Biologically inspired robot grasping through human-in-the-loop robot control

Brian Moore, Emre Ugur and Erhan Oztop

***Abstract*— We have recently proposed a framework for robot skill synthesis that exploits human sensorimotor learning capability. The idea is to consider the target robot platform as a tool that is intuitively controlled by a human. Once the robot can be effortlessly controlled, the successful execution of a task by the human via the robot provides learning data points that are used for designing controllers that operate autonomously. Here we report our ongoing work for obtaining an autonomous grasp controller within this framework. In the experiments reported, the operator directly controls the (simulated) robot using visual feedback to achieve robust grasping with the robot. The data collected is then analyzed for inferring the grasping strategy discovered by the human operator. Finally a method to generalize grasping actions using the collected data is presented, which allows the robot to autonomously generate grasping actions for different orientations of the target object.**

I. INTRODUCTION

Although humans are very skilled at manipulation and in spite the recent developments in robotic manipulation, developing a robotic system that matches human hand dexterity is still elusive. One major impediment is the control complexity, due mainly to the large number of DOF. Reducing this complexity is possible by developing underactuated robotic hands [1] where the ”mechanical intelligence” of the design compensates for the loss of DOF. This is often a good compromise between a simple gripper and a complex humanoid robot hand and can be used for instance, in prosthetics [2] and space robotics [3,4]. However, underactuated hands are limited to certain types of grasps and are not suitable for more advanced dexterous manipulations.

One way to tackle the control complexity problem of highly redundant anthropomorphic robotic systems is to take advantage of the biological similarities between the human and the robot. A first approach is the so called *direct teaching approach* [5-7] where the robot behavior is shaped or molded by directly moving the joints of the robot to obtain the desired behavior. Direct teaching is not practical for complex tasks that may include non-negligible dynamics. Moreover, current visual-based imitation systems may fail to fulfill the precision and robustness requirements of the task at hand as it is often not possible to estimate the motor commands of the demonstrator by pure observation. Another alternative is the *visual-based imitation* approach [8-17] which capture the motion of a human and through some transformations, map this motion to the kinematical structure of a robot. However, due to the different dynamical properties of the robot and the human, the success of this approach heavily depends on the expert knowledge that has been put in the mapping.

A new paradigm for obtaining skilled robot behavior is to utilize an intuitive teleoperation system where humans learn to control the robot joints to perform a given task [18,19]. Once the human manages to control the robot and complete the desired task with it, the control commands produced by the human-robot system during task execution can be used for designing controllers that operate autonomously. This places the initial burden of learning on the human instructor, but allows the robot to ultimately acquire the ability to perform the target skill without human guidance. These ideas have been put in use for obtaining several robot skills like ball swapping [18,19] and reaching without falling over [20]. In short, the ’robot skill synthesis via human learning’ paradigm exploits the human capability to learn to use novel tools for obtaining robot controllers.

In this paper, we describe our ongoing work in applying the ’robot skill synthesis via human learning’ paradigm to the development of a biologically inspired robot grasping controller. In section 2, we present our experimental settings, including the motion tracking system to track the operator motion, the robotic platform and the simulator environment. An intuitive interface mapping the human motion to the robot is also described. In section 3, we analyze the successful robot grasping actions obtained from the human-in-the-loop control using visual feedback for a pre-defined set of object orientations. The quality of these grasp actions is then measured and the most robust grasps are selected as representative grasp actions for each pre-defined object orientation. We also show that the grasping motion controller induced by the operator seems to favor a linear strategy for the wrist positioning for varying object orientations. Finally, in section 4, a method to generalize grasping actions for arbitrary object orientations by merging representative robust grasp actions is presented.

II. AN INTUITIVE REACH AND GRASP INTERFACE

In order for the operator to efficiently learn to control the robot joints and perform tasks on the robots, the interface between the operator and the robot should be as intuitive as

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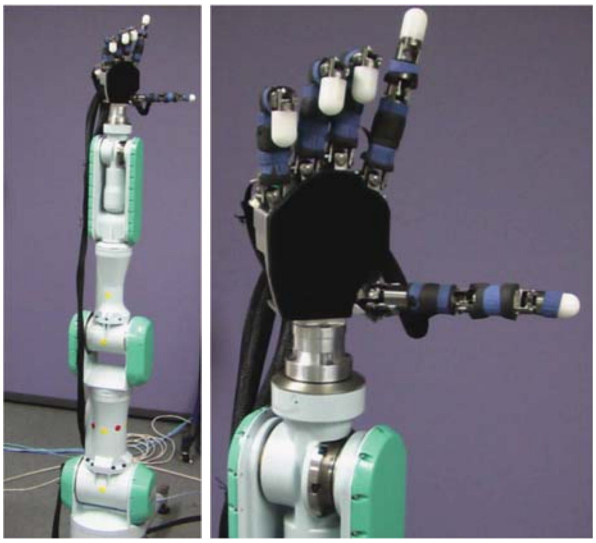

Fig. 1. The robot hand-arm system used in this study.

possible. In other words, the motion adaptation of the operator should be natural in terms of his body motion and readily learnable. Probably the number one requirement for such an intuitive interface is the repeatability of robot's response to human motion. This drastically reduces the operator learning time. We all know the frustration of using an erratically behaving computer mouse due to a bad sensor. The number two requirement is the level of anthropomorphism of the controlled robot. The delay in the robot control is also very critical; but in practice, we have observed that 30-60Hz control rate is sufficient for visually guided tasks. Our robotic platform, shown in Fig. 1 can be considered anthropomorphic as it is composed of a five fingered, 16-DOF robotic hand (Gifu Hand III, Dainichi Co. Ltd., Japan) and a 7-DOF robot arm (PA-10, Mitsubishi Heavy Industries). For actuating the robot arm based on real-time human movements, an inertial-ultrasonic motion tracking system (IS-600, Intersense Inc.) which provides an adequate control rate is used. For the robot hand, a fiber-optic based data glove (5DT Data Glove, Fifth Dimension Technologies) which gives us the joint angles of the hand is used. The robot control architecture was described in [18-20].

Our previous work tend to show that for an intuitive human control of a robot arm for manipulation, mapping human end-effectors to robot end-effectors followed by the computation of the inverse kinematics (IK) is more advantageous than mapping human joint angles to robot joint angles [18-20]. For robustness and repeatability we avoid classical iterative IK methods. We use an analytic inverse kinematics developed in [21] which can take advantage of the redundancy to avoid singularities or obstacles. Fig. 2 shows the location of the motion tracking sensors for measuring the position and the orientation of the arm end-effector.

Mapping of the finger motion of the operator (as measured with the data glove) to the robot finger motion is straightforward since the joint angles of the data glove are directly measured (i.e. they are scaled values of the joint angles between 0 and 1). For most of the robot joints (14 out of 16), each measurement of the operator finger joint angle can be directly mapped to the corresponding robot joint angle. Since the robot thumb has an additional joint and since the finger flexure is measured differently on the glove than on the robot, minor adjustements are required. A particular pose of the robot hand is shown in Fig. 3.

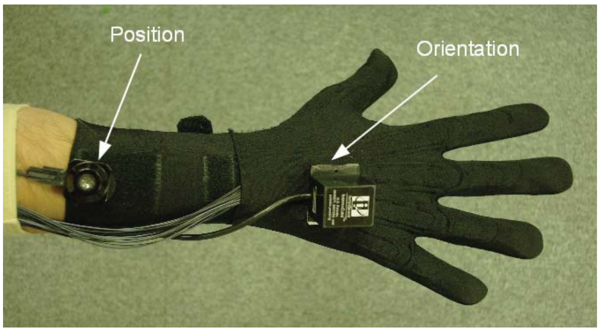

Fig. 2. Motion tracking sensors on the data glove.

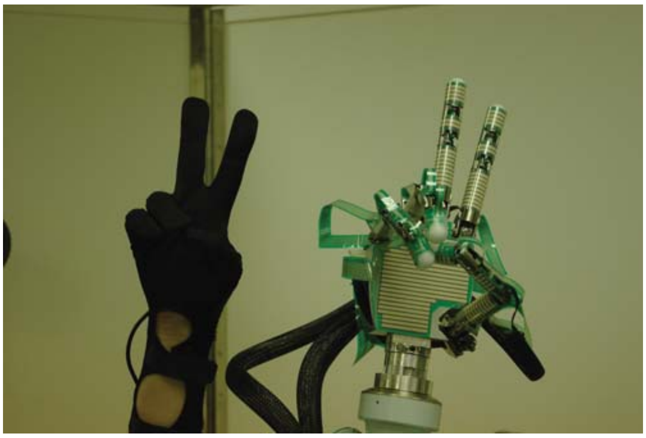

Fig. 3. Control of the robot hand using the glove.

For testing and developing the real-time control of robot hand system, safety is a concern. Therefore we developed the PAGSim, the simulator for the robot hand system. PAGSim is used to reduce the risk of accidents and damage to the robot. For example, any change in the control algorithm is first tested in simulation to ensure safety. Finally, the learned controllers obtained via human motor learning are first tested in the simulator before being deployed on the robot system for autonomous operation.

PAGSim is a dynamics simulation environment that models the hand-arm system and its environment using a commercial quality open-source physics engine, ODE (Open Dynamics Engine). All the parts of the robot and environment are constructed from rigid geometrical objects and articulated joint structures. We use velocity and position modes for controlling the robot hand-arm system, which are also emulated in PAGSim by mimicking the control signal profiles of the robot controller. In addition, in order to provide a seamless execution interface, PAGSim is designed

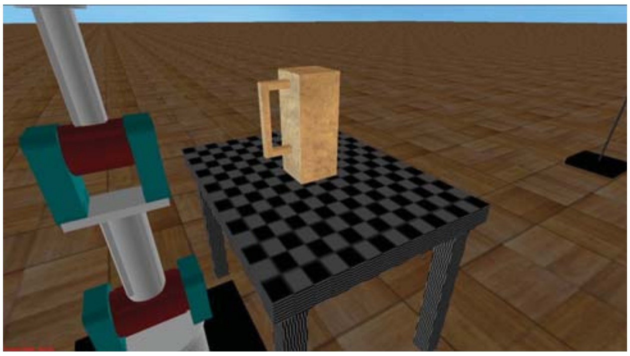

Fig. 4. Object to grasp in the simulator.

to accept the same UDP network calls which the robot hand-arm system accepts for its operation.

The parameters of the simulator such as friction, mass of the objects, forces on robot hand and arm are adjusted so that interactions with the objects have similar effects in real world and simulation. Note that the compatibility of physical interactions in PAGSim was verified in [22] by showing that the controllers that were trained in the simulator can be directly transferred to real robot system without any modification.

Although simulators are useful test-beds and necessary for robotics research, we do not see them as replacements for the physical world as many factors have to be overlooked to make the simulation practical. For example, soft contacts are of utmost importance in manipulation tasks but soft-body dynamics is not supported by many of the simulation engines including ODE that we use.

III. HUMAN-IN-THE-LOOP CONTROL

A. *Experimental setting*

The task of the operator is to perform grasp actions (including reaching, grasping and lifting) in the simulator using his own body (arm and hand) to control the motion of the simulated robot arm and hand. An important component of the system is therefore the visual feedback obtained by the user from the simulator. Although the long term goal is to immerse the user in a 3D virtual reality environment to make the system more intuitive, we only use a normal LCD monitor for this experiment. To compensate for the lack of 3D effect, the location of the camera in the simulator is carefully chosen and a real table (with the same height as the table in the simulator) is put in front of the operator. During the learning phase, the user practice grasping on the simulator to get a feeling of the required motion. This learning phase is slowed down by the lack of 3D visual feedback, but the learning time is still quite short (less than an hour).

For this preliminary investigation, a simple object shown in Fig. 4 is used. A local reference frame is defined on the object and its origin is defined as the *object's centre*. In this paper, the position of the object means the position of the centre of the object. In the experiments, the position of the object is fixed, but the object is rotated about its z axis (local reference frame) using a pre-defined set of orientations ($20, 30, ..., 90, 100$ degrees) as shown in Fig. 5.

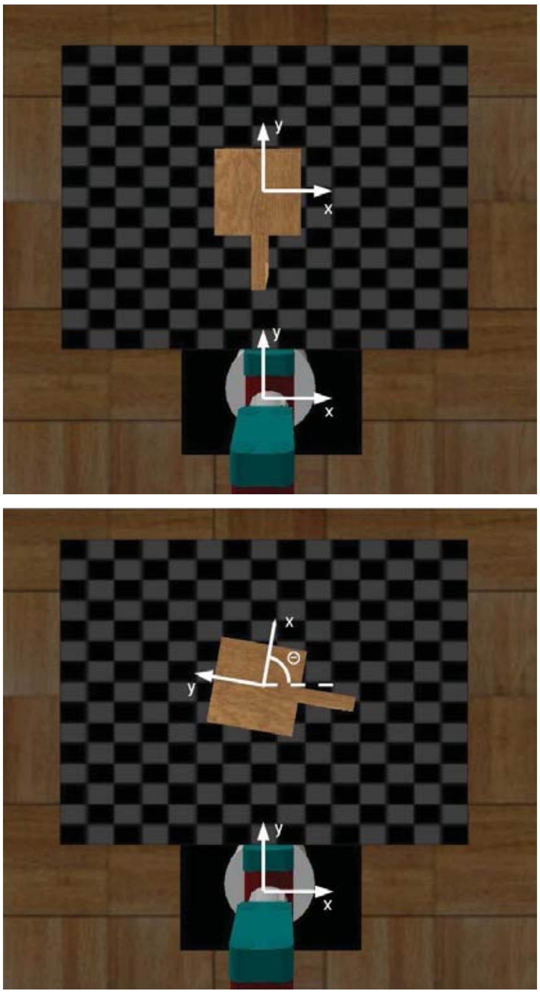

Fig. 5. Top view of different orientations for the object ($\theta = 0, 80$ degrees).

A session consists of a set of grasp actions to be performed for every pre-defined object orientation. For each grasp attempt, a button is pressed to indicate the moment when the grasping of the object takes place and a final key is pressed when the trial is finished. If the position of the object at the end of the trial is above the table, the trial was successful. Otherwise, the grasp action is discarded.

B. *Features extraction and motion representation*

The grasp action is decomposed into three phases: the *reaching motion*, the *grasping motion* and the *lifting motion*. The pose at the transition between the *reaching motion* and the *grasping motion* is called the *pre-grasp pose* while the pose at the transition between the *grasping motion* and the *lifting motion* is known as the *grasp pose* (see Fig. 6). The *grasp workspace region* is a region around the object that specifies the transition between the *reaching motion* and *grasping motion* based on the position of the arm end-effector. The *grasp workspace region* could be a sphere around the object or a cylinder. In this paper a cylinder is

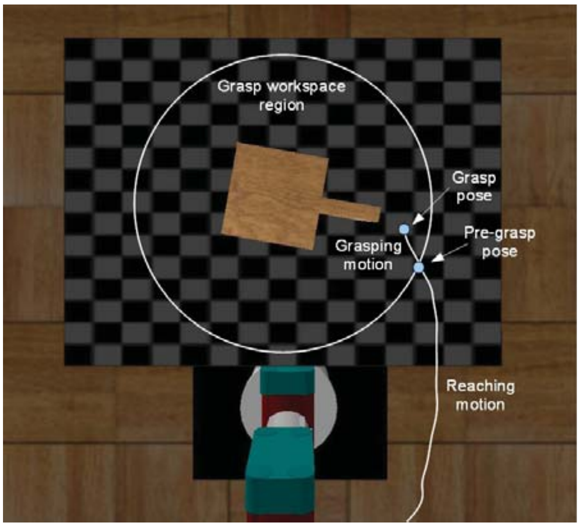

Fig. 6. *A grasp action* (top view).

used due to the shape of the object. Alternatively, one could also consider both the position and the orientation of the end-effector in the definition of the *grasp workspace region* [23]. The *grasp pose* is defined by the user when he presses a button to indicate the instant when the grasp happens. The *pre-grasp pose* is defined as the first pose inside the *grasp workspace region*.

From the recorded data, only the information related to the *grasping motion* is kept. A *grasping motion* $\mathbf{T}$ consists of an ordered list of waypoints $W_i = \{x_i, q_i, f_i\}$ from the *pre-grasp pose* to the *grasp pose* where x_i represents the position of the robot wrist in space, q_i the orientation of robot end-effector in space represented by a unit quaternion and f_i is a 16 dimensional vector representing the joint angles of the robot's fingers.

C. Extracting robust representative grasping motion

Since we have multiple successful *grasping motions*, the most robust *grasping motion* is selected as a representative for each pre-defined orientation. The definition of a robust grasp is not unique and different criteria could be used depending on the object and task. In this experiment, a grasp is robust if it is successful in grasping the object even if the velocity of the motion is changed and if noise is added to the grasping motion. It would also be possible to investigate different combination of robust trajectories for a given object in a given orientation to extract optimal trajectories.

D. Analysis of the human controlled grasping motion

For each pre-defined object orientation and all successful grasp actions, the average *pre-grasp pose* and *grasp pose* with respect to the object's centre is computed. The average position (not considering the height z) are shown in Table I and Fig. 8. The results are expressed using polar coordinates as illustrated in Fig. 7. There are a few important observations related to these experimental results. The range of object orientation is 80^o but the range for the grasp position of the wrist is about 35^o. It clearly demonstrate that the the

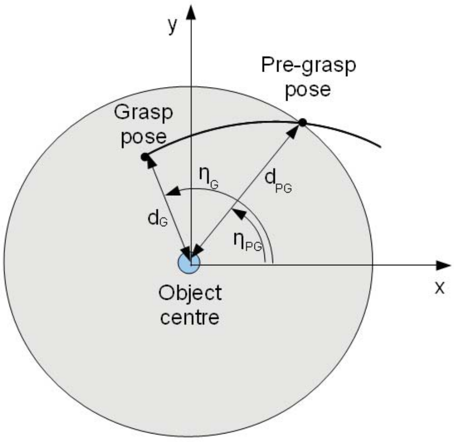

Fig. 7. Grasp position representation (top view).

Object orient.	d_G	η_G	d_{PG}	η_{PG}	Number samples	Symbol
20	0.41	-71.5	-75.3	0.378	5	⋆
30	0.41	-69.7	-73.0	0.371	7	○
40	0.41	-66.1	-71.1	0.358	8	×
50	0.41	-62.6	-69.0	0.350	10	+
60	0.41	-52.4	-63.1	0.345	10	∗
70	0.41	-53.0	-59.2	0.337	10	□
80	0.41	-50.1	-57.3	0.329	6	⋄
90	0.41	-44.1	-47.1	0.326	6	∇
100	0.41	-39.8	-40.6	0.321	5	△

TABLE I

AVERAGE PRE-GRASP AND GRASP POSITION WITH RESPECT TO THE OBJECT CENTER (TOP VIEW).

position of the wrist is influence by the object orientation when grasping. Moreover, it is particularly interesting to observe that the grasp position of the wrist seems to be on a line as shown in Fig. 7.

IV. MOTION GENERALIZATION

The goal of this section is to devise an efficient algorithm to generate *reaching motion* and *grasping motion* for arbitrary object orientations based on the robust *grasping motions* obtained during the learning phase.

A. Motion interpolation

As mentioned earlier, a *grasping motion* corresponds to a set of waypoints describing the position of the wrist, the hand orientation and joint values for the fingers. Therefore, the interpolation of a *grasping motion* requires an algorithm for interpolating each of these components.

To represent the hand orientation, unit quaternions are used. A unit quaternion can be considered as a point on a 4D hypersphere and interpolating two quaternions consists in finding a point on the geodesic path between these two points. However, care must be taken since any given orientation corresponds to two antipodal points on the hypersphere. A first approach is to use linear interpolation between two

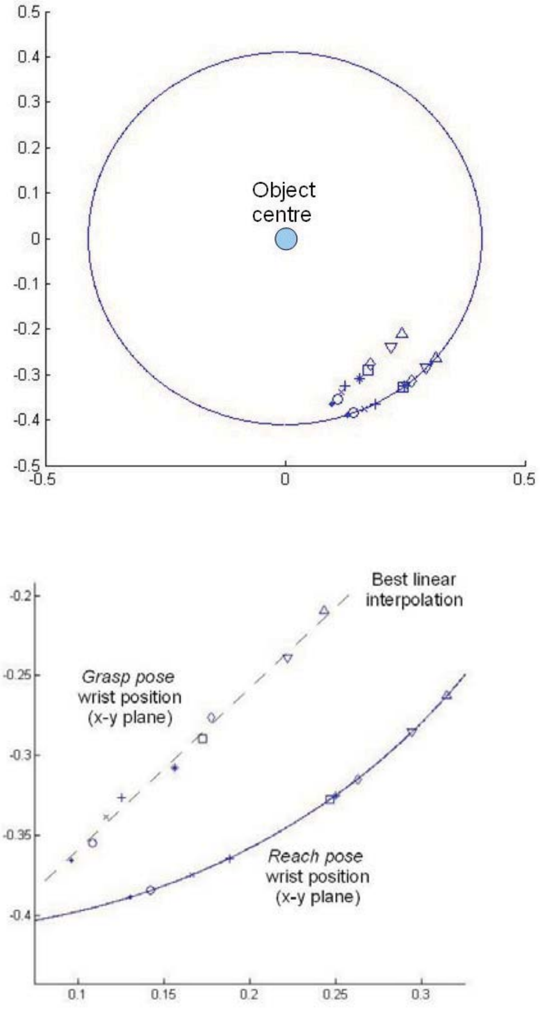

Fig. 8. Average reaching and grasping position for different orientation of the object.

unit quaternions and project it back on the sphere. However, such method does not generate evenly-spaced quaternions. To obtain evenly-spaced quaternions, spherical linear interpolation (known as *slerp*) [24] is used. An efficient algorithm can be found in [25][1]. We will denote by $q = \text{slerp}(q_1, q_2, t)$ the spherical linear interpolation of the unit quaternions q_1 and q_2 and the interpolation parameter t between 0 and 1 (i.e. $t = 0$ corresponding to $q = q_1$ and $t = 1$ corresponding to $q = q_2$).

We now consider the position of the wrist expressed relative to the object's centre and represented by a pure quaternion (a quaternion with scalar part equal to 0). Interpolation of the position of the arm's end-effector can be performed in a similar way than for the orientation. Note that spherical linear interpolation (*slerp*) cannot be directly used since the quaternions representing the position are not of unit length. Therefore, we define the function *average slerp* (*aslerp*) as

$$\text{aslerp}(p_1, p_2, t) = \text{s} \cdot \text{slerp}(\frac{p_1}{\|p_1\|}, \frac{p_2}{\|p_2\|}, t) \tag{1}$$

where s is the scaling factor defined as

$$\text{s} = (1 - t)\,\|p_1\| + t\,\|p_2\| \tag{2}$$

where p_1 and p_2 represents the positions as pure quaternion, t is the interpolation parameter and $\|p\|$ is the quaternion norm defined as:

$$\|a + bi + cj + dk\| = \sqrt{a^2 + b^2 + c^2 + d^2} \tag{3}$$

For interpolating two robot hand configurations f_1 and f_2 which are 16 dimensional vectors, the following convex linear combination is used:

$$f = (1 - t) \cdot f_1 + t \cdot f_2 \tag{4}$$

where t is the interpolation parameter.

B. Generalization of the grasping motion

Given any object orientation θ, it is possible to generate a *grasping motion* $\mathbf{T}$ by merging two robust *grasping motions* $\mathbf{T}_1$ and $\mathbf{T}_2$ obtained from object orientations θ_1 and θ_2 respectively. We assume also that θ_1 and θ_2 are chosen as close as possible as θ and we assume that $\theta_1 < \theta < \theta_2$. Since the number of waypoints for $\mathbf{T}_1$ and $\mathbf{T}_2$ is most likely not the same, the first step is to resample the motions to obtain the same number of waypoint in $\mathbf{T}_1$ and in $\mathbf{T}_2$. Then, corresponding waypoints from $\mathbf{T}_1$ and $\mathbf{T}_2$ are interpolated using the method presented in previous subsection.

C. Generating the reaching motion

Since the initial position and orientation of the robot is not known *a priori*, it is not possible to use directly the recorded values of the human reach to generate the robot *reaching motion*. However, many methods can be used to generate a continuous and smooth trajectory that combines smoothly with the *grasp trajectory*. One could also specify the trajectory either in joint space or in cartesian space (end-effector position and orientation). In this approach, cubic splines are used to generate the reach positions of the end-effector and the orientation of the wrist is obtained by using a spherical linear interpolation between the initial orientation and the pre-grasp orientation. A more biological-inspired alternative to generate the trajectory would be to use DMPs [26,27].

D. Results

Using the algorithm above, reaching and grasping motion can be generated for any orientation of the object. On the simulator, by merging two robust motions, we obtain a motion that can grasp the objects efficiently.

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[1] We use the Quaternion toolbox for Matlab (QTFM) available online at *http://sourceforge.net/projects/qtfm/*.

V. CONCLUSION

In this study we have presented our ongoing work on extending the robot skill synthesis via human learning paradigm to grasping actions. Although the experiments conducted so far are preliminary, we were able to discover interesting features of the grasps generated by the human using the robot as an extension of the body, albeit different kinematics of the robot. The data indicates that the human operator positioned the robot wrist on a line segment as the orientation of the handle was rotated in fixed increments. This is interesting as one could expect that the position of the wrist would follow the radial change in the handle orientation. The linear wrist positioning strategy could be beneficial since it helps to decouple the control of position and orientation of the hand. A long standing question in human motor control is whether the control of reach and grasp are controlled independently or through a single control mechanism. The current results cannot help answer this question as the human operator might have formulated a different solution for the robot limb he controlled. However it will be extremely important if it turns out that the human grasping has also this property; because this would suggest that human operator had utilized his control strategy for the robot limb he was given control of. In the spirit of robot skill synthesis via human learning framework, the human discovered grasping strategy can be used in designing an effective grasping controller for the robot. There two ways one can proceed. First alternative is extracting a high level principle (e.g. Linear wrist positioning) from the human discovered strategy, and designing a conventional controller based on this principle. The second alternative is using the individual grasp examples of the robot obtained by human operator to synthesize a grasping controller. In this study we have shown how the latter can be efficiently done and showed synthesized grasp executions in simulation and with the real robot (not included in this version of the paper).

VI. ACKNOWLEDGMENTS

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