Learning Task-Specific Models for Reach to Grasp Movements: Towards EMG-based Teleoperation of Robotic Arm-Hand Systems

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

***Abstract*— A learning scheme based on Random Forests is used to decode the EMG activity of 16 muscles of the human arm-hand system to a continuous representation of kinematics in reach-to-grasp movements in 3D space. Classification methods are used to discriminate between significantly different reach to grasp strategies, formulating a switching mechanism that may trigger the use of position and object-specific decoding models (task-specificity). These task-specific models can achieve better estimation results than the general models for the kinematics of different reach-to-grasp movements. The efficacy of the proposed methodology is assessed through a strict validation procedure, based on everyday life reach-to-grasp scenarios and data not previously seen during training. Finally, for demonstration purposes, the authors teleoperate an arm-hand model in the OpenRave simulation environment using the estimated from the EMG signals human motion.**

Index Terms: **ElectroMyoGraphy (EMG), EMG-Based Teleoperation, Robotic Arm-Hand System, Learning Scheme, Model Switching, Random Forests**

I. Introduction

Over the last decades the field of EMG-based teleoperation of robotic systems has received increased attention. The interest is motivated by the large variety of applications, in remote or dangerous environments, in robotics assisted rehabilitation, as well as in prosthetics by the amputees hope to regain dexterity using the next generation of prosthetic limbs. Most of the previous studies in this field have focused on the EMG-based teleoperation of robotic arms in two-dimensional (2D) and three-dimensional (3D) spaces, using the musculoskeletal model approach or other methods such as State-Space models and Neural Networks.

EMG signals have been used in several studies in the past in order to build a control interface for robotic devices. One of the main difficulties that the researchers faced is the highly nonlinear relationship between the EMG signals and human kinematics [1]. Thus in most cases, researchers chose to focus on binary control, such as the directional control of a robotic wrist [2] or the control of multifingered robotic hands to a series of discrete postures [3] - [8].

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The usage of finite postures for the control of a robotic system may cause problems such as the lack of motion smoothness. Moreover in teleoperation studies where the execution of everyday life tasks is of critical importance, the suggested methodology must address the issues of continuous and smooth control, decoding a continuous representation of human kinematics from the captured myoelectric activity. Another type of continuous model that has been proposed in order to decode arm motion from EMG signals is the Hill-based musculoskeletal model [9], which is one of the most frequently used methods in the related literature [1], [10] and [11]. However in these studies only a few degrees of freedom (DoFs) are analyzed (i.e. 1 or 2) due to the nonlinearity of the model equations and the large number of unknown parameters per muscle that make the overall analysis rather difficult. Similar studies that used musculoskeletal models, focusing on a limited number of muscles and actuated DoFs, are [12] and [13].

Furthermore an artificial neural network has been used by [14] in order to estimate the continuous motion of the fingers, using the myoelectric activity from muscles of the forearm. However in this paper only one degree of freedom (DoF) per finger was decoded. Another study that uses a neural network-based model in order to decode arm motion using EMG signals, restricting though the analyzed movements to single-joints isometric motions, is [15]. Similarly in [16], a one DoF robot arm was controlled using EMG signals through neural networks.

Artemiadis et al. in [17] used a state-space model in order to successfully estimate human arm kinematics from the myoelectric activity produced from certain muscle groups. 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). Finally the authors in [18] and [19] propose a novel metholodology for mapping between the muscles activation and the arm motion in a low dimensional space using a state space model.

A recent study that focuses on the teleoperation and manipulation of the DLR LWR-III (Arm-Hand system) [20], presents an interesting methodology for decoding human arm kinematics in 3D space, based on support vector machines (SVM). Although the approach is interesting, the studied DoFs are seven (7), six for the arm and one (1) DoF for the human grasp, which limits its applicability to every-day life tasks, where independent finger motion is of paramount importance. Moreover, the method requires smooth and quite slow movements, which are far from realistic reach-to-grasp movements.

In this paper, we propose a novel methodology based on emerging techniques (Random Forests classification and regression) for controlling an anthropomorphic robotic arm-hand system in reach-to-grasp movements using surface myoelectric recordings (sEMG) from muscles of the upper-arm and the forearm. More specifically we use a learning scheme, that help us discriminate the execution of different reach-to-grasp strategies and consequently select different decoding models for different reach to grasp tasks. The system is composed by a training and real-time operation phase. In the training phase, the user was instructed to perform reach to grasp and grasp movements towards different objects placed in different positions in 3D space, while EMG recordings were taken.

The principal component analysis (PCA) was used in order to represent in lower dimensional manifolds the EMG recordings as well as the kinematic recordings (extracted from the position tracking system). The low dimensional embeddings of the arm-hand kinematics and the low dimensional embeddings of the EMG signals captured from the selected muscles, were used to train different models for different reach to grasp tasks in order to form the switching mechanism that we introduce. The estimated output of the trained models can be then transformed back in the high dimensional space in order to give an estimate of the arm-hand kinematics in 3D space.

The proposed learning scheme incorporates in the control loop a switching variable that depends on the classification decision that helps us to discriminate between different reach-to-grasp strategies, based on muscular co-activation patterns. Then, once the decoder outputs the desired motion in the low-dimensional space, a projection to the original high-dimensional space is performed.

The efficacy of the proposed scheme was assessed through a strict validation procedure involving a large number of experiments as well as using a simulated paradigm for the EMG-based teleoperation of a robotic arm-hand system model (the five fingered 15-DoF robotic hand DLR-HIT Hand 2, and the 7-DoF anthropomorphic robotic arm Mitsubishi PA-10) in the OpenRAVE simulation environment. More details regarding the OpenRAVE simulation environment can be found in [21] as well as in [22].

The rest of the paper is organized as follows: Section II analyzes the proposed system architecture, reports the methods that were used as well as the verification procedures, Section III focuses on results presentation (classification - motion decoding), comparison of different decoding methods and simulation, while Section IV concludes the paper.

II. Methods

A. Background and problem definition

1) Data Acquisition and Processing: The motion of the upper limb in the 3-D space was analyzed. More precisely three rotational DoFs were used to model the shoulder joint, one rotational DoF for the elbow joint, one rotational joint for pronation-supination, two rotational joints for the wrist and 20 rotational joints for the fingers (3 rotational joints for each finger's flexion-extension and 1 rotational joint for abduction-adduction). For the training of the proposed system the motion of the upper limb was recorded and the joint trajectories were extracted.

In order to record the motion and then to extract the joint angles of the 27 modeled DoFs, a magnetic position tracking system and a dataglove were used. The position tracking system was equipped with two position tracking sensors and a reference system, with respect to which the 3-D position of the tracking sensors was provided. To compute the first five joint angles (3 DoFs for the shoulder, elbow flexion-extension and pronation-supination), one position tracking sensor was placed at the user's elbow and the other one at the wrist joint. The reference system was placed on the user's shoulder. Details on the computation of arm kinematics are included in [23]. To compute the rest 22 DoFs a dataglove measuring finger angles and the wrist flexion-extension and abduction-adduction was used.

EMG signals were recorded from sixteen (16) different muscles, 8 muscles of the upper arm and 8 muscles of the forearm. More specifically the selected muscles are the following: flexor pollicis longus, flexor digitorum superficialis, flexor carpi ulnaris, flexor carpi radialis, extensor pollicis longus, extensor indicis, extensor carpi ulnaris, extensor carpi radialis, deltoid anterior, deltoid posterior, deltoid middle, trapezius, teres major, brachioradialis, biceps brachii and triceps brachii. The selection of the chosen muscle groups, as well as the placement of the electrodes, was based on the related literature [7], [24].

For the myoelectric activity of the muscles to be captured surface bipolar active EMG electrodes were used following the directions given in [11]. As far as the EMG signals are concerned they were band-pass filtered (20-450 Hz), sampled at 1 kHz, full-wave rectified and at last low-pass filtered (Butterworth, fourth order, 8 Hz). The position tracking system provided the position measurements at the frequency of 30 Hz. Using an antialiasing finite-impulse-response filter (low pass, order: 24, cutofff frequency: 100 Hz), these measurements were resampled at a frequency of 1 kHz to be consistent with the muscle activation sampling frequency.

2) System Requirements: Two aspects that each EMG-based teleoperation method should have, are to decode a continuous representation of the motion to allow its application at a robot control scheme and to be easily trainable to different users, since musculoskeletal and arm-hand dynamics may vary significantly across subjects.

Moreover even within the same subject, repositioning of the electrodes can require retraining, so the proposed decoding architecture should be easy and fast enough in terms of training. In order to achieve easy, portable and fast to use training schemes several researchers have chosen to place the EMG electrodes not in specific regions but in random positions [20]. We believe that the next generation of epidermal electronics [25] 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.

3) Experimental Protocol: 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. During the training phase, each subject performed with the dominant hand (the right hand for all subjects), repeated reach to grasp movements in 3D space, in order to reach and grasp three different daily-life objects; a rectangular-shaped object, a marker and a mug, placed in five (5) different positions. Adequate resting time (1 min) was used in order for the users to be able to rest between concecutive trials and each subject conducted several trials (approximately 30), for each object and object position. More precisely the three objects were placed on three shelves with heights 105 cm, 135 cm and 165 cm respectively. Two object positions were marked at the edges of the 1st self (105cm) and the distance between them was 60cm. One object position was marked in the middle of the 2nd shelf (135cm) while the 3rd shelf (165cm) had also two object positions marked at its edges like the first shelf. More details regarding the experimental setup can be found in [26].

B. Random Forests Based Decoding Model

1) Dimensionality Reduction: In order to represent our signals in a low-dimensional space, the principal components analysis method (PCA) was used. It was found that for the EMG signals a 4-D space could represent most of the original high-dimensional data variance (more than 92%). As far as the kinematics are concerned, the 27-DoF motion was found that can be described also 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. Moreover PCA has been proposed as the easiest to implement and the most computationally effective method for dimensionality reduction and data compression [27].

2) Decoding Model based on Random Forests: Random Forests are an ensemble classification and regression algorithm proposed by Tin Kam Ho of Bell Labs in 1995 [28] and Leo Breiman [29] in 1999. Random Forests are quite easy to be implemented and trained, are very fast in terms of time spent for training and prediction, can be parallelized, can handle thousands of input variables, 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 e.t.c.).

Moreover, random forests consist of many decision trees and trees can help us achieve highly non-linear mappings, splitting the original problem into subproblems. These subproblems can then be solved with quite simple predictors. As far as random forests generalization ability is concerned, Breiman et al. [29] showed that despite the fact that standard decision trees suffer from overfitting, a collection of randomly trained trees has significant generalization power.

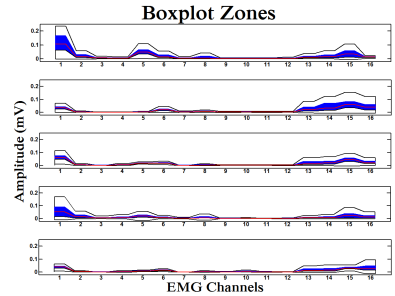

Fig. 1: Boxplot Zones visualization of different muscular co-activation patterns across sixteen (16) muscles of the upper arm and the forearm for one (1) subject performing reach to grasp movements towards five (5) different positions, to grasp a specific object (Rectanglular shaped object).

In this paper we use Random Forests for two different purposes; as a classification technique to discriminate between different muscular co-activation patterns responsible for different reach-to-grasp strategies, and as a regression technique in order to map the non-linear relationship of the myoelectric activity of the selected muscles to the human arm-hand system kinematics.

C. Visualization of Muscular Co-Activation Patterns

We use our data in order to extract and visualize muscular co-activation patterns, using the novel statistical representation method "Boxplot Zones" that we introduced.

In order to acquire more information regarding the extraction of muscular co-activation patterns and boxplots zones formation the reader should refer to [26]. Fig. 1 presents boxplot zones for different reach-to-grasp strategies expressed through different muscular co-activation patterns.
As it is shown in Fig. 1, the co-activations of muscles of the upper arm and the forearm, are significantly different between different reach-to-grasp movements (for different positions), although the same fingers and joints of the arm were involved (for different task).

In order to assess the statistical significance of muscular co-activation patterns differentiation between different subjects and reach to grasp movements towards different positions and objects placed in the same position, statistical tests were conducted. More specifically the Kruskal-Wallis and the Wilcoxon rank sum tests were performed proving that there is indeed a significant differentiation of muscular co-activation patterns between different strategies (subject, object or position-specific). Details can be found in [26].

D. Classification of Reach-to-Grasp Strategies

Synergistic profiles depicted in Fig. 1 imply a significant differentiation of muscular co-activation patterns between different reach-to-grasp strategies. We use the definition strategies to imply the selection of different movement coordination patterns to execute reach-to-grasp movements towards different objects or object positions, thus to execute different tasks. Furthermore human triggers different muscular co-activation patterns not only for reach to grasp movements towards different positions but also for different objects placed in the same position.

Thus there is a significant differentiation of the patterns not only in kinematics but also in the myoelectric activity captured from the selected muscles. In order to take advantage of this characteristic, we apply classification techniques in our dataset, in order to be able to discriminate these different reach-to-grasp strategies.

Five types of classification techniques were compared in [26], in terms of classification accuracy and training time spent; Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), a k - Nearest Neighbours (k-NN) classifier, a Support Vector Machines classifier, a Neural Network classifier and a Random Forest classifier. Random Forests classifier was proved to outperform all others in classification accuracy and achieved very good results with respect to speed of execution (better from ANN and SVM).

Furthermore we also take advantage of electromechanical delay (EMD) of a muscle (onset of the EMG signal (electrical event) precedes onset of muscle contraction (mechanical event)) that ranges from 25 to 100 ms, in order to use the majority vote criterion as described also in [26].

The majority vote criterion, classifies all the samples, of a set of N samples, in the class that was the most common between them, improving significantly the classification results. As shown in Table I and Table II, the classification results were improved by using the majority vote criterion in a sliding window of 50 samples.

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

E. Experimental and verification procedures

As far as the experimental setup is concerned three Personal Computers (PCs) were used. One of the two Linux OS based PCs had the simulated environment installed, while the other acquired the EMG signals and the position tracker measurements during the training phase. The third Windows OS based PC was used to acquire the cyberglove measurements. All PCs were connected through serial communication (RS-232) interface for synchronization purposes. 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). The position tracking system (Isotrak II, Polhemus Inc.), was connected with one of the Linux PCs through serial communication (RS-232). The size of the position sensors is 2.83 (width) x 2.29 (length) x 1.51 (height) cm.

Since the robot and the user have links with different lengths, the direct control in joint space would lead the robot's end-effector to a different position in 3D space than the desired by the user. Consequently we use the forward kinematics of the human arm to compute the user's end effector position from the estimated joint angles.

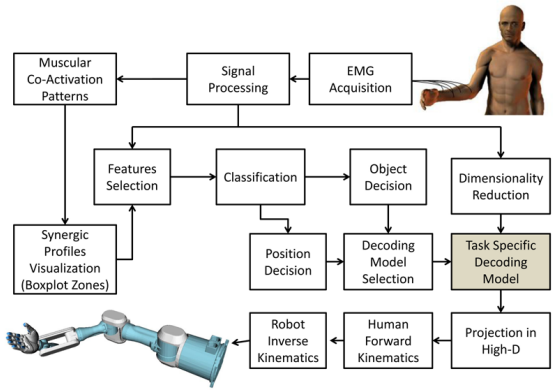

Fig. 2: Block diagram of the proposed learning scheme.

In order for the robot to be able to position its end effector at the same point in 3D space, we solve the inverse kinematics for the robot arm to drive its end effector to the same position as described in [23]. As far as the control of the remaining two DoFs of the PA10 robot arm (two (2) DoFs for the wrist) and the 15 DoFs of the robot hand is concerned, we can directly use the estimated joint angles of the human wrist and the human hand. More precisely, given the fact that each finger of the robot hand has only three DoFs (the last two joints of each robotic finger are coupled) we only use the estimated values of the 2nd joint, overriding the estimated 3rd joint values for each finger.

III. Results

In this section we present the results of the learning scheme. Random forests regression provided the best task-specific motion-estimation models, outperforming in all benchmarks the results of other previously used methods.

A. Classification results

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 strategy. 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 are the average values over the 5 rounds of the cross-validation method applied. Results of classification accuracy across different reach to grasp strategies for a specific position and different objects for Subject 1 are listed in Table I while classification accuracy across different reach to grasp strategies for a specific object and different object positions again for Subject 1 is assessed in Table II. For details regarding the classification results and how accuracy evolves over time, the reader should refer to [26].

B. Comparison of different Decoding Methods

The regression problem that we had to solve was to map using the PCA the low-d space (4 dimensions) of the myoelectric activity (EMG signals) to the low-d space (4 dimensions) of the kinematics. Then the estimated low-d kinematics were back-projected to the high-d space.

TABLE I: Classification accuracy across different reach to grasp strategies for a specific position (Pos III) and different objects for Subject 1, using Random Forests (RF) and Random Forests with Majority Vote Criterion (RF with MVC)

Methods	Objects		
	Mug	Marker	Rectangle
RF	89.92%	88.51%	86.26%
RF with MVC	100%	100%	100%

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

Positions	RF	RF with MVC
Pos I	87.03%	100%
Pos II	91.61%	100%
Pos III	90.51%	100%
Pos IV	86.25%	100%
Pos V	92.61%	100%

More specifically we performed Multiple Linear Regression (MLR), we created a State-Space model as described in [18], we performed SVM regression with RBF kernel and we contructed a single hidden layer Neural Network with ten (10) hidden units, trained with the Levenberg-Marquardt backpropagation algorithm. Finally we used Random Forests as a regression technique, growing ten (10) decision trees in order to increase computational efficiency.

As far as the estimation accuracy is concerned we compare the methods for estimating reach-to-grasp movements, towards different positions and different objects placed at the same position.

TABLE III: Comparison of different methods and estimation results, for specific position (Pos III) and specific object (Marker), for Subject 1. Average values for different validation set splittings.

Method	Arm Joints Similarity (%)	Hand Joints Similarity (%)
MLR	81.60%	84.31%
State Space	82.74%	85.10%
ANN	85.10%	86.92%
SVM	86.01%	88.90%
Random Forests	86.93%	90.42%

As it can be seen in Table III random forests outperform the performance of the most well-known regression techniques such as the Support Vector Machines (SVM) and the Artificial Neural Networks (ANN). In order to compare the different classifiers a standard PC with an Intel(R) Core(TM) I5 CPU 611 @3.33GHz was used, equipped with a 4GB RAM (DDR3) Memory. The benchmark was performed using the computing environment MATLAB (Mathworks).

As far as the training time is concerned, we also choose to compare the aforementioned models in terms of time required for training, applying the various methods to reach-to-grasp movements included in a separate dataset, that serves as a benchmark.

As it can be seen in table IV, Random Forests outperform also most other techniques, in terms of speed of execution.

C. Combined Arm-Hand System Model Results

In this subsection we present the estimation results for the Random Forests models that have been triggered by the learning scheme.

TABLE IV: Time spend for the training procedure across different methods for a specific dataset (10000 samples) that serves as a benchmark (Average Values).

Method	Time in sec.
MLR	0.0054 sec
State Space	8.65 sec
ANN	28.83 sec
SVM	27.72 sec
Random Forests	5.89 sec

Results are presented in Table V, Table VI and Table VII, where we can see that the models trained for each position or object separately, outperformed the general models built for all positions (for a marker) and all objects (placed in a specific position). We can further notice 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 positioning the end-effector is much more important than the placement of the fingers, in teleoperation studies. Table VII compares estimation accuracy of Random Forests for reach-to-grasp movements towards a specific position and object across all subjects. Fig. 3 compares the estimated user's end-effector position, versus the ground truth captured during the experiments.

In order to compute the similarity between the estimated and the captured human kinematics we use the criterion: $Similarity(\%) = 100(1 - RMS(q_c - q_e)/RMS(q_c))\%$ where RMS is defined by:

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

where q_c are the captured joint values, q_e are the estimated joint values and n is the number of samples. The similarity criterion is averaged among all different joints.

TABLE V: Estimation Results for the Random Forests based model for a specific object (Marker) across all five (5) 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 (3) 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%

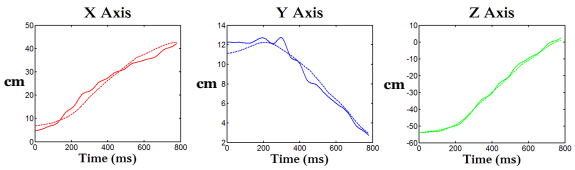

Fig. 3: End effector position estimation. Straight lines represent the captured axis values, while the dashed lines represent the estimated.

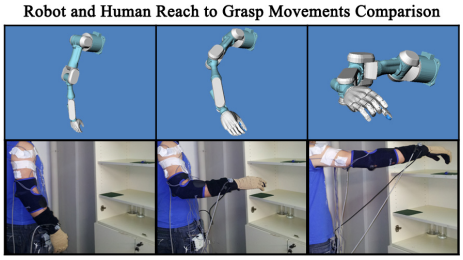

Fig. 4: Simulated paradigm of the EMG-based teleoperation.

D. Simulation

The method described above was used for the simulated EMG-based teleoperation of a robotic arm hand system. The model of the DLR HIT Hand II was used together with the model of the Mitsubishi PA-10 robot arm in the Open Robotics Automation Virtual Environment (OpenRAVE).

A real-time communication protocol supported by Matlab was used for the control of the robot arm hand system by EMG-recordings. Fig. 4 shows a comparison between the human and the teleoperated robotic arm-hand system performing reach-to-grasp movements towards a target.

IV. Conclusions and Discussion

In this paper, a learning scheme for the EMG-based teleoperation of a robotic arm-hand system in reach-to-grasp movements in 3D space, was proposed. EMG signals were used for extracting kinematic variables (i.e. joint angles) to control the anthropomorphic arm-hand system in real time.

The learning scheme helped us discriminate between different reach-to-grasp strategies while a switching mechanism triggered a strategy-task specific decoding model in order to achieve better estimation results for the discriminated task.

Following this approach we split the task-space and confront using task-specific models, the greatest problem that derives from the non-linear relationship between the EMG and the kinematics, the incompetence of general models to describe sufficiently the aforementioned relationship.

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