Postural Synergies and Neural Network for Autonomous Grasping: a Tool for Dextrous Prosthetic and Robotic Hands

Fanny Ficuciello, Gianluca Palli, Claudio Melchiorri, Bruno Siciliano

***Abstract*— In this paper, a neural network model has been designed for planning grasps of a cybernetic hand prototype by means of postural synergies. The synergies subspace is derived by means of a joint-to-joint mapping from a human hand set of grasps. A library of motor primitives of the hand in a synergy-based rendering has been built for a number of selected objects and tasks. The requirement of the task in a simplified approach is specified by the type of grasp, such as precision or power. A feedforward neural network has been trained using the grasping data from the library and running the Levenberg-Marquadt algorithm. By combining postural synergies and neural network the nonlinear relationship between the object geometric features and the hand configuration during grasping can be easily found with a good approximation. The experiments have been performed on the DEXMART hand prototype and the results demonstrate that integration of postural synergies and neural network is a promising tool toward simplified and autonomous grasping for artificial hands, such as anthropomorphic robotic hands and prostheses.**

I. INTRODUCTION

Artificial hands for robotics and prosthetics, require enhanced manipulation skills to reproduce human's abilities. This calls for the design of complex dexterous hands with advanced sensorimotor skills and human-like kinematics [1]. The augmented anthropomorphism and consequently the high multiple Degrees-of-Freedom (DoFs) leads to an increased complexity of control algorithms and, about prostheses, also of the communication interface between the user and the machine.

As a matter of fact, the undergoing research in the field aims at the reproduction of human abilities not only by means of anthropomorphic design but also by the adoption of human-inspired control strategies. Neuroscience and robotics have shown that imitating human prehension is a promising way to simplify and improve grasp planning and control issues related to high DoFs devices. Preliminary studies on the human hand point out that the combination of tendon coupling and muscle activation patterns exhibited by humans leads to significant joint coupling and inter-finger coordination, or, in other words, to postural synergies, that are evidence of simplified control schemes occurring at neurological level for the organization of the hand movements [2]. Hand prostheses with high DoFs requires too many independent control signals with complex EMG signals processing and demanding training by the user. Otherwise, a smart control algorithm and an autonomous controller including a large number of sensors are required. For this reason hand prostheses currently available on the market still work as simple hands [3] or as multi-fingered hand where all fingers open and close simultaneously with one or two DoFs [4]. Indeed, despite the poor dexterity, the device has a simple interface with the patient and simplified control strategies based on few EMG input [5], [6]. To improve dexterity and anthropomorphism, higher technology [7], [8] is required in terms of design, sensors and actuation. Moreover, new control strategies for intelligent automatic control are needed to improve performance and diminish the burden of user's training [9], [10].

Fig. 1. Main representative grasps mapped from the reference set of human hand postures on the DEXMART Hand prototype for the computation of postural synergies.

The complexity of planning and control concerns not only the hand prostheses but, more generally, all the robotic hands with high DoFs. Therefore, it is desirable to find strategies allowing simplification of these tasks. Postural synergies, inherited from neuroscience research on the human hand, are a useful tool for control and grasp synthesis simplification of anthropomorphic artificial hands. In [11], [12], [13] the authors extend the concept of postural synergies to robotic hands showing how a similar dimensionality reduction can be used to derive comprehensive planning and control algorithms that produce stable grasps for a number of different robot hand models. Synergies have been used to solve the

Fanny Ficuciello and Bruno Siciliano are with Dipartimento di Informatica e Sistemistica, Università degli Studi di Napoli Federico II, 80125 Napoli, Italy, (email: {fanny.ficuciello, bruno.siciliano}@unina.it).

Gianluca Palli and Claudio Melchiorri are with Dipartimento di Elettronica, Informatica e Sistemistica, Alma Mater Studiorum Università di Bologna, 40136 Bologna, Italy, (email: {gianluca.palli, claudio.melchiorri}@unibo.it).

dimensionality reduction problem in control and coordination of a 16-DoFs underactuated prosthetic hand prototype (CyberHand), in order to perform the three prehensile forms mostly used in activities of daily living [14].

In order to apply a synergy-based control it is necessary to plan the proper weights of the synergies corresponding to the geometrical characteristics of the object and to the task. The relationship between the weights of the synergies and the object is nonlinear and is hard to obtain in a closed form. The use of neural networks allows approximating this relationship. Recently, transferring grasps capabilities from the human hand to the robotic hand has been addressed using neural networks. In [15] three synergies from data on human grasping experiments have been extracted and mapped to a robotic hand. Then a neural network with the features of the objects and the coefficients of the synergies has been trained and employed to control robot grasping. Neural networks have been utilized also in other works in order to simulate temporal coordination of human reaching and grasping. In [16] the neural network model includes a synergistic control of the whole fingers during prehension and the design of a library of hand gestures.

In [17] and [18], postural synergies of the first DEXMART Hand prototype, the UB Hand IV, have been used for human-inspired control solutions. In this work, neural networks have been integrated to allow synergy-based grasp planning relying only on object geometric features and task requirements avoiding direct mapping of the grasps from the human hand. All the experiments are conducted on the last prototype of the DEXMART Hand, and thus the procedure to compute the synergies subspace in [18] is repeated for the new prototype.

II. MATERIAL AND METHODS

A. The DEXMART Hand

The experiments have been conducted on the last prototype of the DEXMART Hand [19] provided with an improved kinematics with respect to the UB Hand IV [20] (previous prototype). The new kinematics is adopted in the final version of the robotic hand. Is worth underlining that the other design features remain the same and neither of the two prototypes is equipped with sensors. Therefore, the same tendon-kinematics, static and dynamic analysis conducted on the UB Hand IV are still applied and are briefly described in this section. Further details can be found in [20].

The DEXMART Hand is an innovative anthropomorphic hand developed within the DEXMART project [21]. To the end of the maximum design simplification and reduction of the device's cost production and development, the hand has been conceived by taking into account the following driving issues:

- The hand mechanics is based on an endoskeletal structure articulated by means of pin joints integrated into the phalanx body simply consisting in a plastic shaft which slides on a cylindrical surface [22], [23], [24].
- Remotely located actuators with tendon-based transmissions routed by sliding paths (*sliding tendons*) [25] have been adopted for the joints actuation.
- A purposefully designed soft cover mimicking the human skin [26], [27] has been introduced for improving the grasping capabilities of the hand.
- The mechanical structure of the hand has been manufactured adopting additive technologies (Fused Deposition Manufacturing).

The kinematics of the hand aim at a human-like manipulation capabilities and mobility. For this purpose, in the new design the kinematics of the fingers has been differentiated and provided with different joint limits. In particular, the main change regards the kinematics of the thumb: the adduction/abduction base joint and the first flexion joint have been inverted in the kinematic chain order. Thus, the new kinematics is designed to improve the functionality, allowing the opposition of the thumb with the other four fingers.

Taking inspiration from the biological model and in order to reduce the complexity of the hand control, an internal non-actuated (passive) tendon has been introduced to couple the movements of the last two joints of each finger, i.e. the medial and the distal joint. Only three angles are considered for the index, the middle, the ring and the little finger, i.e. the base (adduction/abduction) angle θ_{1f}, the proximal angle θ_{2f} and the medial angle θ_{3f}. About the thumb, the angles are in the sequence: the base (proximal angle) angle θ_{1t}, the adduction/abduction angle θ_{2t} and the medial angle θ_{3t}. Therefore, a total amount of $h = 15$ joint angles is needed to describe the robotic hand configuration. The joint angles ranges for each finger are mechanically constrained by stroke limiters within the intervals:

$$\theta_{1f} \in [-15,\, 15], \quad \theta_{2f} \in [0,\, 90], \quad \theta_{3f} \in [0,\, 110] \quad \text{[deg]} \tag{1}$$

and for the thumb within the intervals:

$$\theta_{1t} \in [0,\, 90], \quad \theta_{2t} \in [0,\, 60], \quad \theta_{3t} \in [0,\, 90] \quad \text{[deg]}. \tag{2}$$

The hand controller developed in the Matlab/Simulink environment is based on the RTAI-Linux realtime operating system. The Matlab Realtime Workshop toolbox has been used for the automatic generation of the real-time application of the UB Hand IV controller. The user interface to the real-time application has been implemented by means of the Simulink External Mode capabilities, for which the RTAI-Linux support has been purposely developed.

B. Human Grasp Mapping and Dimensionality Reduction

A reference set of 36 human hand postures has been selected on the basis of the taxonomy in [28]. Each human hand posture has been mapped to the robotic hand, see Fig. 5, using a joint to joint mapping as in [17] and [18]. Thus, as in our previous works, using Principal Component Analysis (PCA) the kinematic patterns of the first three synergies are obtained for the new kinematics and analyzed. Once the matrix $\mathbf{C} = \{\mathbf{c}_i \mid i = 1, \ldots, 36\}$ of the DEXMART Hand prototype configurations has been built, the vector $\bar{\mathbf{c}}$ representing the mean hand position in the grasp configurations space (the zero-offset position) and the matrix $\mathbf{F} = \{\mathbf{c}_i - \bar{\mathbf{c}} \mid i = 1, \ldots, 36\}$ of the grasp offsets with respect

to the mean configuration have been computed. The PCA has then been performed on the matrix $\mathbf{F}$ and a base matrix $\mathbf{E} = \{\mathbf{e}_1\ \mathbf{e}_2\ \mathbf{e}_3\}$ of the postural synergies subspace has been found by selecting the three predominant components form the PCA.

C. Neural Network Model and Motor Primitives Library

Neural networks are introduced to confer autonomy to the synergy-based method for planning and control grasping tasks. The neural network has been implemented in MatLab using the Neural Network Toolbox (NN Toolbox) [29]. The objective is to approximate the nonlinear relationship between the object geometric features and the hand configuration during grasping. A feedforward neural network is able to approximate with arbitrary precision any function having a finite number of discontinuities, if a sufficient number of internal neurons is considered [30].

From a proper evaluation of the task and training patterns, the network model has been chosen as a feedforward with a non linear hidden layer and five internal neurons. The network receives as input three parameters: diameter, height of the object and the binary input that identifies the type of the grasp. The outputs are the three weights of the synergies (Fig. 2).

In order to train the neural network, twelve spherical objects and twelve cylindrical objects of different size have been considered as training patterns. The diameters of the spheres are included in a range between 2 [cm] and 9,3 [cm]. The cylinders are chosen with the same height of 20 [cm] and with diameters included in a range between 2 [cm] and 9,3 [cm]. Since the input patterns must have all the same dimensionality, for the spheres, the height equal to the diameter has been introduced as the second parameter. Furthermore, the cylinders have been chosen with the same height equal to 20 [cm], greater than the extension of the palm, in such a way that all the fingers can be placed on the lateral surface of the object.

For each object, the joint configuration of the hand prototype corresponding to power and precision grasps have been obtained using joint to joint mapping. Thus, the weights of the first three synergies corresponding to each configuration have been obtained by projection in the synergies subspace. The neural network has then been trained using the synergy weights, in the form of 3×1 vector, representing the desired responses (targets) to the input patterns, that are the object geometric features and the specified task. Indeed, since the synergy weights varies according to the type of the grasp, an additional binary input has been introduced. The binary signal assumes unitary value for a precision grasp and zero value for power grasp.

The normalization and the distribution of patterns among training, validation and test set for the training procedure are retrieved by default from the NN Matlab Toolbox. When running the training function, the network initializes the weights and the bias randomly according to the rule of Nguyen-Widrow, and performs the training algorithm Levenberg-Marquadt, which is a numerical optimization of

Fig. 2. Schematic representation of the trained neural network.

the Back-propagation classic algorithm. The three subsets were formed randomly extracting patterns from the total set with the following percentages: 70% for the training set, 15% for the validation set and 15% for the test set.

III. RESULTS

In this section the results obtained using a neural network model in a synergy-based framework are reported. First of all, the synergies subspace computed for the DEXMART Hand prototype is described and assessments on the kinematic patterns of the first three synergies are provided. Once the training and validation has been performed using NN Toolbox of Matlab, the network has been tested to verify its generalization ability in synthesizing new object grasps.

A. Kinematic Patterns of the three Predominant Synergies

The synergies subspace of the DEXMART hand prototype is derived using the method described in [18] by means of the joint-to-joint mapping.

Only the first three synergies are analyzed since they are used to control the hand in order to perform a given grasp. From the experimental results in [18] it is expected that a control strategy that uses these synergies for robot hand motion allows obtaining very good grasping performance in a configuration space of highly reduced dimensions with respect to the DoFs of the robotic hand itself.

The three synergies are described with the aid of appropriate graphical tools, circular graphs, for the representation of the postural synergy vectors $\mathbf{e}_1$, $\mathbf{e}_2$ and $\mathbf{e}_3$ with the purpose of identify the joints whose rotations are more involved in each synergy.

1) First Synergy: With reference to the first postural synergy $\mathbf{e}_1$ (Fig. 3), in the minimum configuration the proximal and medial flexion joint angles of all the fingers are all almost zero and increase their value during the motion toward the maximum configuration. The adduction/abduction movements of the four fingers are not very involved in this synergy.

Fig. 3. On the left, the circular graphs referred to the first synergy is represented. The adduction/abduction, proximal and medial flexion joints are indicated from 1 to 3 for the thumb, from 4 to 6 for the index finger, from 7 to 9 for the middle finger, from 10 to 12 for the ring finger and finally from 13 to 15 for the little finger. On the right, frontal and lateral view of the first postural synergy in the minimum and the maximum configuration, from left to right, are depicted.

2) Second Synergy: The second postural synergy $\mathbf{e}_2$ (Fig. 4) is characterized by a movement in opposite directions of the proximal and medial flexion joints. The adduction/abduction movements of the four fingers are not very involved also in this synergy.

Fig. 4. On the left, the graphs referred to the second synergy is represented. On the right, frontal and lateral view of the second postural synergy in the minimum and the maximum configuration, from left to right, are depicted.

3) Third Synergy: In the third postural synergy $\mathbf{e}_3$ (Fig. 5) the movement involves especially the index and the thumb. The movement of adduction/abduction of the thumb and of the index increases with respect to the first two synergies.It is easy to observe how the adduction/abduction thumb joint motion (joint #1 in Fig. 5) is more involved in the third synergy rather than in the first two. This characteristic is important for correct index/thumb opposition that allows increasing the grasp accuracy, and thus achieving more stable grasps. This justifies the use of three predominant synergies for the hand control in order to improve the grasp performance, especially for precision grasps and intermediate side grasps, where the position of the thumb and of the index is crucial. In fact, the first two synergies take into account the 70% of the total variance of the data compared to 80% of the first three.

B. Neural Network Grasp Synthesis

Once the neural network has been trained and validated, the synthesis of new object grasps have been investigated to test its ability. A set of cylindrical and spherical objects of intermediate size, compared to the objects of the training set,

Fig. 5. On the left, the graphs referred to the third synergy is represented. On the right, frontal and lateral view of the third postural synergy in the minimum and the maximum configuration, from left to right, are depicted.

were considered. In detail we have considered two cylindrical objects and two circular objects, in both power and precision tasks, for a total amount of 8 grasps. The synergies weights, output of the neural networks, have been then used in the control algorithm developed in [31]. In Fig. 6 the image of the grasps executed by the robotic hand according to the synergy-based control strategy are depicted. The synergies weight utilized in the control strategy is the output of the neural network corresponding to the geometric features of the object and task specification. We can observe that the robotic hand is configured in a satisfactory manner for each type of object and grasp. In order to quantitatively assess the performance of the neural network we have mapped the eight grasps on the robotic hand using the joint to joint mapping technique. The obtained configurations have been compared with the ones synthesized by the neural network. The vector $\mathbf{c}_i$ represents the configuration corresponding to the object i mapped on the robotic hand using the joint to joint mapping technique. The vector $\mathbf{c}_i^n$ represent the corresponding configuration synthesized by the neural network. The average of the joint errors is computed using the Euclidean norm as follows

$$e = \frac{\|\mathbf{c}_i - \mathbf{c}_i^n\|}{15} \tag{3}$$

and is reported in Tab. I for each object. The errors are represented in the table fulfilling the same order of the object in Fig. 6. The values of the table are of the order of few degrees, therefore, they attest a good ability of the neural network model in synthesizing new grasps.

TABLE I

AVERAGE JOINT ANGLE ERRORS ON THE SYNTHESIZED GRASPS

Grasp Type	Average joint angle errors (in degrees)			
Precision Grasps	2,19	1,26	2,22	2,02
Power Grasps	2,90	1,94	2,03	1,93

C. Synergistic Control

The synergy based control strategy used to execute the grasps in Fig. 6 is here briefly detailed. We have tested the goodness of the neural network grasp synthesis by applying a reach to grasp control algorithm as in previous work

[31], using in the final grasping configuration the synergies weights output of the network model. The first three postural synergies have been used to control the hand in order to perform selected grasps. A generic hand grasp posture $\mathbf{c}_i$ can be approximated, by a suitable selection of the postural synergy weights $[\alpha_1\ \alpha_2\ \alpha_3]^T \in \mathbb{R}^3$, as the projection $\hat{\mathbf{c}}_i$ on the postural synergies subspace

$$\hat{\mathbf{c}}_i = \bar{\mathbf{c}} + \mathbf{E} \begin{bmatrix} \alpha_{1,i} \\ \alpha_{2,i} \\ \alpha_{3,i} \end{bmatrix}. \tag{4}$$

In [18] the value of the three eigenpostures weights $[\alpha_1\ \alpha_2\ \alpha_3]^T$ are computed from the desired grasp posture as

$$\begin{bmatrix} \alpha_{1,i} \\ \alpha_{2,i} \\ \alpha_{3,i} \end{bmatrix} = \mathbf{E}^{\dagger} \left(\mathbf{c}_i - \bar{\mathbf{c}} \right) \tag{5}$$

where $\mathbf{E}^{\dagger}$ is the Moore-Penrose pseudo-inverse of the base matrix $\mathbf{E}$. It goes without saying that, in order to use this synergy-based control strategy, it is necessary to know the hand configuration in the joint space that we want to perform. This implies the passage through the configuration space by means of a mapping algorithm, and thus it nullifies the usefulness of a reduced dimensionality representation of the configuration space. Therefore, the utility of neural networks consists of substituting the mapping algorithm and obtaining the weights directly from the features of the object. It is straightforward to note that the motions shown in Fig. 3, 4 and 5, derived by considering separately the three synergies, are obtained from (4) by assuming $\alpha_2 = 0$ and $\alpha_3 = 0$ for the first synergy, $\alpha_1 = 0$ and $\alpha_3 = 0$ for the second synergy and finally $\alpha_1 = 0$ and $\alpha_2 = 0$ for the third synergy. The temporal value of the weights α_1, α_2, α_3 during grasp operations has to be chosen in such a way that, starting from the zero-offset position $\bar{\mathbf{c}}$ (i.e. $\alpha_1 = \alpha_2 = \alpha_3 = 0$), the hand opens during the reach in preparation for object grasp, and then closes reaching a suitable shape determined from neural network output. In the open-hand configuration, namely $\mathbf{c}_0$, all the flexion joint angles are close to zero, and the corresponding values of α_1, α_2 and α_3 can be determined from (5) by posing $\mathbf{c}_i = \mathbf{c}_0$. The intermediate values of the synergy weights have been determined by assuming a suitable time interval for the grasp operation (six seconds for the whole reach to grasp phase, three seconds for both the opening and closing phases) and by linear interpolation of the α_1, α_2 and α_3 values in the three reference configurations $\{\bar{\mathbf{c}},\ \hat{\mathbf{c}}_0,\ \hat{\mathbf{c}}_i\}$.

IV. DISCUSSION AND CONCLUSIONS

In this work, the integration of postural synergies with neural networks been carried by means of experiments on the last prototype of the DEXMART Hand. The DEXMART Hand is an anthropomorphic hand implemented with transmission tendons, very similar to the human hand in functionality and aesthetics. Thus, the prototype can be considered as a platform appropriate for both robotic and prosthetic hand control studies and developments. Relying on a previous work carried out on the UB Hand IV, the postural synergies subspace of the DEXMART Hand prototype has been computed. Thanks to the use of a neural network the postural synergies represent a valuable tool for the simplification of grasp control and planning for anthropomorphic robotic hands with many DoFs.

Fig. 6. Synthesized grasps by means of postural synergies and the neural network. On the top of the figure are represented precision grasps, while power grasps are represented on the bottom.

In fact, using a control strategy based on the first three synergies, the 80% dimensionality reduction of the configuration space is obtained, compared with a loss of data variance of 20%. The use of artificial neural networks can further simplify the problem of planning and control, since it allows correlating the weights of the synergies directly to the features of the object and to the required grasp type. The average of the joint errors for each of the select objects, computed in (3) and reported in Tab. I, is small enough to confirm the efficiency of the neural network in synthesizing new object grasps. The network takes the desired task as input by means of a binary signal that specifies among power and precision grasp. The experiments demonstrate that the output of the network provides synergies weights that correctly produce the desired type of grasp distinguishing among precision and power. About circular objects, the network is also able to correctly decide for the number of fingers involved in the grasp on the basis of its radius.

In conclusion, the use of synergies and neural networks allows planning and executing grasps of a wide variety of objects used in the Activities of Daily Living with a reduced number of control signals. This is an obvious advantage both from a computational and algorithmic point of view. This characteristic can be useful in prosthetic application, since a reduced number of electro-myographic signals are present in an amputee subject compared to a healthy subject. Thereby, it is possible to develop a dexterous device with a good compromise between high technology and performance. In fact, using synergies, with a reduced number of signals it is possible to obtain a behavior of the artificial hand very similar to that of the human hand both in terms of performance and of motion behavior. Furthermore, the use of a small number of electro-myographic signals does not imply a high effort by the patient and long periods of training. Even in the case of robotic hand the advantage is to obtain high performance and reduced complexity for planning and

control of a device with a high number of DoFs.

Future works will focus on improve the autonomy and efficiency of the planning and control strategy. The method for deriving synergies can be improved considering a wider set of grasps and using different mapping methods for synergies subspace derivation. A vision sensor will be used to synthesize grasping in real-time using on-line training of the neural network to improve efficiency, generalization and enhance autonomous grasp synthesis. New experiments will involve also more complex tasks and objects shape.

REFERENCES

[1] A. Bicchi, "Hands for dexterous manipulation and robust grasping: a difficult road toward simplicity," *IEEE Transactions on Robotics and Automation*, vol. 16, no. 6, pp. 652–662, 2000.

[2] M. Santello, M. Flanders, and J. Soechting, "Postural hand synergies for tool use," *Journal of Neuroscience*, vol. 18, no. 23, pp. 10 105–10 115, 1998.

[3] D. OttoBock HealthCare. Duderstdat, http://www.ottobock.com.

[4] U. Touch EMAS Ltd. Edinburgh, http://www.touchbionics.com.

[5] M. Zecca, S. Micera, M. Carrozza, and P. Dario, "Control of multifunctional prosthetic hands by processing the electromyographic signal," *Critical Reviews in Biomedical Engineering*, vol. 30, no. 4-6, pp. 459–485, 2002.

[6] P. Perker, K. Englehart, and B. Hudgins, "Myoelectric signal processing for control of powered limb prostheses," *Journal of Electromyography and Kinesiology*, vol. 16, no. 6, pp. 541–548, 2006.

[7] S. Shulz, C. Pylatiuk, M. Reischl, L. Martin, R. Mikut, and G. Bretthauer, "A hydraulically driven multifunctional prosthetic hand," *Robotica*, vol. 23, no. 3, pp. 293–299, 2005.

[8] C. Cipriani, M. Controzzi, and M. Carrozza, "Objectives, criteria and methods for the design of the smarthand transradial prosthesis," *Robotica*, vol. 28, no. 6, pp. 293–299, 2009.

[9] V. Tenore, A. Ramos, A. Fahmy, S. Acharya, R. Etienne-Cummings, and N. Thakor, "Decoding of individuated finger movements using surface electromyography," *IEEE Transactions on Biomedical Engineering*, vol. 56, no. 5, pp. 1427–1434, 2009.

[10] C. Cipriani, F. Zaccone, S. Micera, and M. Carrozza, "On the shared control of an EMG-controlled prosthetic hand: analysis of user-prosthesis interaction." *IEEE Transactions on Robotics*, vol. 24, no. 1, pp. 170–184, 2008.

[11] M. Ciocarlie, C. Goldfeder, and P. Allen, "Dimensionality reduction for hand-independent dexterous robotic grasping," in *Proc. IEEE/RSJ International Conference on Intelligent Robots and Systems*, San Diego, 2007, pp. 3270–3275.

[12] M. Ciocarlie and P. Allen, "Hand posture subspaces for dexterous robotic grasping," *International Journal of Robotics Research*, vol. 28, no. 7, pp. 851–867, 2009.

[13] ——, "On-line interactive dexterous grasping," in *Proc. 6th International Conference on Haptics: Perception, Devices and Scenarios*, Madrid, 2008, pp. 104–113.

[14] G. Matrone, C. Cipriani, E. Secco, G. Magenes, and M. Carrozza, "Principal components analysis based control of a multi-dof underactuated prosthetic hand," *Journal of NeuroEngineering and Rehabilitation*, vol. 7, no. 16, pp. 1–16, 2010.

[15] T. Geng, M. Lee, and M. Hulse, "Transferring human grasping synergies to a robot," *Mechatronics*, vol. 21, no. 1, pp. 272–284, 2011.

[16] J. Vilaplana and J. Coronado, "A neural network model for coordination of hand gesture during reach to grasp," *Neural Networks*, vol. 19, no. 1, pp. 12–30, 2006.

[17] F. Ficuciello, G. Palli, C. Melchiorri, and B. Siciliano, "Experimental evaluation of postural synergies during reach to grasp with the UB Hand IV," in *Proc. IEEE/RSJ International Conference on Intelligent Robots and Systems*, San Francisco, 2011, pp. 1775–1780.

[18] ——, "Planning and control during reach to grasp using the three predominant ub hand iv postural synergies," in *Proc. IEEE International Conference on Robotics and Automation*, Saint Paul, MN, 2012, pp. 1775–1780.

[19] G. Palli, C. Melchiorri, G. Vassura, G. Berselli, S. Pirozzi, C. Natale, G. De Maria, and C. May, *Advanced Bimanual Manipulation*, B. Siciliano ed., ser. Springer Tracts in Advanced Robotics. Sringer, 2012, vol. 80, ch. Innovative Technologies for the Next Generation of Robotic Hands, pp. 173–218.

[20] G. Borghesan, G. Palli, and C. Melchiorri, "Design of tendon-driven robotic fingers: Modelling and control issues," in *Proc. IEEE International Conference on Robotics and Automation*, Anchorage, 2010, pp. 793–798.

[21] DEXMART Project website, http://www.dexmart.eu/.

[22] G. Berselli, G. Borghesan, M. Brandi, C. Melchiorri, C. Natale, G. Palli, S. Pirozzi, and G. Vassura, "Integrated mechatronic design for a new generation of robotic hands," in *Proc. IFAC Symposium on Robot Control*, Gifu, Japan, 2009.

[23] L. Biagiotti, F. Lotti, C. Melchiorri, G. Palli, P. Tiezzi, and G. Vassura, "Development of UB Hand 3: Early results," in *Proc. IEEE International Conference on Robotics and Automation*, Barcelona, 2005, pp. 4488–4493.

[24] F. Lotti and G. Vassura, "A novel approach to mechanical design of articulated finger for robotic hands," in *Proc. IEEE/RSJ International Conference on Intelligent Robots and Systems*, vol. 2, 2002, pp. 1687–1692.

[25] G. Palli, G. Borghesan, and C. Melchiorri, "Modeling, identification and control of tendon-based actuation systems," *IEEE Transactions on Robotics*, vol. 28, no. 2, pp. 277–290, 2012.

[26] G. Berselli and G. Vassura, "Differentiated layer design to modify the compliance of soft pads for robotic limbs," in *Proc. IEEE International Conference on Robotics and Automation*, Kobe, 2009, pp. 1285–1290.

[27] G. Berselli, M. Piccinini, G. Palli, and G. Vassura, "Engineering Design of Fluid-Filled Soft Covers for Robotic Contact Interfaces: Guidelines, Nonlinear Modeling, and Experimental Validation," *IEEE Transactions on Robotics*, vol. 27, no. 3, pp. 436–449, Jun. 2011.

[28] J. Romero, T. Feix, H. Kjellstrom, and D. Kragic, "Spatio-temporal modelling of grasping actions," in *Proc. IEEE/RSJ International Conference on Intelligent Robots and Systems*, Taipei, 2010, pp. 2103–2108.

[29] M. Beale, M. Hagan, and H. Demuth, "Neural network toolbox: User's guide," http://www.mathworks.com.

[30] K. Hornik, M. Stinchcombe, and H. White, "Multilayer feedforward networks are universal approximators," *Neural Networks*, vol. 2, pp. 359–366, 1989.

[31] L. Villani, V. Lippiello, F. Ruggiero, F. Ficuciello, B. Siciliano, and G. Palli, *Advanced Bimanual Manipulation*, B. Siciliano ed., ser. Springer Tracts in Advanced Robotics. Sringer, 2012, vol. 80, ch. Grasping and Control of Multifingered Hands, pp. 219–266.