WRAPP-up

A Dual-Arm Robot for Intralogistics

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The diffusion of e-commerce has produced larger and larger volumes of varying items to be handled in warehouses, with the effect that the need for picking automation is increasing. Conventionally, automation has been achieved through a custom plant designed for large-scale production of items having well-established characteristics that are expected to change slowly and to only a small degree over time. However, today the challenge is to realize a solution that is flexible enough to handle goods with different shapes, sizes, and physical properties and that require different grasping modes. To solve this problem, we first analyzed how humans perform picking and then synthesized their behavior according to four main tactics. These were then used as guidelines for the design, planning, and control of WRAPP-up, a dual-arm robot composed of two anthropomorphic manipulators: a Pisa/IIT SoftHand and a velvet tray (Figure 1). The system has been validated and evaluated through extensive experimental tests.

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Overview

E-commerce, i.e., buying and selling physical goods via services over the Internet, has now reached its full development. Led by Amazon, which accounted for more than 50% of the growth of the entire e-commerce market, and by Alibaba, in 2017 retail e-commerce sales amounted to more than US$2 trillion with an annual growth rate greater than 25% [1]. The expansion of e-commerce is affecting the way warehouses work, especially the intralogistics, i.e., the internal flow of goods within a distribution center [2].

On one hand, the market growth has led to an increase in employment: data from the U.S. Census Bureau [3] indicate that, from 2015 to 2016 in the United States, there was an annual growth rate of 28% in warehousing and storage employment (North American Industry Classification System, code 493) and that in 2016 the total workforce reached more than 600,000. According to Data USA, the U.S. Census Bureau's American Community Survey Public Use Microdata Sample one-year estimate data show that material movers hold the largest share (20%) of jobs [4].

On the other hand, a strong effort has been devoted to maximize intralogistics efficiency by fully employing optimization techniques [5]: pushing the productivity of human

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operators even if it may cause high workloads [6] and adopting automated solutions. Finally, e-commerce has impacted both business-to-consumer (B2C) and business-to-business (B2B) markets. The market size of B2B e-commerce is more than 10 times that of B2C [7], allowing businesses to present an unprecedented variety of products to customers. This has brought undeniable advantages in terms of sales [7], but it has also increased the flexibility requirements with which the intralogistics system must comply.

Order picking—the process of retrieving products from storage (or buffer areas) in response to a specific customer request—is responsible for 50–75% of the total cost for a conventional warehouse [8]. Hence, order picking is considered one of the highest priority areas for improvement to maximize warehouse productivity. However, despite the crucial importance of picking operations, warehouses still mostly rely on human workers [9].

The major challenge preventing the full automation of picking is represented by the high variability among objects to be handled in terms of, e.g., their shapes or object configurations and the presence of inaccessible or even absent surfaces and also of flexible or pierced surfaces. Regarding object shapes, cuboids constitute the vast majority of items stored in warehouses [10]. According to [11], among shipped packages, the shapes that occur most often are cuboids and, in a lower percentage, cylinders. Thus, strategies to manipulate cuboids and cylinders in different configurations account for a considerably large part of the intralogistics processes for handling goods.

Several components contribute to the realization of a flexible picking solution:

- a robot design able to execute the picking operations in a warehouse environment physically
- a vision system able to detect objects and constraints
- a perception system able to identify desired and undesired contacts
- a planning method able to generate a trajectory accomplishing the task while satisfying the constraints and adapt that trajectory based on the perception outcomes
- a control strategy able to track the desired trajectory.

The present article focuses on the realization of a flexible, autonomous picking solution, leaving for the future integration with the vision system.

Some of the most challenging and common situations an autonomous pick-and-place system might encounter include

- reduced, collision-free end-effector poses due to other goods or containers
- a restricted portion of the external surface of the object being available for gripper contact due to other goods, especially when they are tightly packed together
- deformability of the object, meaning that the shape of the grasped object changes under external forces
- porosity of the object, which prevents the employment of simple and nimble suction grippers.

Despite great effort in the development of picking solutions, as far as we know, no currently existing automatic

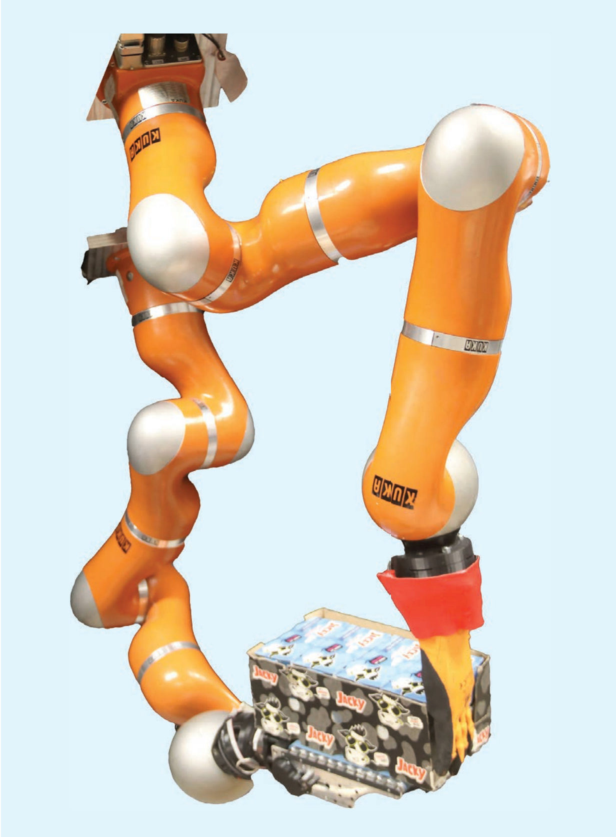


Figure 1. The WRAPP-up: a dual-arm robot composed of two anthropomorphic 7-DoF manipulators, a Pisa/IIT SoftHand, and a velvet tray. WRAPP-up is illustrated picking a box that does not have a top surface.

solution is flexible enough to cope with such challenges, many of which may occur simultaneously.

The main contributions of this article are the design, realization, and testing of WRAPP-up, a novel human-inspired dual-arm robot for intralogistics. The development of WRAPP-up relied upon observing the techniques adopted by human pickers at work in warehouses. Indeed, by observing expert operators, we identified four main maneuvers they commonly adopt; these are detailed in the section "Human Picking Skills." Based on these findings, we designed a dual-arm robot (see the section "The WRAPP-up Design" for more details) composed of two 7-degrees of freedom (7-DoF) manipulators and two different end effectors: a) an adaptive end effector able to both grasp a large variety of objects and stably interact with different shapes and b) a tray with an actuated belt. Moreover, we encoded the observed human picking strategies into parametric motion primitives adopted in the robot's trajectory planning. Finally, an extensive experimental validation was conducted.

To the best of our knowledge, WRAPP-up is the first autonomous picking system able to approach the whole spectrum of intralogistic picking tasks: from bin picking to pallet picking.

Related Work

Picking tasks can be classified based on different parameters, one of the most important of which is the location from which the items should be grasped. On one hand, there is the bin-picking problem in which a single object must be grasped from among objects that have been placed in an ordered way (or not) in a box. Often the object's size and weight are such that it can be handled with a one end effector. The problem of grasping a single object with an ad hoc end effector has been extensively studied from theoretical and experimental viewpoints. However, bin picking still represents an open challenge, especially in unstructured environments. This is also testified to by competitions such as the Amazon Picking Challenge, aimed at enhancing warehouse automation in picking operations [12]. Interested readers are referred to [13] for a comprehensive review of robotic picking and to [14] and [15] for recent results.

On the other hand, there is the picking of items from among those located on a pallet. To automate this, task two main solutions can be adopted: a mobile manipulation approach in which the robot is provided with a mobile base or a grounded manipulation approach in which the pallet (or shelf) is brought to the manipulator by mobile devices [16].

Prominent examples of autonomous mobile manipulation platforms for logistics include: the Little Helper III [17], the DLR omniRob [18], and the Handle [19]. The first two robots are mainly devoted to picking objects from shelves. They consist of a robot arm with a two-fingered parallel gripper mounted on a stable mobile base. The Handle has an unstable two-wheeled mobile base (which requires a more expensive control system but substantially reduces the robot's footprint), is equipped with a vacuum gripper, and is devoted to box handling. Interested readers are referred to [20] for comprehensive literature reviews on the subject. Furthermore, Magazino [21] and InVia Robotics [22] currently sell two products based on suction cups that are mainly devoted to box picking. Both these solutions exploit a picking strategy based on box sliding, which may not be suitable for boxes that are stacked one upon the other and, in general, are not free to slide. TORU, the robot by Magazino, is suitable for picking small boxes from shelves, especially shoe boxes. It has also been integrated with a different picking strategy, but always based on object sliding and additionally requiring the accessibility of the rear surface of the box [23].

A recent example of a grounded manipulation approach is the Dora Picker [24]. Its novelty relies on the soft and adaptive design of its end effector. Ground-based depalletizing robots available on the market, despite their different working principles, share the drawback of being bulky and not easily relocatable [25]–[27]. Moreover, unlike WRAPP-up, they are usually suitable solely for pallet picking, while a different robot would be necessary for bin-picking. See, e.g., the example of Swisslog [28], which proposes on its website two robotic solutions, one for picking larger boxes, ACPaQ, and one for bin picking, ItemPiQ. Another key distinguishing aspect of WRAPP-up compared to the integrated solutions proposed by Swisslog is that WRAPP-up aims to incorporate in a unique platform for both picking and discharging.

The most flexible autonomous systems that may be used to accomplish picking tasks are currently provided with mechanical and vacuum end effectors. A wide overview of the most recent development in gripping devices can be found in [29]. Mechanical end effectors for prehensile tasks are certainly the most widespread and many of them fall into two neatly distinct categories: simple grippers [30], [31] and complex or anthropomorphic hands [32]–[34].

Among them, several devices exist that trade simplicity for flexibility. Examples include underactuated and soft grippers [35]–[37] and end effectors with active surfaces. An example of a versatile mechanical gripper is the Traction Gripper [38]. It has a shaped frame with counter-rotating belts that exploit friction forces to pull boxes toward the corners of the frame and hold them firmly in position. An evolution of this concept is the Fraunhofer Roll-on Gripper [39], a hybrid between a lift and a gripper. In this solution, the belts further allow for manipulating (translating or rotating) the boxes once they are picked up by the gripper. A similar solution is exploited by Premium Robotics [25], whose grippers exhibit limitations when the grasped item is lodged in the object.

Vacuum grippers are widely employed for grasping boxes by their top surface ([26] and [27]), e.g., [40]. The vacuum gripper by Wynright Robotics [41] is able, as are others [21], [22], to grasp boxes from the frontal side. The device relies on an array of vacuum cups to drag the box onto a support surface of the gripper. Vacuum grippers have severe drawbacks when the surface of the object is not suitable to be grasped, e.g., due to the top surface not being present at all or not being robust enough to sustain the weight of the object.

Problem Definition

The task of interest in this article consists of picking several different goods from single-item pallets, that is, pallets composed of several units of an item. The input to the system is the sequence of goods to be picked and their location on the pallet, which may be provided by a vision system. The design of a robot for picking tasks depends on the size and the shape of the objects that must be manipulated as well as on the modes that can be profitably used to grasp them. Picking tasks, the vast majority of which are currently executed by human operators, can be classified into two main categories: those that can be accomplished with one hand and those that must be accomplished with two hands. The problem of picking objects with a single end effector has been extensively treated in the literature and in previous articles of ours [42], [15]. The present article focuses on the problem of picking objects that humans cannot pick with one hand. Notably, the solution proposed here will accomplish both categories of picking tasks. In the following, a list of items that represents 40% of the volume of a food warehouse is reported together with their main features. Note that the food and beverage segment is one of the market segments most affected by the e-commerce revolution, which today allows customers to have their shopping bags delivered directly to their homes. In the next sections, we consider the functional requirements a picking system should satisfy in order to work in such a warehouse profitably. Finally, we describe the main challenges to be tackled in the design and realization of this device.

Objects

The complete list of objects to be picked, along with their size and weight, is reported in Figure 2. The objects can be grouped into two sets depending on their shape: boxes or cylinders. For the boxes, the values for the length (L), height (H), and width (W) expressed in centimeters are reported, while for the cylinders, the values for the diameter (D) and height (H) are listed.

Functional Requirements

A list of functional requirements that a picking system should match is reported in Table 1. It is important to stress that these should not be taken as absolute values for every intralogistics company but, rather, for operators that manage a set of objects comparable to the one reported in Figure 2. These requirements are grouped into key performance areas and indicators. Their quantitative value should be considered as a target for the picking system.

Productivity performance indicators have been computed based on the fact that such a robot would be economically sustainable if it were able to perform three picking movements every minute (corresponding to 180 picks per hour). Given that a Euro-pallet (80- × 120-*cm* base piled up to 1.5 m high) may contain up to 627 of the smallest or 115 of the largest among the objects reported in Figure 2, the time needed to empty a pallet can be evaluated in 209 or 38 min, respectively. The average of these two values gives the productivity performance indicator reported in Table 1. The picking success rate takes into account the grasping system without considering the vision system.

Challenges

The main challenges of the picking phase can be identified as follows:

- Boxes are often very close to each other, and the two opposite sides, which are the most desirable for a reliable and robust grasp, are usually not easily accessible. Hence, to be properly handled, such boxes should first be moved to guarantee that two opposite faces are accessible and then picked.
- Some items do not have a top surface, or the top surface may not be suitable for grasping the object. These objects cannot be grasped with vacuum grippers.
- The bottom side of some objects is recessed under the upper side of the objects that they lie under—or, more generally, they cannot slide. This means that the objects can translate only along the vertical direction or rotate about a horizontal axis.

Human Picking Skills

There is no systematic method to synthesize all the requirements listed in the section "Problem Definition"; one of the reasons is that it would simultaneously involve the codesign of the robot's structure, planning, and control. Hence, we observed skilled human operators at a food warehouse during the execution of manipulation tasks when picking the objects listed in Figure 2. That is, we recorded two human operators from a food warehouse while performing the picking action. Each picking action was repeated three times. These live observations and the analysis of the video recordings led to two lessons learned.

1) Bi-manual manipulation has a crucial role in picking operations since humans use both hands to manipulate and handle objects. In the majority of tasks, one hand is used to move the object, and the other hand is used as a support.
2) The strategies human operators use to pick items are classifiable into three main categories, as depending on object shape and form, as depicted in Figure 3: rotation about the horizontal axis, rotation about the vertical axis, and sliding.

Rotation About the Horizontal Axis

In the case of thin boxes, i.e., $H > W$, $H > L$, and cylindrical objects or if the support surface of an object cannot slide, the operators use one hand to rotate the goods about a horizontal axis and to put the object on the supporting hand [see Figure 3(a)–(d)].

Rotation About the Vertical Axis

For thick boxes ($H < W$, $H < L$) with no constraints at the base, the horizontal rotation is not convenient because of the less favorable lever arm; thus operators decide to rotate the boxes about a vertical axis to have access to the back surface of the object, as in Figure 3(d). This strategy can then evolve into two different picking continuations. In the first, the box is picked up by two opposite surfaces while the operator uses his/her hands like the jaws of a parallel gripping device. In the second, the box is first dragged toward the worker, acting on the back surface, and then supported by the other hand as the box sticks out from the pallet or underneath the layer of goods. This helps apply two different grasping strategies: 1) grasping the object relying on contacts on two opposite surfaces (front and back) and 2) sliding the object relying on the contact on the back surface.

Sliding

For thick boxes with no constraints at the base, operators push or pull the objects until they reach the support hand at the boundary of the pallet, as in Figure 3(f). Picking strategies that human operators adopt highlight that pickers often naturally choose different functions for each hand. One hand is mainly used to accomplish manipulation tasks: pushing an object in the sliding strategy and adapting to the shapes of the different objects in the other two strategies. The other hand is

Figure 2. The objects considered for picking tasks, with their weight (in kg), size (in cm), and related grasping strategies.

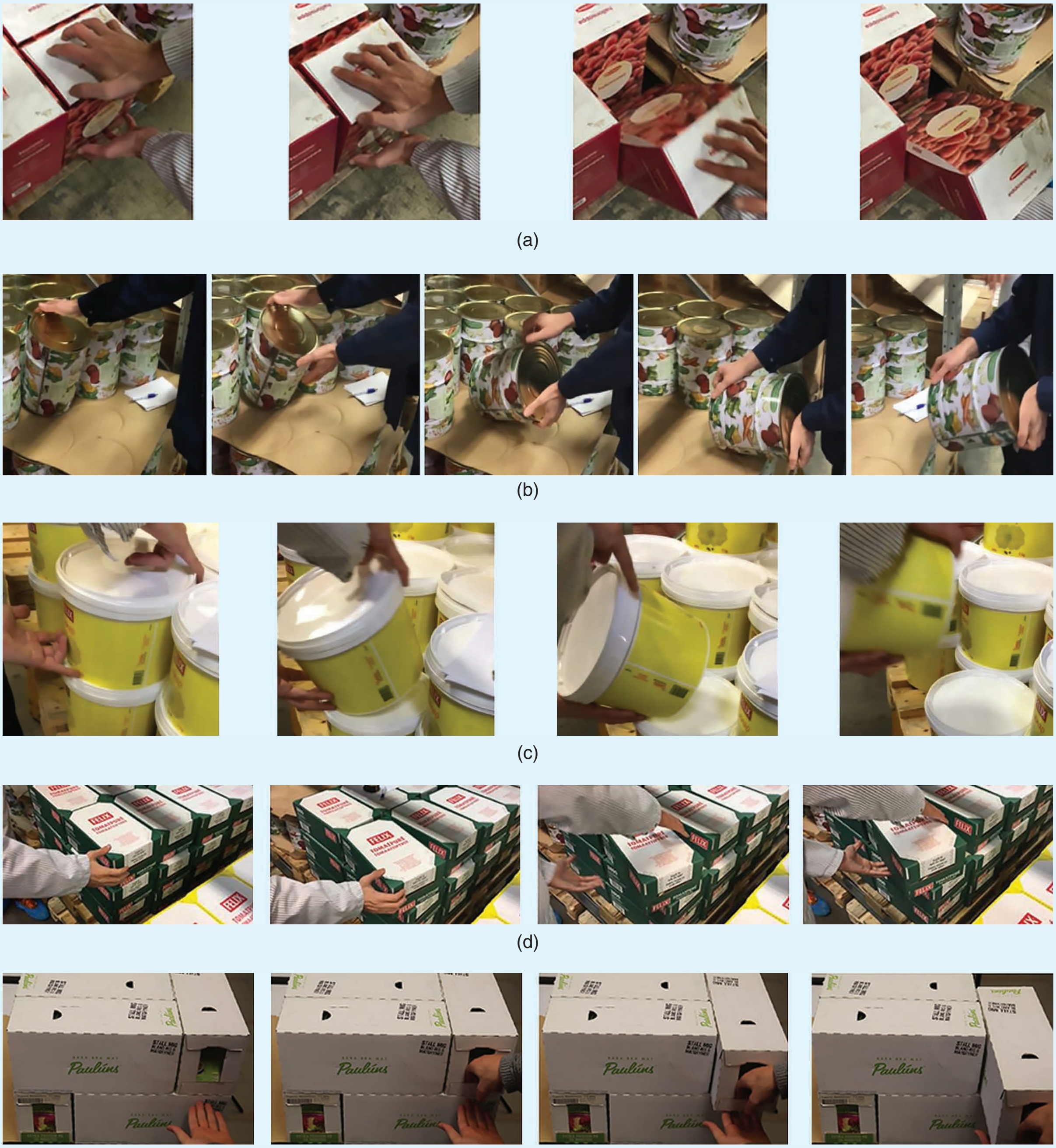
often responsible for supporting the majority of the item's weight and may be used to perform placing operations such as alignment and unloading.

The WRAPP-up Design

Inspired by the techniques adopted by warehouse workers, the envisioned solution is a dual-arm system. The system is composed of two lightweight robots arranged to perform pick-and-place tasks properly. The mounting bases of the arms are fixed at an established relative pose, as better described in the following. Two different end effectors, provided with six-axis force/torque sensors, are attached to the wrists of the robot arms. To perform the dexterous operation, one arm is featured with a Pisa/IIT SoftHand: a human-like, adaptive, robust artificial hand, the closure movement of which is easy to control since it is actuated by a single motor.

Table 1. Picking task target performance.

Performance Area	Performance Indicator	Target	Unit
Productivity	Average time to empty a pallet	123	min
	Picks per hour	180	#
Reliability	First-attempt success rate	90	%



(a) (b) (c) (d) (e)

Figure 3. A human grasping different shaped objects with different strategies: (a) a box-shaped object, (b) and (c) cylinder-shaped objects, and (d) and (e) box-shaped objects.

The second end effector is the velvet tray, which serves as a support tool. A brief description of the design of the two end effectors is provided at the end of this section.

In our preliminary experimental setup, each robotic arm was mounted on an independent movable gate, which allows for 3 DoF in a plane (two translations and a rotation), enabling configurable relative locations of the two arms [see Figure 4(c)]. With this test bench, we could easily test different relative positions of the arms in a store-like environment. The choice of the most suitable relative configuration of the arms is described in the next section, "Relative Pose of the Two Manipulators." In a final use case, the dual-arm robot can be mounted on a fixed or mobile base, depending on the end-user requirements. For instance, the end user may employ a picker-to-goods strategy, thus requiring a mobile base for the picking station, or a goods-to-picker strategy, in which the picking station is fixed and the objects are transferred there. At present, our robot is mounted on a fixed base, but it will be integrated onto an autonomous mobile robot in future studies.

Relative Pose of the Two Manipulators

Once the overall structure of the robot, the end effectors, and the manipulation strategies have been defined, the robot design can be detailed. Particularly important is the location of the two arms with respect to each other and the pallet. A wrong relative location of the arms may prevent the correct execution of a strategy due to two main reasons: 1) one joint (or more) reaches the limit of its range of motion, or 2) a point of the desired trajectory is out of the reachable workspace of the bimanual system.

To properly choose the relative location of the arms, a two-step strategy has been adopted. First, a manipulability index for each arm was evaluated for a set of points to find a relative pose that provides an adequate superposition of the manipulators' dexterous workspaces. Then, a feasibility analysis, conducted by simulating the kinematic execution of the robot trajectories (based on the strategies presented in the section "Translating Human Picking Skills Into Robot Motion Primitives" for the objects listed in Figure 2), was performed to check that the relative pose found in the first step allowed the robot to operate at least over half of the pallet footprint. The feasibility phase took into account constraints due to joint limits and realistic external obstacles, e.g., floor and shelves. It is worth pointing out that, for the first step of the strategy, other metrics could have also been implemented, e.g., to include the direction of maximum force of the arms. Still, at this stage, we preferred to give priority to manipulability. Future study will be devoted to the evaluation of different metrics. Among the manipulability measures suitable to quantify the ability of a robot to execute a movement in an arbitrary direction of the Cartesian space, from a given pose q, we use the one presented in [43]:

$$w(q) = \sqrt{\det(J(q)J(q)^T)}, \tag{1}$$

that is, a measure of the volume of a 3D ellipsoid of which the semi-axis length is represented by the square roots of the singular values of the end effector's Jacobian $J(q)$. The eigenvector of $J(q)$ corresponding to the largest singular value represents the easiest direction of motion. Figure 4(a) is an example graphic result that illustrates the manipulability index $w(q)$ [evaluated according to (1)] and the preferred directions of motion of the two robots.

Given a relative location of the arms, we evaluated the manipulability of the configuration using a scaled average manipulability for the two arms [44] and the volume of the shared workspace. The average manipulability of each arm was evaluated by averaging the manipulability index values at N uniformly sampled feasible configurations in the joint space. The maximum value manipulability index then scales this value according to

$$\bar{w}_i = \frac{\sum_{j=1}^{N} w_i(q_j)}{\max_j\{w_i(q_j)\}N}. \tag{2}$$

Then, we defined the manipulability index for the dual-arm system as

$$\bar{w}_D = \frac{\bar{w}_1 + \bar{w}_2}{2}, \tag{3}$$

where $\bar{w}_1$ and $\bar{w}_2$ are the average manipulability indexes for the first and second arm, respectively. Thus, the configuration manipulability is then expressed as

$$M = \frac{V_I}{V_U}\bar{w}_D\,|_I, \tag{4}$$

where we defined with V_U the workspace of the dual-arm system (obtained by the union of the workspaces of the two manipulators), with V_I the volume of the shared workspace, and with $\bar{w}_D|_I$ the average manipulability index for the dual-arm system [defined as in (3)] computed using only the configurations belonging to the intersection of the workspaces of the two manipulators. The poses with high manipulability are the ones that give large dexterous collaborative workspaces.

The solution provided by the manipulability analysis is a reasonable starting point. However, its selection does not take into account the tasks that the robot should execute. To evaluate the quality of the selected configuration for our task, we simulated the execution of picking tasks using the strategies described in the section "Human Picking Skills" for different positions of the target object and registered the associated Cartesian error. To perform this analysis, we considered the object as placed on a 0.8- × 0.6- × 1.5-m pallet in front of the robotic platform so that it would lie within its reachable workspace. This width corresponds to half of the width of a Europallet. We simulated the task for every pose an object could assume on this reference pallet (the possible poses are limited and depend on the shape and the dimensions of the object),

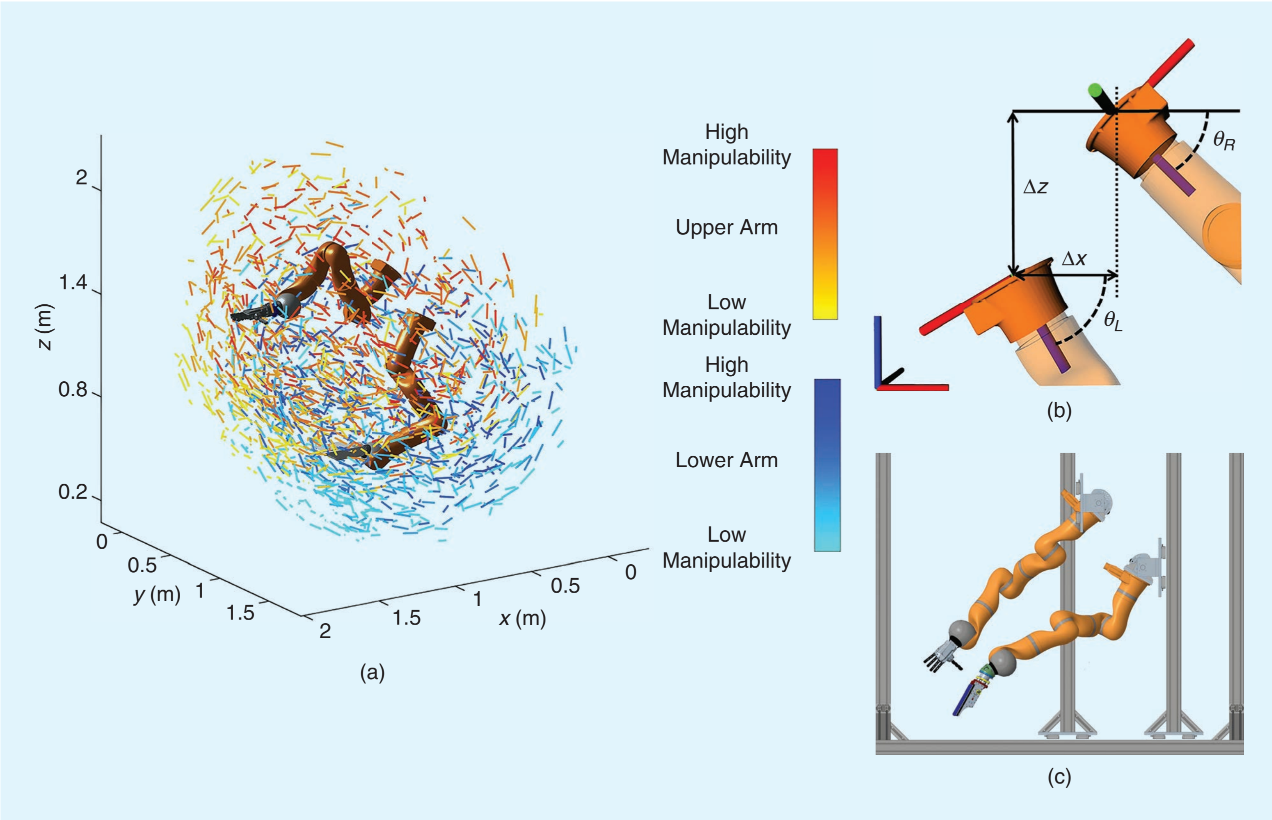


Figure 4. An analysis of the relative configuration of the manipulators, resulting relative configuration, and CAD model of the experimental setup. (a) An example of the manipulability analysis exhibiting the manipulability measure and preferred directions of motion. (b) The configuration of the two arms in the current setup: $\Delta_x = 20$ cm, $\Delta_z = 30$ cm, $\Delta_\theta = 15^\circ$ ($\theta_R = 45^\circ$ and $\theta_L = 60^\circ$). (c) A CAD model of the experimental setup.

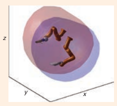
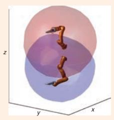
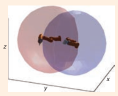
and we checked that, in the selected configuration, the robot was able to execute the task with a limited Cartesian error (under 1 cm of error).

To reduce the complexity of the search of the relative configuration, we predefined a set of reasonable candidate poses, evaluated the manipulability for each of them, and evaluated the task performance for the most promising. Examples of the manipulability for three different candidate configurations are reported in Table 2, where the values were obtained using $N = 20{,}000$ samples. It is worth noting that the first configuration (the one we eventually selected) is the one with the higher manipulability. A detail of the manipulators' base relative location is depicted in Figure 4(b).

Mechanical Design of the Manipulation End Effector

The manipulation end effector is the Pisa/IIT SoftHand [Figure 5(a)]. Its mechanical robustness and adaptability, together with the ease of control, make it particularly suitable for the type of use required to accomplish the picking task. For an in-depth description of the hand, readers can refer to [45]. In Figure 5(a), the Pisa/IIT SoftHand ⑦ is attached to the wrist flange of the robotic arm ① through a six-axis force/torque ATI-Mini45 sensor ② and four rubber beams ⑥. The ATI sensor detects changes in the state of the hand, such as contact with the objects to be manipulated in regular functioning but also undesired collisions, preventing the end effector from damaging the object being picked. The rubber beams are located between the end effector and the ATI sensor. They favor the slowdown of the external force loading rate in case of collision, increasing the time for a rapid emergency-stop response. A toothed flange ⑤ crimps together a plate ③ (fixed to the sensor) and another plate ④ (fixed to the hand side).

Table 2. Manipulability analyses for different configurations of the two arms.

			
Workspace volume [V_U (m^3)]	5.91	7.13	6.43
Shared workspace volume [V_I (m^3)]	2.60	1.38	1.23
Intersection average manipulability [$\bar{w}_D\|_I$]	0.43	0.46	0.47
Manipulability [M]	0.19	0.09	0.09

Mechanical Design of the Support End Effector

The end effector that functions as a support for the goods to be manipulated is the velvet tray. Figure 5(b) shows a 3D model of the velvet tray. Its design and principle of operation are inspired by research we carried out about grippers with active surfaces [46]–[48]. The tray is equipped with an actuated belt to ease the loading maneuvers of the goods. As shown in Figure 5(c), it is attached to the flange wrist ① of the KUKA arm through a flange ②. Between the KUKA arm and the velvet tray, a six-axis force/torque ATI-Mini58 sensor ③ and rubber beams ④ are interposed with the same aim as in the Pisa/IIT SoftHand. The elastic junction is here composed of 10 rubber beams ④ arranged in a circle, which slow down the loading rate of the external forces in collision events. The belt ⑧ is coated with high-grip polyurethane with a coefficient-of-static-friction polyurethane steel of 0.8, which allows an inclination of 38° with respect to a horizontal plane without a mass on the belt sliding down. This value of friction coefficient provides the worst-case for the torque of the motor, guaranteeing that the target mass of 2.5 kg can be held with the velvet tray inclined 38°. A Maxon motor DCX22 actuates the belt with gear-head GPX83 ⑤, which is able to move a mass of 2.5 kg with an inclination of 38° within the continuous functioning condition of the driver. The power transmission between the motor and the driver roll of the belt is due to gears ⑥. The tension roller ⑦ ensures a proper tension in the belt of at least 20 N, necessary to transmit the required torque. Finally, a set of idle rollers ⑨ sustains the objects and forms an approximately flat surface under the belt.

Translating Human Picking Skills Into Robot Motion Primitives

Inspired by observation of the strategies adopted by the human pickers (described in the section "Human Picking Skills"), parametric motion primitives were defined to plan the motion of the robot during the task execution.

- *Sliding*: One end effector is used to push (or pull) an object toward the other end effector, which secures the grasping and may support the weight of the object, as demonstrated in Figure 6(a).
- *Horizontal rotation*: One end effector is used to gently tilt the object about a horizontal axis. This can be achieved in two different cases: 1) about a horizontal axis on the front-bottom edge of the bounding box enveloping the object [see Figure 6(b)] and 2) about an axis on the back-bottom edge of a bounding box enveloping the object [see Figure 6(d)]. In the first case, the object rotation will end when it is lying on the support end effector. This strategy is intended to be used with objects (boxes or cylinders), the height of which is the largest dimension. In the second case, the object's rotation will allow the second end effector to be placed under the object as support.
- *Vertical Rotation*: One end effector approaches the object's side then rotates it about a vertical axis ideally located at one edge of the object. Once the rotation has produced enough room for the end effector, it slides inside this gap and proceeds to slide the object toward the pallet's exterior. This strategy is suitable when objects are compactly packed [see Figure 6(c)] and it is necessary to make room for the end effectors to perform a successful grasp.

For each object, the choice of the strategy was made based on its shape and on how the objects are stacked on the pallet. Each motion primitive is defined as a set of Cartesian waypoints for the two end effectors, expressed with respect to a frame placed on the object. The definition of waypoints that allows for a correct manipulation of the object, e.g., to rotate or tilt it to produce enough room for positioning an end effector as in Figure 6(c) or (d), is the result of simulations and real experiments on the objects. Thus, they depend on the physical properties of the end effectors and the objects. Once the pose of the object is retrieved and the correct primitive is selected, the waypoints expressed in the object-fixed frame are transformed into the world frame.

To take into account the robot kinematics and the joint limits for motion planning, we determined the path at the joint level via the reverse priority algorithm described in [49], which allowed us to define a set of tasks with different priorities including unilateral constraints (e.g., joint-position limits). For each of the two arms, we set the Cartesian pose

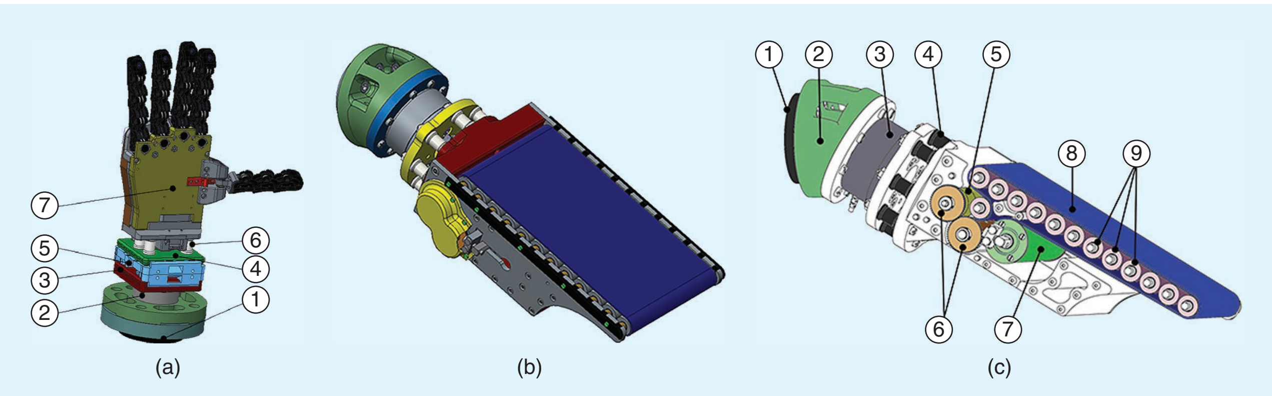


Figure 5. The manipulation end effector (Pisa/IIT SoftHand) and the support end effector (velvet tray). (a) The Pisa/IIT SoftHand is the dexterous end effector of WRAPP-up. All the components attached to the wrist of the robotic arm are described in the text. (b) The velvet tray is the support end effector of WRAPP-up. A 3D view is provided. (c) A cut view of (b) illustrates the power transmission group and the conveyor belt with the components described in the text.

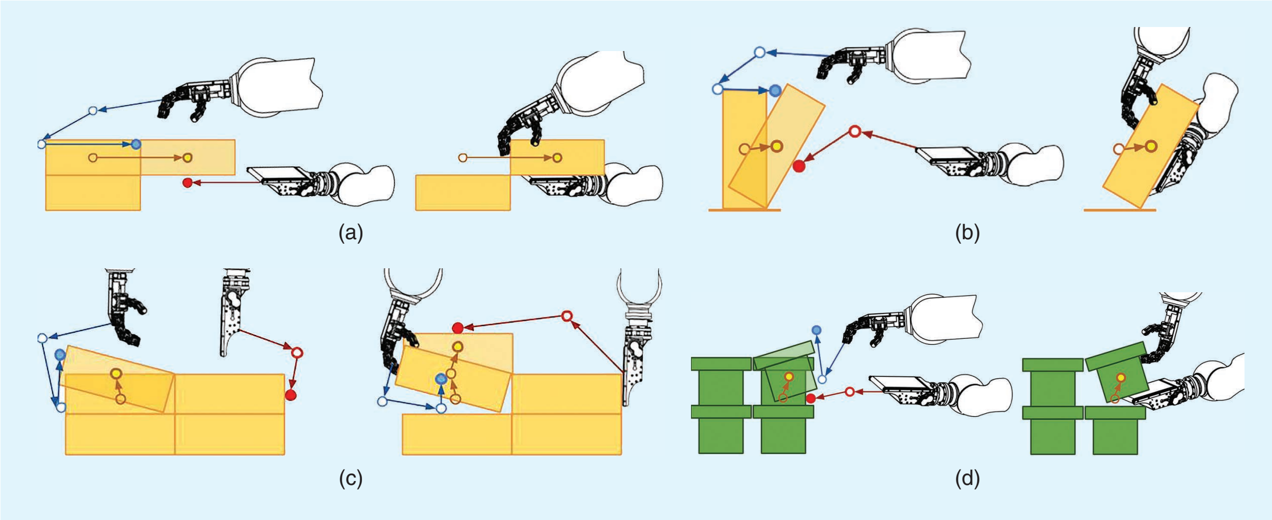


Figure 6. The robot grasping strategies. (a) The strategy to grasp an object from behind (side view). (b) The strategy to roll a tall object (side view). (c) The strategy to rotate an object exploiting environmental constraints, such as another object used as a pivot point (top view). (d) The strategy to lift an object and put it on the tray (side view).

tracking, i.e., the position and orientation of the end effector, as the low priority task and the joint-position constraints as the high priority tasks. Then, the path following could be achieved by the minimum-time approach presented in [50].

Accounting for realistically imperfect knowledge of the object position provided by a vision system in a future integration, the force/torque sensors were exploited to plan the trajectories based on contacts with the objects reactively. Indeed, the measured forces can be used to detect possible contact with an object whenever they exceed a user-defined threshold. Our reactive planning approach [see Figure 7(a) for a schematic representation of the architecture] was accomplished by decomposing each picking strategy into consecutive basic phases represented by states of a finite state machine. Each phase was planned online [the block “Plan Picking Phase” of Figure 7(a)] and generated the Cartesian trajectory for the end effectors. For each of the phases, the kinematic feasibility of the planned trajectory was checked [the block “Feasible” in Figure 7(a)]. In this block, the generation of a path for the joints of the robot was performed using the reverse priority algorithm. If the desired motion was not feasible because of, e.g., the constraints on the joint ranges, the task was aborted, allowing the intervention of a human operator. The transition between a phase and the following phase was triggered online based on the information coming from the force/torque sensors and the joint-position sensors of the robot. This information could be used to detect two possible events [the block “Event” in Figure 7(a)]: a detected contact (or the loss of contact) or the end effectors reaching their target position. The reaction of the system at these events depends on the typology of the picking phase. Indeed, the phases are of two types: approaching phases and manipulation phases. Approaching phases are the ones in which the end effectors have to establish contact with the object. This was a critical step of the manipulation process since an incorrect positioning of the end effector with respect to the object, possibly due to errors on the estimate of the object pose, could cause picking failure. Hence, the end effector would start moving toward the object along a specified direction until contact is detected. Then, it would stop, and the end-effector position at the contact would be used to update the object pose estimate. This refined estimate is used to update the planned trajectory for the following phases. If the expected contact does not happen within a certain region, the system enters an emergency state, and, eventually, a human operator will be alerted. Conversely, manipulation phases are the ones for which a contact is already established and the end effectors are manipulating the object. The condition used to trigger the transition to the successive phase is defined based on the end effector reaching the target position. Sensing of unexpected forces causes the system to enter an emergency state and eventually alert a human operator, regardless of the specific phase. At the end of the picking strategy, since the object will be placed on the velvet tray, the force measurements can be used to identify whether the object has been picked or if it fell.

An example of the described reactive approach is reported in Figure 7(b) and (c), where the states of an example trajectory and the corresponding force sensor readings are depicted. For this example, we considered a worst-case scenario where the uncertainties on the pose estimate are such that additional pose refinement steps are required. Indeed, in phase (A) the hand is approaching the object laterally to refine its pose. As reported in Figure 7(b), when contact is correctly detected (the magnitude of the force F_x along the contact direction exceeds the threshold set at 10 N), the pose along this direction is updated, and the hand is placed in front of the object and starts moving toward it. Once again, the force measurements inform about the established contact, and the robots enter the third phase, (C), of the manipulation. In this case, since a horizontal rotation is used, the hand lifts the bucket to create space for the velvet tray. Therefore, the transition

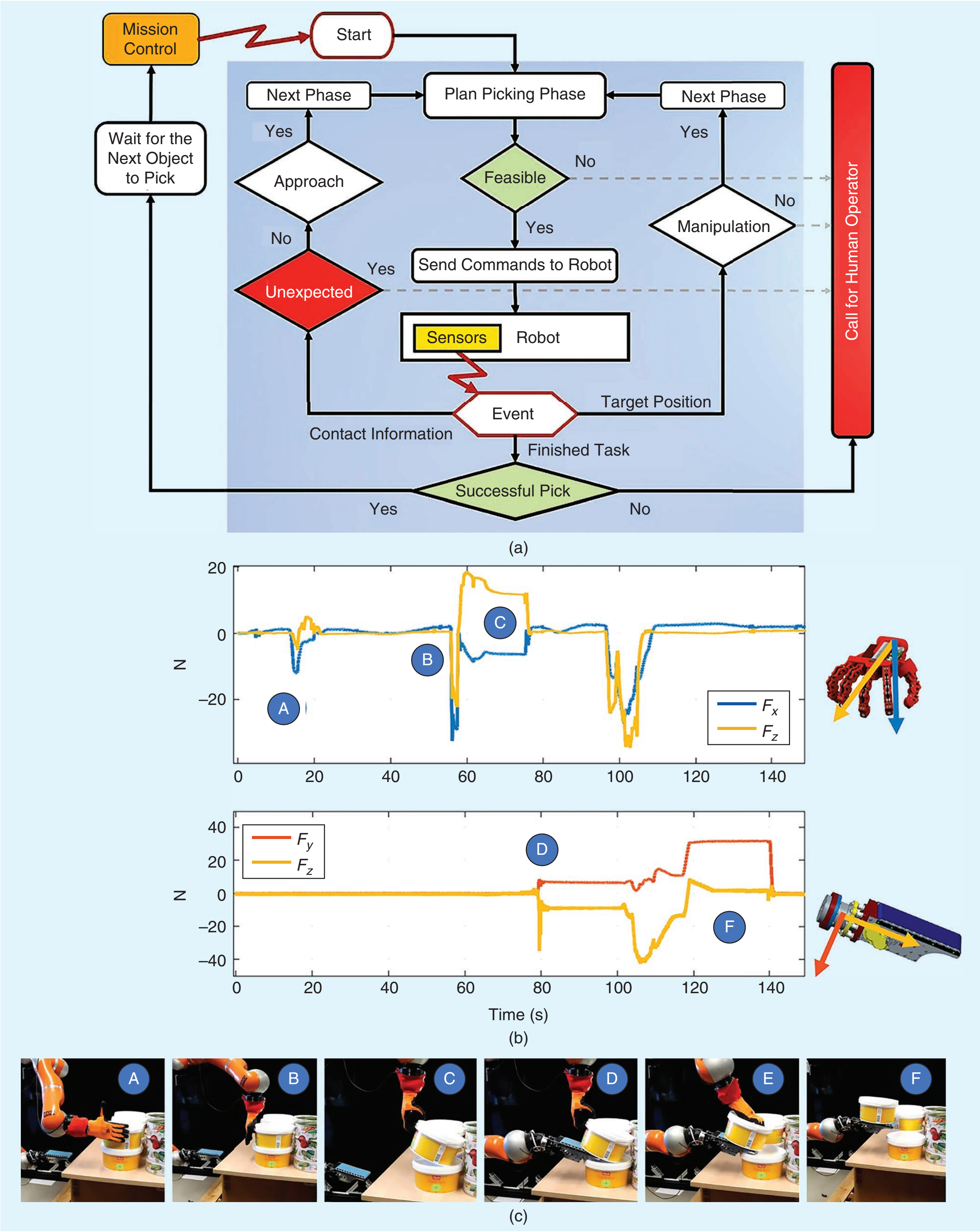


Figure 7. The reactive planning approach. (a) The reactive planning architecture. The picking strategy is divided into basic consecutive phases planned online. The information from the sensors is used to detect contacts between the robot and the environment or if the end effectors reached their target position. Depending on the typology of the picking phase (i.e., approach or manipulation), these events trigger the transition to the next phase or an emergency state. (b) Force sensor readings for the two end effectors during the strategy execution. The transitions between the states into which the strategy is decomposed are highlighted. (c) The sequence of a picking strategy in which each block corresponds to a state of the finite state machine on which the planner is built.

toward the next phase is triggered by the hand reaching the target Cartesian pose, and no force information is required. Note that, to increase the robustness of the system, the force measurements in this phase could detect the loss of contact between the hand and the object and be used to abort the current picking action. Regarding the other phases, contact information is again used to trigger the transition from (D) to (E), where the velvet tray is placed under the object in contact with it, and (E) to (F), where the hand is approaching the object from the top to perform a collaborative sliding.

As described previously, the example shows the effectiveness of the reactive approach even in case of an imprecise knowledge of the pose, which requires the execution of the redundant and time-consuming lateral approach [phase (A)]. Depending on the level of uncertainties on the pose estimated by the perception system, such redundant steps could be unnecessary.

Experimental Validation

In this section, we report the preliminary experimental validation of WRAPP-up. The picking capabilities of the system are demonstrated on a representative set of objects from the ones in Figure 2. Indeed, the objects used for the tests allowed us to cover the two main shapes we identified to be relevant for logistics, i.e., cuboids and cylinders. Furthermore, they allowed us to test all four of the motion primitives we have presented and validate the platform's performance in different picking scenarios.

Figure 8(a) depicts the strategy used to manipulate objects that have a characteristic cylindrical shape, better suited for a horizontal rotation strategy. With this approach, the hand is placed in front of the bucket and grasps its edge, allowing it to lift and tilt it. This movement permits the velvet tray to be placed beneath it as a support. Once the tray has been correctly positioned, the hand can release the object [see, e.g., the last frame of Figure 8(a)], and the tray can be used to collect and deploy the bucket. In this case, the hand can be employed

(a)

(b)

Figure 8. The WRAPP-up picking cylindrical objects. (a) The horizontal rotation primitive. (b) Cylindrical objects being picked using the horizontal rotation strategy.

to ease the tray during the picking phase. An example of the described approach used to collect three rows of objects placed on a pallet is presented in Figure 8(b).

The horizontal rotation strategy is also effective for picking thin boxes [see Figure 9(b)]. In this case, the hand is placed behind the box and tilts it until the box lies on the tray placed in front of the object with a proper inclination. Then, the hand is used to ease the object picking, keeping it on the velvet tray while the latter is returning parallel to the horizontal plane. The former approach has been tested for successfully picking eight boxes close to one another, as in Figure 9(b), illustrating the robustness of the designed strategy even in the presence of other objects behind the handled box.

The best picking strategy is not chosen based solely on the object's shape but also depends on the location of the object on the pallet and the position of the other possible items. To demonstrate this concept, two different picking tests were performed on the same object (with a box-like shape) depending on its different orientation, see Figures 10 and 11.

In the first test, the boxes are easily picked using a sliding approach due to their configuration. The hand is placed behind the box and used to pull the object toward the tray. The situation is different and requires a more complex strategy if the boxes are in a different configuration, e.g., they are rotated by 90° around the vertical axis with respect to the previous case and they are compactly packed, as shown in Figure 10. This condition requires the use of a vertical rotation strategy where the hand approaches the box's side and, eased by the tray, rotates it about a vertical axis located at one edge. Then, the hand slides inside the created gap and proceeds to slide the box toward the tray.

Table 3 presents the time for picking every individual object during the performed experiments. Then, an estimation of the time to empty an entire pallet full of that object is reported. To estimate the total number of boxes contained in the pallet, the standard Euro-pallet dimensions were

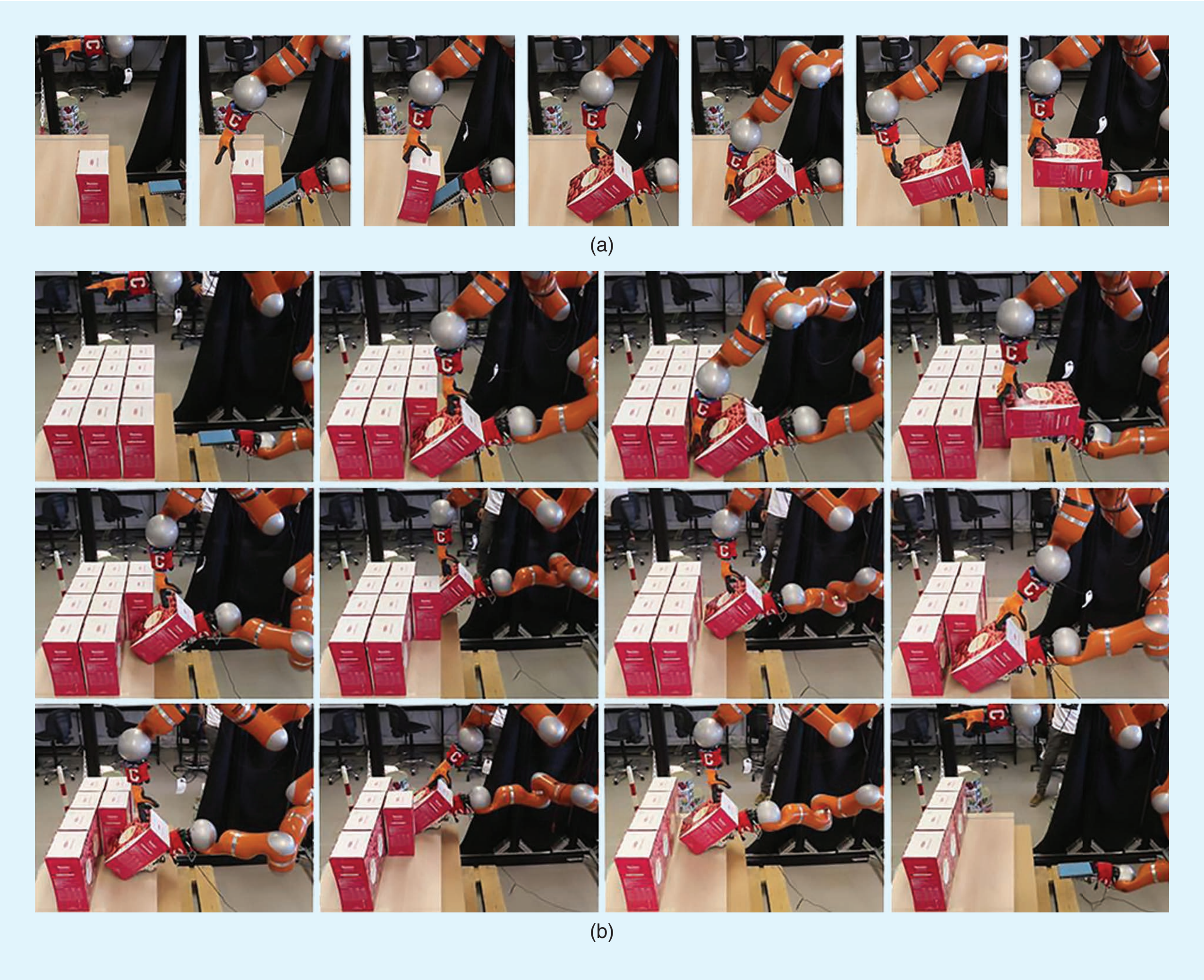


Figure 9. The WRAPP-up picking thin boxes. (a) The horizontal rotation primitive. (b) Two rows (eight pieces) of thin boxes being picked using the horizontal rotation strategy.

considered for the base of the pallet, and a full pallet was considered to be 1.5 m high. To compute the number of objects that can be contained in such a pallet, the dimensions of the objects were taken into account. Thus, a pallet of thin boxes contains 192 items; a pallet of cylinders, 360 items; and one of thick boxes, 176 items in the first case and 165 items in the other. Hence, the time to empty a pallet was estimated, multiplying the average time to pick an object by the number of objects in the full pallet. Table 4 reports the global performance indicators we obtained for the picking task. The time to empty a pallet was computed as the average of the values reported in Table 3. Fifty picking actions were performed for each case to test the system and estimate the values of the performance indicators. The success rate is the average of the four cases.

Discussion

This set of experiments was aimed at verifying the effectiveness of the hardware and picking strategies in an unloading simulation of goods on a pallet. These experiments demonstrate that the WRAPP-up robotic platform is suitable to fulfill the picking tasks of goods stacked on a pallet. A comparison with the performance requirements specified in Table 1 highlights that the reliability requirement is met, but the productivity should be improved through optimization techniques (not yet integrated) that will be the subject of future work. The performance reported in Table 4 is expressed for the platform in its current setup, i.e., without a perception system and the optimization module for the two arms and for the set of objects we used for the tests. Indeed, the reliability must be intended as an upper bound for the system since it does not include the presence of a perception system. For the average time to empty a pallet, it will have to be evaluated for the fully integrated platform to quantify the impact of the time required by the perception system to retrieve the pose of the objects and the impact the optimization module presented in [50] in the overall performance. It is worth noting that, with the current setup, some of the more burdensome objects in Figure 2 could result in their being difficult to handle because they exceed the nominal payload of the arms. Strategies and solutions to effectively handle those objects will be investigated. Subjects for the future will be a more specific study on the robustness of the platform for different objects and setups and an evaluation of how different friction forces could impact the reliability of manipulations that involve the exploitation of environmental constraints.

Conclusions and Future Work

In this article, we addressed the problem of realizing a proof-of-concept robot that is flexible enough to manipulate a variety of goods relevant to the intralogistics of warehouses. Inspired by the picking strategies that skilled human operators adopt in the execution of these tasks, we realized a dual-arm robot provided with a Pisa/IIT SoftHand and a velvet tray. The first end effector is adaptable; hence, it is used for establishing stable grasps to rotate and slide goods with various shapes; the second end effector is mainly used to support the weight of the objects. The robot has been experimentally validated in

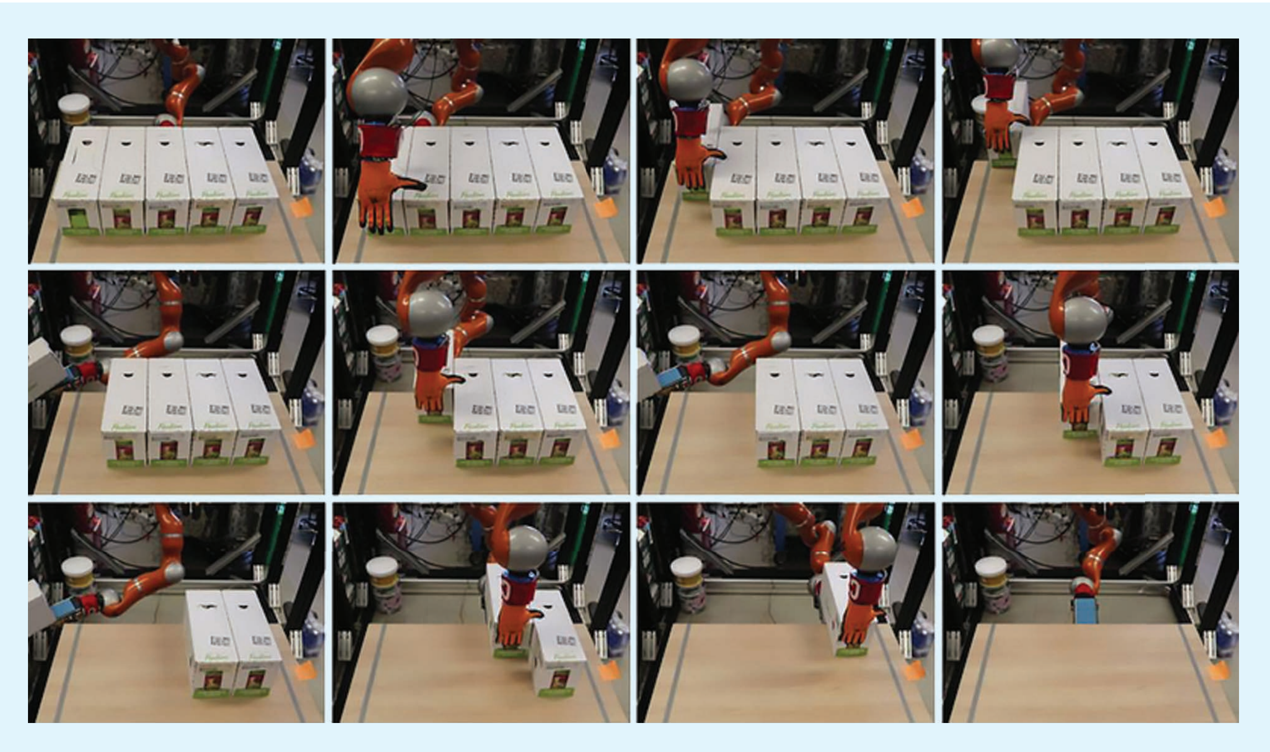


Figure 10. The WRAPP-up picking thick boxes using the sliding primitive.

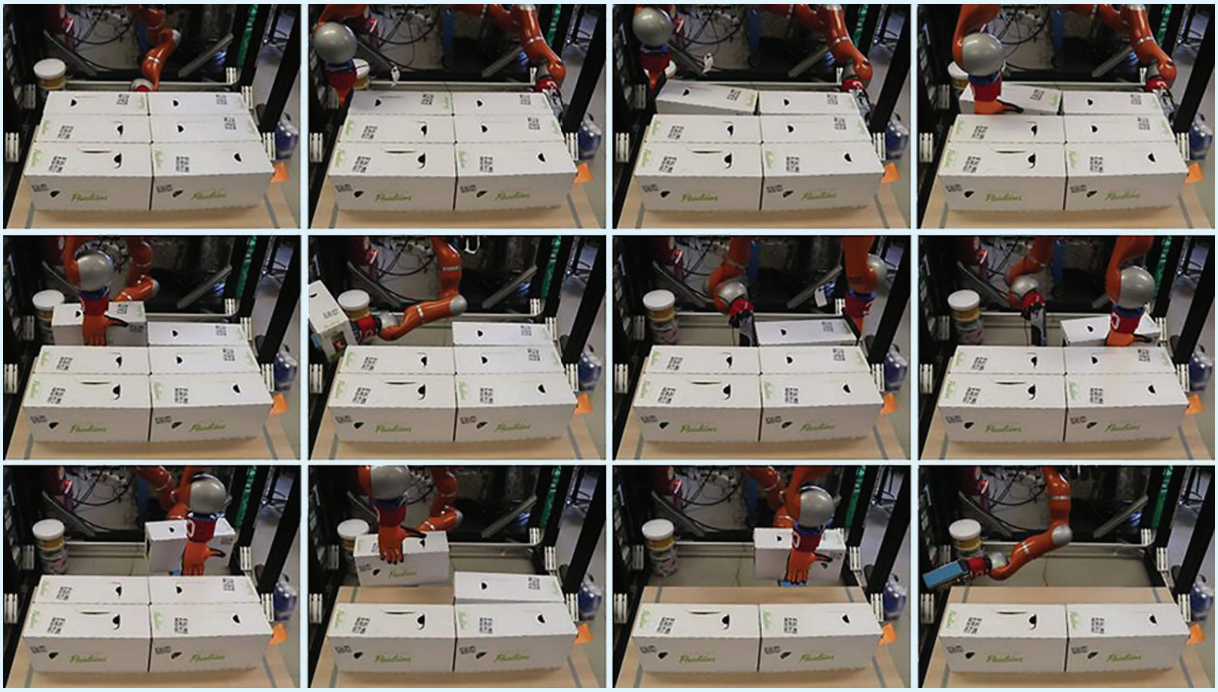


Figure 11. The WRAPP-up picking thick boxes using the vertical rotation primitive.

Table 3. Picking performance indicators for the four scenarios.

Object				
Picking time per object	55 s	83 s	16 s	82.5 s
Time to empty a pallet	176 min	498 min	47 min	227 min

Table 4. Picking performance indicators.

Performance Area	Performance Indicator	Current	Unit
Productivity	Average time to empty a pallet	237	min
Reliability	Picking success	92.5	%

multiple picking actions on a set of four different representative objects. Future study will be to, on one hand, provide the robot planning with a high-level decision tool that is able to automatically generate the right strategy to adopt on the basis of features of the objects that can be detected by a vision system and, on the other hand, to adopt suitable feedback strategies based on vision, force feedback, and tactile feedback to improve robot reliability. Furthermore, the average picking time will be minimized by adopting suitable optimization algorithms, and the robot will be provided with a mobile base.

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