A Learning Scheme for Reach to Grasp Movements: On EMG-Based Interfaces Using Task Specific Motion Decoding Models

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

***Abstract*—A learning scheme based on Random Forests is used to discriminate between different reach to grasp movements in 3D space based on the myoelectric activity of human muscles of the upper arm and the forearm. Task specificity for motion decoding is introduced in two different levels: subspace to move towards and object to be grasped. The discrimination between the different reach to grasp strategies is accomplished with machine learning techniques for classification. The classification decision is then used in order to trigger an EMG-based task-specific motion decoding model. Task specific models manage to outperform "general" models providing better estimation accuracy. Thus the proposed scheme takes advantage of a framework incorporating both a classifier and a regressor that cooperate advantageously in order to split the task space. The proposed learning scheme can be easily used to a series of EMG-based interfaces that must operate in real time, providing data driven capabilities for multi-class problems, that occur in everyday life complex environments.**

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

I. INTRODUCTION

OVER the last decades, the cross-disciplinary field of electromyography (EMG) based interfaces has received increased attention due to its numerous applications. Some of them include EMG based teleoperation of robots [1], [2] in remote or dangerous environments, EMG controlled prosthetic limbs for amputees [3], EMG enabled exoskeletons for rehabilitation [4] and muscle computer interfaces for human computer interaction [5].

Some early identified difficulties of EMG interfaces were the high-dimensionality and the complexity of the human musculo-skeletal system. A couple of years ago, we introduced muscle and motor synergies in the field of EMG-based interfaces for the case of the upper limb [1], however the synergistic EMG-based control of the hand or the whole arm-hand system have not yet been addressed.

Minas V. Liarokapis and Kostas J. Kyriakopoulos are with the Control Systems Lab, School of Mechanical Engineering, National Technical University of Athens, Greece. Email: `mliaro | kkyria @mail.ntua.gr`

Panagiotis K. Artemiadis is with the ASU Human Oriented Robotics and Control (HORC) Lab, School for Engineering of Matter, Transport and Energy, Arizona State University, USA. Email: `panagiotis.artemiadis@asu.edu`

Elias S. Manolakos is with the Dept. of Informatics & Telecommunications, University of Athens (UOA), Greece. Email: `eliasm@di.uoa.gr`

This work has been partially supported by the European Commission with the Integrated Project no. 248587, THE Hand Embodied, within the FP7-ICT-2009-4-2-1 program Cognitive Systems and Robotics.

Manuscript received, 2012; revised, 2013.

Machine learning techniques and more specifically classification methods were used in [6] and [7] to discriminate between independent human hand's digit movements or different hand postures, based on the myoelectric activity. Forearm surface EMGs were used in [8] for the feed-forward control of a hand prosthesis, discriminating grip postures in real-time. The latter study employs only three different grip types (power grasp, index precision grip and middle-ring-pinky precision grip), thus the methodology presented can not be applied in everyday life scenarios where human fingers may be employed for various tasks. Finally, authors in [9] 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.

The main difficulty that researchers face in EMG based control of robotic devices, is the highly nonlinear relationship between the EMG signals and human kinematics, as described in [10]. Thus the majority of researchers avoid to decode a continuous representation of human kinematics and choose to focus on the binary control of robotic devices, such as the directional control of a robotic wrist [11] and the control of multifingered robotic hands to a series of discrete postures [6], and [7, 12, 13]. A major drawback of the discrete EMG based control approach is the fact that the use of finite postures may cause problems such as the lack of motion smoothness.

A well known model used to provide continuous EMG based control of robotic devices and decode human motion from EMG signals is the Hill-based musculoskeletal model [14]. The Hill model is one of the most frequently used methods in the related literature [10] and [15]. However all these studies focus only on a few degrees of freedom (DoFs) due to the nonlinearity of the Hill model equations and the large number of unknown parameters per muscle.

Artificial neural networks (ANN) have been used in [16] to estimate the continuous motion of the fingers, using the myoelectric activity from muscles of the forearm (only one degree of freedom (DoF) per finger was decoded) and in [17] to decode from EMGs the arm motion, restricting the analyzed movements to single-joints isometric motions. A state-space model was used by Artemiadis et al. in [18] to estimate human arm kinematics from the myoelectric activity produced from certain muscle groups of the upper-arm and the forearm. In this latter study, emphasis was given to the non-stationary characteristics of the EMG signals and the evolution of signal quality over time (i.e. due to muscle fatigue etc.). Authors in

[1] proposed a metholodology for mapping muscles activations to human arm motion using low dimensional embeddings of myoelectric activity and kinematics and a state space model for decoding. A recent study, presents a methodology for decoding the human arm hand system motion from EMG signals, using support vector machines (SVM) [2] (the position and orientation of the human wrist as well as the human grasp (1 DoF) are decoded). This latter study focused on the EMG based teleoperation of a robot arm hand system and requires smooth and slow movements from the user.

In this paper we propose a novel learning scheme for reach to grasp movements based on random forests. The scheme consists of a classifier combined with a regressor. EMG signals are used in order to discriminate different reach to grasp strategies executed to perform different tasks in 3D space. We introduce task specificity in two different levels, suggesting that the myoelectric activity differentiates for reach to grasp movements towards different subspaces and different objects. The classifier is able to discriminate between those different reach to grasp strategies, from myoelectric activity. The regressor is used to train task-specific models for all possible strategies (i.e. different tasks). The classification decision is taken at a frequency of 1kHz therefore our scheme is able to identify the task in real time. Classification decision in finally used to trigger a task-specific EMG-based motion decoding model. The proposed scheme provides continuous estimates of the full human arm hand system motion (27 DoFs modelled).

The rest of the paper is organized as follows: Section II analyzes the apparatus and the experimental procedure, Section III focuses on the methods used to formulate the proposed EMG-based learning scheme, results for classification and task specific EMG based motion estimation are presented in Section IV, while Section V concludes the paper.

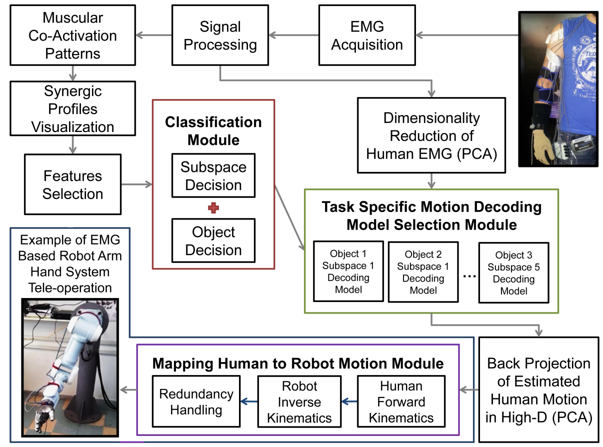

Fig. 1. Block diagram of the proposed learning scheme. Two main modules formulate the learning scheme, the classification module and the task specific model selection module. Classification module provides decision for subspace to move towards and object to be grasped. Task specific model selection module examines classication decisions and triggers a subspace and object specific motion decoding model. The decoding model estimates the human arm hand system motion (27 joint values) based on the human myoelectric activity. Finally an EMG-based interface can take advantage of the proposed scheme and the estimated human motion. For example a human to robot motion mapping procedure [19], may take as input the estimated human arm hand system motion to generate equivalent robot motion, for EMG-based teleoperation of a robot arm hand system. EMG-based teleoperation of a robot arm hand system is presented as a possible application of the scheme.

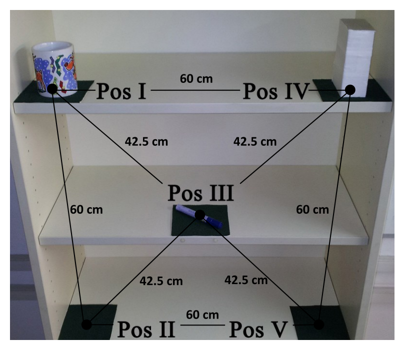

Fig. 2. Picture of the bookcase containing three different objects, a marker, a rectangular-shaped object and a mug, placed in five different positions, in three different shelves. The distances between the object positions are also provided in terms of a superimposed diagram.

II. Apparatus and Experiments

A. Experimental Protocol

Experiments were performed by five (4 male, 1 female) healthy subjects 21, 24, 27, 28 and 40 years old. All subjects gave informed consent. The Institutional Review Board of the National Technical University of Athens approved the hereby presented procedures. Subjects performed the experiments with their dominant arm (right arm 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 three different objects: a rectangular-shaped object, a marker and a mug. The three objects were placed at five different positions in 3D space. A picture of the bookcase and the object positions is shown in Fig. 2. Adequate resting time (one min) was used between concecutive trials. Each subject conducted several trials, for each object and object position combination.

B. Data Acquisition and Processing

In order to describe the motion of the human upper limb in 3-D space we used three rotational DoFs to model the shoulder joint, one rotational DoF for the elbow joint, one rotational DoF for pronation-supination, two rotational DoFs for the wrist and twenty rotational DoFs for the fingers. Regarding the fingers we used for each of the four kinematically identical fingers (index, middle, ring and pinky) three rotational DoFs for flexion-extension and one rotational DoF for abduction-adduction, while for the thumb we used two rotational DoFs for flexion-extension, one rotational DoF for abduction-adduction and one rotational DoF to model the palm mobility that allows thumb to oppose to other fingers.

In order to record the motion of the human arm hand system and to extract the corresponding joint angles (27 modeled DoFs), we used a magnetic position tracking system and a dataglove. The magnetic position tracking system Isotrak II® (Polhemus Inc.) was equipped with two position tracking sensors and a reference system. Two sensors were placed on the elbow and wrist respectively, while the reference system was placed on the shoulder. In order to measure the rest 22

DoFs of the wrist (flexion-extension and abduction-adduction) and the human hand (joints of the fingers) the Cyberglove II® (Cyberglove Systems) was used.

Regarding EMG signals, we recorded the myoelectric activity of sixteen muscles, of the upper arm (eight muscles) and the forearm (eight flexor and extensor muscles) as depicted in Fig. 3. The selection of the muscles, as well as the placement of the electrodes, was based on the related literature [6, 20]. EMG signals were acquired using single differential surface EMG electrodes (DE-2.1®, Delsys Inc.) and conditioned using an EMG system (Bagnoli-16®, Delsys Inc.).

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). The position measurements were provided by the position tracking system at the frequency of 30 Hz. An antialiasing finite-impulse-response filter (low pass, order: 24, cutoff frequency: 100 Hz), was used to resample the measurements at a frequency of 1 kHz, in order to be consistent with the sampling frequency of the EMG signals.

C. Muscular Co-Activation Patterns Visualization

In order to visualize muscular co-activation patterns we used a novel statistical representation technique that we call "Boxplot Zones" [21]. The statistical significance of muscular co-activation patterns differentiation for different subjects and for different reach to grasp movements towards different positions or different objects placed in the same position, was assessed using the Kruskal-Wallis and the Wilcoxon rank sum statistical tests. Those tests proved that muscular co-activations vary significantly not only between different subjects but also between different reach to grasp strategies, and therefore should be considered and analyzed as subject-specific and task-specific characteristics. More information can also be found in [21]. Fig. 3 shows boxplot zones visualization of muscular co-activation patterns across sixteen muscles of the upper arm and the forearm, for one subject (Subject 1) performing reach to grasp movements towards five different positions, in order to grasp three different objects, a marker, a rectangle and a mug. In Fig. 3, its also evident that the co-activation patterns of the human arm and hand muscles differ significantly for reach to grasp movements towards different subspaces or different objects, although the same fingers and upper-arm joints are involved. More precisely, if we examine the muscular co-activation patterns across different subspaces, we notice that the activity of the muscles of the upper-arm (EMG channels 1-8) reflects most of the differentiation, while across different objects, placed in the same subspace (specific position), the activity of the forearm muscles (EMG channels 9-16) reflects most of the differentiation.

III. Methods

A. Multiclass Classification of Reach to Grasp Movements

Synergistic profiles depicted in the form of "boxplot zones" in Fig. 3 denote that there exists a significant differentiation of muscular co-activation patterns between the different reach to grasp movements. In order to be able to take advantage of this differentiation, we choose to discriminate the different reach to grasp strategies in the 16-dimensional space of the myoelectric activations, concluding from EMG to the task to be performed. In Fig. 4 we present a typical classification problem of discriminating (from the myoelectric activity of 16 muscles) two different strategies for reaching a specific object placed in two different positions. Reaching, grasping and return phases are shown. More specifically in the top plot we can see how the distance between the two classes in the 16-dimensional space is evolved. Distance between two classes give us a measure of classes separability, i.e. how easily the classes can be discriminated. In the bottom plot, we see that the accumulation of misclassified samples is reasonable for the time periods that the distance between the two strategies is not significant (i.e. beginning and end of the experiment, when the human arm hand system is close to starting position).

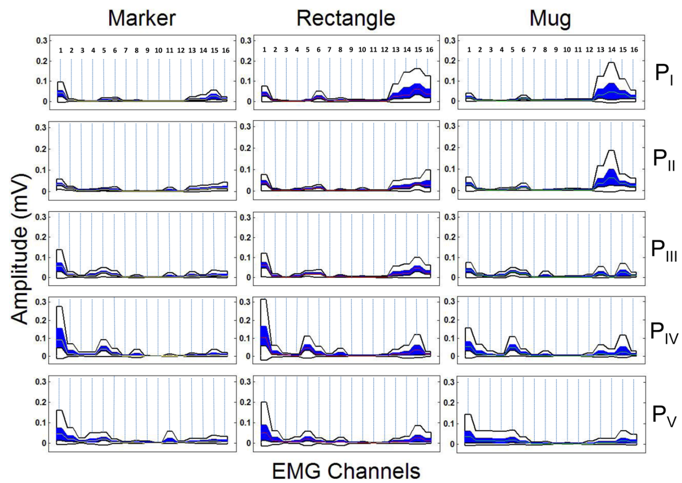

Fig. 3. Boxplot Zones visualization of different muscular co-activation patterns across sixteen muscles of the upper arm and the forearm for one subject (Subject 1) performing reach to grasp movements towards five different positions P_{I}, P_{II}, P_{III}, P_{IV} and P_{V}, to grasp three different objects, a marker, a rectangle and a mug. The 16 muscles appear in this paper in the following order (1 to 16): 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.

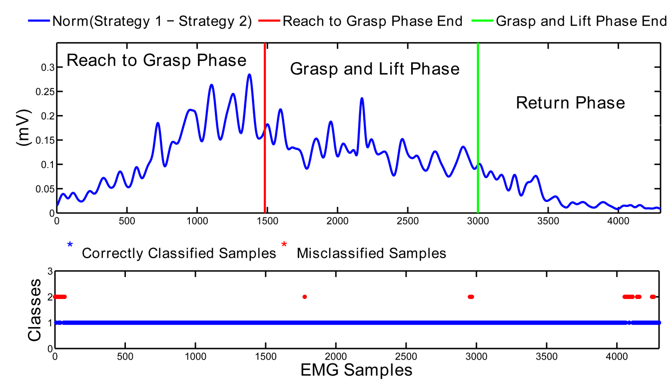

Fig. 4. Comparison of two reach to grasp strategies. First subplot presents the distance of the two strategies in the m-dimensional space where m=16 the number of the EMG channels. The second subplot focuses on the evolution of classification decision per sample over time. The two different strategies are: reach to grasp movements towards a marker in position I (Strategy I) and reach to grasp movements towards a marker in position II (Strategy II).

1) Random Forests Classifier: 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 [22, 23]. 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 $\mathbf{x}$.

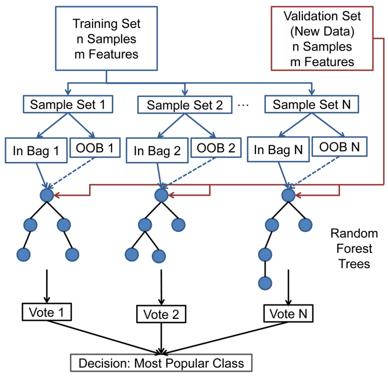

Fig. 5. Random Forests based classification procedure for N trees grown. OOB stands for out-of-bag samples.

The classification procedure for N trees grown is presented in Fig. 5. Some advantages of the random forests technique is the fact that runs efficiently and fast on large databases, provides high accuracy, does not overfit, provides consistent interpretability, provides variable importance, and is able to handle thousands of input variables without variable deletion.

2) Features Selection with Random Forests: In random forests, each tree is constructed using a different bootstrap sample set from the original data. About 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. A diagram presenting the random forests feature variable importance calculation procedure, is presented in Fig. 6.

In cases where the number of variables is very large, Random Forests can be initially run with all the variables and then run again using only the most important variables selected from the first run. In Fig. 7 the importance plots for 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. This latter evidence can also be verified by the fact that for different reach to grasp movements towards different subspaces the muscular co-activation patterns of the upper-arm muscles appear to be significantly different in Fig. 3, while for the case of reach to grasp movements towards different objects, there is still some significant differentiation in upper-arm muscles but the muscular co-activation patterns of the forearm muscles (responsible for grasping), reflect most of the differentiation. More derails for features selection can be found in [24].

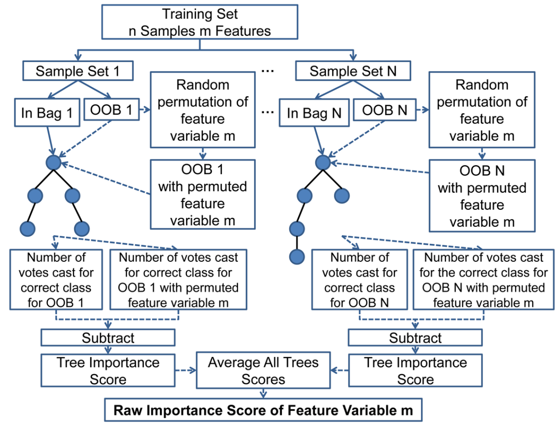

Fig. 6. Diagram of the Random Forests feature variable importance calculation procedure. OOB stands for out-of-bag samples.

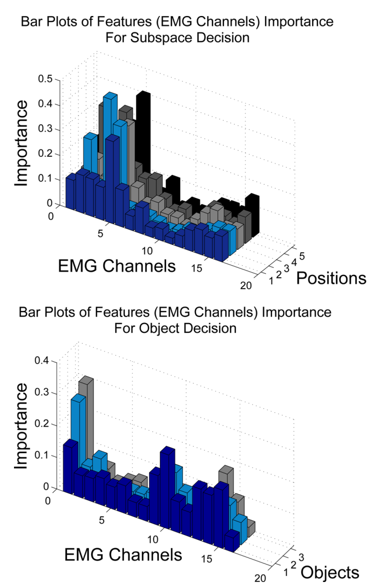

Fig. 7. Importance plots for feature variables (EMG Channels) importance - expressed as mean decrease in accuracy - for Subject I, for the cases of subspace discrimination and object discrimination subsequently. For the case of subspace discrimination data involving all objects are used, while for object discrimination, feature importance is examined for a specific position (P_I) and different objects. Positions 1 to 5 correspond to positions P_I to P_V, while objects 1, 2 and 3 correspond to mug, marker and rectangle respectively.

B. Task Specific Motion Decoding Models

1) Dimensionality Reduction: In order to represent our signals in a low-dimensional space, the Principal Components Analysis (PCA) method was used. For the EMG signals recorded, a 4-D space could represent most of the original high-dimensional data variance (more than 92%). Regarding the human arm hand system kinematics, the 27-DoF motion could also be described adequately by a 4-D space that represents most (94%) of the original data variance. We used the PCA as a dimensionality reduction technique in order to take advantage of the underlying covariance of our data representing the same variability in a lower dimensional space without losing any dimension of the original data. More information regarding PCA can be found in [1].

2) Task Specific EMG Based Motion Decoding Models based on Random Forests Regression: Random Forests can also be used for regression, growing trees depending on a random vector Θ such that the tree predictor $h(\mathbf{x},\Theta)$ takes on numerical values as opposed to class labels (used for classification). The random forest predictor, is formed similarly to the classification case, as appeared in Fig. 5, by taking the average over the N trees of the forest $\{h(\mathbf{x},\Theta_N)\}$, instead of the most popular class. Random Forests are easily implemented and trained, are very fast in terms of time spent for training and prediction, can be parallelized, can handle thousands of input variables (as in the case of classification), are resistant to outliers, run efficiently on large databases, have very good generalization properties and at last can output more information than just class labels (e.g. sample proximities, visualization of output decision trees etc.).

IV. Results

A. Classification Results

In order to select the most appropriate method we have applied a wide variety of classification techniques in our dataset, comparing them in terms of classification accuracy and time required for training for a specific dataset (that serves as benchmark). We performed support vector machines (SVM) based classification with a radial basis function (RBF) kernel and we constructed a single hidden layer Neural Network (NN) with ten hidden units. We trained NNs with the Levenberg-Marquardt backpropagation algorithm for neural network-based classification. k nearest neighbors (kNN) classifier was compared for the simplest case where $k = 3$ and Random Forests were grown with ten trees for speed. Random Forests outperformed the classification performance of other classifiers. For more information regarding the comparison of classification results the reader should refer to [21].

In order to assess the classification methods accuracy, we define the success rate as the percentage of EMG data points classified to the correct reach to grasp task. The classification is done for every acquired EMG data point, allowing the system to be able to decide in real-time the reach to grasp strategy that is being used (for a specific task), and even switch between different tasks online. Finally, we must note that classification results presented below are the average values over the five rounds of cross-validation method applied.

First, we present the classification results across different reach to grasp strategies for a specific position and different objects (three classes corresponding to the three objects) for all subjects in Table I. In Table II we use Random Forests in order to compare the classification accuracy across different reach to grasp strategies for a specific object and varying object position (five classes corresponding to the five positions) for all subjects. Finally in Table III we present Random Forests accuracy across reach to grasp movements towards different positions (five classes corresponding to the five positions), for all objects and subjects.

Typically the classification decision is taken at a frequency of 1 kHz. However, we can also use a sliding window of width N, in order for all the N samples to be used for the classification decision. The majority vote criterion, classifies all the samples, of a set of N samples, in the class that was the most common between them, i.e. the class that gathers the most votes. The use of the majority vote criterion (MVC) inside the aforementioned window, can improve the classification results acquired with the proposed methods.

More details regarding the sliding window and the MVC can be found in [21]. In Table IV, we present improved classification results using the majority vote criterion in a sliding window of $N = 50$ samples for Subject 1 performing reach to grasp movements towards a specific object (marker) and varying object position.

TABLE I
CLASSIFICATION ACCURACY ACROSS DIFFERENT REACH TO GRASP STRATEGIES TOWARDS A SPECIFIC POSITION AND THREE DIFFERENT OBJECTS, FOR ALL SUBJECTS (USING RANDOM FORESTS)

Positions	**Objects** (Classes)		
	Mug	**Marker**	**Rectangle**
Pos I	87.82% (±4.52)	91.15% (±5.31%)	88.82% (±4.63%)
Pos II	84.24% (±5.99%)	90.40% (±4.52%)	91.81% (±5.41%)
Pos III	84.78% (±5.78%)	86.72% (±5.16%)	85.39% (±4.95%)
Pos IV	83.24.% (±6.14%)	84.17% (±6.21%)	86.93% (±4.83%)
Pos V	86.55% (±4.39%)	89.32% (±3.81%)	90.74% (±3.78%)

TABLE II
CLASSIFICATION ACCURACY ACROSS DIFFERENT REACH TO GRASP STRATEGIES FOR A SPECIFIC OBJECT AND FIVE DIFFERENT OBJECT POSITIONS FOR ALL SUBJECTS (USING RANDOM FORESTS)

Positions (Classes)	Mug	**Objects** Marker	Rectangle
Pos I	86.01% (±4.16%)	89.83% (±4.01%)	87.01% (±6.57%)
Pos II	83.76% (±6.24%)	87.95% (±4.78%)	88.43% (±5.51%)
Pos III	89.74% (±3.41%)	87.23% (±4.92%)	90.30% (±4.01%)
Pos IV	91.23% (±2.39%)	90.05% (±4.86%)	90.51% (±3.92%)
Pos V	91.80% (±3.45%)	92.34% (±2.69%)	90.90% (±3.01%)

TABLE III
CLASSIFICATION ACCURACY ACROSS DIFFERENT REACH TO GRASP STRATEGIES IN DIFFERENT POSITIONS FOR ALL OBJECTS AND SUBJECTS (USING RANDOM FORESTS)

Positions				
Pos I	**Pos II**	**Pos III**	**Pos IV**	**Pos V**
88.51%	86.29%	87.91%	89.20%	91.02%

TABLE IV
CLASSIFICATION ACCURACY ACROSS DIFFERENT REACH TO GRASP MOVEMENTS TOWARDS A SPECIFIC OBJECT (MARKER) AND VARYING OBJECT POSITION FOR SUBJECT 1, USING RANDOM FORESTS AND RANDOM FORESTS WITH MVC APPLIED INSIDE A SLIDING WINDOW OF N=50 SAMPLES

Object	**Subject1**				
Rectangle	**Pos I**	**Pos II**	**Pos III**	**Pos IV**	**Pos V**
Random Forests	87.03%	91.61%	90.51%	86.25%	92.61%
RF with MVC	100%	100%	100%	100%	100%

B. Task Specific Motion Decoding Results

In order to evaluate the efficiency of different methods we examined and compared a series of regression techniques. More specifically we used the Multiple Linear Regression (MLR), we created a State-Space model as described in [1], we performed SVM regression with RBF kernel and we contructed a single hidden layer Neural Network with ten (10) hidden units. Finally Random Forests were also used as a regression technique, growing ten trees for computational efficiency. Regarding estimation accuracy we compared the aforementioned methods for estimating reach to grasp movements, towards different positions and different objects placed at the same position (using a benchmark dataset). Random forests outperformed the other regression techniques in terms of estimation accuracy, performing quite well also in terms of speed of execution. More details regarding the comparison results for the different regression techniques, can be found in [25]. Results for subspace specific and object specific models are presented in Table V and Table VI respectively, where we can see that the models trained for each position or object separately, outperformed the "general"[1] models built for all positions (for a marker) and all objects (placed in a specific position, Pos III).

TABLE V
ESTIMATION RESULTS FOR THE RANDOM FORESTS BASED MODEL FOR A SPECIFIC OBJECT (MARKER) ACROSS ALL FIVE OBJECT POSITIONS, FOR SUBJECT 1.

Position	**Arm** Similarity (%)	**Hand** Similarity (%)
Pos I	83.78% ±4.01%	83.43% ±13.77%
Pos II	88.80% ±3.98%	86.60% ±15.02%
Pos III	86.93% ±3.95%	90.42% ±10.47%
Pos IV	89.47% ±6.25%	83.73% ±16.12%
Pos V	91.53% ±6.57%	89.04% ±10.09%
ALL	80.19% ±7.32%	81.15% ±16.24%

TABLE VI
ESTIMATION RESULTS FOR THE RANDOM FORESTS BASED MODEL FOR A SPECIFIC POSITION (POS III) AND ALL THREE DIFFERENT OBJECTS, FOR SUBJECT 1.

Object	**Arm** Similarity (%)	**Hand** Similarity (%)
Marker	86.93% ±3.95%	90.42% ±10.47%
Rectangle	87.76% ±4.13%	82.33% ±12.31%
Mug	89.62% ±5.13%	83.52% ±13.57%
ALL	83.26% ±7.2%	80.47% ±11.72%

TABLE VII
ESTIMATION RESULTS FOR THE RANDOM FORESTS BASED MODEL FOR SPECIFIC POSITION (POS III) AND SPECIFIC OBJECT (RECTANGLE), FOR ALL SUBJECTS.

Subject	**Arm** Similarity (%)	**Hand** Similarity (%)
Subject 1	87.76% ±4.13%	82.33% ±10.47%
Subject 2	85.91% ±6.21%	81.59% ±11.78%
Subject 3	89.44% ±4.30%	84.93% ±14.93%
Subject 4	87.32% ±5.34%	85.28% ±10.16%
Subject 5	82.11% ±7.79%	80.54% ±16.32%

We can further notice in Table VII, that the estimation results were usually better in the case of the human arm than in the case of the human hand. This is an interesting finding, which supports the applicability of our method, since precisely estimating the position of the arm, is much more important than the placement of the fingers. Similarity between the estimated and the captured human motion is defined as:

$$S = 100(1 - RMS(q_c - q_e)/RMS(q_c))\% \tag{1}$$

where RMS is:

$$RMS(q_c - q_e) = \sqrt{\frac{\sum_{i=1}^{n}(q_c - q_e)^2}{n}} \tag{2}$$

where q_c are the captured joint values, q_e the estimated joint values and n the number of samples.

[1]With the term "general" models we mean the models trained for all positions in 3D space or all objects placed in a specific position. Thus, the training of the "general" models requires a training set that contains data for all the classes of a specific problem (i.e. object or subspace discrimination).

V. CONCLUSIONS AND DISCUSSION

In this paper we proposed a complete EMG-based learning scheme for reach to grasp movements. Principal Component Analysis (PCA) was applied to represent in lower dimensional manifolds the EMG activity and the human motion captured. These low dimensional embeddings were then used to train different task-specific Random Forest models for different reach to grasp movements. The scheme was formulated so as to combine a regressor with a classifier, to discriminate first the different reach to grasp strategies and trigger then a task-specific EMG based motion decoding model, that achieves better estimation results than the "general" models. The estimated output of the trained models was back projected in the high dimensional space (27 DoFs) to give an accurate estimate of the full human arm-hand system kinematics. The proposed methodology can be used to a series of EMG-based interfaces.

REFERENCES

[1] P. K. Artemiadis and K. J. Kyriakopoulos, "EMG-based control of a robot arm using low-dimensional embeddings," *Trans. Rob.*, vol. 26, no. 2, pp. 393–398, Apr. 2010.

[2] J. Vogel, C. Castellini, and P. P. van der Smagt, "EMG-based teleoperation and manipulation with the DLR LWR-III." in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2011, pp. 672–678.

[3] C. Cipriani, F. Zaccone, S. Micera, and M. C. Carrozza, "On the shared control of an EMG-controlled prosthetic hand: Analysis of user prosthesis interaction," *Trans. Rob.*, vol. 24, no. 1, pp. 170–184, Feb. 2008.

[4] L. Lucas, M. DiCicco, and Y. Matsuoka, "An EMG-controlled hand exoskeleton for natural pinching," *Journal of Robotics and Mechatronics*, vol. 16, no. 5, pp. 482–488, 2004.

[5] T. S. Saponas, D. S. Tan, D. Morris, and R. Balakrishnan, "Demonstrating the feasibility of using forearm electromyography for muscle-computer interfaces," in *Proceedings of the twenty-sixth annual SIGCHI conference on Human factors in computing systems*, ser. CHI '08. New York, NY, USA: ACM, 2008, pp. 515–524.

[6] S. Maier and P. van der Smagt, "Surface EMG suffices to classify the motion of each finger independently," in *Proceedings of the International Conference on Motion and Vibration Control (MOVIC)*, 2008.

[7] S. Bitzer and P. van der Smagt, "Learning EMG control of a robotic hand: towards active prostheses," in *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA)*, may 2006, pp. 2819–2823.

[8] C. Castellini, A. E. Fiorilla, and G. Sandini, "Multi-subject/daily-life activity EMG-based control of mechanical hands," *Journal of NeuroEngineering and Rehabilitation*, vol. 6, pp. 1–11, 2009.

[9] T. Brochier, R. L. Spinks, M. A. Umilta, and R. N. Lemon, “Patterns of muscle activity underlying object-specific grasp by the macaque monkey,” *Journal of Neurophysiology*, vol. 92, no. 1, 2004.

[10] F. E. Zajac, “Muscle and tendon: Properties, models, scaling and application to biomechanics and motor control,” *CRC Critical Reviews in Biomedical Engineering, J. R. Bourne, Ed. Boca Raton, FL: CRC Press*, vol. 19, no. 2, pp. 210–222, apr 1986.

[11] O. Fukuda, T. Tsuji, M. Kaneko, and A. Otsuka, “A human-assisting manipulator teleoperated by EMG signals and arm motions,” *Robotics and Automation, IEEE Transactions on*, vol. 19, no. 2, pp. 210–222, apr 2003.

[12] J. Zhao, Z. Xie, L. Jiang, H. Cai, H. Liu, and G. Hirzinger, “Levenberg-marquardt based neural network control for a five-fingered prosthetic hand,” in *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA)*, april 2005, pp. 4482–4487.

[13] M. Zecca, S. Micera, M. C. Carrozza, and P. Dario, “Control of multifunctional prosthetic hands by processing the electromyographic signal,” in *Critical Reviews in Biomedical Engineering*, 2002, pp. 459–485.

[14] A. Hill, “The Heat of Shortening and the Dynamic Constants of Muscle,” *Proceedings of the Royal Society of London. Series B*, vol. 126, no. 843, Jan. 1938.

[15] P. Artemiadis and K. Kyriakopoulos, “Teleoperation of a robot manipulator using EMG signals and a position tracker,” in *Intelligent Robots and Systems, (IROS). IEEE/RSJ International Conference on*, aug. 2005, pp. 1003–1008.

[16] R. J. Smith, F. Tenore, D. Huberdeau, R. Etienne-Cummings, and N. V. Thakor, “Continuous decoding of finger position from surface EMG signals for the control of powered prostheses,” in *Engineering in Medicine and Biology Society, 30th Annual International Conference of the IEEE EMBS*, aug. 2008, pp. 197 –200.

[17] Y. Koike and M. Kawato, “Estimation of dynamic joint torques and trajectory formation from surface electromyography signals using a neural network model,” *Biological Cybernetics*, vol. 73, pp. 291–300, 1995.

[18] P. Artemiadis and K. Kyriakopoulos, “A switching regime model for the EMG-based control of a robot arm,” *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on*, vol. 41, no. 1, pp. 53 –63, feb. 2011.

[19] M. Liarokapis, P. Artemiadis, and K. Kyriakopoulos, “Functional anthropomorphism for human to robot motion mapping,” in *21st IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*, Sept. 2012, pp. 31–36.

[20] J. R. Cram, G. S. Kasman, and J. Holtz, *Introduction to Surface Electromyography*, 2nd ed. Jones and Bartlett Publishers, 2010.

[21] M. Liarokapis, P. Artemiadis, P. Katsiaris, K. Kyriakopoulos, and E. Manolakos, “Learning human reach-to-grasp strategies: Towards EMG-based control of robotic arm-hand systems,” in *IEEE International Conference on Robotics and Automation (ICRA)*, May 2012, pp. 2287–2292.

[22] T. K. Ho, “Random decision forests,” in *Document Analysis and Recognition, 1995., Proceedings of the Third International Conference on*, vol. 1, aug 1995, pp. 278–282 vol.1.

[23] L. Breiman, “Random forests,” *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, Oct. 2001.

[24] M. Liarokapis, P. Artemiadis, and K. Kyriakopoulos, “Task discrimination from myoelectric activity: A learning scheme for EMG based interfaces,” in *IEEE International Conference on Rehabilitation Robotics (ICORR)*, June 2013.

[25] M. Liarokapis, P. Artemiadis, P. Katsiaris, and K. Kyriakopoulos, “Learning task-specific models for reach to grasp movements: Towards EMG-based teleoperation of robotic arm-hand systems,” in *4th IEEE RAS EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob)*, June 2012, pp. 1287–1292.

Minas V. Liarokapis received his Diploma in Computer Engineering & Informatics from University of Patras in 2008 and his MSc in ”Bioinformatics” from the ”Information Technologies in Medicine and Biology” MSc program of the Department of Informatics and Telecommunications, University of Athens, Greece, in 2010. Currently he is a PhD student at the Control Systems Lab, School of Mechanical Engineering, National Technical University of Athens (NTUA), Greece. His research interests include: Neuro-Robotics, Brain-Machine Interfaces (BMI) and Human-Robot Interaction (HRI). He has served as a reviewer to a number of journals and conferences and worked in EC projects.

Panagiotis K. Artemiadis received the Diploma and Ph.D. in Mechanical Engineering from National Technical University of Athens (NTUA) Greece, in 2003 and 2009 respectively, followed by a Postdoctoral appointment at the Newman Lab for Biomechanics and Human Rehabilitation at MIT, from 2009-11. He is currently with the School for Engineering of Matter, Transport and Energy, Arizona State University, where he is an Assistant Professor and Director of the Human-Oriented Robotics and Control Lab. His research interests include: Rehabilitation Robotics, Neuro-Robotics, Brain-Machine Interfaces and Human-Robot Interaction. Prof. Artemiadis has published close to 50 papers to journals and refereed conferences, while 3 of them have been included in the top papers in international conferences. He is editor or editorial member of international journals and conferences and has worked in projects funded by the EC, NSF and the Greek secretariat for Research & Technology.

Kostas J. Kyriakopoulos received a Diploma in mechanical engineering (Honors) from NTUA, in 1985 and the MS & Ph.D. in Electrical, Computer & Systems Engineering from Rensselaer Polytechnic Institute, Troy, NY in 1987 and 1991, respectively. Between 1988-91 he did research at the NASA Center for Intelligent Robotic Systems for Space Exploration. Between 1991-93 he was an Assistant Professor at RPI and the New York State Center for Advanced Technology in Automation and Robotics. Currently he is with the Mechanical Engineering Dept. at the National Technical University of Athens, Greece, where he is as a Professor & Director or the Control Systems Lab. His current interests are in the area of Nonlinear Control Systems applications in Sensor Based Motion Planning & Control of multi-Robotic Systems: Manipulators & Vehicles (Mobile, Underwater and Aerial) and Micro- & Bio- Mechatronics. Dr. Kyriakopoulos has published close to 250 papers to journals and refereed conferences and serves as a regular reviewer to a number of journals and conferences. He has contributed to a large number of projects funded by the EC and the Greek secretariat for Research & Technology. He serves in the editorial committee of a number of (including IEEE) journals and has served as an administrative member of a number of international conferences.

Elias S. Manolakos is a Visiting Scholar at the Wyss Institute for Biologically Inspired Engineering, Harvard University and the Director of the Multidisciplinary Program ”Information Technologies in Medicine and Biology” (http://itmb.di.uoa.gr/indexEng.html), Dept. of Informatics and Telecommunications, University of Athens. Before returning to Europe he was tenured faculty with the ECE Dept. Northeastern University, Boston where he directed the Communication and DSP Research Center spearheading student-centered innovation through academia-industry collaborations. His research interests include embedded systems, machine learning, image analysis, high performance computing, and their applications in biomedicine. He has served in the Editorial Board of the IEEE Trans. on Signal Processing, IEEE Signal Processing Letters, Journal of Signal Processing Systems, Springer etc. He has authored, or co-authored with his students, more than 110 refereed articles in scientific journals and Conference Proceedings. Dr. Manolakos holds a Ph.D. in Computer Eng. from University of Southern California, M.Sc. from University of Michigan and Diploma in Electrical Eng. from the National Technical University of Athens. He is a Senior Member of IEEE, and elected member of IEEE TC on Machine Learning for Signal Processing (MLSP).