consecutive trials. Each subject conducted several trials, for each position, object and task combination.

Fig. 3. Tasks that were executed for the second set of experiments. The tall glass tasks were: task 1, side grasp (to drink from it) and task 2, front grasp (to transpose it). The wine glass tasks were: task 1, side grasp (to drink from it) and task 2, stem grasp (to drink from it). The mug tasks were: task 1, handle grasp (to drink from it) and task 2, top grasp (to transpose it). Finally the mug plate tasks were: task 1, side grasp (to lift and hold it) and task 2, top grasp (to transpose it).

B. Electrode Positioning, Data Acquisition and Processing

For the first set of objects we recorded the myoelectric activity of sixteen muscles, of the upper arm (eight muscles) and the forearm (eight flexor and extensor muscles). More specifically the selected muscles appear in this paper in the following order: deltoid anterior, deltoid middle, deltoid posterior, teres major, trapezius, biceps brachi, brachioradialis, triceps brachii, flexor pollicis longus, flexor digitorum superficialis, flexor carpi ulnaris, flexor carpi radialis, extensor pollicis longus, extensor indicis, extensor carpi ulnaris and extensor carpi radialis. The selection of the muscles, as well as the placement of the electrodes, was based on the related literature [9], [22]. For the second set of objects we had available only fifteen EMG channels so the same set of muscles was used and the order remained the same with the exception of triceps brachii (was the less significant, according to our previous studies).

EMG signals were recorded using single differential surface EMG electrodes and were acquired and conditioned using an EMG system (Bagnoli-16, Delsys Inc.). The digitization and acquisition was done using a signal acquisition board (NI-DAQ 6036E, National Instruments). EMG signals were band-pass filtered (20-450 Hz), sampled at 1 kHz, full-wave rectified and low-pass filtered (Butterworth, fourth order, 8 Hz).

III. Methods

A. Using a Random Forest Classifier to Discriminate the Task to be Executed

Random forests classifier is an ensemble classifier that consists of many decision trees and outputs the class that is the mode of the class's output by the individual trees [23], [24]. More specifically, a random forest is a classifier consisting of a collection of tree structured classifiers $\{h(\mathbf{x},\Theta_N), N=1,\ldots\}$ where $\{\Theta_N\}$ are independent identically distributed random vectors and each tree casts a vote for the most popular class at input $\mathbf{x}$. The classification procedure for a Random Forests classifier with N trees grown is presented in Fig. 4. In this paper we used a Random Forests classifier to discriminate between different reach to grasp movements towards a specific position and object combination but to execute two different tasks with the same object. The discrimination must be done in the m-dimensional space where $m = 15$ is the number of the EMG channels containing the myoelectric activations of the selected aforementioned muscles. More details regarding the Random Forests advantages can be found in [2].

In Fig. 5 we present a typical classification problem of discriminating two different tasks. In the top plot we can see how the distance between the two classes in the 15-dimensional space is evolved as well as the reaching, grasping and return phases. The distance between the two classes give us a measure of their separability (i.e. how easily the classes can be discriminated). In the bottom plot, we can notice an accumulation of misclassified samples for the time periods that the distance between the two tasks is not significant (i.e. begin and end of the experiment).

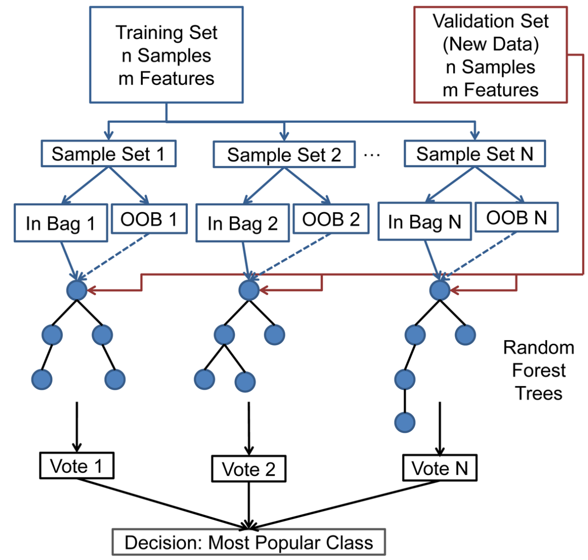

Fig. 4. Random Forests based classification procedure for N trees grown. OOB stands for out-of-bag samples.

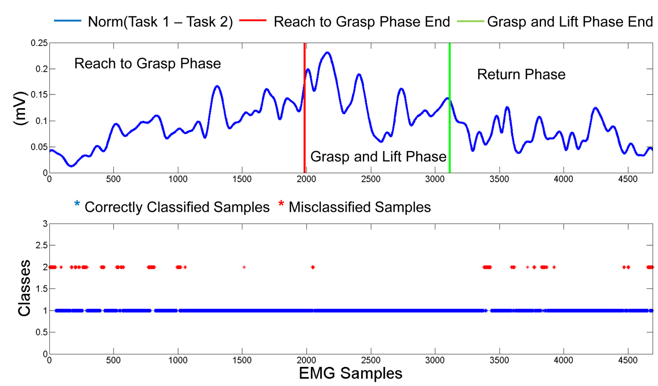

Fig. 5. Comparison of two reach to grasp movements towards Position I to grasp a Tall Glass with two different tasks (side grasp and front grasp). First subplot presents the distance of the two tasks in the m-dimensional space where $m = 15$ the number of the EMG channels. The second subplot focuses on the evolution of classification decision per sample over time.

B. Features Selection with Random Forests

In order to perform efficient features selection with Random Forests, we can use their ability to compute the importance score of each feature variable and consequently assess the relative importance for all variables. Random forests use for the construction of each tree, a different bootstrap sample set from the original data. One-third of the samples are left out of the bootstrap sample set and are not used in the construction of the Nth tree. These samples are called out-of-bag samples. In order to compute features importance, the random forests can be used as follows; in every grown tree in the forest, we put down the out-of-bag samples and count the number of votes cast for the correct class. Then the values of a variable m are randomly permuted in the out-of-bag samples and these samples are put down the tree. Subtracting the number of votes casted for the correct class in the m-variable permuted out-of-bag data from the previously computed number of votes for the correct class in the untouched out-of-bag data, we get the importance score of each tree. The average importance score for all trees in the forest is the raw importance score for the variable m. Thus, the importance for feature variable m can be computed subtracting the error rate for the original data from the error rate when the variable m is permuted. The random forests feature variable importance calculation procedure, is presented in terms of a diagram in Fig. 6.

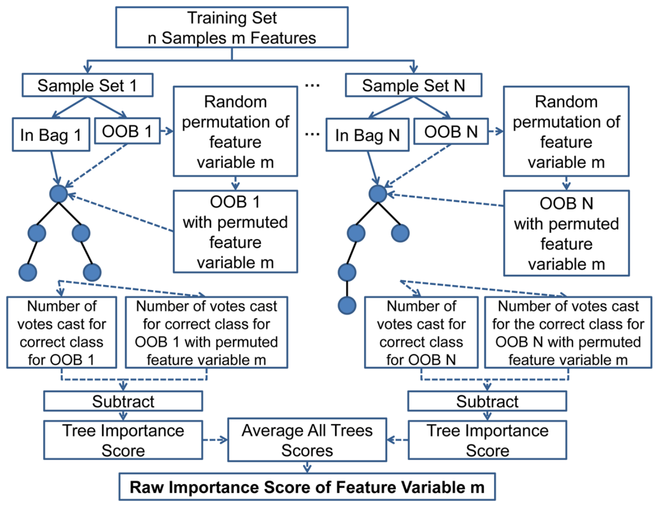

Fig. 6. Diagram of the Random Forests feature variable importance calculation procedure. OOB stands for out-of-bag samples.

If the number of variables is very large (in this paper we have a problem formulated in 15th dimensional space), Random Forests can be initially run with all the variables and then run once again using the most important variables selected from the first run. For example in our case we can run the random forests classifier with all 15 EMG channels, compute the feature variables importance, assess the relative importance of all variables and then re-run the random forests classifier using the most "important" EMG channels. Before doing so, we proceed with the computation of feature variables importance for different subspaces, different objects and different tasks, as follows.

In Fig. 7 the importance plots of different feature variables (EMG channels) are presented, for two different cases, subspace discrimination and object discrimination. For the case of subspace discrimination the feature variables corresponding to upper-arm muscles (first 8 EMG channels) accumulate most of the importance, while for the case of object discrimination the feature variables corresponding to the forearm muscles (last 8 EMG channels) appear to have increased importance. The latter evidence is also verified by the fact that for reach to grasp movements towards different subspaces, the muscular co-activation patterns of the upper-arm muscles accumulate most of the differentiation, while for the case of reach to grasp movements towards different objects the muscular co-activation patterns of the forearm muscles (which are responsible for grasping), accumulate most of the differentiation [1].

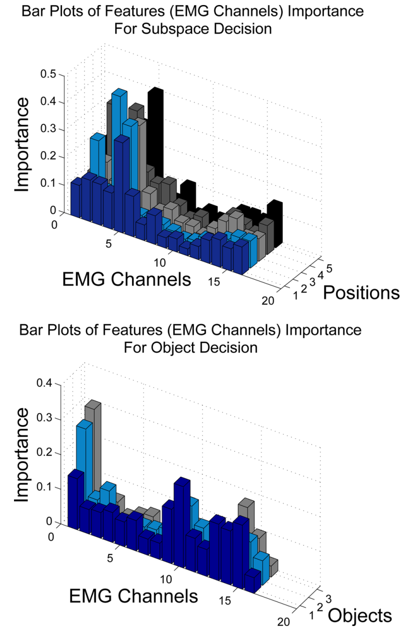

Fig. 7. Importance plots for feature variables (EMG Channels) importance - expressed as mean decrease in accuracy - for Subject I, for the cases of subspace discrimination and object discrimination subsequently. For the case of subspace discrimination data involving all objects are used, while for object discrimination, feature importance is examined for a specific position. Objects 1, 2 and 3 correspond to mug, marker and rectangle respectively. EMG channels follow the muscles order described in Section II - B.

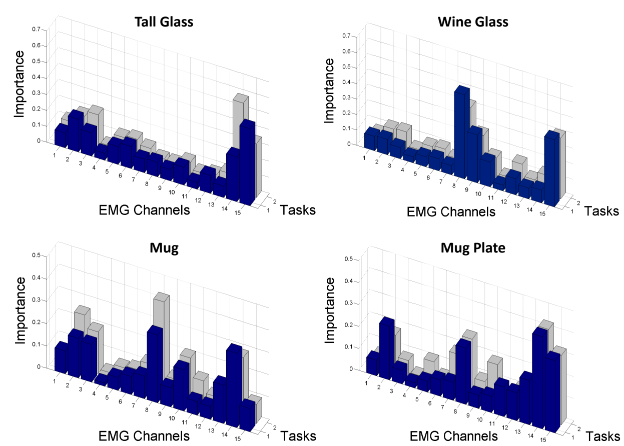

Fig. 8. Importance plots of feature variables for task discrimination. Reach to grasp movements towards all objects placed in Position I and two different tasks, were executed per object. The tasks executed are those appeared in Fig. 3. EMG channels follow the muscles order described in Section II - B.

In Fig. 8 the importance plots of different feature variables (EMG channels) are presented, for the case of task discrimination. Four different barplots are depicted, containing the importance scores per variable for all objects placed in position I. For task discrimination the feature variables corresponding to the forearm muscles (last 8 EMG channels) appear to have once again increased importance (as in the case of object discrimination), evidence that seems to be quite reasonable as the forearm muscles are responsible to preshape the hand in order to grasp and manipulate objects.

IV. RESULTS

A. Classification Results

In order to assess the accuracy of the proposed methods, we define the classification success rate as the percentage of EMG data points classified to the correct task. It must be noted that classification is done for each EMG data point, allowing our system to be able to decide in real-time the task to be executed or even switch between different tasks online. The classification results presented in the following tables are the average values over the five rounds of the cross-validation method applied. According to [1], the Random Forests classifier outperformed other well-known classifiers (e.g. kNN, ANN, SVM etc.), so we chose to use it in this paper without further comparisons. First, we present the classification results achieved, using all 15 EMG channels to discriminate between reach to grasp movements towards specific position and object combinations (for all objects and positions), to execute two different tasks per object (two classes). Results are reported in Table I.

TABLE I

CLASSIFICATION ACCURACY ACROSS DIFFERENT REACH TO GRASP MOVEMENTS TOWARDS DIFFERENT POSITIONS AND OBJECTS TO EXECUTE TWO DIFFERENT TASKS (TWO CLASSES). RANDOM FORESTS CLASSIFIER WAS USED FOR ALL 15 EMG CHANNELS, OF SUBJECT 1.

Tall Glass

Tasks	Side Grasp	Front Grasp
Pos I	76.31% (±7.41%)	78.87% (±4.72%)
Pos II	89.77% (±5.43%)	87.88% (±9.42%)
Pos III	84.86% (±8.27%)	85.75% (±2.38%)
Pos IV	89.69% (±5.61%)	86.82% (±8.06%)
Pos V	87.56% (±8.20%)	90.36% (±4.77%)

Wine Glass

Tasks	Side Grasp	Stem Grasp
Pos I	84.14% (±4.15%)	85.20% (±4.59%)
Pos II	71.23% (±5.19%)	79.72% (±9.31%)
Pos III	66.64% (±8.15%)	77.71% (±11.47%)
Pos IV	87.98% (±5.21%)	89.02% (±5.81%)
Pos V	66.44% (±8.66%)	64.28% (±7.62%)

Mug

Tasks	Handle Grasp	Top Grasp
Pos I	89.33% (±6.66%)	90.74% (±6.78%)
Pos II	79.77% (±6.74%)	82.31% (±7.02%)
Pos III	75.98% (±9.63%)	83.52% (±7.03%)
Pos IV	84.91% (±3.83%)	86.99% (±5.20%)
Pos V	77.83% (±5.79%)	77.36% (±3.95%)

Mug Plate

Tasks	Side-Pinch Grasp	Top Grasp
Pos I	84.98% (±2.52%)	81.76% (±4.99%)
Pos II	89.58% (±6.11%)	92.76% (±4.27%)
Pos III	86.73% (±7.57%)	95.58% (±1.92%)
Pos IV	87.16% (±6.59%)	85.64% (±9.86%)
Pos V	91.62% (±3.08%)	90.78% (±2.98%)

Classification accuracy is consistently high across different positions, different objects and different tasks, proving the efficiency of the proposed methods. It is also evident in the results, that classification accuracy and the overall ability of our scheme to discriminate different tasks (executed with the same object), depends on the distance (configuration space) between the final postures of the full human arm hand system, as well as on the position of the object to be grasped.

The two tasks of the tall glass, mug and mug plate result to completely different human wrist angles (the motion of which affects most of the forearm muscles). Thus those tasks can be more easily discriminated and better classification results can be achieved, in contrast to the wine glass tasks that involve mainly finger motions and variations of the aperture. Different positions result to different classification accuracies for the same object and tasks. For example positions I,IV give better results for wine glass and mug while positions II, V give better results for tall glass and mug plate.

Despite the fact that we achieve high classification accuracy, we use a lot of EMG channels which are typically not available, due to hardware or cost limitations. Moreover, a large number of EMG channels, requires careful electrode positioning, is time consuming and may increase user's discomfort. Thus in this paper we use the Random Forests to first compute the feature variables importance for each position and object combination and we then resolve the classification problems using the six most important EMG channels acquired from the feature selection procedure. Results are reported in Table II and we can notice that for the reduced number of electrodes, classification accuracy remains high and the results appear to be almost equal or even better, comparing them with the initial results (of the 15 EMG channels case).

TABLE II

CLASSIFICATION ACCURACY ACROSS DIFFERENT REACH TO GRASP MOVEMENTS TOWARDS DIFFERENT POSITIONS AND OBJECTS TO EXECUTE TWO DIFFERENT TASKS (TWO CLASSES). RANDOM FORESTS WERE USED FOR ONLY 6 EMG CHANNELS SELECTED USING THE FEATURES SELECTION METHOD PRESENTED, OF SUBJECT 1 DATA.

Tall Glass

Tasks	Side Grasp	Front Grasp
Pos I	81.43% (±2.64%)	79.91% (±7.69%)
Pos II	89.79% (±7.35%)	90.79% (±7.97%)
Pos III	82.84% (±9.12%)	88.76% (±3.34%)
Pos IV	89.82% (±5.89%)	87.71% (±7.97%)
Pos V	84.66% (±9.98%)	92.85% (±4.14%)

Wine Glass

Tasks	Side Grasp	Stem Grasp
Pos I	86.77% (±3.72%)	84.30% (±3.77%)
Pos II	74.50% (±9.81%)	81.20% (±9.64%)
Pos III	72.62% (±8.66%)	79.39% (±13.56%)
Pos IV	86.90% (±8.40%)	87.61% (±5.95%)
Pos V	63.41% (±6.88%)	64.24% (±9.72%)

Mug

Tasks	Handle Grasp	Top Grasp
Pos I	87.17% (±4.67%)	87.85% (±4.59%)
Pos II	80.10% (±7.36%)	83.72% (±5.87%)
Pos III	77.90% (±5.40%)	81.43% (±6.98%)
Pos IV	85.35% (±4.14%)	84.98% (±6.07%)
Pos V	81.06% (±8.29%)	78.95% (±9.57%)

Mug Plate

Tasks	Side-Pinch Grasp	Top Grasp
Pos I	84.34% (±5.57%)	83.60% (±3.44%)
Pos II	90.74% (±4.59%)	94.01% (±3.49%)
Pos III	85.55% (±12.07%)	95.61% (±2.89%)
Pos IV	86.74% (±10.18%)	83.79% (±7.27%)
Pos V	91.00% (±2.23%)	92.28% (±3.03%)

We have already noted that typically the classification decision is taken at a frequency of 1 kHz. However, in order to further improve the classification results we can also use a sliding window of width N, so as for all N samples to be used for the classification decision. The use of majority vote criterion (MVC), can classify all the samples, of a set of N samples, in the class that was the most common between them (i.e. that gathers the most votes). More details regarding the sliding window and the MVC can be found in [1].

V. Conclusions and Discussion

In this paper we extended the learning scheme presented in [1] in order to be able to discriminate also the task to be executed (with the object) for different reach to grasp movements. Classification results are once more highly accurate proving the efficiency of the proposed methods. Moreover we presented a features selection method based on Random Forests that help us reduce the number of electrodes required by our scheme, selecting the most "important" muscles. The hereby presented learning scheme can be used at a variety of EMG-based interfaces, from rehabilitation devices, to human computer interaction applications and EMG controlled prosthetic hands.

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