Learning Grasps in a Synergy-based Framework

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Abstract. In this work, a supervised learning strategy has been applied in conjunction with a control strategy to provide anthropomorphic hand-arm systems with autonomous grasping capabilities. Both learning and control algorithms have been developed in a synergy-based framework in order to address issues related to high dimension of the configuration space, that typically characterizes robotic hands and arms with human-like kinematics. An experimental setup has been built to learn hand-arm motion from humans during reaching and grasping tasks. Then, a Neural Network (NN) has been realized to generalize the grasps learned by imitation. Since the NN approximates the relationship between the object characteristics and the grasp configuration of the hand-arm system, a synergy-based control strategy has been applied to overcome planning errors. The reach-to-grasp strategy has been tested on a setup constituted by the KUKA LWR 4+ Arm and the SCHUNK 5-Finger Hand.

Keywords: Postural Synergies, Supervised Learning, Hand-arm Anthropomorphic Systems

1 Introduction

Grasp control of high Degree-of-Freedom (DoF) devices in unstructured environment presents several difficulties such as the need to have a good model of the world and to develop a reliable and smart strategy in the case of underactuated devices and redundant kinematics. The human being is a good example to learn how to perform efficiently prehension tasks. For this purpose human observation is the first issue to be addressed. In this work, motion tracking strategies using vision and a bio-kinetic suite have been used for the hand and the arm to learn grasping by imitation. Supervised learning based on Multiple Neural Networks (MNN) has been adopted in a synergy-based framework to generalize the results obtained with imitation learning. To overcome the limits of the MNN in generalizing grasps it is of great interest to use control strategies together with learning strategies. The main idea is to use the control strategy, developed in [1], to optimize the execution of planned grasps synthesized in the synergies subspace. The synergy coefficients corresponding to the final grasp configuration learned by human imitation are used to train the artificial neural network and, in turn, to generalize grasp planning of unknown objects. The KUKA LWR 4+ Arm has been used to perform the reaching phase towards the object, because its human-like kinematics allows replicating the human behavior accurately.

2 Technical Approach and Motivation

The learning strategy relies on dimensionality reduction of the configuration space of both the hand and the arm, and it is based on the imitation of human hand-arm motion during the execution of reach-to-grasp tasks commonly performed in daily life. The supervised learning algorithm has the role of generalizing the reach-to-grasp tasks, learned by imitation, to different object, grasp type and different environment conditions, such as different shape and dimension of the object as well as different orientation and position with respect to a defined frame in the workspace. In order to learn by imitation, a mapping method of the human hand-arm motion to the robotic system is needed. This procedure is necessary to reproduce the configuration on the robotic system as close as possible to the human reference. Once a variety of hand-arm configurations, chosen to cover a complete grasping taxonomy [2], have been mapped and stored in a data base of robot grasps, it is possible to compute the synergy subspaces of the hand and of the arm. Afterwards, dimesionality reduction will be used to make possible the application of NN supervised learning to high-DoFs devices. Indeed, synergies reduce the search space of the learning algorithm ensuring convergence and performance and allowing generalization from mimicked examples. The hand and arm synergies subspaces have been computed independently and in two steps.

2.1 Experimental setup

The robotic system used for the experimental tests is constituted by the SCHUNK 5-Finger Hand (S5FH) [3] and the KUKA LWR 4+ Arm. The hand possesses 20 degrees of mobility and it is designed with mechanical synergies that regulate the kinematic couplings between the finger joints while decreasing the number of motors from 20 to 9. Thearm has 7 DoFs, thus it is one-degree redundant like the human arm. The Robot Operating System (ROS) is used to control both the SCHUNK 5-Finger Hand and the KUKA LWR 4+ Arm. A SVH Driver suite has been developed by Forschungszentrum Informatik (FZI) for the low-level interface and enables an easy control of the hand using a customized library written in C++, while the KUKA LWR 4+ Arm is controlled by means of the FRI library. For the motion acquisition, commercial low-cost RGB+Depth (RGBD) camera, such as the Kinect from Microsoft Corp., has been used for 3D human hand fingertips detection. For the arm, the Xsens MVN suite motion capture system has been used. It consists essentially of 17MTx inertial and magnetic measurement units and comprises 3D gyroscopes, 3D accelerometers and 3D magnetometers sensors through which it is possible to obtain the position measurement and orientation of parts of the body of the wearer.

2.2 Methods for observation and synergies computation

Different methods can be used for synergies computation. The first issue to address consists in evaluating the more effective solution between two separated synergies subspaces for the hand and the arm rather than the whole subspace. As a matter of fact, the hand and the arm have two different workspaces, i.e. the hand is a redundant branched device and presents a behavior (small motions) different from that of the arm (large motions) involving not only different joint motions and velocities, but also different inertia and kinematics. Furthermore, despite the smaller workspace, the hand has the possibility to take a higher number of combinations of joint values than the arm, thus the motions related to the various grasps are differentiated from each other and may require a greater number of synergies to be reproduced while ensuring a small error. According to this, we have decided to compute two separated synergies subspace for dimansionality reduction. Starting from synergy-based planning and control algorithms, developed for anthropomorphic hands [4], [1], [5] an incremental work to extend previous studies to the arm has been addressed.

2.3 The hand

A data set of grasps, measured on five human subjects and available from [6], is used. For this purpose, a synergies Jacobian can be computed and suitably used in the Closed-Loop Inverse Kinematics (CLIK) algorithm to map the grasps from the human hand to the robotic hand. The method developed in [6] has been adapted and tested to evaluate the first three synergies on the S5FH under-actuated five-fingered hand. The details of the grasping data and mapping method can be found in [6], [1].

2.4 The arm

In order to map movements from the human to the robotic arm, several solutions can be adopted. The MTx sensors, mounted on the Xsens suite, provide position and orientation, in the global frame of the motion capture system, of the segments of the human body on which they are positioned. For this reason, an immediate solution would be to map directly the position and the orientation of the human hand palm into the base frame of the robotic arm and afterwards to apply the CLIK algorithm, based on the robot kinematics, to reconstruct the arm configuration. In this way, the hand trajectory is accurately reproduced. On the other hand, due to kinematic differences between the human and the robotic arm and to the one degree of redundancy, the mapped motion is not human-like.

To reproduce human-like motion, an alternative mapping method has been implemented. Two different CLIK algorithms have been used, taking respectively the elbow and wrist orientation as reference input. The first CLIK algorithm utilizes the kinematics of the first three joints of the robot corresponding to the spherical joint of the human shoulder. To compute the elbow orientation reference for the CLIK algorithm, the orientation matrix of the elbow $\boldsymbol{R}_e$, provided by MVN in the global frame, has been expressed with respect to the sternum frame to overcome changes due to sternum rotation:

$$\boldsymbol{R}_e^s = \boldsymbol{R}_z^T(\alpha)\boldsymbol{R}_s^T\boldsymbol{R}_e, \tag{1}$$

where $\boldsymbol{R}_s$ is the sternum rotation matrix expressed with respect to the global frame and $\boldsymbol{R}_z(\alpha)$ represents a rotation of $\alpha = \pi$ about z axis, that is required to align the global reference frame of the MVN with the base frame of the KUKA LWR 4+ Arm.

However, the initial configurations of the KUKA LWR 4+ Arm and of the human arm cannot be the same. Therefore, the mutual rotation matrix between the initial and the current frame of the human arm has been evaluated:

$$\boldsymbol{R}_{m_e} = \boldsymbol{R}_e^s \boldsymbol{R}_{i_e}^T, \tag{2}$$

where $\boldsymbol{R}_{i_e}$ represents the initial arm orientation expressed into the sternum reference frame. Finally, the desired CLIK reference has been obtained by premultiplying the initial KUKA LWR 4+ Arm elbow rotation matrix $\boldsymbol{R}_{k_e}$, expressed in the robot base frame, by the mutual rotation matrix (2):

$$\boldsymbol{R}_{d_e} = \boldsymbol{R}_{m_e} \boldsymbol{R}_{k_e}, \tag{3}$$

The second CLIK algorithm is related to the last four joints of the elbow and wrist. In this case, the reference is constituted by the rotation matrix between the initial and the current human hand frame, reported in the elbow frame:

$$\boldsymbol{R}_h^s = \boldsymbol{R}_z^T(\alpha) \boldsymbol{R}_s^T \boldsymbol{R}_h \qquad \boldsymbol{R}_{m_h} = \boldsymbol{R}_h^s \boldsymbol{R}_{i_h}^T \qquad \boldsymbol{R}_{d_h} = \boldsymbol{R}_{d_a}^T \boldsymbol{R}_{m_h} \boldsymbol{R}_{k_h}, \tag{4}$$

where $\boldsymbol{R}_h$ is the hand orientation matrix provided by MVN, $\boldsymbol{R}_{i_h}$ represents the initial hand orientation expressed into the sternum reference frame and $\boldsymbol{R}_{k_h}$ is the initial robotic hand rotation matrix expressed into the base frame of the robotic arm.

Thus, the manipulator is seen as constituted by two kinematic chains with three and four DoFs. Since only the orientation is given as input to the two CLIK algorithms, the second kinematic chain has a redundant DoF. Thus, the angle between the arm and the forearm, computed using MVN measurements and geometric properties, has been mapped in the null space of the Jacobian matrix of the second kinematic chain in order to reproduce the forearm flexion/extension movements.

About the arm, as preliminary study, we have chosen the Cartesian space for synergies computation since it has 6 DoFs despite the 7 DoFs of the configuration space. Moreover, the pose of the hand palm has a crucial role on the successful execution of the grasp. Nevertheless, in future works we reserve to make further evaluations on the convenience of choosing the Cartesian space rather than the configuration space for synergies representation.

The target hand pose for a set of objects and grasps has been learned from demostration, by teleoperating the KUKA LWR 4+ Arm with the Xsens suite, as shown in Fig. 1. Let $\boldsymbol{p}_h^{obj}$ the hand position and $\boldsymbol{Q}_h^{obj} = \{\eta_h, \boldsymbol{\epsilon}_h\}$ the unit quaternion representation of the hand orientation with respect to the object rereference frame, the robotic hand pose can be represented with a vector $\boldsymbol{x} \in \mathbb{R}^7$:

$$\boldsymbol{x} = \begin{bmatrix} \boldsymbol{p}_h^{obj} \\ \eta_h \\ \boldsymbol{\epsilon}_h \end{bmatrix}. \tag{5}$$

For synergies computation, two matrices have been built: the position matrix $\boldsymbol{P} = \{\boldsymbol{p}_{h_i}^{obj} \mid i = 1, \ldots, 38\}$ and the matrix of the quaternions $\boldsymbol{E} = \{\boldsymbol{\epsilon}_{h_i}^{obj} \mid i = 1, \ldots, 38\}$, where 38 is the number of the learned grasps from human demonstration. Then, the matrices $\boldsymbol{F}_P = \{\boldsymbol{p}_{h_i}^{obj} - \bar{\boldsymbol{p}}_h^{obj} \mid i = 1, \ldots, 38\}$ and $\boldsymbol{F}_E = \{\boldsymbol{\epsilon}_{h_i}^{obj} - \bar{\boldsymbol{\epsilon}}_h^{obj} \mid i = 1, \ldots, 38\}$ have been computed, where $\bar{\boldsymbol{p}}_h^{obj}$ and $\bar{\boldsymbol{\epsilon}}_h^{obj}$ are the mean vectors. The PCA has been performed on the matrices $\boldsymbol{F}_P$ and $\boldsymbol{F}_E$ and two bases of eigenvectors, $\boldsymbol{S}_p \in \mathbb{R}^{3\times3}$ and $\boldsymbol{S}_\epsilon \in \mathbb{R}^{3\times3}$, ordered in decreasing order of variance, have been found. By considering only the first principal component of the two bases, $\boldsymbol{e}_p \in \mathbb{R}^3$ and $\boldsymbol{e}_\epsilon \in \mathbb{R}^3$, the position and orientation of the hand can be found in the synergies subspaces, by specifying only two parameters, namely α_{p_i} and α_{ϵ_i}:

$$\boldsymbol{p}_{h_i}^{obj} = \bar{\boldsymbol{p}}_h^{obj} + \boldsymbol{e}_p \alpha_{p_i} \tag{6}$$

$$\boldsymbol{\epsilon}_{h_i}^{obj} = \bar{\boldsymbol{\epsilon}}_h^{obj} + \boldsymbol{e}_\epsilon \alpha_{\epsilon_i}, \tag{7}$$

while the scalar part of the quaternion can be found as follows:

$$\eta_{h_i} = \sqrt{\left(1 - \left(\boldsymbol{\epsilon}_{h_i x}^2 + \boldsymbol{\epsilon}_{h_i y}^2 + \boldsymbol{\epsilon}_{h_i z}^2\right)\right)}. \tag{8}$$

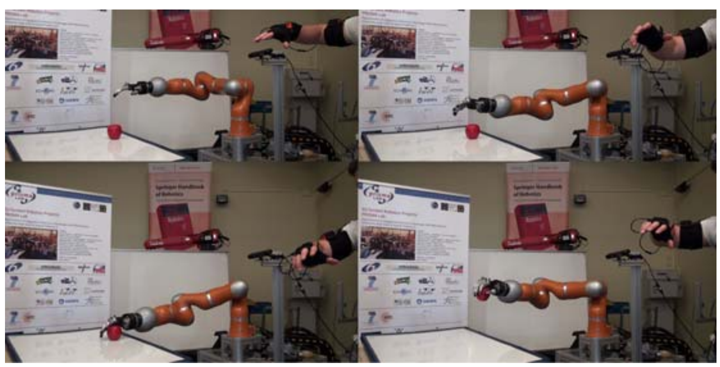

Fig. 1. Snapshots of the experimental set-up during the telemanipulation control of the robot.

3 Supervised learning for the hand-arm system

To confer autonomy to the grasping method, two Multilayer Neural Networks (MNNs) with the same architecture have been designed for the hand and for the arm. A multilayer feedforward neural network with nonlinear transfer function has been adopted thanks to the ability to learn any function with a finite number of discontinuities.

In order to train the MNNs, a library of grasp examples is needed. The training set is constituted by eleven spherical objects, whose diameters are included in a range between 2.7 [cm] and 9.6 [cm], eleven cylindrical objects, with height between 16 [cm] and 25 [cm] and diameters included in a range between 1.2 [cm] and 7.5 [cm]. Since the input patterns must have the same dimension for all the objects, about the spheres a second parameter, namely the height, has been introduced and obviously it is chosen equal to the diameter. Finally, a third object category of parallelepiped-shaped objects has been considered. For this category a further input it is needed, i.e. the length, and it has been included in a range between 8.5 [cm] and 12 [cm], while, for both cylinders and spheres, this parameter has been set to zero. Furthermore, in order to identify the type of the grasp, an additional binary input has been introduced.

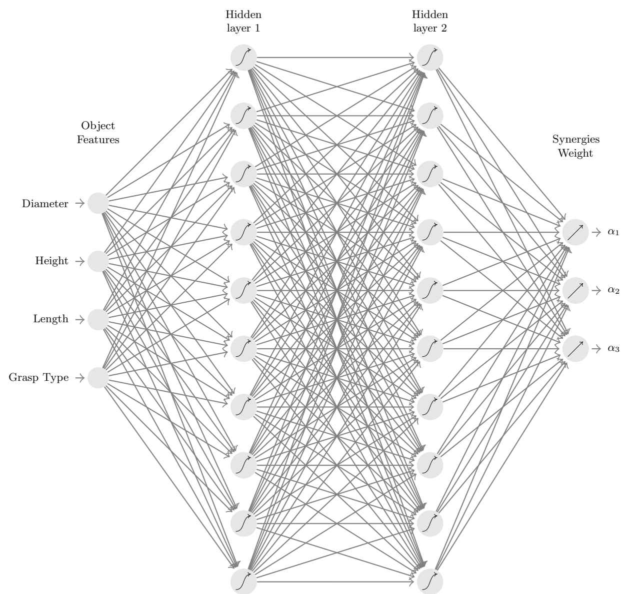

Fig. 2. Schematic representation of the implemented neural network for the hand.

The latter, for both cylinders and spheres, assumes unitary value for precision grasp and zero value for power grasp. Instead, for the parallelepiped-shaped objects this input assumes unitary value for a lateral grasp and zero value for the other cases. The use of synergies reduces the search space of the learning algorithm addressing a simplification in the neural network architecture design, especially regarding the number of hidden layers and the neurons in each of them. In the same way, a simplified representation of the hand pose reduces the output number hand MNN.

Therefore, the networks receive as input four parameters: diameter, height and length of the object and the "grasp type input". The outputs of the hand

MNN are the three coefficients of the S5FH motor synergies coefficients that determine the fingers configuration, while the output of the arm MNN are the two coefficients of Cartesian space synergies that determine the hand palm pose relative to the target object. The MNNs have been implemented in Matlab using the Neural Network Toolbox (NN Toolbox). The network architecture has been experimentally chosen by changing the number of neurons and hidden layers, and in turn by analyzing the corresponding NN performance in terms of Mean-Squared Error (MSE). As a result of those experimental evaluations, the network model has been chosen as a feedforward NN with two hidden layer and ten sigmoid neurons for each layer. The complete scheme of the implemented NN is shown in Fig. 2, where the hand NN is represented. Furthermore, in order

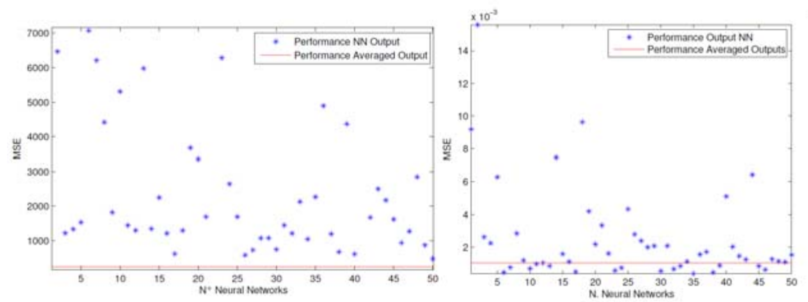

Fig. 3. Performance comparison between NN outputs and averaged output for the hand (left) and for the arm (right).

to improve the generalization, multiple neural networks have been trained and an average of their outputs has been considered for the experiments. Precisely, in this work fifty neural networks have been trained and their MSEs have been compared to the MSE of their average. The result of this comparison is reported in Fig. 3 for the NN of the hand and reveals a striking result, i.e. the average MSE is at least an order of magnitude less if compared with all the individual performance. Therefore, the use of multiple neural networks greatly improves the network generalization. In this way, it is possible to find the synergies coefficients corresponding to the object geometric features with higher accuracy.

4 Demonstration of synergy-based autonomous grasping

In this section, the experimental results obtained using the Multiple Neural Network method are reported. A Matlab ROS node, to connect the MNNs to a control ROS node, has been implemented using ROS Toolbox. The control node communicates with the SCHUNK S5FH control node and to the KUKA LWR 4+ Arm control node using a specific topic on which the synergies coefficients are published. Therefore, the outputs of the MNNs are used as a reference for the hand control node and for the KUKA LWR position control.

The hand control allows the S5FH to reach the final grasp, starting from an open-hand configuration. The control of the hand is constituted by a kinematic algorithm that simply moves the hand in the synergies subspace toward the target. The control strategy uses the motor current measurements and introduces thresholds to avoid finger configurations that can cause high contact forces on the object. Once the feature and the pose of the object are known, the MNNs provides the control commands in terms of synergies coefficient of the desired hand configuration and hand palm pose. The arm control is a first-order kinematic control law based on the right pseudo-inverse of the geometric Jacobian matrix, since the unit quaternion has been used as end-effector orientation representation. The planned path is a linear segment in the operational space which connects the initial end-effector position $\boldsymbol{p}_i$ to the final position $\boldsymbol{p}_f$ learned with the MNN, whose parametric representation is the following:

$$\boldsymbol{p}(s) = \boldsymbol{p}_i + \frac{s}{||\boldsymbol{p}_f - \boldsymbol{p}_i||}\left(\boldsymbol{p}_f - \boldsymbol{p}_i\right), \tag{9}$$

where the time law $s\left(t\right)$ is given by:

$$s\left(t\right) = a_5 t^5 + a_4 t^4 + a_3 t^3 + a_2 t^2 + a_1 t + a_0, \tag{10}$$

whose coefficients have been computed by imposing the conditions for $t = 0$ and $t = t_f$ on the end-effector position and on its first two derivatoves. The end-effector orientation trajectory is given by:

$$\boldsymbol{R}_e\left(t\right) = \boldsymbol{R}_i \boldsymbol{R}^i\left(t\right), \tag{11}$$

where $\boldsymbol{R}_i$ is the initial end-effector orientation and $\boldsymbol{R}^i\left(t\right)$ is the rotation matrix that describes the transition from $\boldsymbol{R}_i$ to $\boldsymbol{R}_f$. The latter is the rotation matrix computed using the output of the MNN, i.e. the α_{ϵ_i} synergy coefficient related to the palm orientation, as well as (7) and (9). The hand palm trajectory for the orientation is expressed in terms of angle axis representation:

$$\boldsymbol{R}^i\left(t\right) = \boldsymbol{R}^i\left(\theta\left(t\right), \boldsymbol{r}^i\right), \tag{12}$$

where $\boldsymbol{r}^i$ is fixed and the timing law of $\theta(t)$ is given by a fifth-order polynomial as in (10). The learning method has been tested for a total amount of 10 grasps, 5 cylinders and 5 spheres, including objects that the networks have never seen before, i.e not included in the training set. Both precision and power grasp have been tested for each object. The learned hand position and orientation is used as a reference for a simple arm control strategy described above. When the palm of the hand reaches the desired position the hand starts to move. While the arm control relies only on the reference output of the learning process, without adjustment of the planned position, the hand follows a different strategy. The planned desired configuration output of the MNN is further improved using a synergy-based control strategy described in [1]. The combination of an initial learned position with a control strategy in the synergy subspace allows overcoming planning errors due to the approximation of the relationship between the object features and the system configuration introduced by the hand and the arm MNNs. Moreover, the arm planning errors affect the hand synergies that can change even for the same object. This inconvenience is overcome by integrating learning and control in the synergies subspace. Some of the results are shown in Figs. 5 and 6.

Fig. 4. Tripodal precision grasp.

5 Conclusions and future work

The experiments demonstrate that multiple neural networks are able to approximate with a high quality level the relationship between the synergies coefficients and the geometrical object features. Thus, MNN is a useful tool to plan grasps directly in the synergies subspace, with obvious advantages both from a computational and algorithmic point of view. Indeed, on the basis of object shape and size information, the synthesized synergies coefficients produce the desired grasp distinguishing among precision and power grasps, and also the number of fingers involved. Moreover, the use of combined synergy-based control and learning strategies for the hand allows overcoming planning errors due to uncertainties introduced by the learning process. As future experiments we plan to integrate this method to an object recognition algorithm using an RGB-D Vision sensor and to improve the coordination between the hand and the arm using human-like control strategies for the arm taking into account the motion of the hand. Moreover, we intend to explore different synergies subspaces for the arm, such as synergies of the configuration space as for the hand, and comparing the results.

Fig. 5. Cylindrical power grasp.

Fig. 6. Other examples of performed grasps.

Acknowledgments This research has been partially funded by the EU Seventh Framework Programme (FP7) within RoDyMan project 320992.

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