Underactuated Gripper with Forearm Roll Estimation for Human Limbs Manipulation in Rescue Robotics

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***Abstract*— The emergence of new robotic technologies such as compliant control and soft robotics, has contributed to safe physical Human-Robot Interaction (pHRI) mainly for assistive applications. However, a robot capable of directly manipulating the human body, which is key for the implementation of autonomous rescue robots, has not been developed so far. In this paper, the development of a gripper and methods for the robotic manipulation of a laying victim's forearm, initiated by the robot is addressed, and validated based on experimental results. An underactuated gripper with added proprioceptive sensors has been designed, with environment sensing and tactile recognition capabilities. This method provides a stable grasping of a human forearm that lays on a surface and is capable of estimating the roll angle of the grasped arm for precise location and safe manipulation. The roll-angle estimation method is based on Machine Learning and has been trained with experimental data obtained from experiments with human volunteers. The resulting method provides robust and precise grasping, tolerant to location inaccuracy with inexpensive sensors. This is one of the very first works on the robotic human-body manipulation.**

I. Introduction

Recent trends in robotics pursue the incorporation of robotic systems among people, not only in the industry, as collaborative robots (i.e. cobots) [1], but also in everyday life as social robots [2] mostly for assistive applications, helping patients [3] or elderly people [4].

Physical interaction between robots and humans is necessary for many applications that include rehabilitation [5], exoskeletons [6], or prosthesis [7]. The interaction between robots and humans must be stable and safe [8] when physical contact occurs. This way, the emergence of innovative technologies such as Variable Stiffness Actuators [9] or soft robotics [10] among others, have contributed to safe physical Human-Robot Interaction (pHRI).

Other applications require that the robot initiates the contact. Those applications in which a robot intentionally touches or even manipulates people are useful for diverse fields such as assistive robotics [11] and necessary for search and rescue missions [12] or healthcare applications [13] among others.

Not many research studies regarding robot-initiated pHRI can be found in literature. In [14], a robot that cleanses limbs of disabled people is presented, and a simulated robotic repositioning controlled by an impedance Model Predictive Control (MPC) is described in [15].

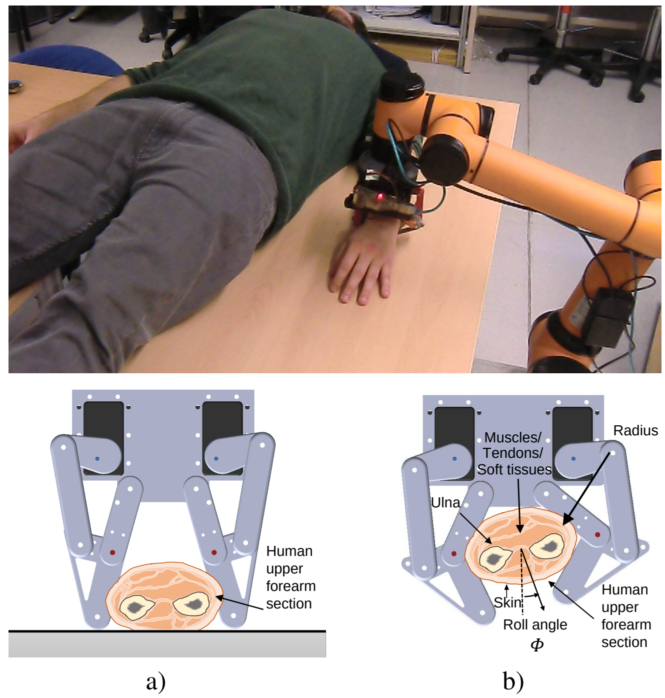

Fig. 1. Robot-initiated grasping of the forearm of a laying person using an underactuated adaptive gripper (top), and manipulation problems to solve (bottom): a) Difficulty of getting a stable grasping of a human upper forearm laying on a surface. b) Estimation of the actual roll grasping angle.

The choice or design of the end-effector is important for the safe manipulation of human limbs. This way, multiple grippers have been considered in previous works [16], however, there is still a need to develop robotic hands which allow a robot to perform safe and autonomous grasps with enough robustness and reliability to manipulate human limbs.

Although there is a growing interest on the development of soft-grippers [17], the need for precise manipulation often requires an adaptive but rigid solution. The use of grippers with underactuated fingers based on rigid links [18] or tendon-driven [19] provide adaptive and precise grasping that can be adopted for pHRI.

Apart from the proprioceptive position-torque sensing capabilities of the finger actuators, grippers can have pressure sensors to detect stable grasp conditions [20] or recognize grasped objects [21]. In previous works we used high-resolution tactile sensors to distinguish between human-body

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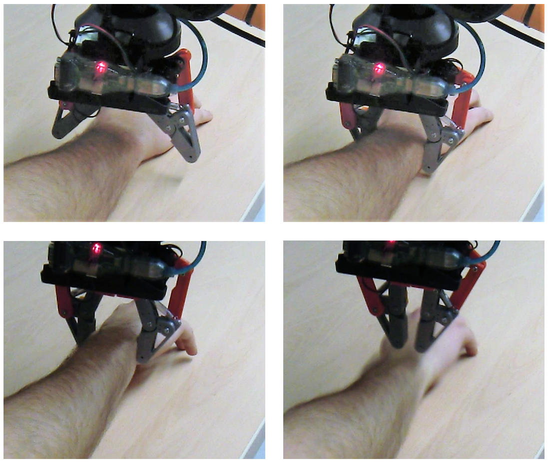

Fig. 2. Sequence of 4 images of an unstable grasping using a conventional underactuated gripper (From top to bottom and from left to right). This grasp is unpleasant for a human, and unreliable.

parts and inert objects [22] through deep learning-based techniques using rigid and flexible grippers [23].

This work is focused on the robot-initiated grasping of the forearm of a laying person using grippers with two underactuated fingers with two-phalanx (see Fig. 1), where the main problems can be found:

- Unstable grasping of the forearm: The low profile of the forearm over the laying surface (floor, table, bed, etc.) makes difficult to make a stable grasp, where all phalanx make stable contact with the arm, due to the collisions with the floor and the inability of the finger to bend without previous contact, as shown in figure 2.
- It is important to estimate the roll-angle of the grasped arm in order to make a safe autonomous motion planning. Depending on this angle, the movements constraints of the forearm may change and the robot could hurt the subject. In addition, it is also useful to find the right area for biomedical sensor placement or performing other procedures on the human body.

In this work, we present a new method based on the addition of one angular sensors to each underactuated finger to have full measurement of the finger position when combined with the actuator position information, for the detection of both of the contact with environment and the angular position of the grasped object, plus its application to the stable and precise grasping of human arms. First, the sensor is used to have precise positioning relative to the surface, and then, used to estimate the roll-angle of the grasped arm.

This method makes a gentle and precise grasping of human limbs that lie on a surface using grippers with underactuated fingers without external pressure sensors possible, due to the addition of a single proprioceptive angular sensor. This is specially important when visual human detection method provide approximate positioning of the human and the environment.

Manipulation of human limbs is a basic step for the physical human robot interaction needed in autonomous rescue robots. However, no previous works have been found on robot-initiated manipulation of human limbs.

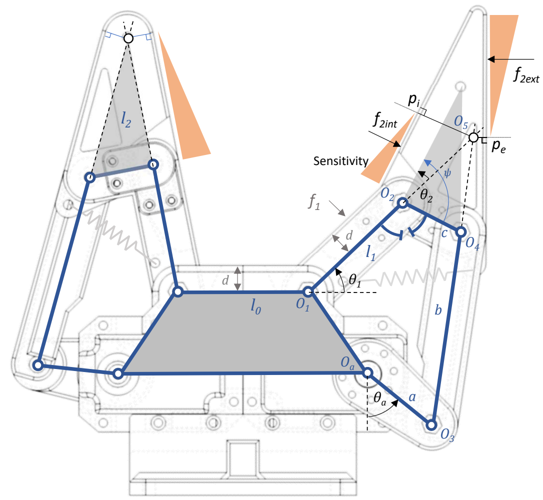

Fig. 3. Kinematic design of the gripper for pHRI. The shape of the distal phalanxes and the joint limits are different to provide two kinds of behaviours under external and internal forces whose sensitivity is illustrated in orange color. Right finger is in the open position and left finger is in an intermediate position rejecting all the forces coming from the external side of the gripper. For clarity, only one finger has been labeled, and no l or r sub-indexes are used.

TABLE I

PARAMETER VALUES OF THE UNDERACTUATED FINGER.

Parameter	Value	Parameter	Value
$\overline{O_1 O_a}$	[16, −20] mm	c	20 mm
l_0, l_1, l_2	40 mm	d	8 mm
a	25 mm	ψ	90°
b	60 mm	width	15 mm
θ_{2min}	0 (left), 20° (right)		

This paper is structured as follows: In section II the design of the gripper is presented. Then, in section III the method for roll-angle estimation is presented, and in section IV the method for stable grasping and roll-angle compensation of a human forearm is described. Finally, some conclusions and future work are included.

II. ADAPTIVE GRIPPER

The designed gripper has two independent underactuated fingers with two phalanxes and a single actuator each. The use of tendons (e.g. Yale OpenHand Model T42) as in [19] has been discarded, due to the displacements of the contact surfaces which pinch the skin of the forearm. For this reason, a rigid linkage approach has been used.

The kinematic design is shown in Figure 3. The parameter values, summarised in Table I, have been designed to adapt to the shape and size of a regular human upper-forearm with a perimeter between 15.3 and 18.8 cm. The shape of the distal phalanx are different to provide two kind of behaviours under external and internal forces. The values of the θ_{2l} y θ_{2r} are also different.

A mechanical limit makes the distal phalanx angle $\theta_2 \geq \theta_{2min}$. The actual position of the finger depends on the balance between external forces f_1, f_2 and the actuator torque. The spring ensures contact between the finger pads and external objects and make the finger stable when no external forces are applied. The extension springs are made with $0.6mm\oslash$ steel wire and a stiffness of 164N/m.

A. *Compliance to external forces*

The gripper has to adapt to the grasped object, and one of the fingers has been modified to allow better compliance to the environment. In Figure 3, the sensitivity to internal and external forces normal to the contact surfaces of the distal phalanxes is shown. The right finger is in open position

For a given actuator position θ_a, the finger position can be modified applying external or internal (applied to inner surfaces of the gripper) based on a four-linkage system with vertices O_1, O_2, O_3 and O_4. Considering $\overline{O_1O_3}$ as a fixed segment, the opposite segment $\overline{O_2O_4}$ rotates around an instantaneous center of rotation O_5, which is a virtual axis O_5 located at the intersection of the lines defined by segments $\overline{O_1O_2}$ and $\overline{O_3O_4}$. If we consider only the surface-normal component of the external forces, neglecting the friction of the contact surfaces, the resulting torque around O_5 depends mainly on the magnitude of the force and the distance between the force vector and the centre of rotation O_5. The spring stiffness has been chosen to provide the torque enough to overcome the friction and gravitational effects. For the rest of the analysis, frictions and other dynamic components are neglected. The points p_i and p_e define the nearest surface point to the instantaneous rotation centre from the interior and exterior sides respectively, and define the sign of the resulting rotation torque. When $O_2 = O_{2min}$ negative torques are rejected due to the mechanical limit of the joint.

The right finger has been redesigned to make it compliant to exterior forces, while also adapting to the grasped objects, in the following ways: The length of the distal phalanx has been increased to have larger torques from side forces, and the range of θ_{2r} has been mechanically limited with a minimum of 20° to bend the finger when the forces are applied on the fingertip. This finger will be used here to measure distance with environment surfaces and to prepare the grasping, bending one finger, before grabbing the human arm.

The left finger has been kept with the original size to bend under contact with objects with interior side of the gripper. The position of the left finger in Figure 3 shows how this configuration is rigid to exterior forces but sensible to any interior force. In figure 4 a picture of the actual gripper under external forces can be seen.

The prototype has been designed for easy manufacturing using FDM 3D-printers, and its design has been made available in a public repository [1].

B. *Grasping force*

Due to the parallel rigid linkage system, the forces at the center of the interior contact areas of the phalanxes in this gripper depends also on the joint values [20], as it is shown in the equation 1.

$$f = J^{-T}T^{-T}t \tag{1}$$

Where f are the interior contact forces vector, t is the actuator torque vector, T is the Transfer matrix, that relates the velocities of the actuators to the joint velocities, J is the Jacobian matrix that relates the finger joint velocities to the speed of the contact points. T^{-T} means the inverse of the transposed of the Transfer matrix. Although if the Jacobian and Transfer matrices depend on the actual positions, if the same final grasping position (i.e. grasping the same object) is kept, the magnitude of the closing forces of each finger (f_1 and f_2) are proportional to the actuator torque t_a. With a maximum torque for each of the *Dynamixel MX-28* servos of 2.5 Nm, the effective closing forces for each finger have been measured from 4.9 N (20%) to 27.4 N (100%).

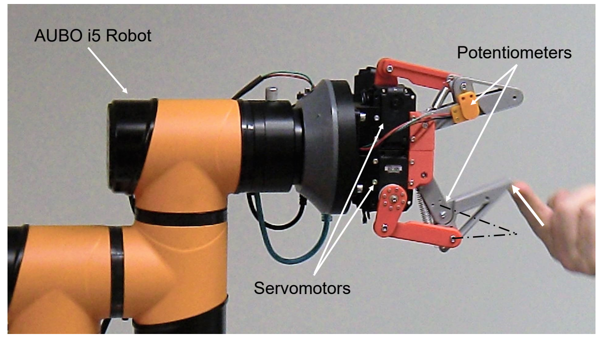

Fig. 4. Prototype of the robot gripper for pHRI with different compliance to external forces: Left finger (Up) reject exterior forces and right finger (Down) bends when in contact with the environment.

C. *Proprioceptive sensing*

By adding proprioceptive angular sensors, the angles O_{2l} and O_{2r} are measured. This way, with the position information provided by the servos (θ_{al} and θ_{ar}), the position of the remaining phalanxes (θ_{1l} and θ_{1r}) can be computed. As a result, the position of the external objects can be estimated using the θ_{2r} and the shape of the grasped object can be inferred with the positions of the two fingers θ_l and θ_r.

Two potentiometers (*muRata* SV01 $10k\Omega$ linear) have been used for the measurement of the distal joints, and a micro-controller with 10-bits ADC, (0.26° resolution) has been added to the gripper as a DAQ with a 50Hz sample rate. The two *Dynamixel MX-28* servos include a 12-bits digital magnetic encoder (0.088° resolution). They provide feedback of the servo positions θ_{al} and θ_{ar} at a rate of up-to 50Hz.

III. Roll-Angle Estimation

To manipulate the arm of a victim it is critical to know the roll-angle (ϕ) of the forearm during the grasping process (see Fig.5). For this purpose, the use of machine learning techniques have been considered and regression models have been obtained to estimate ϕ.

[1] /github.com/TaISLab/umahand

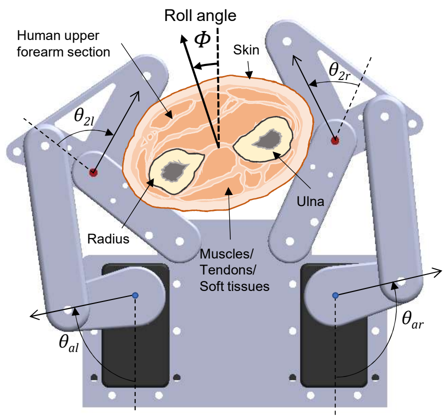

Fig. 5. Cross section of a human upper forearm grasped by the under-actuated gripper, showing the variations in the passive (θ_{2l},θ_{2r}) and active (θ_{al},θ_{ar}) DOF's, based on the roll grasping-angle (Φ).

A grasping operation has been programmed as a constant-velocity trajectory for both actuators in opposite directions with a stiff proportional-only controller with programmable torque limits. When both actuator velocities ($\dot{\theta}_{a_r}, \dot{\theta}_{a_l}$) are null, the goal point is set to the current position, stopping the motion of the fingers.

A torque of 1.15 Nm (46% of the maximum torque) that provides a closing force of about 11.76 N per finger has been selected as the closing torque for the experiments, because it has been considered by the volunteers as a firm and gentle grasp.

In order to obtain the ground-truth angular measurement of the human forearm, a device that includes an accelerometer has been implemented. The device is held by the human in their hand during the experiments. As the attitude of the robot gripper is known, the relative rolling angle of the human forearm with respect the gripper can be obtained and used as a reference data for training and performance evaluation of estimation methods.

The data collection procedure is carried out with the gripper placed on a table, and volunteers are asked to put their hands inside the gripper with different angles while the gripper grasps their forearm and collects data. An illustration of this procedure and the data collected from one volunteer are presented in Fig.6.

The relationships between $\theta_{a_r}, \theta_{a_l}, \theta_{2_r}, \theta_{2_l}$ and ϕ can be seen in Fig.7. This figure shows a set of data used for training and testing the regression models.

Three machine learning methods have been trained to get an estimation model: Gaussian Process (GPR), Regression Tree (RT) and Bagging Regression Tree (BRT). The training and evaluation processes have been carried out using *Matlab R2018b*, the *Statistics and Machine Learning Toolbox* and the *Regression Learner application*. A dataset formed by 1110 combinations of joint angles and ϕ from the left arm of one person are used to train and test the methods. The performance of the regression models is presented in Fig.8. GPR obtains the better performance with a Maximum Error of $9.24o$ and a Mean Absolute Error of $3.77o$.

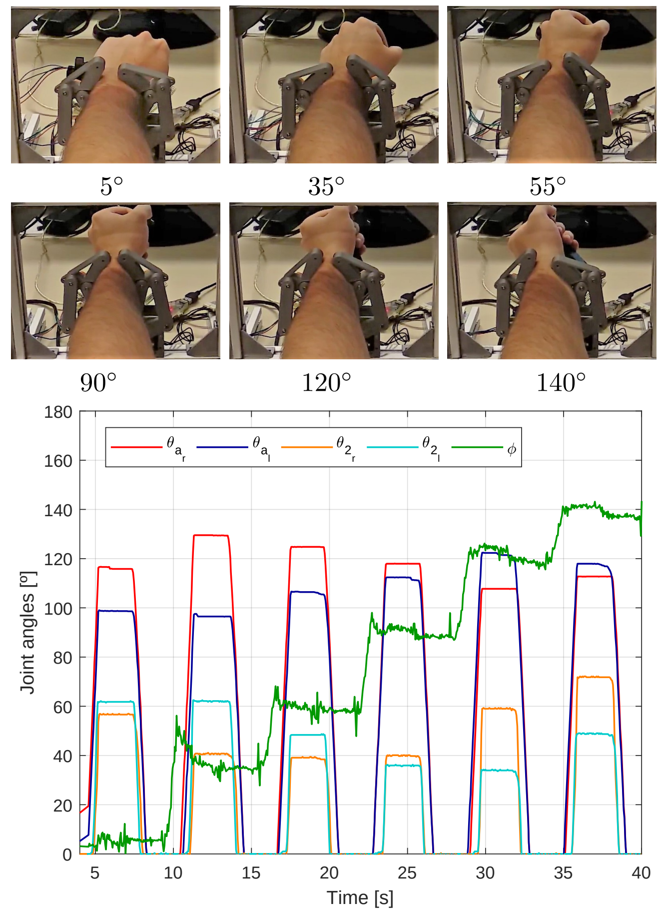

Fig. 6. Sequence of 6 grasps during the data collection process of one volunteer (top). Motors, joints and roll angle positions during a data collection process (bottom). Note that in this graph the open-and-close process is repeated each 6 seconds. Angle ϕ is measured using the data from an accelerometer integrated in a device held by the subject.

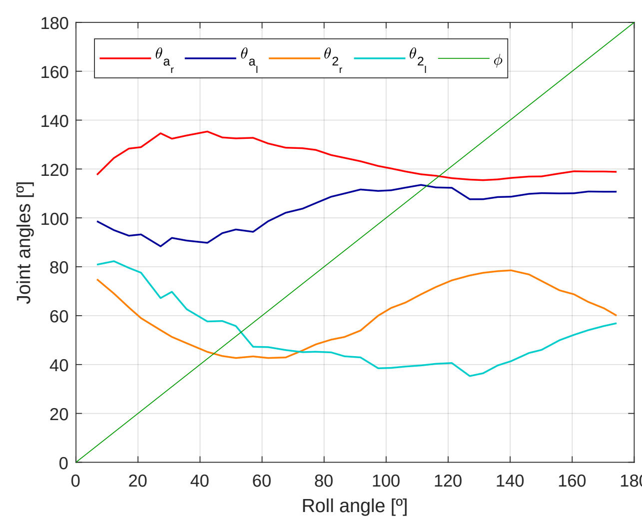

Fig. 7. Joint values for 36 grasps, measured at different angles from 0^o to 180^o, on the left arm of a volunteer with a perimeter of 17.9 cm, against the roll angle.

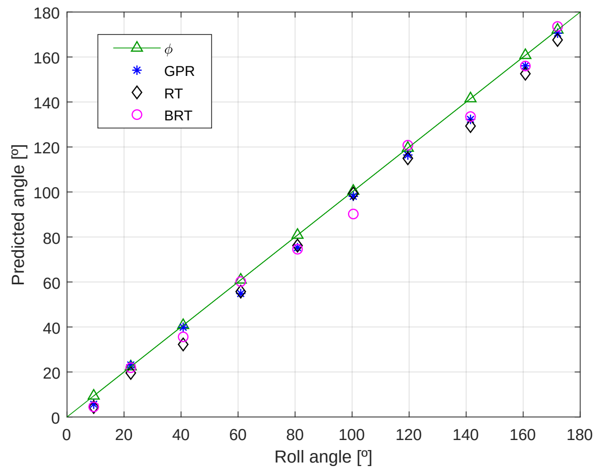

Fig. 8. Performance of Gaussian Process (GPR), Regression Tree (RT) and Bagging Regression Tree (BRT) models.

IV. Grasping and roll-angle compensation of a human forearm

The purpose of this procedure is to perform the relocation of the arm of a laying person, as a basic step for further operations. Some assumptions have been made during the definition of the forearm manipulation procedure: The victim is considered to be static on a flat surface. The approximate position of the upper forearm is known, and the victim is passive during all the procedure. There are computer vision methods [24] for the detection of human bodies that provide approximate 3D location of the human joints, although this problem is not considered here. The experiments presented in this paper have been carried out with the consent of the subjects.

Instead of using a traditional pick-and-place procedure, an alternative strategy, inspired by the manipulation strategy for small objects on a table presented in [25], has been developed. Fig. 9 shows the sequence of the grasping procedure with the following steps:

1) Approach: The robot gripper is placed near the human arm, opposite to the rest of the body with a pitch angle of $-30°$ looking toward the target position, with the right finger described in section 3 looking down.
2) Find the surface: The robot moves vertically towards the surface until the right finger is almost parallel to the surface. This condition is detected thanks to the proprioceptive sensors integrated in the underactuated gripper.
3) Surface following: The gripper is moved toward the human arm keeping the desired reading at the potentiometer to follow the shape of the surface until the estimated distance to the human forearm is traveled.
4) Grabbing: This phase combines two actions at the same time. The manipulator sets the tool center point (TCP) aligned with the O_4 axis and starts a rotation of 70^o over it to wrap the human forearm. Meanwhile, the fingers start moving to the closing position with velocity and torque limits.
5) Lift: When the servo positions are steady, the goal positions are updated to the actual positions and the grasping is considered stable to be gently lifted.
6) Roll-angle Estimation: In this step, once the forearm is grasped, the robot estimates ϕ using the current angle of the joints of the finger ($\mathcal{Q} = [\theta_{a_r}, \theta_{a_l}, \theta_{2_r}, \theta_{2_l}]$) and a Gaussian Process regression model (GPR) previously obtained, with outcomes the estimated roll-angle (ϕ_e). The estimation process and the regression model are explained in detail in section III.
7) Relocation: Once ϕ_e is obtained, the robot initiates the relocation process. This phase consists of three steps: in first place, the robot rotates the forearm an angle ϕ_e to get it parallel to the contact surface. Then, the manipulator performs an horizontal circular trajectory in order to separate the forearm to the body. Finally, the manipulator realize a perpendicular approach to the contact surface to place again the arm on the surface. The gripper opens and releases the wrist, finishing the manipulation procedure.

V. Conclusions

In this paper an initial method for the manipulation of human limbs with robot-initiated contact, has been presented. This method is based on the design of an asymmetrical gripper with modest sensing capabilities that add enhanced environment sensing and tactile recognition to a robot arm for autonomous physical human-robot interaction.

The gripper has environment sensing and compliant interaction capabilities, without the need for expensive sensors or additional actuators, which provide robust grasping under location uncertainty, as the manipulator accommodates to the support surface with tactile sensing and performs a wide grasping robust to moderate position inaccuracies. Results demonstrate the reliability of the manipulation methodology as the task has been carried out with satisfactory results in every test with different people.

Furthermore, to reduce the uncertainty on the position of the human forearm once grasped, a new method based on the same proprioceptive sensors, has been designed and implemented for the estimation of the roll-angle of the human forearm when grasped. It has been evaluated using experimental data obtained with a collaborative robot and a set of human volunteers. Note that the Gaussian Process Regression model (GPR) depends on the data acquired for each person, hence, different GPRs are used for different people.

This method provides a gentle and precise grasping of human limbs that lie on a surface using grippers with underactuated fingers without external pressure sensors, just with the addition of two inexpensive potentiometers. This is specially important when visual human detection methods do not provide roll angle of the human limbs or the forearm roll angle may change during grasping due to the robot gripper or movement of the human.

The interaction capabilities of the compliant gripper could be extended, as the stiffness of the distal phalanx of the finger

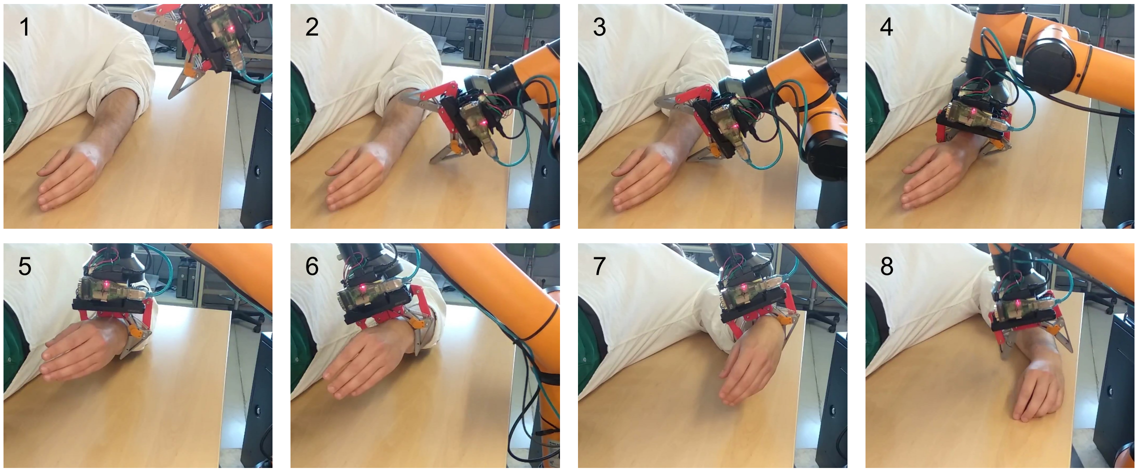

Fig. 9. Steps of the manipulation task during experimentation with a person laying on a table. Frames 1 to 5 illustrate the picking operation and frames 6 to 8 show the forearm roll-angle correction and relocation.

depends on the actuator position. This way, one finger may work as a variable-impedance end-effector, with possible new interaction applications.

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