Relating Postural Synergies to Low-D Muscular Activations: Towards Bio-inspired Control of Robotic Hands

P. T. Katsiaris
Control Systems Lab
School of Mechanical Eng.
National Technical Univ. of Athens
Email: pkatsiar@mail.ntua.gr.

P. K. Artemiadis
Human-Oriented Robotics and Control Lab
School for Engineering of Matter, Transport and Energy
Ira A. Fulton Schools of Eng.
Arizona State University, USA
Email: panagiotis.artemiadis@asu.edu.

K. J. Kyriakopoulos
Control Systems Lab
School of Mechanical Eng.
National Technical Univ. of Athens
Email: kkyria@mail.ntua.gr.

***Abstract*—Studying human motor control has received increased attention during the past decades. Both the design and control of robotic artifacts may benefit from observation of human behavior. In this paper a novel method for capturing the dynamic behavior of the human hand is presented. The low dimensional kinematics of the human hand, including the wrist, and the low dimensional representation of the muscular activations were correlated through a linear time invariant (LTI) state space model. A linear output regulation controller was used in order to drive a simulated hand and the resulting trajectories were compared with the experimentally captured trajectories.**

I. Introduction

The development of robotic hands that resemble the human hand in terms of kinematic similarity and dexterity along with dynamically smooth behavior has been extensively pursued e.g. [1], [2], [3], [4]. The use of such hands can prove very useful in a wide repertoire of tasks, including: neuro-prosthetic devices, entertainment robots, robots that operate in hazardous environments etc. Therefore, it is of great importance to design controllers that are capable of driving these hands in such a way that the resulting movements will be as close as possible to the movements conducted by humans. Thus, studying human motor control can inspire the design of appropriate controllers.

One of the most important hypotheses regarding the control of the human hand is the notion of synergies. Synergies have been proposed as a way of describing the underlying mechanism responsible for the coordination of human hand movements. Experimental evidence indicates that the motion coordination of the fingers is characterized by co-variation patterns that reduce the number of independent degrees of freedom (DoF) to be controlled. Principal component analysis (PCA) can be applied on a dataset containing the captured kinematics of the human hand, during grasping tasks, so as for the initial data to be projected to a low dimensional space characterized by a number of elemental control variables, [5], [6]. Based on the aforementioned notion of synergies several control laws have been proposed [7], [8], [9]. In [7], an optimization algorithm, expressed on the low dimensional space spanned by a selected number of principal components, was formulated so as to drive a robotic hand to predefined contact locations on an object. The authors in [8], investigated the extent to which a hand with many DoFs can exploit postural synergies in order to control force and motion of the grasped object. In [9], the concept of synergies, called principal motion directions for the particular case, is used in order to reduce the dimension of the search space in which a probabilistic roadmap planner is defined. Finally, in [10], Filippidis et al. proposed a method for constructing Navigation Function (NF) controllers from experimental trajectories projected on the synergy space. Several other researchers have attempted to model human inter-joint coordination based on probabilistic techniques, [11], [12]. However, in none of the above studies the dynamics of motion have been taken into account.

Apart from postural synergies recent studies have proven the existence of a similar synergistic actuation of the human muscles responsible for controlling the movement of the hand, [13], [14], [15]. In most of these studies EMG signals are used in order to train models that reconstruct human hand motion based on muscular activation and focus on teleoperation scenarios.

In the present paper we propose a novel method for incorporating the dynamic behavior of the human hand, as it can be expressed through surface electromyography, in a closed loop control scheme responsible for driving a simulated hand during reach to grasp movements. Human hand motion, including the wrist, and muscular activations from a predefined set of muscles during reach to grasp movements have been recorded. PCA has been applied on both the kinematics of the human hand and EMG signals. The number of the principal components (PCs) was chosen so as to meet certain criteria regarding the proposed control methodology. In order to correlate muscular activations with kinematics a linear time invariant (LTI) state-space model has been trained, in a similar

fashion as in [16]. Finally, a state feedback controller with output regulation is used for driving the simulated hand. The rest of the paper is organized as follows: in section II the experimental setup, the techniques used for data analysis and the design of the corresponding control law are presented. The experimental validation of the proposed methodology is discussed in section III. Finally, section IV concludes the paper.

II. Materials and Methods

A. Experimental setup

There is no doubt that the human hand possesses unsurpassed dexterity and this feature can be perceived as being closely related to its structural complexity. Several models describing its kinematic structure have been proposed [17], [18]. In this paper it is modeled as being consisted of 5 fingers; the thumb, the index, the middle, the ring and the pinky, that are placed on a body, the palm.

The role of synergies during reach to grasp movements was identified by the following experiment; a subject is seated on a chair, while his trunk is holded to the chair by means of elastic straps, so as to restrain body movements. His hand was placed at the top of the table with the palm facing downwards. Objects of varying shape and size were placed on the surface of a table at a higher point than the starting hand position. The user is instructed to move his arm in order to reach and grasp the object. For each trial the starting position of the hand and the position of the object were kept the same. The grasped objects are listed in Table I. The experimental setup is presented in Fig. 1.

TABLE I
Table of Grasped Objects

Number	Object	Task
1	Tall Glass	Grasp from side to drink
2	Tall Glass	Grasp from side to move
3	Tall Glass	Grasp from top to move
4	Tall Glass	Grasp from side and rotate
5	Bottle	Grasp from side to move
6	Mouse	Grasp to slide
7	Mouse	Grasp to left click
8	Mouse	Grasp to right click
9	Cup	Grasp from side to drink
10	Cup	Grasp from side to move
11	Cup	Grasp from top to move
12	Cup	Grasp from side and rotate
13	Hammer	Grasp to use
14	Ashtray	Grasp to move
15	Pen	Grasp to move
16	Pen	Grasp to write
17	Jar Lid	Grasp from top remove the lid
18	Jar Lid	Grasp from side to move
19	Screwdriver	Grasp to use
20	Book	Grasp to look at it
21	Mobile	Grasp to look at it
22	Scissor	Grasp to move
23	Scissor	Grasp to use
24	Stapler	Grasp to use

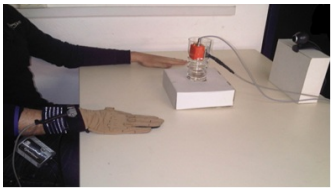

Fig. 1. A human subject before the initiation of a reach to grasp movement. The two position trackers are placed on the user's wrist joint and on the object. The human hand kinematics are captured with CyberGlove 2 motion capture glove and the IMU is placed inside the object.

In order to capture the human hand kinematics a motion capture glove and more specifically the CyberGlove 2 was used. It possesses 22 sensors; three flexion-extension sensors per finger, four adduction-abduction sensors, a palm-arch sensor, and sensors to measure wrist flexion and abduction. Each sensor's resolution is less than one degree, while 0.6 % of maximum nonlinearity is observed over the full joint range. This glove is interfaced with the PC responsible for data recording through a serial RS-232 port and offers data rates up to 90 samples/sec. The motion of the wrist in space has been recorded through the use of a magnetic position tracking system (Isotrak II, Polhemus Inc.). The particular system is equipped with two position trackers and a reference system, with respect to which, the 3D position and orientation of the trackers are provided. In order to capture the motion of the wrist with respect to the position of the object, one position tracker was placed on the user's wrist while the other one was properly attached on the object to be grasped. The reference system was placed on a solid surface above the user's shoulder. The position tracking system was connected with a PC through serial communication interface (RS-232) and provided measurements at the frequency of 60 Hz. The myo-electric activation of the muscles responsible for wrist and finger movements was captured through the Bagnoli-16 EMG system (Delsys Inc). We recorded the activation of the following 8 muscles: extensor carpi ulnaris, extensor carpi radialis, flexor carpi ulnaris, flexor carpi radialis, extensor digitorum, flexor digitorum superficialis, abductor policis longus, extensor policis brevis and flexor policis brevis. 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). Using an antialiasing finite-impulse response filter (low pass, order: 24, cutoff frequency: 100 Hz), the measurements from all sensors were resampled at a frequency of 1 kHz to be consistent with the muscle activation sampling frequency. Finally, an Inertial Measurement Unit (IMU) was attached on most of the objects, for the detection of the timing of initial contact of the hand with the object.

B. Extracting kinematic and muscular synergies

In order to extract the kinematic synergies of the human hand PCA has been applied on the captured trajectories. The central idea of PCA is to reduce the dimensionality of a data

set consisting of a large number of interrelated variables, while retaining as much as possible of the variance present in the data set. This is achieved by transforming the original dataset to a new set of variables, the principal components (PCs), which are uncorrelated, and which are ordered so that the first few retain most of the variance present in all of the original variables. For more details regarding PCA the reader should refer to [19]. Let the joint space of the human hand be described by a vector $q \in R^{22}$. Let $Q \in R^{k\times 22}$ be a matrix containing the measurements provided by the CyberGlove, where k is the number of data samples. After subtracting from each measurement the overall mean of the data set, PCA can be applied and the principal components, describing the synergies, may be extracted. The principal components appear as columns in the matrix $P \in R^{22\times 22}$ in order of decreasing component variance. Let the number of principal components, chosen to describe the corresponding space, be denoted by n_1, then the matrix $W \in R^{22\times n_1}$ may be defined. The principal component transformation of the joint space data can now be defined as:

$$\sigma = W^T q \tag{1}$$

where $\sigma \in R^{n_1}$, denotes the low dimensional representation of the human hand kinematics. In the case that the number of principal components is chosen to be equal to the dimension of the high-dimensional space and since the principal components are orthogonal then the following equality holds:

$$WW^T = I \in R^{22\times 22} \tag{2}$$

As a result for the case of $n_1 = 22$, that is to have the same number of PCs as the dimension of the original high dimensional data the transformation between the low-dimensional space and the high-dimensional space is given by:

$$q = W\sigma + q_{mean} \tag{3}$$

where $q_{mean} \in R^{22}$ denotes the mean of the original data set. Let the configuration space of the human hand be denoted by $C \subset R^{22}$ and the space spanned by the selected PCs be denoted by $S \subset R^{n_1}$. Then, matrix $W \in R^{22\times n_1}$ is a linear map from the low-dimensional synergy space to the high-dimensional configuration space of the human hand, $W : S \rightarrow C$. For the case of $n_1 < 22$, eq. (2) is not valid anymore, however, eq. (3) may still be used if principal components are perceived as vector fields. A vector field is a smooth map from configurations q to velocities $\dot{q}$. The velocities defined over the synergy space belong to the tangent bundle of the manifold defined by the principal components. Thus, $\dot{q} = W\dot{\sigma}$ and for small displacements $\delta q = W\delta\sigma$. So, locally $q = W\sigma + q_{mean}$. In the right side of the last equation the mean configuration from the whole dataset has been added. A similar explanation to the above may be found in [20]. For the case of the muscular activations let $m \in R^8$ be a vector containing the measurements provided by the bio-amplifier for a specific time instant and $M \in R^{k\times 8}$ be a matrix containing the measurements from all the trajectories conducted by the user, where k denotes the number of data samples. In a similar fashion as in the case of human hand kinematics the muscle synergies may be extracted by application of PCA. The principal component transformation of the muscular activations can now be defined as:

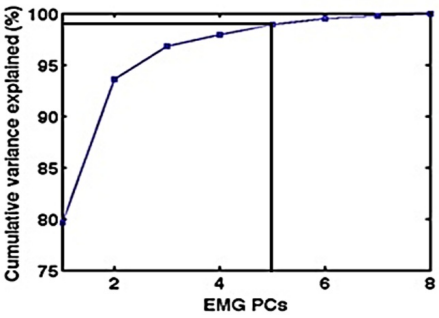

Fig. 2. The cumulative variance for the principal components extracted from the EMG signals.

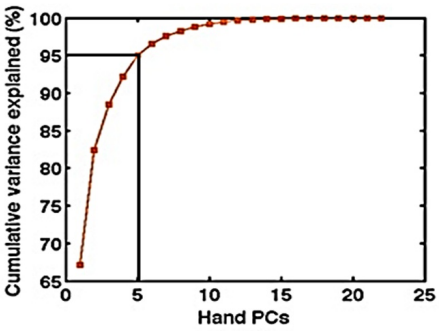

Fig. 3. The cumulative variance for the principal components extracted from the hand kinematics.

$$\xi = V^T m \tag{4}$$

where $\xi \in R^{n_2}$, denotes the low dimensional representation of the EMG signals and $V \in R^{8\times n2}$ defined over the muscular activations is the equivalent of the matrix $W \in R^{22\times n_1}$ defined over the human hand joint space. The cumulative variance for the principal components extracted from the EMG signals and the hand kinematics are depicted in Fig.2 and Fig.3 respectively. Five principal components were used for defining the low-dimensional representation of the hand data, based on the total variance they could explain (95%). Regarding EMG data, although 3 principal components could represent a large percentage of the data variance (95%), we decided to include 5 so as to match the number of the principal components describing the low dimensional kinematic space, which can facilitate the grasp planner designed later in this paper. The selected PCs defined over the low dimensional space of the muscular activations account for almost 98% of the total variance.

C. Relating muscle synergies with kinematic synergies

Most of the synergy-based controllers presented in previous research, have benefited from postural synergies either as a means of reducing dimensionality or as a feature ensuring

that human like postures will be derived from the proposed controllers, while, neglecting the dynamics of motion. In this paper, we attempt to blend synergies defined over the low-dimensional space of the muscular activations with the synergies defined over the low-dimensional space of the human hand kinematics. EMG signals contain information regarding the dynamics of the movement thus we believe that a better representation of the mechanism that is responsible for driving the human hand can be extracted by the correlation of these two, ostensibly uncorrelated, low-dimensional spaces. From a physiological point of view, a model that would describe the function of skeletal muscles in actuating the human joints would be generally a complex one. Using such a model for controlling a robot hand would be problematic. For this reason, we can adopt a more flexible decoding model in which we introduce hidden, or latent variables we call x. These hidden variables can model the unobserved, intrinsic system states, and thus facilitate the correlation between the low-dimensional muscular activations ξ and the low-dimensional kinematics σ. Since this paper focuses on driving an animated human hand and our ultimate goal is to control anthropomorphic robot hands we chose to use an LTI state-space model since dynamical systems described by this type of models can be easily controlled. Mapping of the muscular activation to low dimensional joint space can be achieved by defining a discrete time invariant state space model:

$$\begin{aligned} x_{k+1} &= Ax_k + B\xi_k \\ \sigma_k &= Cx_k \end{aligned} \tag{5}$$

where $x_k \in R^n$ is the vector of hidden states at time instant kT, $k = 1, 2, \ldots, n$, where T is the sampling period, $A \in R^{n\times n}$ is a matrix that describes the dynamic behavior of the hidden state, $B \in R^{n\times m}$ is the input matrix that relates muscle activations to the state vector, $C \in R^{m\times n}$ is the output matrix that represents the relationship between the joint space kinematics and the state vector, $\sigma \in R^m$ is the vector of low dimensional hand kinematics and $\xi \in R^m$ is the vector of low dimensional EMG signals. Model training entails the estimation of the matrices A, B and C. This is achieved through the application of an iterative search algorithm so as to minimize a quadratic prediction error criterion. Several models of order up to 12 were trained and a model of order 8 was finally chosen. As it is evident from Fig. 4 a model of order 8 efficiently captures the dynamics of the relationship between the muscular activations and the low-dimensional representation of hand motion during grasping. In other words, it essentially describes the relationship between a kinematic-synergy space and the motor synergies, as described in the muscular co-activation space. The introduction of the dynamics of the hidden state vector x introduces a dynamic aspect in the grasping synergies, which can provide significant insight in the way muscular activations and postural hand synergies are related. The latter provides an extension of the hand synergy space beyond the static representation studied in the literature so far, and can provide a significant insight on the human hand motor control.

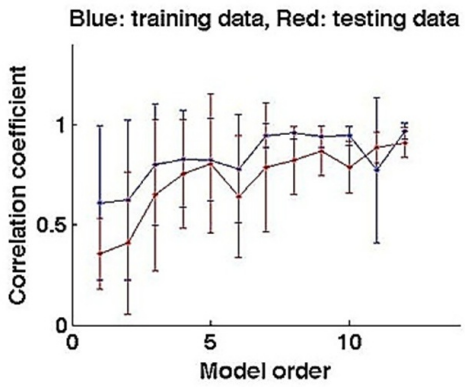

Fig. 4. The mean and standard deviation values of the correlation coefficients for both testing (red lines) and training data (blue lines).

D. Bio-inspired control of the human hand

Once the LTI state space model describing the dynamics of the human hand is trained, a *muscle level activation* controller is built. We intend to construct a controller that given a desired configuration, in the low-dimensional space, will drive a simulated hand to it's final destination following trajectories that will be similar to those conducted by the human subject. The proposed control law is a state feedback controller with output regulation. It consists of two parts; the state feedback part, which is responsible for shaping the response of the simulated system, and an input gain that ensures a zero steady-state error. The proposed controller is presented below:

$$\begin{aligned} \dot{x} &= Ax + Bu \\ y &= Cx \end{aligned} \tag{6}$$

where $x \in R^8$ is the system's state, $A \in R^{8\times 8}$, B $\in R^{8\times 5}$, $C \in R^{5\times 8}$, $y \in R^5$ is the low dimensional kinematic representation and $u \in R^5$ is the control input. It should be noted that eq. 6 is the continuous time equivalent of the model presented by eq. 5. The closed loop output regulation is of the form:

$$u = -Kx + G\sigma_d \tag{7}$$

where $\sigma_d \in R^5$ is the desired configuration and $K \in R^{5\times 8}$ is a gain matrix, appropriately selected so as to ensure that the poles $(sI - A + BK)$ of the closed loop system are effectively placed in order to guarantee stability, i.e. they lie in the left half plane, and appropriate system response. Finally the input gain matrix $G \in R^{5\times 5}$ is given by:

$$G = -\left[C\left(A - BK\right)^{-1} B\right]^{-1} \tag{8}$$

The block diagram of the proposed control law is depicted in Fig.5.

III. Results

In order to test the effectiveness of the proposed methodology, grasping simulations were conducted. For a captured trajectory the final hand configuration was extracted, it was transformed to a low dimensional configuration, and it was

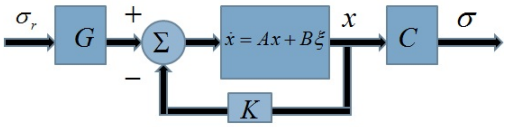

Fig. 5. The block of the proposed control law. The desired configuration is denoted by $\sigma_r \in R^5$.

used as an input to the controller. It should be noted that the pole placement was conducted once and the same control law was used in all the simulation results. The initial states of the system $x(0)$ were estimated in order for the simulated hand to start its motion from an initial posture resembling the initial posture of the subject. The simulated hand may be perceived as a virtual robotic hand that has the same dimensions and the same number of motors as the human hand. The resulting trajectory representing the motion of the robotic hand in low dimensional space is then transformed back to a high dimensional kinematic trajectory through the transformation defined in eq. 3. In Fig. 6 the low dimensional kinematics of the human subject during one grasping trial and the low dimensional kinematics that resulted from the controller previously described are depicted. From these figures it is evident that a zero steady-state error has been achieved. However, this was dictated by the fact that an input gain matrix was introduced in the proposed control law. In addition to the fact that a zero steady-state error is achieved, there is a resemblance between the resulted and the original trajectories, originated from the bio-inspired dynamics of the state space model that was used. To the best of our knowledge there is a lack in the relevant literature of a metric responsible for defining the level of anthropomorphism that is achieved by an automatically generated trajectory. To this end an additional evaluation of the generated trajectories was introduced by visually comparing the resulting discrete postures with the discrete postures followed by the human subject during a reach to grasp movement. This was achieved by using the "GraspIt!" simulation environment [21]. For two of the tasks conducted by the human subject, grasp a bottle from side and grasp a glass from top, the captured joint space trajectories were projected to the low dimensional space. The final configuration of the human hand, i.e. the configuration of the hand at the time instant that the first contact is detected through the IMU system, was used as the reference input of the controller. The generated trajectories were projected to the high dimensional space and they were used as inputs to the "GraspIt" simulator so as to drive a simulated hand. For the same objects the captured trajectories were also used as inputs to the simulator. Snapshots from both the human hand while executing the task, and the hand controlled by the aforementioned controller, are shown in Fig.7, Fig.8, Fig.9 and Fig.10. It should be noted that in these simulations the movement of the human hand is synchronized with the captured movement of the human arm.

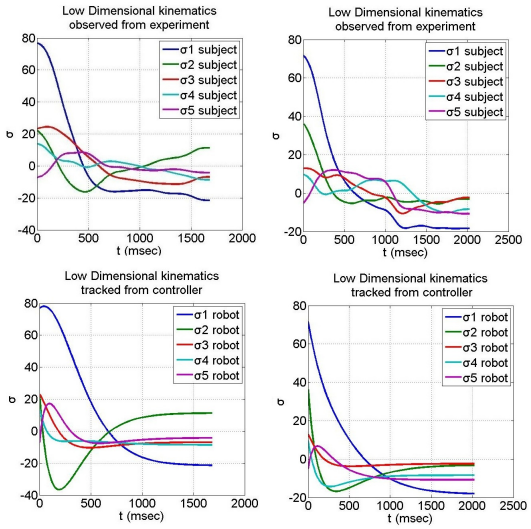

Fig. 6. The experimental trajectory, captured during reach to grasp a bottle is depicted on the top left figure, this trial is the fifth one depicted in Table I. On the bottom left figure the equivalent trajectory generated by the controller is depicted. Equivalently the experimental trajectory, captured during reach to grasp a glass from top is depicted on the top right figure, this trial is the third one depicted in Table I. On the bottom right figure the equivalent trajectory generated by the controller is depicted.

Fig. 7. On the top figure snapshots of the trajectory conducted by the human during grasping a glass are depicted. On the bottom figure snapshots of the simulated hand following the trajectory generated by the proposed control law during grasping a glass are depicted. In this figure the side view of the grasping experiments is depicted.

IV. Conclusions and Future Directions

The dexterity of the human hand, its mechanics and the coordination of the fingers have always acted as inspiration for the design and control of robotic hands. One of the most important hypothesis regarding the motor control of the human hand is the notion of synergies. Recently, synergies have received increased attention among the robotics community. This attention is attributed to the fact that synergies not only describe efficiently the coordination of the human fingers but they also introduce a reduction in the high dimensionality of the human hand joint space. Most of the previous studies in this field have benefited from a static representation of the hand synergy space.

In this paper a novel method for capturing the dynamic behavior of the human hand is presented. The low dimensional kinematics of the human hand, including the wrist, and the low dimensional representation of the muscular activations

Fig. 8. On the top figure snapshots of the trajectory conducted by the human during grasping a glass are depicted. On the bottom figure snapshots of the simulated hand following the trajectory generated by the proposed control law during grasping a glass are depicted. In this figure the top view of the grasping experiments is depicted.

Fig. 9. On the top figure snapshots of the trajectory conducted by the human during grasping a bottle are depicted. On the bottom figure snapshots of the simulated hand following the trajectory generated by the proposed control law during grasping a bottle are depicted. In this figure the side view of the grasping experiments is depicted.

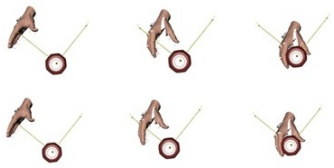

Fig. 10. On the top figure snapshots of the trajectory conducted by the human during grasping a bottle are depicted. On the bottom figure snapshots of the simulated hand following the trajectory generated by the proposed control law during grasping a bottle are depicted. In this figure the top view of the grasping experiments is depicted.

were correlated through a LTI state space model. A linear output regulation controller was used in order to drive a simulated hand and the resulting trajectories were compared with the experimentally captured trajectories. In addition to that, simulations using the "GraspIt" simulation environment were conducted so as to verify the effectiveness of the proposed methodology.

Future work involves the development of a methodology responsible for mapping the generated trajectories to robotic hands that are different for the human hand, i.e. they have different geometric characteristics and possess a different number of actuators. Additionally, the possibility of placing the poles of the closed loop system following optimality principles will be investigated.

V. Acknowledgement

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.

References

[1] S.C. Jacobsen, J.E. Wood, D.F. Knutti, and K.B. Biggers. "The utah/m.i.t. dextrous hand: Work in progress", International Journal of Robotics Reasearch, 3(4):2150, 1984.

[2] K.J. Kyriakopoulos, J. Van Riper, A. Zink, and H.E. Stephanou. "Kinematic analysis and position/force control of the anthrobot dextrous hand", Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on, 27(1):95 104, feb 1997.

[3] H. Liu, K. Wu, P. Meusel, N. Seitz, G. Hirzinger, M. H. Jin, Y. W. Liu, S. W. Fan, T. Lan, Z. P. Chen, "Multisensory five-finger dexterous hand: The DLR/HIT Hand II", In Intelligent Robots and Systems (IROS), 2008 IEEE/RSJ International Conference on, pages 3692 - 3697 , oct. 2010.

[4] Shadow Robot Company, "Design of a dextrous hand for advanced clawar applications", In Proc. of the Climbing and Walking Robots and the Supporting Technologies for Mobile Machines: CLAWAR, pages 691698, 2003.

[5] M. Santello, M. Flanders, and J. F. Soechting, "Postural hand synergies for tool use", J. Neurosci., vol. 18, no. 23, pp. 10 105-10 115, December 1998.

[6] E. Todorov, Z. Ghahramani, "Analysis of the synergies underlying complex hand manipulation", EMBS 2004. Conference Proceedings. 26th Annual International Conference of the, Vol. 2 (2004), pp. 4637-4640 Vol.6.

[7] M.T. Ciocarlie and P.K. Allen, "Hand posture subspaces for dexterous robotic grasping", The International Journal of Robotics Research, 28(7):851867, 2009.

[8] M. Gabiccini, A. Bicchi, D. Prattichizzo, and M. Malvezzi, "On the Role of Hand Synergies in the Optimal Choice of Grasping Forces", Autonomous Robots [special issue on RSS2010], 31(2 - 3):235 - 252, 2011.

[9] J. Rosell, R. Suarez, C. Rosales, and A. Prez, "Autonomous motion planning of a hand-arm robotic system based on captured human-like hand postures", Autonomous Robots, 31:87102, 2011. 10.1007/s10514-011-9232-5.

[10] Ioannis Filippidis, Kostas J. Kyriakopoulos and Panagiotis K. Artemiadis, "Navigation Functions Learning from Experiments: Application to Anthropomorphic Grasping", IEEE International Conference on Robotics and Automation, St. Paul, Minnesota, USA, 2012 (ICRA 2012 - to appear).

[11] Ashwini Shukla, Aude Billard, "Coupled dynamical system based arm-hand grasping model for learning fast adaptation strategies", Robotics and Autonomous Systems 60(3): 424-440 (2012).

[12] D. Song, C.H. Ek, K. Huebner, and D. Kragic, "Multivariate discretization for bayesian network structure learning in robot grasping", In Robotics and Automation (ICRA), 2011 IEEE International Conference on, pages 1944 1950, may 2011.

[13] A. dAvella, P. Saltiel, E. Bizzi E, "Combinations of muscle synergies in the construction of a natural motor behavior", *Nature Neuroscience*, 2003, 6(3):300-308.

[14] C. Castellini and P. van der Smagt, "Preliminary evidence of dynamic muscular synergies in human grasping", *International Conference on Advanced Robotics (ICAR)*, pp. 28-33, 2011.

[15] M. V. Liarokapis, P. K. Artemiadis, P. T. Katsiaris and K. J. Kyriakopoulos, "Learning Task-Specific Models for Reach to Grasp Movements: Towards EMG-based Teleoperation of Robotic Arm-Hand Systems", 4th IEEE RAS EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob), 2012.

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

[17] Esteban Pena Pitarch, "Virtual Human Hand: Grasping Strategy and Simulation", Academic Thesis, Universitat Politecnica de Catalunya, October 2007.

[18] Georg Stillfried and Patrick van der Smagt, "Movement model of a human hand based on magnetic resonance imaging (MRI)", *International Conference on Applied Bionics and Biomechanics, ICABB*, 2010.

[19] I.T. Jolliffe, "Principal Component Analysis", Springer, 2nd edition, 2002.

[20] D. Prattichizzo, M. Malvezzi, A. Bicchi, "On motion and force controllability of grasping hands with postural synergies", In Robotics: Science and Systems VI, pp. 49-56, The MIT Press, Zaragoza, Spain, June 2010.

[21] Andrew Miller and Peter K. Allen, "Graspit!: A Versatile Simulator for Robotic Grasping", IEEE Robotics and Automation Magazine, V. 11, No.4, Dec. 2004, pp. 110-122.