Functional Anthropomorphism for Human to Robot Motion Mapping

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Abstract— **In this paper we propose a generic methodology for human to robot motion mapping for the case of a robotic arm hand system, allowing anthropomorphism. For doing so we discriminate between *Functional Anthropomorphism* and *Perceptional Anthropomorphism*, focusing on the first to achieve anthropomorphic solutions of the inverse kinematics for a redundant robot arm. Regarding hand motion mapping, a "wrist" (end-effector) offset to compensate for differences between human and robot hand dimensions is applied and the fingertips mapping methodology is used. Two different mapping scenarios are also examined: mapping for teleoperation and mapping for autonomous operation. The proposed methodology can be applied to a variety of human robot interaction applications, that require a special focus on anthropomorphism.**

Index Terms: Mapping Human to Robot Motion, Functional Anthropomorphism, Inverse Kinematics.

I. Introduction

Over the last decades a lot of studies have focused on the teleoperation of robotic arm hand systems with different interfaces, such as datagloves, magnetic position tracking systems, vision based tracking systems, myoelectric activity (EMG-based control) etc. Most of previous studies focused on the modeling, capture or estimation of human arm hand system kinematics without paying much attention on the mapping that must be performed, in order for the robot to be efficiently teleoperated in performing a specific task.

Moreover, when human is absent and robot must mimic the way a human performs a series of tasks in 3D space, anthropomorphic motion is not trivial, to be defined or accomplished. Regarding hand motion mapping four major methodologies with numerous variants have been proposed: fingertip mapping, joint-to-joint angle mapping, functional pose mapping and object specific mapping.

Fingertips mapping is a methodology proposed in [1], [2], [3], [4] and [5] and is based on the computation of forward and inverse kinematics for each robot finger. More specifically, using the forward kinematics for each finger of the human hand, we compute the positions of the human fingertips in 3D space. Then we use the inverse kinematics for each finger of the robot hand, to compute the sets of angles that lead the robot fingertips, to the same positions with the human hand fingertips, in 3D space.

The linear joint-to-joint angle mapping is based on the assumption that the kinematics of the human and robot hands can be considered quite similar and was used in [6] and later on in [7]. An advantage of this method, is the fact that it can be easily implemented as an one-to-one joint angle mapping between e.g. a calibrated dataglove and the robot hand. Another useful aspect of this approach, is the fact that in free space the replicated by the robot system postures are identical to the human master hand postures, because the human and robot finger links result to same orientations.

Functional Pose Mapping [8] has been proposed as a quite different approach for human to robot hand motion mapping. The principle of FPM is that both the human and the robot hand are placed in a number of similar functional poses and a relationship between each robot and human joint is found (e.g. using the least squares fit method).

The object-specific mapping originally proposed in [9] was extended with very interesting results in [10]. The object-specific mapping, provides a mapping between human and robot hand configurations for the case of a specific object and is a quite promising method that faces two major drawbacks: high computational complexity and inability to generalize for new objects (e.g. arbitrary shapes).

Regarding arm motion mapping, previous studies focused on a forward-inverse kinematics approach, to achieve same position and orientation for the end-effectors of the human and the robot arm. Moreover, most of them used numerical solutions (iterative and slow) to compute inverse kinematics, without paying much attention in anthropomorphism.

In [11] and [12] an analytical computation of inverse kinematics for seven Degrees of Freedom (DoF) redundant manipulators is performed, taking into account the joint limits and formulating an optimization problem to guarantee that joint angles will be kept away from their limits.

A quite interesting biomimetic approach for inverse kinematics of redundant robotic arms, has been presented in [13]. Authors capture human arm kinematics for random movements in 3D space and use them to describe and model the dependencies among the human joint angles using a Bayesian Network. Then an objective function built using the aforementioned model, is used in a closed loop iterative inverse kinematics algorithm. Despite the fact that the latter is a promising approach managing to model human joint

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dependencies and incorporating anthropomorphism in the IK solution search, the iterative nature of the algorithm and the fact that provides only one solution that may be suboptimal, lead us to seek alternative analytic schemes.

In this paper we discriminate between the different notions of anthropomorphism, introducing *Functional Anthropomorphism*. Then, we propose a generic methodology for human to robot motion mapping. More specifically, we compute closed-form solutions of inverse kinematics, to achieve same position and orientation for the end-effectors of the human and the robotic arm hand system in 3D space, using also an anthropomorphic criterion (based on the distance between human and robot elbows) to handle redundancy presented at the solution space of a redundant manipulator. Human to robot hand motion mapping is performed using the fingertips mapping methodology, applying a "wrist" offset to the end-effector of the robot arm, to compensate for differences between the human and the robot hand dimensions.

Moreover, we discriminate two different mapping scenarios: mapping for teleoperation based on human activity as well as mapping for autonomous operation, where human is absent and the human activity is proposed to be learned using an appropriately trained model. The proposed methodology is very efficient for human robot interaction applications that require anthropomorphism and can be easily generalized for other robotic systems such as other redundant robotic manipulators and dexterous robotic hands, as well as humanoids.

The rest of the document is organized as follows: Section II focuses on the discrimination between functional and perceptional anthropomorphism, Section III presents the experimental equipment, the parameters of robotic devices, as well as the kinematic model of the human hand, Section IV focuses on the inverse kinematics, Section V focuses on the methods proposed to handle redundancy, Section VI presents the outline of the mapping procedure and a series of simulated paradigms, while Section VII concludes the paper.

II. Functional and Perceptional Anthropomorphism

The essence of anthropomorphism as described in [14], is to imbue the imagined or real behavior of nonhuman agents with human-like characteristics, motivations, intentions and emotions. Anthropomorphism is derived from the greek word *anthropos* (i.e. human) and the greek word *morphe* (i.e. form). Regarding the perceived similarity, we can distinguish at least between two dimensions of similarity for anthropomorphism, similarity in motion and similarity in morphology.

Why do we need anthropomorphism in the first place ? The last decade we experience an increasing demand for human robot interaction applications, so anthropomorphism becomes a necessity for two main reasons; safety and social connection through robot likeability.

Regarding safety it has been proved that human-like motion can be more easily interpreted by humans. Nearly 140 years ago Charles Darwin suggested anthropomorphism as a necessary tool for efficiently understanding nonhuman agents [15]. Thus, in scenarios where human and robots cooperate advantageously in order to execute a specific task, if robots move anthropomorphically, users can more easily understand or even predict their motion and adjust accordingly their activity, in order to avoid possible injuries.

Regarding social connection through robot likeability, the more human-like a robot is in terms of motion (e.g. co-ordinated motion, synergistic behavior etc.), appearance (e.g. form, synthetic skin etc.), expressions (e.g. facial), perceived intelligence, then the more easily will manage to establish a solid social connection with human beings. For more information regarding anthropomorphism and the social implications that it may have, the reader should refer to [16], [17], [18], [19] and [20].

A first approach to investigate the different expressions of anthropomorphism can be found in [21], where the authors discriminate between functional and structural anthropomorphism for the developement of anthropomorphic technical devices that will assist disabled people. More specifically the *functional way* proposed to develop such a device is to provide a human function independently of the structural form, while the *structural way*, is to more or less accurately imitate some part of the human body.

Hereby, we propose a clear distinction between *Functional* and *Perceptional Anthropomorphism* for human to robot motion mapping. *Functional Anthropomorphism* concerns a mapping approach that has as first priority to guarantee the execution of a specific functionality in task-space and then having accomplished such a prerequisite to optimize anthropomorphism of structure or form, minimizing some "distance" between the human and robot motion. For doing so an adequate metric of this "distance" must be defined, that will lead with low-complexity in unique anthopomorphic solutions.

Perceptional Anthropomorphism is proposed as the sub-category of anthropomorphism that concerns co-ordinated motion, behavior, decisions or even emotions that can be perceived intuitively as human-like (i.e. of human nature). Perceptional anthropomorphism can be further splitted in structural/postural anthropomorphism focusing not only on the instantaneous structural similarity, but also concerning motion co-ordination and synergistic performance, as well as behavioral anthropomorphism named by the imitation of human behavior by robots (e.g. facial expressions by humanoids, decisions taken etc.). As it can be easily hypothesized the boundaries between postural/structural and behavioral anthropomorphism are not easy to be defined, as parameters like the velocity profile of a motion may be classified subjectively in both categories.

Thus, we propose the generic term perceptional anthropomorphism to examine all those cases where anthropomorphism is not constrained, by having as a prerequisite the execution of a specific functionality in task-space. In this paper, we focus on fuctional anthropomorphism as we evaluate the efficiency of the proposed mapping methodology for the case of a robotic arm hand system, whos end-effector must achieve same position and orientation with the human end-effector (functional constraint).

III. Apparatus, Robots and Models

A. Mitsubishi PA10 7DoF Robotic Manipulator

The Mitsubishi PA-10 is a redundant robotic manipulator, which has seven rotational DoFs arranged in an anthropomorphic way: two DoFs at the shoulder, two DoFs at the elbow, and three DoFs at the wrist. The robot servo controller communicates with a personal computer (PC) via the ARCNET protocol. More details regarding the kinematics, the parameters and the control of the Mitsubishi PA10, can be found in [22].

B. DLR HIT II Five Finger Robot Hand

The DLR/HIT II is a five fingered fifteen DoFs dexterous robotic hand jointly developed by DLR (German Aerospace Center) and HIT (Harbin Institute of Technology). DLR/HIT II, has five kinematically identical fingers with three DoFs per finger, two DoFs for flexion and extension (corresponding to the proximal interphalangeal and metacarpophalangeal joints of the human hand) and one DoF for abduction-adduction (corresponding to the metacarpophalangeal joint of the human hand). The last joint of each finger is coupled with the middle one, using a mechanical coupling based on a steel wire, with transmition ratio 1:1.

The dimensions of the robotic hand are considered to be quite human-like and the total weight is quite low, 1.6 kgr. More details regarding the kinematics or other specifications of the DLR/HIT II, can be found in [23].

C. Experimental Equipment

In order to capture human arm kinematics the Isotrak II (Polhemus Inc.) magnetic motion capture system was used. It consists of a reference system and two magnetic position sensors. The acquisition frequency of this system is 30 Hz and it provides high accuracy in both position and orientation, 0.1 in and 0.75 deg respectively. One sensor is placed on the user's wrist and the other one on the elbow.

The human hand kinematics were captured with the CyberGlove II (Cyberglove Systems) motion capture system. This glove has 22 sensors capturing all twenty DoFs of the human hand and the two DoFs of the human wrist. More specifically, the abduction-adduction and flexion-extension of the wrist, the flexion-extension of the proximal, metacarpal and distal joints of each finger and the abduction between the fingers, can be measured. The acquisition frequency of the Cyberglove II is 90 Hz and the accuracy is 1 degree.

D. Kinematic Model of the Human Hand

The kinematic model of the human hand that we use is inspired by the positioning of Cyberglove II flex sensors. More specifically our model consists of twenty DoFs, four DoFs for index, middle, ring and pinky (three for flexion/extension and one for abduction/adduction) and four DoFs for thumb (two for flexion/extension, one for abduction/adduction and one to model thumb's ability to oppose to other fingers). It must be noted that each finger is considered as an independent serial kinematic chain.

Although human hand digit lengths, are quite easy to be measured, expressing the base of each finger relatively to the base of the wrist is a difficult problem, which requires advance techniques such as fMRI [24]. In this paper we use the parametric models for each digit derived from hand anthropometry studies [25].

IV. Inverse Kinematics

A. Inverse Kinematics of Robotic Arm Mitsubishi PA-10

In this section we focus on the inverse kinematics (IK) of the Mitsubishi PA-10 robot arm. According to Craig [26] due to their iterative nature, numerical solutions are much slower than the corresponding closed-form solutions and according to Siciliano [27], they do not allow computation of all admissible solutions.

Closed-form solutions are desirable for fast motion planning for the following two reasons:

1. Closed form solutions are much faster than those of the numerical IK solvers. (e.g. closed-form methods can produce solutions on the order of 6 microseconds, while most numerical methods provide solutions on the order of 10 milliseconds, facing also the issue of convergence).
2. We can explore the null space of the solution set, as all solutions are computed. The latter can be really useful in applications where anthropomorphism is required, as we can choose the most anthropomorphic solution of the complete set computed.

Thus, in this paper we choose to acquire closed-form solutions provided by an inverse kinematics solver extracted by the IKFast algorithm, that is part of the Open Robotics Automation Virtual Environment (OpenRAVE).

Mitsubishi PA10 is an anthropomorphic - redundant manipulator which can be solved using the above analyses (using submodules) by assuming that the translation and rotation components are separable. Such a kind of separability allows much simpler solutions involving quadratic polynomials. More precisely, Mitsubishi PA10 has seven DoFs while we need only six in order to compute inverse kinematics. In this case we pick a joint that is the least important and we call it **free joint** keeping it fixed, for every inverse kinematics computation for the rest **active joints**. The least important joint is chosen so as for the first three or the last three joints, to intersect at a common point. During planning, we discretize the range of the free joint, using a desired step of x rad (e.g. $x = 0.01$) for its full range.

The full solution space for specific end-effector position and orientation can be then searched, in order to select a solution that satisfies joint limits and all other planning constraints and optimizes some appropriately defined metric of anthopomorphism. Details regarding the IKFast algorithm and the OpenRAVE can be found in [28] and [29].

B. Inverse Kinematics of Robotic Hand DLR/HIT II Fingers

Regarding the DLR/HIT II robot hand inverse kinematics, we choose to solve the IK analytically, for each of the five kinematically identical robot fingers. It must be noted that each robot finger is considered as an independent serial kinematic chain, that has a finger base frame, expressed relatively to the center of the wrist. It must be also clarified that the last joint of each robot finger is coupled with the middle one, using the aforementioned mechanical coupling. Thus, this coupling as well as joint limits, should always be taken into account when computing the inverse kinematics.

V. Handling Redundancy and Anthropomorphism

The inverse kinematics technique applied for the robotic arm that we described in the previous section leads us, due to the redundant design of Mitsubishi PA10, to multiple solutions. All these solutions achieve desired position and orientation for the robotic end-effector in 3D space, but the robotic arm configuration may be far from anthropomorphic.

In this point its very significant to define what anthropomorphic motion means for the case of the robot arm hand system and how this anthropomorphism can be measured. The answer is not trivial, as it is very difficult to propose a metric that would be able to easily quantify and measure anthropomorphism, without a human reference. So, in this paper we propose not to try to measure anthropomorphism as an independent quantity, but to define and quantify it, through the comparison of human and robot motion.

A. "Distance" Between Human and Robot Elbow Positions in 3D Space as a Metric of Anthropomorphism

More specifically for the case of a robot arm hand system, given the fact that the end-effector of the robot arm must achieve same position and orientation with the end-effector of the human arm and that the "shoulder" is always the common base frame, a good criterion is to minimize the area of the two triangles defined by the common "shoulder", the common "end-effector" and the two positions of the human and the robot "elbows". In order for our method to be able to generalize, we propose as a metric of anthropomorphism, the volume of the convex hull created by the human and the robot joint positions in 3D space.

The convex hull of a set Q of points is the smallest convex polygon P for which each point in Q is either on the boundary of P or in its interior. We denote the convex hull of Q by $\mathrm{CH}(Q)$. There are plenty of methods available to compute the convex hull of a set Q of points. In this study we choose to use the well known quickhull algorithm for convex hulls, that has been proposed in [30].

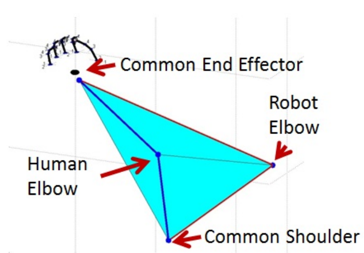

Fig. 1. Convex hull created by the joint positions of the human arm (blue line) and the joint positions of robot arm (red line). Simulations were performed with Robotics Toolbox for Matlab.

B. Learning Human Elbow Position for Autonomous Operation

In order to be able to use the aforementioned anthropomorphic metric even when the human is absent, we choose to learn using random forrests regression, the position of the human elbow from human wrist (i.e. end-effector) positions. For doing so, we train task-specific random forests models as described in [31] and [32] that are able given robot end-effector positions to estimate with high accuracy the "ficticious" human elbow positions. In order to train the aforementioned models we use the dataset of the experiments conducted in [31]. More specifically, the regression problem that we address, involves as three inputs the position coordinates of the human wrist (i.e. end-effector) and as three outputs the position coordinates of the human elbow.

The task-specific random forest models that we trained were grown for ten trees for simplicity and speed of execution. In Table I we present the estimation accuracy for reach-to-grasp movements, executed by five different subjects towards five different positions in 3D space. Estimation accuracy remains consistently high for movements executed in task-specific subspaces. In other words each task-specific model managed to efficiently estimate, given a desired robot end-effector position where the human elbow would be (i.e. to estimate the "ficticious" human elbow position), if the user was to perform the specific task in 3D space.

TABLE I
Estimation Accuracy for Learned Human Elbow Positions for Reach to Grasp Movements Executed by Five Subjects, Towards Five Different Positions in 3D Space (Pos I - V).

Subj	Pos I	Pos II	Pos III	Pos IV	Pos V
1	96.20% sd:0.29%	95.58% sd:0.43%	96.34% sd:0.38%	96.12% sd:0.40%	96.57% sd:0.30%
2	95.02% sd:0.35%	95.01% sd:0.39%	92.46% sd:0.44%	93.85% sd:0.42%	95.95% sd:0.35%
3	93.24% sd:0.39%	93.34% sd:0.42%	94.08% sd:0.46%	92.84% sd:0.51%	93.46% sd:0.41%
4	93.07% sd:0.46%	94.88% sd:0.47%	93.76% sd:0.49%	93.09% sd:0.52%	94.85% sd:0.42%
5	92.94% sd:0.48%	92.92% sd:0.44%	92.87% sd:0.50%	92.43% sd:0.47%	91.11% sd:0.53%

C. Handling Redundancy Presented at the Solution Spaces of the Robot Arm and the Robot Hand

For the case of the robot arm (Mitsubishi PA10), the problem of acquiring an anthropomorphic solution from the multiple IK solutions computed (due to the redundancy) becomes to find an IK solution that minimizes the volume of the convex hull created by the human and the robot joint positions in 3D space. Even if a solution is found, it might not be unique. In this case we still have to handle for a specific configuration of the robot arm, the redundancy caused by "internal motions" as described in [27]. Thus, we choose from the remaining multiple solutions, the one that maximizes velocity manipulability at the end effector of the robot arm.

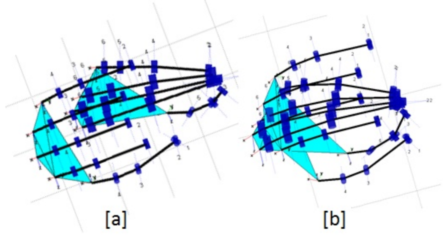

Fig. 2. Subfigure [a] represents human and robot hand convex hulls before "wrist" offset elimination, while subfigure [b] represents human and robot hand convex hulls after incorporating the "wrist" offset elimination, as part of the mapping procedure (without fingertips mapping).

More precisely, we choose the solution that maximizes the manipulability measure, which is defined as:

$$w(\mathbf{q}) = \sqrt{\det(\mathbf{J}(\mathbf{q})\mathbf{J}^T(\mathbf{q}))}$$

where $\mathbf{J}$ is the Jacobian matrix and $w(\mathbf{q})$ vanishes at singular configurations. Maximizing this measure, redundancy is exploited to move away from singularities.

For the case of the robot hand (DLR/HIT II), we explore the solution space of each finger, choosing those IK solutions that respect the joint limits that we have set (e.g. hardware or even software joint limits). Then if/when multiple solutions exist, we choose to acquire the one that maximizes manipulability measure, at the fingertip of each robot finger.

D. *Wrist (Robot Arm End-Effector) Offset to Compensate for Human and Robot Hand Dimensional Differences*

Typically the human hand and the robot hand (e.g. DLR/HIT II) have quite different dimensions. In order to achieve same position and orientation for the human and the robot hand fingertips in 3D space, using the fingertips mapping methodology, we must first eliminate those dimensional differences. For doing so, we apply an appropriately defined "wrist" offset, that may move robot "wrist" away from the human, but will bring robot fingertip positions closer to the human's.

In order to acquire this offset we compute the convex hulls created by the robot hand fingertips and the human hand fingertips. The wrist offset is then defined as the translation required to eliminate the distance between the centers of the two convex hulls. In Fig. 2 we can see a graphical representation of the wrist offset elimination procedure, which maximizes the covering between the human and the robot hand workspaces.

VI. Mapping Methodology Outline and Simulation Paradigms

To summarize, the outline of the mapping methodology proposed, is the following:

- Human wrist (i.e. end-effector) and elbow positions are captured with Isotrak II.
- Human hand joint angles are captured with Cyberglove II.
- Fingertip positions of the human hand are computed using human hand forward kinematics.
- All possible IK solutions of the robot arm are computed for desired end-effector position (closed form).
- Redundancy at the solution space of the robot arm is handled with anthropomorphic criterion (convex hull volume minimization) and manipulability measure maximization.
- "Wrist" offset is introduced to eliminate dimensional differences between human and robot hand.
- All possible IK solutions for each finger of the robot hand are computed for desired fingertip positions.
- Redundancy presented at the solution space of the robot hand fingers is handled keeping solution inside joint limits and maximizing manipulability measure.

In order to simulate our models and check the correctness of the forward and inverse kinematics computations, the OpenRave simulation environment has been used together with the ninth version of Robotics Toolbox (MATLAB) developed and distributed by Peter Corke [33].

In Fig. 3[a] the proposed mapping scheme is used to acquire the most anthropomorphic solution of the robot arm IK for teleoperation purposes. In Fig. 3[b] the most anthropomorphic IK solution is selected based on the estimated "ficticious" human elbow position, for autonomous operation purposes.

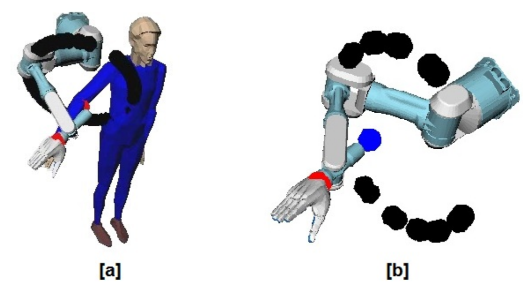

Fig. 3. Simulation paradigms for different mapping scenarios. Subplot [a] presents a simulation performed for the teleoperation scenario. IK solution selection is based on the criterion of anthropomorphism, a robotic "shoulder" offset (to scale the workspace) and a robotic "wrist" offset. The two red spheres represent human elbow and wrist. Black spheres represent alternative solutions for the robotic elbow. Subplot [b] presents a simulation paradigm for the autonomous operation scenario. IK solution selection is based on the proposed anthropomorphic criterion. Blue sphere represents the estimated "ficticious" human elbow position while red sphere represents end-effector goal position. Black spheres represent alternative solutions for the robotic elbow (all simulations were performed with OpenRAVE).

VII. Conclusions and Future Directions

In this paper we discriminated between the different notions of anthropomorphism and we introduced functional anthropomorphism, for the problem of human to robot motion mapping. Moreover we proposed a methodology to map human to robot motion for the case of Mitsubishi PA 10 - DLR/HIT II robotic arm hand system.

For doing so we computed forward and inverse kinematics to achieve same position and orientation for the end effectors of the human and the robot arm in 3D space (functional constraint) and we used the fingertips hand motion mapping methodology combined with a wrist offset to compensate for dimensional differences between the human and the robot hands. To handle redundancy, we introduced an anthropomorphic criterion based on the distance between the human and robot elbow positions in 3D space. The proposed mapping scheme serves two different scenarios: mapping for teleoperation and mapping for autonomous operation.

Regarding future directions the authors plan to extend the proposed methodology for the case of robotic arm hand systems with arbitrary kinematics.

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