Touch-Based Grasp Primitives for Soft Hands: Applications to Human-to-Robot Handover Tasks and beyond

Touch-Based Grasp Primitives for Soft Hands: Applications to Human-to-Robot Handover Tasks and Beyond

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Abstract— **Recently, the avenue of adaptable, soft robotic hands has opened simplified opportunities to grasp different items; however, the potential of soft end effectors (SEEs) is still largely unexplored, especially in human-robot interaction. In this paper, we propose, for the first time, a simple touch-based approach to endow a SEE with autonomous grasp sensory-motor primitives, in response to an item passed to the robot by a human (human-to-robot handover). We capitalize on human inspiration and minimalistic sensing, while hand adaptability is exploited to generalize grasp response to different objects.We consider the Pisa/IIT SoftHand (SH), an under-actuated soft anthropomorphic robotic hand, which is mounted on a robotic arm and equipped with Inertial Measurement Units (IMUs) on the fingertips. These sensors detect the accelerations arisen from contact with external items. In response to a contact, the hand pose and closure are planned for grasping, by executing arm motions with hand closure commands. We generate these motions from human wrist poses acquired from a human maneuvering the SH to grasp an object from a table. We obtained 86% of successful grasps, considering many objects passed to the SH in different manners. We also tested our techniques in preliminary experiments, where the robot moved to autonomously grasp objects from a surface. Results are positive and open interesting perspectives for soft robotic manipulation.**

I. Introduction

Human-robot (HR) handover represents a well-studied topic in robotics, see e.g. [1], [2], [3], [4] ,which comes with important challenges related to human-to-robot communication [5], human safety and acceptance [6], human intention prediction [7], human-aware planning and execution [8], [9]. According to [4], HR handover consists of three main phases, i.e. *approach*, *passing*, *retraction*. In this work we focus on the *passing* phase, which corresponds to the physical transfer of the object from human to robot. Here, the detection of the interaction is mandatory not only to guarantee operator's safety, but also to execute a successful robot grasp response [10]. In biology, we refer to this behavior as sensory-motor response [11]. Robotic sensing is commonly achieved through the employment of visual and/or tactile sensory systems, see e.g. [12], [13], [10], [14], which acquire the needed information on the object (and/or on human hand gesture). Such an information can be then processed to plan meaningful autonomous response [8]. Focusing on the specific action of object grasping, classic approaches, both analytic [15] and data-driven [16], have usually dealt with grasp planning, grasp adaptation and force control. For real-world grasps, which often come with a certain level of uncertainty, visual and/or tactile sensory information can be combined with learning and statistical techniques to enable robots to autonomously manage novel and uncertain situations, see e.g. [17], [18], [19], [20].

Recently, the introduction of under-actuated and soft robotic hands has given new options respect to the traditional way robotic grasping was usually planned and performed with *rigid* end-effectors. Indeed, the embodied capability of *soft* hands to comply and adapt to different objects and the environment, together with the simplicity in control derived from under-actuation – e.g. following the principled simplification approach inspired by human hand synergies [11] – has led to simple, adaptable yet robust systems. These systems can mold around items and exploit physical environmental constraints as opportunities to guide adaptive grasping of different objects [21], [22]. Thanks to these characteristics, a rough approximation of object geometry and robot hand pose are enough to generate candidate successful grasps despite external uncertainty [23], e.g. due to partial knowledge through point-cloud data. In this case, final grasping pose can be refined using low-cost infrared sensors [24].

The latter result further sustains the evidence that more effective grasps can be obtained when information from short-range or non-ranged sensors is used [25]. Under this regard, touch/contact - based sensing allows for a more direct and less problematic detection of important contact-related aspects than artificial vision [26], as well as for a simplified sensor-based implementation of *reactive* behavior [27], [25], [24]. This aspect is particularly crucial in proximate human-robot interaction (HRI), hence in handover tasks, where a prompt robot reaction is a key factor for a successful implementation of the *sense-plan-act* model [28].

To the best of authors' knowledge, there are no solutions that combine (i) the adaptability of soft robotic hands, (ii) a minimalistic tactile sensing and (iii) a reactive robotic behavior for robotic autonomous grasping in human to robot object passing tasks. In this work, we propose a solution that, for the first time, targets points (i), (ii), (iii). The goal is to endow a soft robot hand/arm system with purely touch-based grasp primitives. We refer to grasp primitives as coordinated

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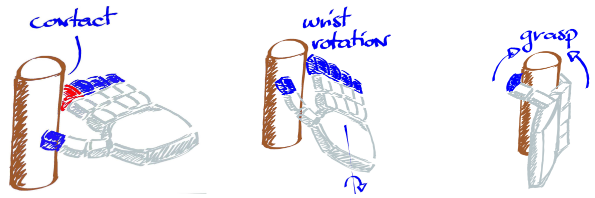

(a) Contact detection. (b) Primitive trigger. (c) Grasp.

Fig. 1: The leading idea of our approach. In blue the sensorized fingertips, in red the contact.

hand closure and wrist movements of a soft manipulator, triggered by touch-based sensor readings. Our leading idea is to take inspiration from the human example, to implement effective sensory-motor response on the robot side, having in mind the trade-off between performance maximization and resource usage minimization.

II. The Method

Looking at biology, the simplest level of sensory-motor integration consists of primitive reflex actions [29], i.e. nearly instantaneous (and automatic) motor reactions in response to a sensed event. Robotics often takes inspiration from biology [11], and the implementation of primitive-based control in robots is no exception. In this context the term *primitives* (or, sometimes, *reflexes* [24]) is used to define automated movements that are triggered in response to certain sensory inputs experienced by the robot. In the last years, primitive control has become somewhat popular in different fields of robotics. In [30], predefined biologically inspired postural primitives were used with a robotic arm to imitate reflex-like withdrawal behaviors. Similar approaches were used e.g. in [31], [32]. For what concerns grasp, the specific definition of *grasp primitives* can vary slightly, but it usually involves an automated control mechanism triggered by certain conditions. In [33], authors implemented grasp reflexes for robotic manipulation using leaky integrate-and-fire neurons. The work in [34] developed specialized reflexes for an anthropomorphic robotic hand based on force and velocity control. Tactile-based grasp reactive behavior was implemented e.g. in [27], [25], [24], although in these cases a partial knowledge of object pose and location was needed. To the best of our knowledge, our work is the first one where a primitive-based approach is used with a soft manipulator, relying only on contact based information as triggering input.

We use as end effector the Pisa/IIT SoftHand (SH), an under-actuated anthropomorphic soft robotic hand [21], which is mounted on a robotic arm and equipped with six IMUs, five on the back of the fingertips and one on the back of the hand. The fingertip sensors detect the accelerations arisen from contact with external items, while the IMU on the back of the hand is used to keep track of the acceleration generated by the robot movement. In response to a given contact, the hand pose and closure state are planned for grasping, by executing arm motions with hand closure commands, i.e. a primitive. Data used to generate these motions are extracted from an experiment, where a human user controlled the SH through a suitable interface to grasp a tennis ball placed on a pole, considering a set of approaching directions and contact locations at distal phalanxes. Since the SH can adapt to grasp different items with various geometrical properties [21], the crucial part for a successful grasp is the correct determination of the pose of the hand w.r.t. the target. To do this, we correlate the accelerations with the user's wrist pose to devise primitive grasp strategies (see Fig. 1), which we evaluated in a simple human to robot object passing task. More specifically, the SH was still and placed over the wrist of a 7 DOF Kuka LWR 4+ arm, and the user passed the object to it. During the experimental evaluation, we considered many objects passed to the SH along different contact directions. Our working hypothesis was that despite the fact that the primitives were obtained for only one object and limited number of contact conditions, the hand should have been able to perform successful grasps with novel situations, thanks to its intrinsic adaptability.

Our choice to use human-inspired motion primitives was motivated by several studies in literature, which proposed human-like robotic actions to improve robot-motion legibility [35], [4]. However, a comparison between different planning methods (including anthropomorphic vs. non-anthropomorphic) is currently out of the scope of this work.

Finally, it is worth noticing that we are aware that a human-to-robot handover task would require a combination of both feed-forward and feedback control components, the latter is crucial to assess the correctness of task execution and modify the action if needed. In this work, we decided to focus only on the feed-forward part, since our goal was to verify to which extent the combination of reactive primitives and robotic hand softness enables to generalize to different object grasps, under controlled conditions. Future works will be devoted to include also a feedback part, which will allow to take into account unforeseen events related to human behavior and provide a control method to check for the success of the robotic response and eventually to change it, also to guarantee users safety. Further tests in more unstructured environments are envisioned. The inclusion of additional sensors is also under evaluation (e.g. increasing the number of IMUs in use or adding force sensors to the SH, still keeping in mind the trade-off between resource usage and system performance.

We conducted additional experiments with some objects placed on the table, while the robotic hand was controlled to move and contact them at different locations. Although it is well-known that humans tend to naturally adapt to robot grasping capabilities in handover tasks [36], the objective of these experiments was to preliminarily evaluate the success of our approach, against possible helps from the human operator. This is important, especially for the interesting scenarios that could be opened by the proposed method,colorblueThis is important, especially for the interesting scenarios that could be opened by the proposed method , e.g. for purely tactile-based autonomous grasps of soft robotic hands.

In the following, we describe the experimental apparatus for primitive extraction and the implementation on the robot side.

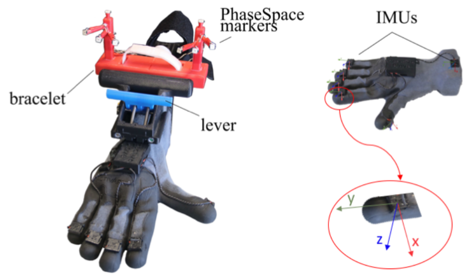

Fig. 2: Experimental setup used for primitive identification.

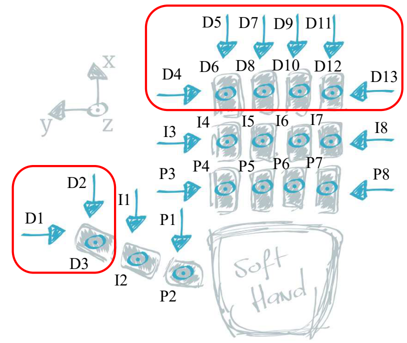

Fig. 3: The regions of contact during the acquisition phase and the 13 approaching directions D_i, defined w.r.t. the system of reference in figure. In this phase contacts occur only on the sensorized Distal (D) phalanx (Highlighted in red rectangles), while during the experiments Intermediate (I) and Proximal (P) phalanges were also considered.

The Human-Robot Interface and Motion Capture System

The SH was mounted on a human-robot interface [23] (hereinafter, we will refer to it as the handle), which enabled the user to control SH aperture through a lever. In the primitive identification experiments we used the PhaseSpace Motion Capture system to record the pose of the wrist of the user. More specifically, the system recorded the *x*-*y*-*z* coordinates of eight active infra-red markers (sampling frequency of 480 Hz) attached to a bracelet in ABS fastened on the handle immediately before the SH.

During the experiments, an off-the-shelf working glove with padded rubber surface was placed on the SH to increase contact compliance and grip. Five IMUs were glued on the glove, in correspondence with the back of the distal phalanx of each finger, roughly speaking where the “nails” of the SH should be (Fig. 2). An additional IMU was placed on the back of the hand to be able to compensate both for acceleration caused by movement of the hand and for the contribution due to the gravity. In other terms, the accelerometer mounted close to the wrist of the hand (from now on it will be called reference IMU) is used to reject the common mode noise, as it follows. First, a calibration procedure computes five rotation matrices that describe the orientations of the fingertips IMUs w.r.t. the reference IMU, through a passive complementary filter [37]. Second, during the task, for each step the accelerations read from the fingertips IMUs are expressed in the frame associated to the reference IMU, then the common mode between reference and fingertips IMUs is removed.

We used the InvenSense MPU-9250 IMU, endowed with an on-board Digital Motion Processor (DMP) (capable to process complex 9-axis Motion Fusion algorithms), but relying only on the acceleration signals provided by the embedded 3-axis accelerometer. Data communication was realized via a custom made electronic board through RS485 with a frequency of 60 Hz (for more details on the platform please refer to [38]).

III. Grasp Primitives

To build a database of primitives we performed first an acquisition phase, where the poses of the wrist of the human user maneuvering the SH were recorded as well as the acceleration signals, and then an extraction phase, where we defined the primitives w.r.t. the contact data provided by IMU-measured accelerations.

A. Data Acquisition

During the acquisition phase, we asked a human user to wear the handle and to control the SH to grasp an object, which was placed on the top of a pole, from different approaching directions. The user was instructed to trigger the grasp (re-)action as soon as he realized the contact. To do it, he relied on both visual information and contact vibration conveyed by the handle. Since the SH was endowed with the sensing glove and the wrist bracelet, we were able to acquire both the *Detection* (acceleration contact signals) and the *Motion* (wrist motion alongside the hand closure commands).

For what concerns the grasped object, we focused on a single spherical object, i.e. a tennis ball, choosing to leverage upon SH adaptability to generalize to different items (see Section IV). The ball was placed on top of a pole and attached to the center of a small table (50×40 cm) covered with Velcro, at around 120 cm height. This enabled the subject to freely approach the object from several directions: in particular, we chose 13 directions as a good trade-off between exhaustiveness and ease of implementation, as reported in Fig. 3. We decided to not consider bottom-up approaching direction, since we associated this to unwanted and undesired contact with external objects in HRI (i. e. false positives, see Section IV). At the same time, the fact that the object was attached through Velcro at the table required a firm grasp to remove it from the support.

For each approaching direction, the starting configuration was about 20 cm from the object, along that direction. The subject was asked to try to move at constant speed. In addition to that, the subject was asked to initiate contact with the object on the distal phalanges of the SH. The approach and grasp depended on subject’s skills: for this reason, preliminary training with the handle was imparted to the subject, until motion with the SH, contact detection and object grasp were as natural as possible.

The experiment protocol to gather relevant data was as follows:

1) We randomly chose an approaching direction, hence a

starting configuration (SH palm down, parallel to the ground).
2) A visual signal was sent to the subject to let him know that the SH was in the starting configuration.
3) The subject moved the SH and initiated a grasp as soon as the hand was in contact with the object.
4) To consider the grasp successful, the subject had to detach the object from the table, lift it up and hold it for 15 seconds. If this was not verified, he had to repeat the action for the current approaching direction.
5) A visual signal was sent to the subject to let him know that he was allowed to lower the SH and release the object.
6) A 5 minutes rest followed, after which the cycle started over from 1) for a different approaching direction/starting configuration.

Acceleration data and wrist poses were recorded through the IMUs, and PhaseSpace system, respectively, and synchronized. Each approaching direction was presented three times in the randomized sequence; we used the average values of the sensed signals to perform the primitive extraction phase, for an overall number of 13.

B. Primitive Identification

The goal was to build a map from IMU measured acceleration to wrist pose evolution (in particular, the final wrist pose used for the grasp action), in order to devise grasping strategies. To do that, we performed the following steps:

A) **Common-mode rejection:** using the IMU mounted on the back of the hand;
B) **Cropping:** We identified the moment when the contact occurred, and selected a time window where to perform the acceleration processing. In particular, we chose to identify the contact instant t_c as the sample where the first acceleration spike (greater than 0.5 g) occurred, followed by a lower rebound. We heuristically identified this threshold since it guarantees a good signal to noise ratio for contact detection. The window width was 30 samples, starting 10 samples before the contact time (Fig. 4);
C) **Reshaping:** Acceleration components in the considered time window were reshaped in a single vector, as detailed at the bottom of Fig. 4;
D) **Normalization:** All acceleration values were normalized by the maximum absolute value in the considered time window.

At the end of this procedure we have a vector A of acceleration scalar components in $\mathbb{R}^{3nW}$, where $n = 5$ is the number of fingertip inertial sensors and $W = 30$ is the contact window size.

To complete the primitives extraction, wrist poses need to be associated to the previously considered acceleration values. Wrist poses can in general be represented by six-dimensional vectors, containing position and Roll-Pitch-Yaw orientation; however, since the roll variation was significantly greater than the other two during the grasp phase, as depicted in Fig. 4, we chose to simplify the representation of the

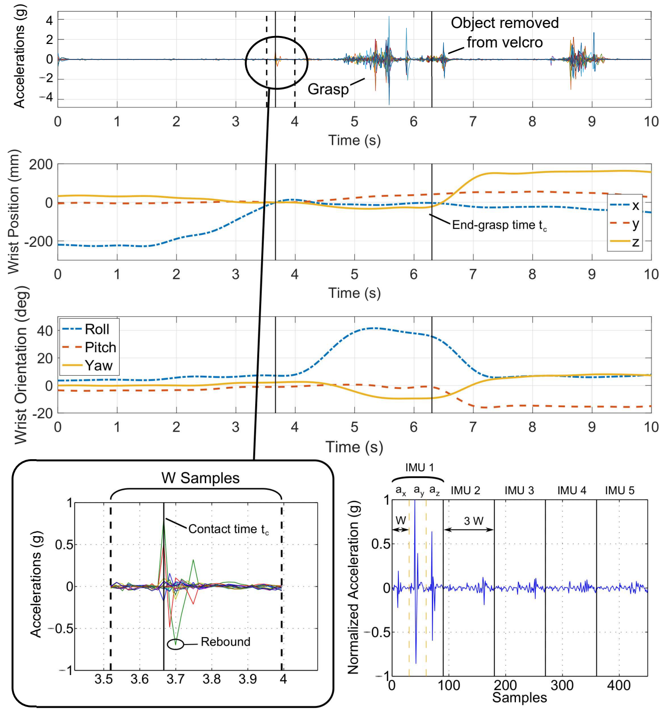

Fig. 4: The acceleration signals (top) and wrist position and orientation signals (middle) were synchronized in time. Here the term filtered refers to signals after the application of common mode rejection. A detail of the contact detection with the corresponding time-window of width $W = 30$ samples for primitive synthesis purposes is shown in the left-bottom corner of the figure. The right-bottom corner shows a plot of the acceleration signals normalized and reshaped in a vector ordered per IMU and per acceleration component: in this way we obtain a single signal of $30 \cdot 3 \cdot 5 = 450$ samples that can be used in the identification process.

problem and only consider Roll values for primitives extraction (corresponding to the wrist rotation around the forearm axis). This result is not surprising, since during primitive identification the human subject maneuvered the SH through the handle, which constrained wrist movements mainly along Roll direction. Future works will consider more complex designs, e.g. using the SH in conjunction with an actuated artificial wrist as in [39].

We are thus considering relative translations and Roll values of the final wrist pose measured at the end-grasp time t_{eg}. For a correct association, we need to select the samples of interest: this was done by cropping data considering a window that begins at the contact time t_c and ends at t_{eg} (see Fig. 4, middle), which we identified as the time when a variation greater than 5 mm occurs on the vertical (z) component of the human user wrist position. The final wrist pose was then related to the corresponding accelerations in A. At the end of this phase, we got a set of 13 final wrist poses, each associated to acceleration profiles at t_c detected on the distal phalanges of robotic fingers (see Fig. 5). It can be interesting to note that the primitives for contacts at thumb are very similar each other: this is caused by the fact that the primitive grasp action generates positive roll rotations, independently from the direction of contact. However, for the moment, we decided to maintain and implement all these primitives.

IV. EXPERIMENTS

In this section we first describe how we implemented the primitives for the robotic arm and then how we validated our approach through experiments.

A. Implementation

In order to implement the 13 grasp primitives previously described we developed a software library composed of two main parts: *Detection* and *Motion*. As the names suggest, the *Detection* implements the sensory system. Here, the raw signals from the IMUs are continuously acquired and quickly processed to infer information about the external environment (contact detection) and to trigger a desired reaction (retrieved from the database of primitives), according to the main steps described in the following lines. The *Motion* part is in charge of the execution of the triggered reaction. During the initialization phase, the robotic system was placed in a starting posture where the proposed perception-action loop was engaged at. After the execution of any primitive, the system came back to the starting posture. The *Motion* and the *Detection* play the server and the client, respectively. The preemption policy was such that only one goal can be active until the action was finished. In other words, it means that once a primitive motion starts, the client becomes "deaf" to any contact until the complete grasp primitive has finished the execution, and the system has came back to the starting posture.

The Detection logic selects the wrist pose, based on the cross-correlation between the acceleration profile recorded by the robot and the 13 acceleration profiles obtained from human demonstration. Of note, each acceleration profile is associated to a given wrist pose, i.e. motion primitive, as described in Section III-B. More specifically, this procedure selects the primitive for which the associated acceleration profile presents the highest correlation with the profile observed by the robot.The procedure is structured as follows:

1) A stream of IMUs data was continuously monitored and common mode rejection applied.
2) Acceleration peaks (threshold 0.5 g) followed by a rebound of the signal revealed the contact occurrences.
3) After a contact was heuristically detected, a time window was selected for the acceleration data stream where the measurements were reshaped and normalized as done for the phase of extraction of primitives (see the bottom right image in Fig. 4).
4) Cross correlation of the acceleration between the measured and 13 stored profiles over the time window, in order to select the most similar associated wrist pose.

Steps 1-3 are analogous to the ones reported in Section III for the extraction of grasp primitives.

The method described above is implemented for both the first handover task and the second experiment presented in this section, where the object is grasped from a table.

TABLE I: List of objects

(A) screwdriver	(B) wrench	(C) reel
(D) battery (AA)	(E) pincers	(F) plier
(G) hammer	(H) hotglue gun	(I) caliper
(J) pen	(K) stapler	(L) bottle
(M) torch	(N) computer mouse	(O) cell phone
(P) eraser	(Q) lighter	(R) table tennis ball
(S) human hand	(T) mug	(U) can
(V) teddy bear		

B. Experiments with robotic arm: handover task

For the validation phase the SH was mounted on the Kuka Light Weight Robot (LWR) 4+. The same sensorized glove used for the primitives acquisition was put on the hand.

In the starting configuration, the robotic system was placed with the SH palm facing down, similarly to what was done by the human user in the previous phase. Then, a person, different from the one who performed primitive identification, handed over an object to the SH in a given direction and the acceleration signals due to the contact triggered a grasp primitive, with the directions as shown in Fig. 3. The wrist position associated with the triggered primitive is fed as setpoint to a standard motion planning algorithm [40], with the SH closing to grasp the object after the wrist reaches the target posture. The detection process had a duration of about 200 ms, after which the grasp was completed in about 5 seconds.

A grasp was considered successful if the grip held for 15 s, and was robust to external disturbances applied by the experimenter. More specifically, at the end of the grasp, the experimenter hit the SH: in this phase, as soon as any acceleration above 0.5 g was detected from any finger, the SH opened releasing the object and the manipulator returned to the starting configuration, waiting for another input from the user (see Fig. 6 for an example. This procedure was repeated three times per object (see Tab. I), for every direction and target zone on the hand (Fig. 3), for a total of 1914 trials. The total average success percentage was around 86%. As previously mentioned in the introduction, the first mandatory requirement for human-robot-interaction is user's safety. To meet this requirement, in our experiments, we considered objects coming in contact with the hand from underneath or from a side. In other terms, we do not want any primitive to be executed for contacts from above the hand, that could be risky for the user or affect task success, e.g. leading to kinematic singularities of the robot arm. Of note, we do not want to claim anything about the safety of our procedures against unforeseen human movements: in these cases, the inclusion of a feedback action is needed as discussed in Section II and investigate in future works. To detect this kind of contacts as false positives, we used the readings from the gyroscope of IMUs to complete accelerometer data: whenever an acceleration peak was detected, if the z-axis reading from the gyroscope was positive and above a threshold of 15 deg/s, then no primitive was implemented. We tested the effectiveness of this approach by hitting the back of the fingers in different zones 10 times, using a wrench: 88% of false positive scontacts were correctly rejected. All the code developed in this work is in ROS.

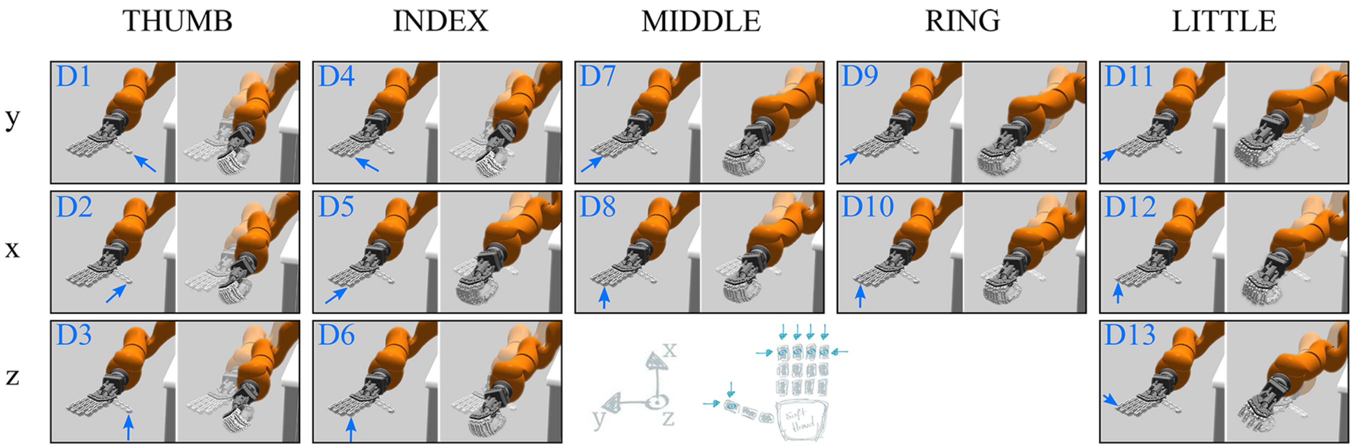

Fig. 5: Visual representation of grasp primitives synthesized from the experiments. Contact and sensing areas are indicated with blue arrows, while the corresponding motion primitive are in fade.

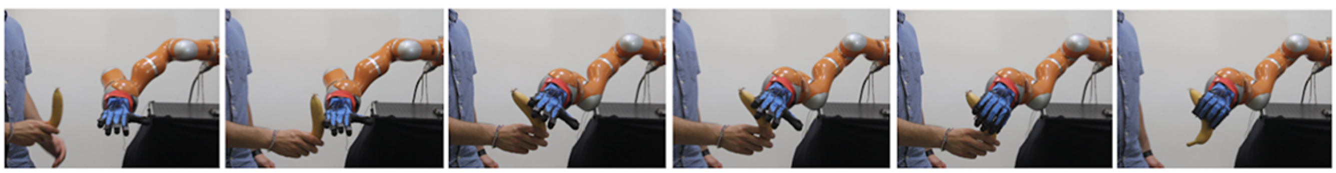

Fig. 6: Snapshots of one of the experiments on human-to-robot handover. The contact occurred at the little finger.

It is worth pointing out that, respect to the grasp primitive identification described in Section III, in this experiment we used a considerably higher number of objects (22 against the single tennis ball) and contact approaches (29 against 13). That is, the proposed solution was able to generalize with respect to those variables, also leveraging on the adaptability of the SH.

TABLE II: Results

Object	Successes	Failures	Success %
(A)	71	16	81.61%
(B)	84	3	96.55%
(C)	77	10	88.51%
(D)	78	9	89.66%
(E)	77	10	88.51%
(F)	80	7	91.95%
(G)	65	22	74.71%
(H)	78	9	89.66%
(I)	68	19	78.16%
(J)	77	10	88.51%
(K)	78	9	89.66%
(L)	59	28	67.82%
(M)	70	17	80.46%
(N)	75	12	86.21%
(O)	73	14	83.91%
(P)	79	8	90.8%
(Q)	73	14	83.91%
(R)	74	13	85.06%
(S)	82	5	94.25%
(T)	72	15	82.76%
(U)	74	13	85.06%
(V)	81	6	93.1%

(a) Results by object.

Direction	Successes	Failures	Success %
D1	58	8	87.88%
D2	63	3	95.45%
D3	61	5	92.42%
D4	62	4	93.94%
D5	63	3	95.45%
D6	65	1	98.48%
D7	65	1	98.48%
D8	66	0	100%
D9	59	7	89.39%
D10	63	3	95.45%
D11	56	10	84.85%
D12	59	7	89.39%
D13	53	13	80.3%
I1	66	0	100%
I2	58	8	87.88%
I3	58	8	87.88%
I4	63	3	95.45%
I5	63	3	95.45%
I6	63	3	95.45%
I7	52	14	78.79%
I8	48	18	72.73%
P1	56	10	84.85%
P2	54	12	81.82%
P3	47	19	71.21%
P4	50	16	75.76%
P5	45	21	68.18%
P6	54	12	81.82%
P7	40	26	60.61%
P8	35	31	53.03%

(b) Results by direction.

We can have a better insight in the results by considering the number of successes by object (Table IIa) and by direction (Table IIb). For what concerns the former, the lowest success rate (around 68%) was obtained for the bottle, which resulted difficult to grasp for contacts occurred at the distal phalanx of the ring and little finger. Only two other items had a success rate inferior to 80% (the hammer with a 75% success percentage, and the caliper with 78%), on a total of 22 objects. This can be ascribed to the long shape and asymmetric inertial properties, which also affected performance for the bottle that had some water moving inside. In these cases, a feedback action would be required to modify the grasp location on the object, thus counterbalancing external torques due to long shape and inertial properties of some of the objects. Conclusions that can be drawn are that our method enables to generalize to different objects passed to the hand, thus opening interesting perspectives for human to robot handover, without any claim of exhaustiveness. To properly affirm that our techniques can be applied to real-world HRI tasks, the inclusion of feedback controller and a thorough testing with a larger number of naif human users are needed and will be performed as future works.

C. Experiments with robotic hand: grasping an object from a table

In the previous subsection, we have reported an implementation of the reactive grasp approach we are proposing in a task where a human is handing over an object to the robot. While the success rate in that experiment was fairly high, since a human experimenter was actively participating in the task it is not easy to discriminate between the contribution

Fig. 7: Snapshots of one experiment performed on a table. Contact was on the L/R zone with the hand following traj. 1.

of the human and the contribution of the robot to the task. This is common in HRI, since humans naturally tend to adapt to robot behavior [36]. To preliminarily evaluate the success of our approach for robotic grasping, against possible helps from the human operator, we also performed a second set of experiments, where the object was autonomously grasped from a table. We placed different objects extracted from our list on a test surface, on which Velcro was attached in order to fix the starting position and to avoid undesired movements before and during the contact. This also required a firm robotic grasp to remove objects from the support. The robotic system was controlled to approach the object with three different trajectories:

1) *Vertical trajectory* - approaching direction from the top - contact with the bottom part of the phalanges;
2) *Horizontal trajectory* - approaching direction from the side - contact with the lateral index/little;
3) *Horizontal trajectory* - approaching direction from the front - contact with the frontal fingertips/thumb.

In Fig. 7 an example of reactive grasping using the trajectory no.1 is reported. The arm is controlled in order to cyclically follow the selected trajectory. Once the contact is detected from the IMUs, the logic board compute the correct grasp primitive using the approach reported in section IV-A. We tested this approach using three objects with different shapes, i.e. a tennis ball, a teddy bear and a water bottle. We arbitrarily changed the contact point with the hand, targeting different regions of the phalanxes and varying robot motion velocity (from 11.5 to 17.5 cm/s). Without any claim of exhaustiveness, since only a reduced set of conditions was tested, we can affirm that the hand was able to grasp the object from the table while approaching on it with the internal phalanges, with the frontal side of the fingertips, with the lateral side of the thumb and the little. In the future, a more thorough validation will be performed. The aim of this second type of experiments was to show a certain degree of robustness of our techniques against possible helps from the users, which is intrinsically unavoidable in HRI. At the same time, the positive outcomes we have obtained, although preliminary, open interesting perspectives for purely tactile based autonomous grasps with soft end effectors.

V. Discussions and Conclusions

In this work, we have presented a minimalistic approach to endow soft manipulators with human-inspired touch-based sensory-motor grasp primitives in a simple human to robot object passing task. These primitives were then implemented to control the pose of the robotic wrist where the SH was mounted on. We have demonstrated how the adaptability of the SH enables to generalize these primitives for the successful grasp of a wide number of objects, considering a large set of object-to-hand approaching directions and regions of contact on the robotic fingers. We also performed preliminary experiments where the hand was controlled to autonomously grasp objects from a table. The latter results open fascinating perspectives for a new generation of soft robotic manipulators with embedded sensory-motor capabilities. By combining our feed-forward approach with a feedback component, these manipulators could take advantage from these capabilities, and purposefully exploit the contact and the interaction with the environment to increase their autonomy and extend their grasping capabilities, e.g. in purely touch-based environment exploration.

Envisioned applications of the approach reported in this paper can be also within the framework of shared-control, e.g. in assistive robotics, where robot autonomy is used to help user's input for task accomplishment [41]. The integration of user's intention with the primitives described in this work could increase the effectiveness of assistive-rehabilitative systems for motor-impaired people. Indeed, our solution represents a perception-action algorithm that can autonomously generate goals (in our case, human-like object grasps), without the usage of markers on the object, which limit the applicability of shared-control systems only to a set of labeled targets.

Future works will further investigate these methods for a complete handover implementation, addressing all the phases described in [4], together with an implementation of a feedback-feedforward action which could increase safety and generarization. Additional experiments will be suitably designed to evaluate HR communication [6], as well as the effectiveness and users' acceptance of different motion planners. It is important to note that our approach combines the intrinsic adaptability of the SoftHand and tactile-triggered wrist primitive control. To fully highlight the contribution of the latter, future works will aim at providing a quantitative comparison of grasping success/failure results between with and without actively selecting grasp primitives. Finally, we will continue to investigate with more quantitative results the preliminary evidence that demonstrate the success of our approach when the robot grasps the objects from a supporting table by itself - hence without any active role of the human operator.

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