Learning Human Reach-to-Grasp Strategies: Towards EMG-based Control of Robotic Arm-Hand Systems

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***Abstract*— Reaching and grasping of objects in an everyday-life environment seems so simple for humans, though so complicated from an engineering point of view. Humans use a variety of strategies for reaching and grasping anything from the simplest to the most complicated objects, achieving high dexterity and efficiency. This seemingly simple process of reach-to-grasp relies on the complex coordination of the musculoskeletal system of the upper limbs. In this paper, we study the muscular co-activation patterns during a variety of reach-to-grasp motions, and we introduce a learning scheme that can discriminate between different strategies. This scheme can then classify reach-to-grasp strategies based on the muscular co-activations. We consider the arm and hand as a whole system, therefore we use surface ElectroMyoGraphic (sEMG) recordings from muscles of both the upper arm and the forearm. The proposed scheme is tested in extensive paradigms proving its efficiency, while it can be used as a switching mechanism for task-specific motion and force estimation models, improving EMG-based control of robotic arm-hand systems.**

***Index Terms:* ElectroMyoGraphy (EMG), Muscular Co-Activation Patterns, Synergistic Profiles, Random Forests, Box-plot Zones, Learning Scheme, Classification**

I. INTRODUCTION

It has been almost 30 years since surface ElectroMyo-Graphic (EMG) signals have been proposed to detect the user's intention for the control of advanced prosthetic hands [1]. However, the high-dimensionality and complexity of the human musculo-skeletal system hinders the development of EMG-based control systems, capable of discriminating a plethora of reach-to-grasp or grasping strategies, that can provide effortless use of advanced prosthetic hands or arm-hand systems. The introduction of muscle and motor synergies into the EMG-based control interfaces has been proposed in the past for the upper limb [2], however the synergy-based EMG control of the hand and the whole arm-hand system have not been studied to the same extent.

Recent studies mainly focus on the kinematic investigation of human hand synergies, both in the motor and kinematic space, based on motion capture systems. Optical markers were mounted on 23 different points on the hand and data were acquired during an unconstrained haptic exploration task in [3]. Principal components analysis was used in order to evoke a set of hand postures that is representative of most naturalistic postures during object manipulation. A limited number of postural synergies were identified across a wide variety of object grasps, using camera-based motion capture system in [4] and dataglove measurements in [5] and [6].

Glove measurements combined with EMG activity from subjects using the American Sign Language (ASL) manual alphabet were also used to reveal temporal synergies across muscles during hand movement in [7]. The ability of muscle synergies to form a predicting framework to associate EMG patterns with untrained static hand postures was assessed in [8]. Classification methods to discriminate between independent digit movements as well as between different postures were proposed in [9] and [10]. In [11] forearm surface EMG were used for the feed-forward control of a hand prosthesis, using machine learning techniques capable of discriminating grip postures in real-time. Despite the promising results, the latter study employs only three different grip types (power grasp, index precision grip and middle-ring-pinky precision grip), which is a factor that limits the method's applicability. Finally, in [12] authors capture myoelectric activity from two adult macaque monkeys grasping 12 objects of different shapes, in order to distinguish between EMG activation patterns that have been associated with different grasping postures.

In this paper, we focus on the characterization of different muscular co-activation patterns for reach-to-grasp movements for a wide variety of daily life objects as well as different object positions in 3D space. For doing that, we record EMG signals from the muscles of the human forearm and the upper arm while executing reach-to-grasp movements. Then, we use statistical methods to extract and visualize muscular co-activation patterns captured in our recordings. Furthermore we build EMG classifiers in order to discriminate between different reach-to-grasp strategies for different objects and object positions. The proposed methodology can be used as a switching mechanism that can help us improve EMG-based human force and motion estimation, by employing strategy-specific decoders.

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* Research partially carried out at the Dept. of Informatics & Telecommunications, Post-Graduate Program "Information Technologies in Medicine & Biology" [http://itmb.di.uoa.gr], University of Athens (UOA), Greece, for partial fulfillment of the requirements of the MSc degree.

This work has been 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.

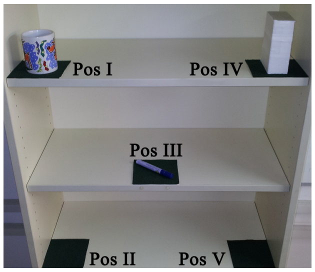

Fig. 1: Birdview of the experimental setup consisting of three (3) everyday life objects, a marker, a rectangle and a mug, placed on three (3) different shelves of a bookcase, in five (5) different positions

The rest of the paper is organized as follows: Section II analyzes the methods, the equipment and the experimental protocol, Section III presents and compares the results of different classification methods, while Section IV concludes the paper.

II. Materials and methods

A. Apparatus

The purpose of the experiments conducted was to study the muscular co-activations during different reach-to-grasp tasks. Five healthy subjects (21, 24, 27, 28 and 40 years old) participated in the experiments. The subjects gave informed consent and the procedures were approved by the Institutional Review Board of the National Technical University of Athens. All subjects performed the experiments with their dominant hand (the right hand for all subjects).

Objects of varying shape and size were placed on different positions inside the 3D arm workspace. For this purpose, a bookcase was utilized and the objects were placed on three different shelves. The vertical distance between concecutive shelves was approximately thirty-five (35) cm. The subject's arm was initially in resting position, fully relaxed, pointing downwards. Each subject was instructed to move his arm in order to perform reach-to-grasp movements towards an object, grasp the object, and once the object is firmly grasped to lift it approximately 5 cm from the initial setting. During the training phase, the user was instructed to perform repeated reach to grasp and grasp movements towards five positions in 3D space, reaching and grasping one of the three different daily life objects used. Those were a rectangular-shaped object, a marker and a mug. Thirty (30) trials per object placed at each of the five possible positions in 3D space were conducted, while a resting time of 1 minute was given to the subjects between them. The starting position of the arm-hand system was kept constant for all trials. The horizontal distance of two locations on the same shelf was 60 cm. The second shelf has only one middle object position. The experimental setup is presented in Fig. 1.

In order to achieve easy, portable and fast to use training schemes several researchers have chosen over the years to place the EMG electrodes in specific regions but in random positions [13]. We believe that the next generation of epidermal electronics [14] will make the electrode positioning faster and easier, thus in this paper we choose to take advantage of the higher signal to noise ratio that the specific electrode positions offer, reducing crosstalk e.t.c. More specifically: Surface EMG signals were recorded using single differential surface EMG electrodes (DE-2.1, Delsys Inc.). The signals 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).

Sixteen muscles of the forearm and the upper-arm were recorded. The muscles chosen are used with 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 [6], [15]. For the myoelectric activity to be captured, surface bipolar active EMG electrodes were used following the direction given in [16]. EMG signals were band-pass filtered (20-450 Hz) and sampled at 1 kHz. Then, EMG signals were full-wave rectified and low-pass filtered (Butterworth, fourth order, 8 Hz).

B. Muscular co-activation patterns extraction

EMG recordings from all experiments were pre-processed and epochs of data were created, including the different reach-to-grasp strategies captured in the experiments. Then, all data were resampled at 100 Hz, where each new value at the new frequency was calculated as the mean value of ten (10) samples of the original frequency (1kHz). The technique for resampling the EMG recordings for these kinds of experiments is described in [7]. The final EMG activations from all muscles are used as a function of samples in the low frequency (100 Hz). Based on those profiles, the onset of muscular activation is defined by the direct comparison of the amplitude of each muscle compared to it's relaxed state. Finally, the epochs including only the muscular activation during the task are created, and used in order to formulate synergistic profiles using a novel statistical representation technique that we call "Boxplot Zones".

In descriptive statistics, a boxplot (alt. box-and-whisker plot) is a convenient way of graphically depicting groups of numerical data, through the following five-number summaries: smallest observation (sample minimum), lower quartile (Q1), median (Q2), upper quartile (Q3), and largest observation (sample maximum) [17]. Boxplot zones are an equivalent of boxplots, while more visually informative representation of muscular co-activations or synergistic profiles. Boxplot zones are splitted in three different layers. The first layer includes the median line that connects the medians of all boxplots. The second layer consists of the box zone (blue zone) connecting the boxes that include all the values between the lower and the upper quartile, while the third layer consists of the whisker zone (white zone) connecting the whiskers that mark the largest and the smallest observation.

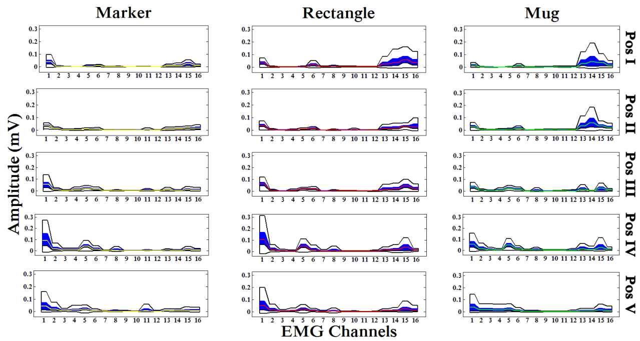

Fig. 2: Boxplot Zones visualization of different muscular co-activation patterns across sixteen (16) muscles of the upper arm and the forearm for one subject (Subject 1) performing reach to grasp movements towards five (5) different positions, to grasp three (3) different objects.

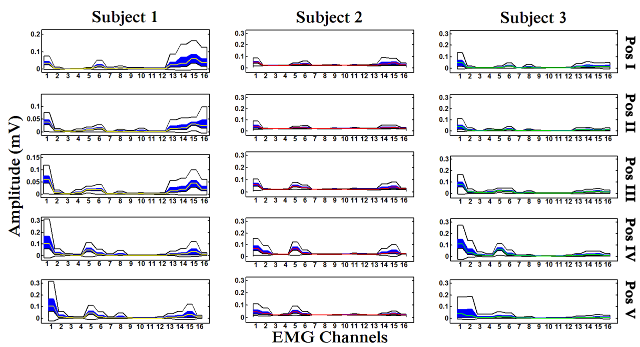

Fig. 3: Boxplot Zones visualization of different muscular co-activation patterns across sixteen (16) muscles of the upper arm and the forearm for three (3) different subjects performing reach to grasp movements towards five (5) different positions, to grasp a specific object (Rectangle).

Fig. 2 shows boxplot zones visualization of the muscular co-activation patterns across sixteen (16) muscles of the upper arm and the forearm for one subject (Subject 1) performing reach to grasp movements towards five (5) different positions, in order to grasp three (3) different objects. Fig. 3 shows the muscular co-activation patterns differentiation across the 16 muscles of the human upper-arm and forearm while the subject performs reach to grasp movements towards five (5) positions in 3D space for a specific object (rectangular-shaped object). As it is shown, the co-activation of muscles are significantly different between the different reach-to-grasp movements, although the same fingers and joints of the upper-arm were involved, but for a different task.

In order to assess the statistical significance of muscular co-activation patterns differentiation, statistical tests were conducted. Lilliefors test, (an adaptation of the Kolmogorov-Smirnov test) was used to test the null hypothesis that our myoelectric data come from a normal distribution. The test returned the logical value $h = 1$ rejecting the null hypothesis at the 5% significance level ($p = 0.05$), so our data are not normally distributed.

Thus we choose to test the significance of the differentiation of the muscular co-activation patterns for different strategies, using non parametric tests such as the Kruskal-Wallis and the Wilcoxon rank sum test. More specifically the Kruskal-Wallis compares the medians of the EMG activity

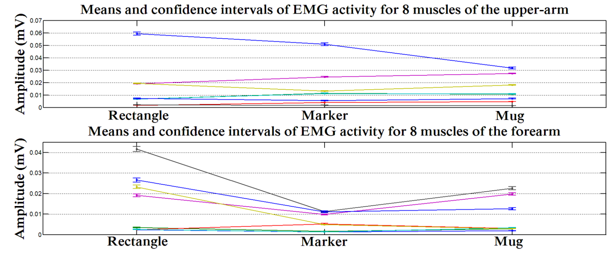

Fig. 4: Means and confidence intervals of EMG activity across eight (8) muscles of the upper arm and the eight (8) muscles of the forearm for one subject (Subject 1) performing reach to grasp movements towards three (3) different objects placed at the same position (Pos 3).

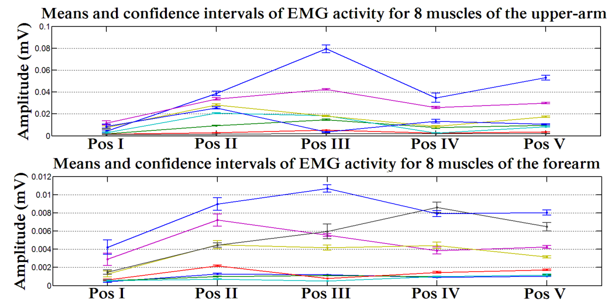

Fig. 5: Means and confidence intervals of EMG activity across eight (8) muscles of the upper arm and the eight (8) muscles of the forearm for one subject (Subject 1) performing reach to grasp movements towards a marker placed at five (5) different positions.

of each muscle for different co-activation patterns (used by different strategies), and returns the p value for the null hypothesis that all samples are drawn from the same population (or equivalently, from different populations with the same distribution).

The Wilcoxon rank sum test performs a two-sided rank sum test of the null hypothesis that data of different muscular co-activation patterns are independent samples from identical continuous distributions with equal medians. For more information regarding the statistical procedures used in this paper, the reader should refer to [18].

We performed the tests in order to check the differentiation of musclular co-activation patterns for three cases: i) for the same strategy between different subjects ii) between reach to grasp movements towards different positions in 3D space iii) between reach to grasp movements towards three different objects placed at a specific position in 3D space. Confidence levels for all analysis were set at 95%. Both tests null hypothesis for all three cases was rejected, proving muscular co-activation patterns differentiation for different subjects and tasks. Fig. 4 and Fig. 5, present the means and the confidence intervals of EMG activity for different muscular co-activation patterns for the case of different objects (Fig. 4) as well for the case of different positions (Fig. 5). Therefore, we conclude that the 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.

C. Multiclass Classification of Reach to Grasp Movements

Synergistic profiles depicted in Fig. 2 and Fig. 3 imply a significant differentiation of muscular co-activation patterns between the different reach-to-grasp strategies that we investigated. To take advantage of this differentiation, we apply a wide variety of classification techniques in our dataset, in order to compare them in terms of accuracy and time required for training and consequently assess their ability to discriminate between different reach-to-grasp strategies. Moreover in this section we introduce a novel classifier (random forests classifier), which we prove that outperforms all others in terms of classification accuracy while performing quite well as far as time required for training is concerned. Such types of learning schemes can boost the performance of a grasping controller used by an EMG-based teleoperation scheme or an advanced prosthetic hand, since a larger repertoire of grasping strategies can be decoded from muscular recordings.

In human-driven robotics, classification techniques should not be just accurate but also compatible with multiclass classification problems. More specifically in EMG-based studies, we have to classify a multidimensional feature space (m channels of EMG data capturing the myoelectric activity of the selected muscles) and we need to discriminate between multiple classes. These classes may incorporate information for different subspaces of the workspace, characterizing strategies for reach to grasp movements towards different positions in 3D space (where the EMG signals appear to have different muscular co-activation patterns) or information for the different objects, characterizing strategies for reach-to-grasp movements towards various objects (one class per object) placed in the same position. Thus the selected classifier must be highly accurate, fast enough for large datasets and be able to face multiclass problems.

In this study six different types of classification techniques were used; Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), a k-Nearest Neighbours (k-NN) classifier, an Artificial Neural Network (ANN) classifier, a Support Vector Machine (SVM) classifier and a Random Forest classifier. The input to all classifiers was a matrix of size $16 \times N$ including N samples of the processed activity of the sixteen (16) recorded muscles. The LDA is a method used in pattern recognition problems, in order to find a linear combination of features which characterize or separate two or more classes of objects. The resulting combination can be used as a linear classifier. The QDA involves a quadratic classifier which is used in statistical classification in order to separate measurements of two or more classes of objects by a quadratic surface. The QDA can be described as a more general version of the LDA.

The k-NN algorithm is a method for classifying objects based on the closest to them training examples, in the feature space. k-NN is a type of lazy learning where the function is locally approximated and computation is deferred until classification. The idea of kNN classifier is that an object is classified by a majority vote of its neighbors and assigned in the class where most of its k nearest neighbors belong [19].

The support vector machine (SVM) is a supervised learning method that is commonly used for classification analysis. The standard SVM classifier as proposed by Vapnik in 1963 is a non-probabilistic binary linear classifier using an optimal hyperplane algorithm. Although later on Bernhard Boser, Isabelle Guyon and Vapnik [20] suggested a way to create nonlinear classifiers by applying the well-known kernel trick one of the main disadvantages of the SVM approach is the fact that is computationally expensive and that in order to face multi-class problems it must reduce the multi-class problem into multiple binary classification problems.

Neural networks have been successfully used as a tool for classification by numerous studies in the past [11] serving as a promising alternative to traditional classification methods. Neural networks can adjust themselves to the data without any knowledge for the underlying model (giving the fact that they are universal functional approximators) and they can also be used as a nonlinear method modeling real world complex relationships.

Random forests classifier was proposed by Tin Kam Ho of Bell Labs [21] and Leo Breiman [22] and 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. Some of the main advantages of the random forests technique is the fact that runs efficiently on large databases, and is able to handle thousands of input variables without variable deletion.

Regarding the training procedure, we used the five-fold cross-validation method to measure the accuracy of our classifiers. To reduce variability, multiple rounds of cross-validation were performed using different partitions, and the validation results were averaged over the rounds.

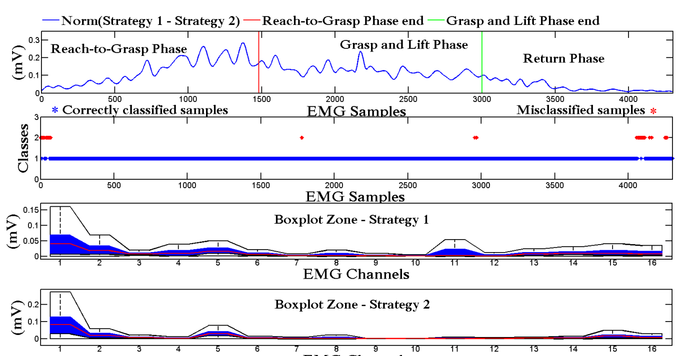

Fig. 6: Comparison of two reach-to-grasp strategies. First subplot presents the distance of the two strategies in the m-dimensional space where m=16 the number of the EMG channels. The second subplot focuses on the classification results per sample while the last two subplots present the boxplot zones of the different strategies. The two strategies are reach to grasp movements towards a marker: in position I (Strategy I) and in position II (Strategy II).

In Fig. 6 we present a typical classification problem of discriminating (using EMG) two different strategies for reaching a specific object placed in two different positions, grasping it and returning to the initial position. More specifically in the first subplot we can see how the distance between the two movements (caused by the strategies) in the m-dimensional space is evolved ($m = 16$, the number of the muscles).

Distance between two strategies give us also a measure of their separability, i.e. how easily they can be discriminated. Then in the second subplot of Fig. 6 the accumulation of misclassified samples is reasonable for the time periods that the distance between the two strategies is not significant (beggining and end of the experiment where the movements are close to the starting position). Finally in subplots 3 and 4 of Fig. 6 we can see that the differentiation of these two strategies can be illustrated efficiently using boxplots zones.

III. Results

A. Classifiers Comparison

In this section we compare the state-of-the-art classifiers against the Random Forests classifier that we introduce for the problem of discriminating different reach to grasp strategies from myoelectric activity. Classification success rates (%) are listed in Table I. As it can be seen Random Forests outperform the performance of the most well-known classifiers such as SVM and ANN classifiers.

As far as training time and speed of execution are concerned, Random Forests outperform SVM and Neural Network, performing quite well also compared to the linear and quadratic methods such as the QDA and the LDA. More specifically we performed SVM based classification with a RBF kernel and we constructed a single hidden layer Neural Network with ten (10) hidden units, trained with the Levenberg-Marquardt backpropagation algorithm for neural network-based classification. kNN classifier was compared for the simplest case where $k = 3$ and Random Forests were grown with ten (10) trees for speed. The training task that was used to compare classifiers in terms of speed of execution, was to learn how to discriminate between two reach-to-grasp movements towards different objects placed: in Position I (Class I) and in Position II (Class II). Results are reported in Table II. The benchmark was performed using MATLAB (Mathworks) in a standard PC with Intel(R) Core(TM) I5 CPU 611 @3.33GHz and 4GB RAM (DDR3) memory.

B. Classification Results

As previously mentioned, individual muscular activity is consistent across experiments under the same conditions, while significantly different across different reach-to-grasp parameters i.e. different shape and position of the objects. Therefore, and 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. It must be noted that the classification is done for every acquired EMG data point, allowing the system to be able to decide in real-time the grasping task, and even switch between different tasks online. Finally, we must note that classification results presented below are the average values over the 5 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 for all subjects in Table III. In Table IV 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 for all subjects. Finally in Table V we present the classification accuracy of random forests across different reach to grasp strategies in different positions for all objects and subjects.

TABLE I: Comparison of Classifiers for discriminating two different grasping strategies for two objects placed across three different positions in 3D space (Subject 1)

Classifiers	Positions	Mug	Rectangle
LDA	Pos I	96.75%	83.36%
	Pos III	96.50%	90.40%
	Pos V	91.44%	95.00%
QDA	Pos I	95.34%	80.52%
	Pos III	97.30%	91.45%
	Pos V	92.30%	95.60%
kNN	Pos I	96.33%	81.63%
	Pos III	98.20%	94.50%
	Pos V	96.50%	98.68%
ANN	Pos I	94.67%	84.63%
	Pos III	98.50%	94.76%
	Pos V	94.52%	98.87%
SVM	Pos I	97.46%	87.42%
	Pos III	98.81%	94.50%
	Pos V	98.00%	96.50%
Random Forests	Pos I	99.67%	89.02%
	Pos III	100%	96.50%
	Pos V	98.87%	99.00%

TABLE II: Comparison of classifiers in terms of time required for training, for a dataset of sixteen dimensions (16 muscles).

Classifiers	Samples	Training Time
LDA	2 Classes of 1500	0.011 sec
	2 Classes of 15000	0.058 sec
QDA	2 Classes of 1500	0.005 sec
	2 Classes of 15000	0.051 sec
kNN	2 Classes of 1500	0.014 sec
	2 Classes of 15000	1.65 sec
ANN	2 Classes of 1500	1.06 sec
	2 Classes of 15000	16.05 sec
SVM	2 Classes of 1500	0.34 sec
	2 Classes of 15000	7.09 sec
Random Forests	2 Classes of 1500	0.06 sec
	2 Classes of 15000	0.87 sec

TABLE III: Classification accuracy across different reach to grasp strategies towards a specific position and 3 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 IV: 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 V: 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%

C. Majority Vote Criterion

The electromechanical delay (EMD) of a muscle is defined as the time interval between the onset of the myoelectric activity, indicating its activation by the neural system and the onset of the resulting change in the mechanical variable observed (e.g. movement or force). This delay ranges from 25 to 100 ms for different muscles and tasks. Thus, onset of the EMG signals (electrical event) precedes onset of muscle contraction (mechanical event). Given the fact that we are capturing the EMG signals with a sampling frequency of 1 kHz, we need at least 25 samples for a grasping strategy to be detected (practically most of the times over 50 samples).

In order to take advantage of the EMD, we use a sliding window of size $M = 50$, inside which we apply the majority vote criterion [19]. The majority vote criterion, classifies all the samples, of a set of M 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 a window of length M, can improve significantly the classification results acquired with the proposed methods. As shown in Table VI, the classification results were improved by using the majority vote criterion in a sliding window of 50 samples. However, the choice of window size affects computational complexity and therefore it must be carefully chosen in order not to compromise the real-time character of the methodology.

TABLE VI: Classification accuracy across different reach to grasp strategies for a specific object (Marker) and varying object position for Subject 1, using Random Forests and Random Forests combined with the Majority Vote Criterion

Object Rectangle	Subject1				
	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%

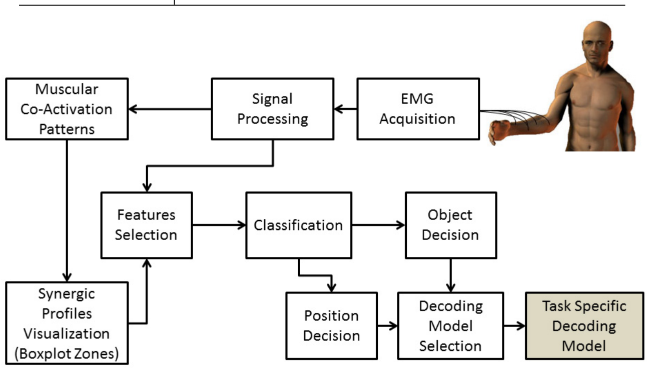

Fig. 7: Block diagram of the proposed methodology.

IV. Conclusions and Discussion

In this paper we recorded muscular activity from sixteen (16) muscles of the forearm and the upper-arm during reach-to-grasp movements towards different objects and object positions in 3D space. Boxplot zones were introduced as a novel statistical representation technique capable to give a direct visual estimate of the muscular co-activation patterns. Furthermore an emerging classifier based on Random Forests, not previously used in neurobotics was used to classify EMG signals in different classes, according to the reach-to-grasp features (i.e. object size and position). A block diagram is shown in Fig. 7.

The methodology proposed here is able to benefit a switching mechanism that will trigger task-specific (reach-to-grasp strategy) motion and force estimation models improving EMG-based control of robotic arm-hand systems.

References

[1] D. Graupe, J. Salahi and K. Kohn, "Multifunctional prosthesis and orthosis control via microcomputer identification of temporal pattern differences in single-site myoelectric signals," *Journal of Biomedical Engineering*, vol 4(1), pp. 17-22, 1982.

[2] P. K. Artemiadis and K. J. Kyriakopoulos, "EMG-based Control of a Robot Arm using Low-Dimensional Embeddings," *IEEE Transactions on Robotics*, vol. 26(2), pp. 393-398, 2010.

[3] P. H. Takur, A. J. Bastian and S. S. Hsiao, "Multidigit Movement Synergies of the Human Hand in an Unconstrained Haptic Exploration Task," *The Journal of Neuroscience*, vol. 28(6), pp. 1271-1281, 2008.

[4] C. R. Mason, J. E. Gomez and T. J. Ebner, "Hand Synergies During Reach-to-Grasp," *AIP Journal of Neurophysiology*, vol. 86(6), pp. 2896-2910, 2001

[5] M. Santello, M. Flanders and J. F. Soechting, "Postural Hand Synergies for Tool Use," *The Journal of Neuroscience*, vol. 18(23), pp.10105-10115, 1998.

[6] S. Maier and P. van der Smagt, "Surface EMG suffices to classify the motion of each finger independently," *Proceedings of MOVIC 2008, 9th International Conference on Motion and Vibration Control*, 2008.

[7] M. D. Klein Breteler, K. J. Simura and M. Flanders, "Timing of Muscle Activation in a Hand Movement Sequence,"*Cerebral Cortex*, vol. 17, pp. 803-815, 2007.

[8] A. B. Ajiboye and R. F. Weir, "Muscle synergies as a predictive framework for the EMG patterns of new hand postures," *Journal of Neural Engineering*, vol. 6, 2009.

[9] E. Todorov and Z. Ghahramani, "Analysis of the synergies underlying complex hand manipulation," *Proceedings of the 26th Annual International Conference of the IEEE EMBS*, 2004.

[10] S. Bitzer and P. van der Smagt, "Learning EMG control of a robotic hand: Towards Active Prostheses", *Proceedings of the 2006 IEEE International Conference on Robotics and Automation*, 2006.

[11] 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(41), 2009.

[12] 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, pp. 1770-1782, 2004.

[13] J. Vogel, C. Castellini, P. van der Smagt, "EMG-Based Teleoperation and Manipulation with the DLR LWR-III" *Proc. IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2011.

[14] Kim, Dae-Hyeong et al., "Epidermal Electronics", *Science*, v. 333, 6044, pages 838-843, 2011.

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

[16] P. K. Artemiadis and K. J. Kyriakopoulos, Teleoperation of a robot manipulator using EMG signals and a position tracker, *in Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, 2005, pp. 1003-1008.

[17] C. R. Brown, "Exploratory Data Analysis", *Addison-Wesley*, 1977.

[18] D. J. Sheskin, "Handbook of Parametric and Nonparametric Statistical Procedures", *CRC Press*, 4th edition, 2007.

[19] S. Theodoridis, K. Koutroumbas, "Pattern Recognition," *Academic Press - Elsevier Science*, 4th edition, 2009.

[20] B. E. Boser, I. M. Guyon, and V. N. Vapnik, "A training algorithm for optimal margin classifiers" *5th Annual ACM Workshop on COLT*. pp. 144152, Pittsburgh, PA, 1992.

[21] T. Ho, "Random Decision Forest", *3rd Int'l Conf. on Document Analysis and Recognition*. pp. 278282, 1995.

[22] L. Breiman, "Random Forests", *Machine Learning*, vol. 45 (1): 532. doi:10.1023/A:1010933404324, 2001.