WRAPP-up: a Dual-Arm Robot for Intralogistics

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***Abstract*— The diffusion of the e-commerce has produced larger and larger volumes of different items to be handled in warehouses, with the effect to increase the need for picking automation. Conventionally, automation can be achieved through a custom plant in case of large scale productions where the items have well-known characteristics that are expected to change slowly and little over time. However, today the challenge is to realize a solution that is flexible enough to handle goods with different shapes, sizes, physical properties, and grasping modes. To solve this problem we first analyzed how humans perform picking and then synthesized their behavior in four main tactics. These have been used as guidelines for the design, the planning and the control of WRAPP-up: a dual arm robot composed of two anthropomorphic manipulators, a Pisa/IIT SoftHand and a Velvet Tray. The system has been validated and evaluated through extensive experimental tests.**

I. Introduction

E-commerce, i.e., buying and selling physical goods via services over the internet, has now reached his full development. Led by Amazon, which accounted for more than 50% of the growth of the whole e-commerce market, and by Alibaba, in 2017, retail e-commerce sales amounted to more than 2 USD trillion with an annual growth rate higher 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 side, the market growth led to an increase of the employment: data from the Census Bureau [3] show that, in the U.S., there was an annual growth rate in the Warehousing and Storage (North American Industry Classification System - NAIC - 493) employment of the 28% (from 2015 to 2016) and that in 2016 the total workforce reached more than 600K units. An analysis conducted by Data USA on the Census Bureau ACS PUMS 1-Year Estimate data shows that material movers are the largest share (20%) of jobs [4].

On the other side, a strong effort is devoted to maximize intralogistics efficiency by fully employing optimization techniques [5], by pushing the productivity of human operators even if it may cause high workloads [6], and by adopting automated solutions. Finally, e-commerce impacted both business-to-consumer (B2C) and business-to-business (B2B) markets. The market size of B2B e-commerce is more than ten times the one of B2C [7], allowing to show an unprecedented variety of products to the customers. This brought undeniable advantages in terms of sales [7] but also increased the flexibility requirements with which the intralogistics system must comply.

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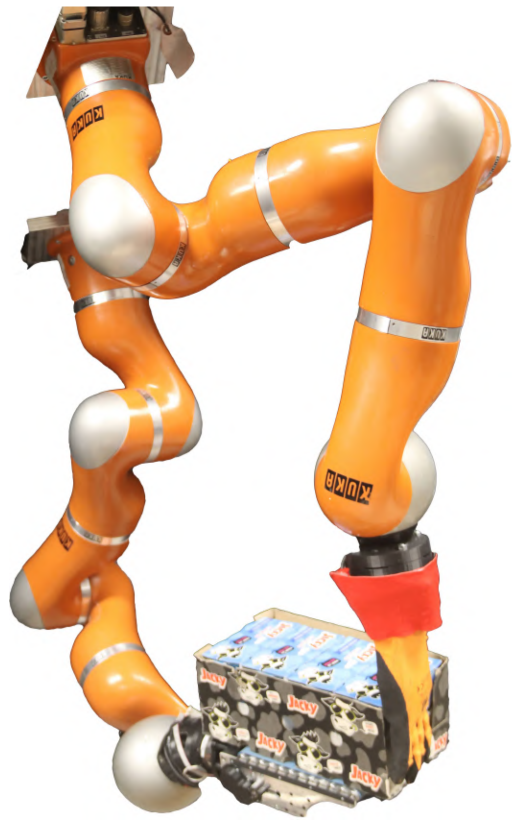


Fig. 1. WRAPP-up: a dual arm robot composed of two anthropomorphic 7-dof manipulators, a Pisa/IIT SoftHand, and a the Velvet Tray. In the picture WRAPP-up is picking a box that does not have the top surface.

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

The major challenge preventing the full automation of picking is represented by the high variability of objects to handle in terms of shapes or object configurations, not accessible or even absent surfaces, flexible or pierced surfaces, to name a few. Regarding object shapes, cuboids constitute the vast majority of all the items stored in warehouses [10]. According to [11], among the shipped packages, the shapes that occur more often are cuboids and, even if in a lower percentage, cylinders. Thus, strategies to manipulate cylinders and cuboids in different configurations handle a considerably large part of the goods in intralogistics processes.

Several are the components that concur 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 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 it based on the perception outcomes; a control strategy able to track the desired trajectory. This work is focused on the realization of a flexible, autonomous picking solution, leaving for future works the integration with the vision system.

Some of the most challenging and common situations an autonomous Pick and Place system might encounter are: 1) reduced collision-free end-effector poses due to other goods or containers; 2) restricted portion of the external surface of the object available for gripper contact due to other goods especially when tightly packed together; 3) deformability of the object, meaning that the shape of the grasped objects changes under external forces; 4) porosity of the object, which prevents the employment of simple and nimble suction grippers. Despite the great effort in the development of picking solutions, as far as the authors know, no existing automatic solution is flexible enough to cope with such challenges, many of which may occur together. A detailed problem statement is reported in Sec. III, while an overview of the existing solutions on the market is reported in Sec. II.

The main contributions of this work are the design, realization, and testing of WRAPP-up, a novel human-inspired dual arm robot for intralogistics. The development of WRAPP-up relies 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, which are detailed in Sec. IV. Based on these findings, we designed a dual arm robot (see Sec. V for more details) composed of two 7 degrees-of-freedom manipulators and two different end-effectors: an adaptive end-effector able both to grasp a large variety of objects and to stably interact with different shapes, and a tray with an actuated belt. Moreover, we encoded the human observed picking strategies into parametric motion primitives adopted in the trajectory planning of the robot. Finally, an extensive experimental validation (see Sec. VII) has been conducted.

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

II. Related Work

Picking tasks can be classified based on different parameters, of which one of the most important is the location from which the items should be grasped.

On one side, there is the bin-picking problem in which the objects are typically placed either in an ordered way (or not) in a box and a single object has to be grasped. Often the object has size and weight such that it can be handled with 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 by challenges aimed to enhance the warehouse automation in picking operations, such as the Amazon Picking Challenge [12]. The interested reader is referred to [13] for a comprehensive review of robotic picking and to [14] and [15] for recent results.

On the other side, there is the picking of items that are located on a pallet. To automate this task two main different 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 the shelf) is brought to the manipulator by mobile devices [16].

Prominent examples of autonomous mobile manipulation platforms for logistics include: Little Helper III [17], DLR omniRob [18], and 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. Handle instead has an unstable two-wheeled mobile base, which requires a more expensive control but substantially reduces the robot's footprint, is equipped with a vacuum gripper, and is devoted to box handling. The interested reader is referred to [20] for comprehensive literature reviews on the subject. Furthermore, Magazino [21] and InVia Robotics [22] sell two products on the market, mainly devoted to box picking and based on suction cups. Both the solutions exploit a picking strategy based on box sliding, which may not be suitable for boxes stacked one upon the other and, in general, 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, always based on objects 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 the end-effector. The ground-based depalletizing robots available in 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 the former is aimed to incorporate in a unique platform both picking and discharging.

Currently, the most flexible autonomous systems that may be used to accomplish picking tasks are 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, which exploits the friction forces to pull the boxes towards the corners of the frame and firmly hold them in position. An evolution of this concept is the Fraunhofer Roll-on Gripper [39], which is a hybrid between a lift and a gripper. In this solution, the belts also allow for manipulating (translate or rotate) the boxes once picked up by the gripper. A similar solution is exploited by Premium Robotics [25]. These grippers alone show limitations when the grasped item is lodged in the object below.

Vacuum grippers are widely employed for the grasping of boxes by their top surface ([26], [27]), e.g., [40]. The vacuum gripper by Wynright Robotics [41] is able, as well as others ([21], [22]) to grasp from the frontal side. The device relies on an array of vacuum cups to drag the box on a support surface of the gripper.

Vacuum grippers show severe drawbacks when the interested surface of the object is not suitable to be grasped, e.g., because the top surface is not present at all, or it is not robust enough to sustain the weight of the object.

III. Problem Definition

The task of interest, in this work, consists of picking several different goods from single-item pallets, namely pallets composed of several units of an item. The input to the picking system is the sequence of goods to be picked and their location on the pallet that 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, and on the modes that can be profitably used to grasp them. Picking tasks, the vast majority of which is currently executed by human operators, can be classified into two main categories: the ones that can be accomplished with a hand and the ones 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 works of the authors [42] and [15]. This work is focused on the problem of picking objects that humans cannot pick with one hand. Notably, the solution that will be proposed in this work will be able to accomplish both categories of picking tasks. In the following, a list of items that represents the 40% of the volume of a food warehouse is reported together with their main features. Notice that the food & beverage is one of the market segments most affected by the e-commerce revolution, which today allows customers to have their shopping bags directly delivered at home. In the next subsections, the functional requirements that a picking system should satisfy to work in such a warehouse profitably are stated. Finally, the main challenges to be tackled in the design and realization of this device are described.

A. Objects

The complete list of objects to be picked with their size and weight is reported in Table II. 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 the height (H) are listed.

B. Functional Requirements

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

TABLE I
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	%

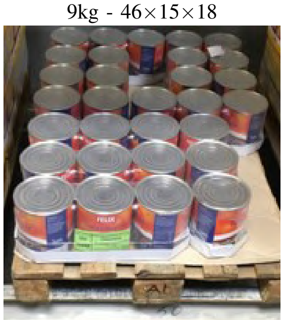
Productivity performance indicators have been computed based on the fact that such a robot would be economically sustainable if it is able to perform 3 picking movements every minute (corresponding to 180 picks per hour). Given that a Euro-pallet (80 x 120 cm base piled up to 1.5 meters) may contain up to 627 smallest items, and up to 115 largest items (among the objects reported in Table II), the time needed to empty a pallet can be evaluated in 209 and 38 minutes, respectively. The average of these two values gives the productivity performance indicator reported in the table. The picking success rate takes into account the grasping system without considering the vision system.

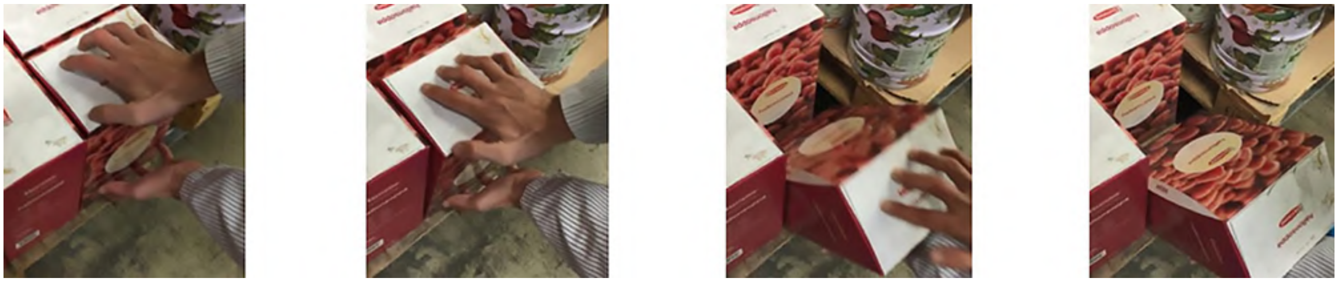
C. Challenges

The main challenges of the picking phase can be identified in the following 3 points:

- boxes are often very close to each other, with two opposite sides, which are the most desirable for a reliable and robust grasp, usually not easily accessible. Hence, to be properly handled, they should be first moved to

TABLE II
OBJECTS CONSIDERED FOR PICKING TASKS, WITH THEIR WEIGHT (KG), SIZE (CM), AND RELATED GRASPING STRATEGIES

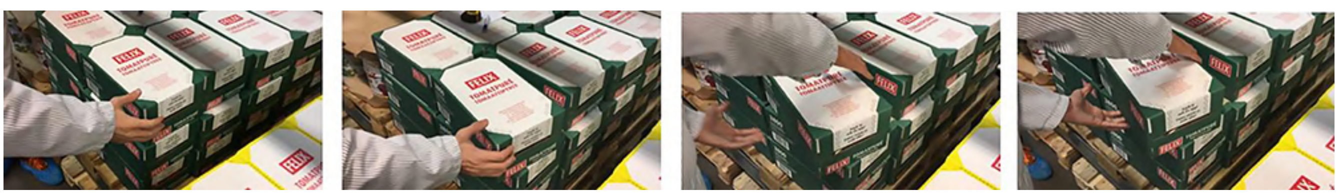
9.1kg - 22×26	4.3kg - 20×25	3.2kg - 16×18	3kg - 20×13
			
Horizontal Rotation	Horizontal Rotation	Horizontal Rotation	Horizontal Rotation
3kg - 19×29×14	2.7kg - 40×7×30	2kg - 40×8×30	1.8kg - 15×13
			
Horizontal Rotation	Horizontal Rotation	Horizontal Rotation	Horizontal Rotation
9kg - 46×15×18	6.0kg - 40×10×26	5kg - 46×18×15	2.5kg - 38×18×14
			
Vertical Rotation - Sliding	Vertical Rotation - Sliding	Vertical Rotation - Sliding	Vertical Rotation - Sliding
2.5kg - 36×15×23	2.0kg - 38×23×20	1.9kg - 35×13×16	0.4kg - 40×18×25
			
Vertical Rotation - Sliding	Vertical Rotation - Sliding	Vertical Rotation - Sliding	Vertical Rotation - Sliding



(a) Human grasping a box–shaped object.

(b) Human grasping a cylinder–shaped object.

(c) Human grasping a cylinder–shaped object.



(d) Human grasping a box–shaped object.

(e) Human grasping a box–shaped object.

Fig. 2. Human grasping different shaped objects with different strategies.

guarantee that two opposite faces are accessible and then picked.
- some of the items do not have a top surface, or it may not be suitable to grasp the object. These objects cannot be grasped with vacuum grippers.
- the bottom side of some objects is recessed in the upper side of the objects which lie under, or more in general, they can not slide. This means that the objects can only translate along the vertical direction or rotate about a horizontal axis.

IV. Human Picking Skills

There is not a systematic method to synthesize a system that matches all the requirements listed in Sec. III, and one of the reasons is that it simultaneously involves the co-design of the robot 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 Tab. II. More in detail, we recorded two human operators from a food warehouse while performing the picking action. Each picking action has been repeated three times. These live observations and the analysis of the video recordings led to two lessons learned:

- bi-manual manipulation has a crucial role in picking operations since humans use both hands to manipulate and handle the objects. In the majority of the tasks, one hand is used to move the object, and the other hand is used as a support;
- the strategies to pick the items are classifiable in three main classes.

The strategies, shown in Fig. 2, that human operators adopt while manipulating goods fall into 3 groups depending on object shape and form factor:

a) Rotation about Horizontal Axis: In case of thin boxes, i.e., $H > W, H > L$, 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 Fig. 2(a,b,c) and Fig. 2(d)).

b) Rotation about 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 the operators decide to rotate the boxes about a vertical axis to have access to the back surface of the object, as in Fig. 2(d). This strategy can then evolve in two different picking continuations. In the first one, the box is picked up by two opposite surfaces while the operator uses his hands like the jaws of a parallel gripping device. In the second one, the box is first dragged towards the worker acting on the back surface and then supported by the other hand as the box sticks out the pallet or the underneath layer of goods. This helps apply two different grasping strategies: grasp the object relying on contacts on two opposite surfaces (front and back) and slide the object relying on the contact on the back surface.

c) Sliding: For thick boxes with no constraints at the base, the operators push or pull the objects until they reach the support hand at the boundary of the pallet, as in Fig. 2(f).

Picking strategies that human operators adopt highlight that often, pickers 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 often responsible for supporting the majority of the item weight and may be used to perform placing operations such as alignment and unloading.

V. WRAPP-up Design

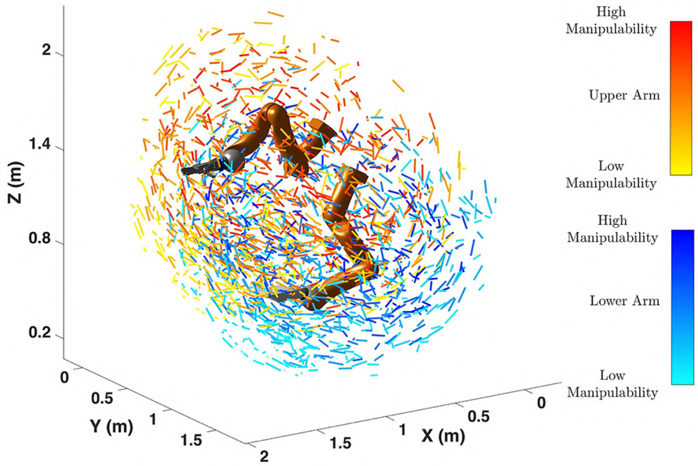
Inspired by the techniques adopted by warehouse workers, the envisioned solution is a dual arm system. The system is composed of two Lightweight Robots arranged to perform pick and place tasks properly. The mounting bases of the arms are fixed at an established relative pose, as better described in the 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. 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 set up each robotic arm has been mounted on an independent movable gate, which allows for three DOFs in a plane (two translations and a rotation), enabling configurable relative locations of the two arms (see Fig. 3(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 subsection. In a final use case, the dual arm robot can be mounted on a fixed base as well as on a mobile base, depending on the end-user requirements. For instance, the end-user may employ a picker-to-goods strategy, thus needing a mobile base for the picking station, or a goods-to-picker strategy, in which the picking station is fixed and the objects are brought there. At the moment, our robot is mounted on a fixed base, but it will be integrated on an autonomous mobile robot in future works.

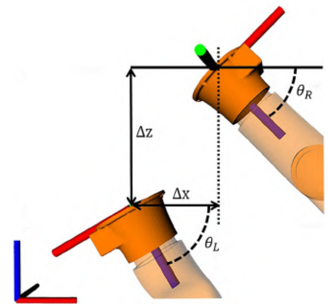
A. Relative pose of the two manipulators

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 w.r.t. each other and the pallet. A wrong relative location of the arms may prevent the correct execution of a strategy because of two main reasons: one joint (or more) reaches the limit of its range of motion, or a point of the desired trajectory is out of the reachable workspace of the bimanual system.

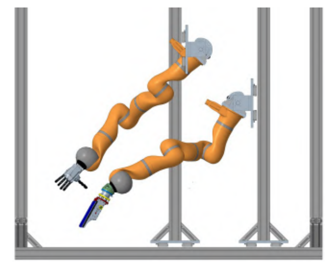
To properly choose the relative location of the arms, a two-step strategy has been adopted. First, a manipulability index for each arm has been evaluated for a set of points to find a relative pose that provides an adequate superposition of the manipulators' dexterous workspaces. Then, a feasibility analysis, conducted by simulating the kinematic execution of the robot trajectories (based on the strategies presented in Sec. VI for the objects listed in Tab. II), has been 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 the manipulability. Future works will be devoted to the evaluation of different metrics. Among the manipulability



(a) An example of the manipulability analysis showing the manipulability measure and the preferred directions of motion.



(b) Configuration of the two arms in the current setup. $\Delta_x = 20$cm, $\Delta_z = 30$cm, $\Delta_\theta = 15\,$deg ($\theta_R = 45\,$deg and $\theta_L = 60\,$deg).

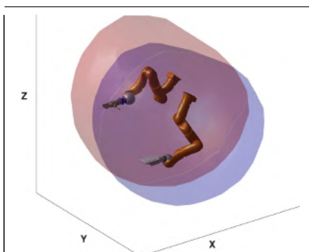
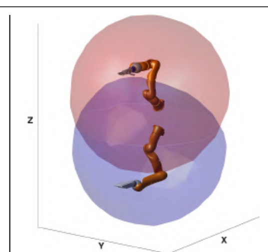
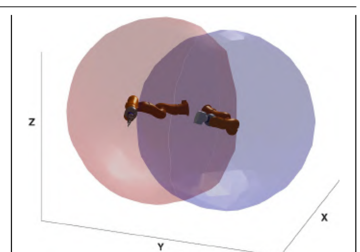


(c) CAD Model of the experimental setup

Fig. 3. Analysis of the relative configuration of the manipulators, resulting relative configuration, and CAD Model of the experimental setup.

TABLE III

MANIPULABILITY ANALYSIS 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

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]

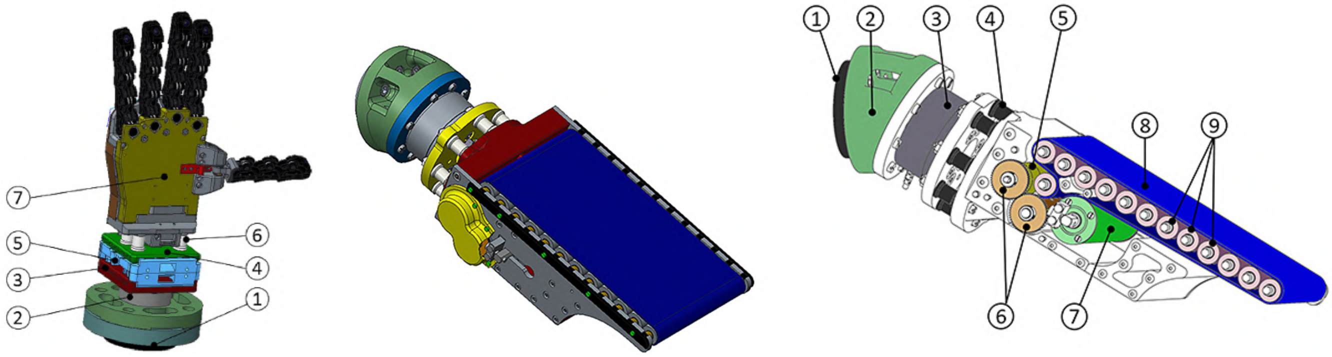
$$w(q) = \sqrt{\det(J(q)J(q)^T)}, \tag{1}$$

that is a measure of the volume of a six-dimensional ellipsoid of which the semi-axes length is represented by the square roots of the singular values of the end-effector Jacobian $J(q)$. The eigenvector of $J(q)$ corresponding to the largest singular value represents the easiest direction of motion. Fig. 3(a) represents an example of a graphic result that shows the manipulability index $w(q)$ (evaluated according to Eq. 1) and the preferred directions of motion of the two robots.

Given a relative location of the arms, we evaluate 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 is 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



(a) The Pisa/IIT SoftHand is the dexterous end effector of WRAPP-up. Furthermore, the picture shows also all the components attached to the wrist of the robotic arm.

(b) The Velvet Tray is the support end effector of Wrapp-up. On the left a 3D view is shown. On the right a cut view shows the power transmission group and the conveyor belt.

Fig. 4. The Manipulation End-Effector (Pisa/IIT SoftHand) and the Support End-Effector (Velvet Tray).

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 $\bar{w}_D|_I$ we denote 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 Sec. IV for different positions of the target object and registered the associated Cartesian error. To perform this analysis, we considered the object as they were placed on a 0.8m×0.6m×1.5m pallet in front of the robotic platform so that it would lie within its reachable workspace. The width corresponds to half of the width of a EURO-pallet. We simulated the task for every poses an object could assume on this reference pallet (the possible poses are limited and depend on the shape and the dimension of the object), and we checked that, in the selected configuration, the robot was able to execute the task with a limited Cartesian error (under 1cm of error).

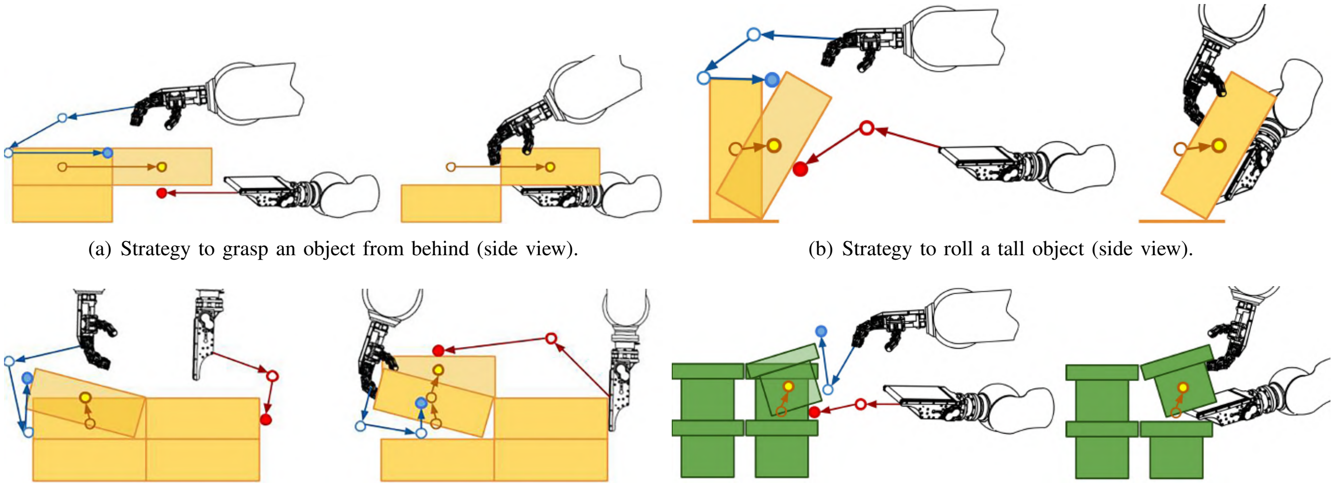
To reduce the complexity of the search of the relative configuration, we predefined a set of reasonable candidate poses and evaluated the manipulability for each of them and evaluated the task performance for the most promising one. Examples of the manipulability for three different candidate configurations are reported in Tab. III, where the values have been obtained using $N = 20000$ samples. It is worth noting as the first configuration (the one we have eventually selected) is the one with the higher manipulability. A detail of the manipulators' base relative location is depicted in Fig. 3(b).

B. Mechanical Design of the Manipulation End-effector

The manipulation end-effector is the Pisa/IIT SoftHand (Fig. 4(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 the reader can refer to [45]. The Pisa/IIT SoftHand (7) is attached to the wrist flange of the robotic arm (1) through a 6-axes 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 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. Toothed flange (5) crimps plate (3) (fixed to the sensor) and plate (4) (fixed to the hand side) together.

C. 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. Fig. 4(b) shows a 3-D model of the Velvet Tray. Its design and principle of operation are inspired by research carried out by the Authors about grippers with active surfaces [46]–[48]. It is equipped with an actuated belt to ease the loading maneuvers of the goods. It is attached to flange wrist (1) of the KUKA arm through flange (2). Between the KUKA arm and the Velvet Tray, a 6-axes Force/Torque ATI-Mini58 sensor (3) and rubber beams (4) are interposed with the same aim as in



(a) Strategy to grasp an object from behind (side view).

(b) Strategy to roll a tall object (side view).

(c) Strategy to rotate an object exploiting environmental constraints, such as another object used as a pivot point (top view).

(d) Strategy to lift an object and put it on the tray (side view).

Fig. 5. Robot grasping strategies.

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. 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 the friction coefficient provides the worst-case for the torque of the motor that guarantees to hold the target mass of $2.5kg$ with the Velvet inclined 38°. A Maxon motor DCX22 actuates the belt with gear-head GPX83 (5) that is able to move a mass of $2.5kg$ 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). Tension roller (7) ensures a proper tension in the belt of at least $20N$ necessary to transmit the required torque. Finally, a set of idle rollers (9) sustain the objects and form an approximately flat surface under the belt.

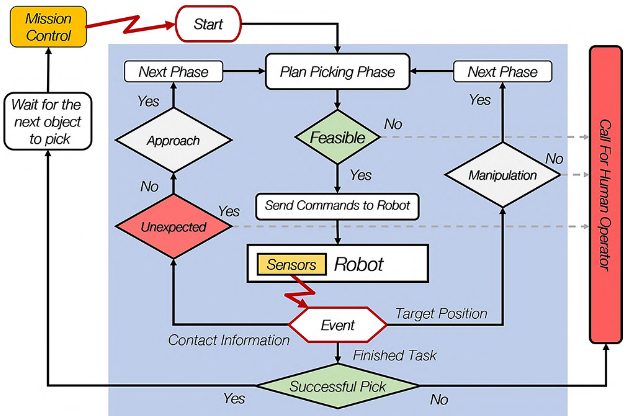
VI. Translating Human Picking Skills into Robot Motion Primitives

Inspired by the observation of the strategies adopted by the operators (described in Sec. IV) parametric motion primitives have been defined to plan the motion of the robot during the task execution:

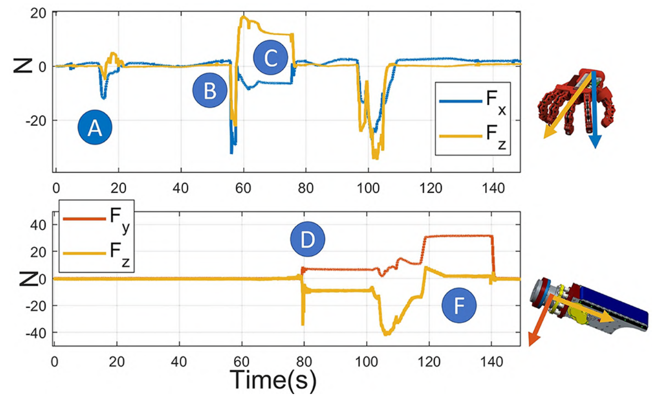
- **Sliding** one end-effector is used to push (or pull) an object towards the other end-effector, which secures the grasping and may support the weight of the object, as shown in Fig. 5(a).
- **Horizontal Rotation** one end-effector is used to tilt the object about a horizontal axis gently. This can be achieved in two different cases: i) about a horizontal axis on the front-bottom edge of the bounding box enveloping the object (see Fig. 5(b)); ii) about an axis on the back-bottom edge of a bounding box enveloping the object (see Fig. 5(d)). In the first case, the object rotation will end when it lays on the support end-effector. This strategy is intended to be used with objects (boxes, cylinders) of which the height 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 towards the pallet's exterior. This strategy is suitable when the objects are compactly packed (see Fig. 5(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 has been 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 w.r.t. 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 in order to produce enough room for positioning an end-effector as in 5(c) or 5(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 in the world frame.

In order to take into account the robot kinematics and the joint limits for the motion planning, we determined the path at the joint level via the reverse priority algorithm described in [49], which allows us to define a set of tasks with different priorities including unilateral constraints (e.g., joint-position limits). More in detail, for each of the two arms, we have set the Cartesian pose tracking, i.e., the position and orientation of the end-effector, as the low priority task, and the joint-



(a) Reactive planning architecture. The picking strategy is divided into basic consecutive phases planned online. The information from the sensors are 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 (Approach or Manipulation), these events trigger the transition to the next phase or an emergency state.



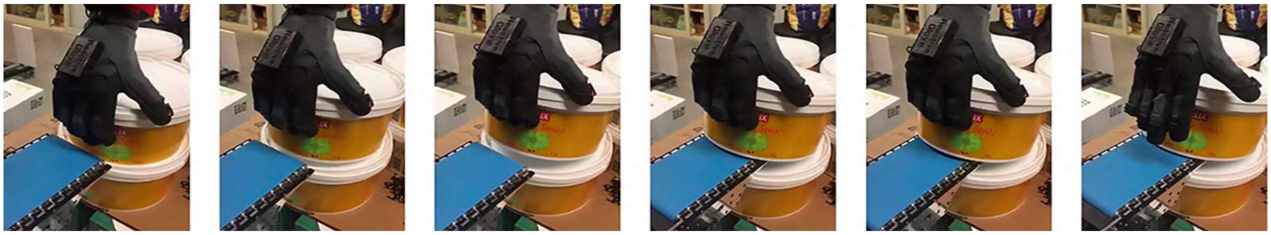
(b) Force sensors readings for the two end-effectors during the strategy execution. The transitions between the states into which the strategy is decomposed are highlighted.

(c) Sequence of a picking strategy in which each block corresponds to a state of the state machine on which the planner is built.

Fig. 6. Reactive Planning Approach.

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 have been 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 Fig. 6(a) for a schematic representation of the architecture) is accomplished by decomposing each picking strategy into consecutive basic phases represented by states of a finite state machine. Each phase is planned online (block ”Plan Picking Phase” of Fig. 6(a)) and generates the Cartesian trajectory for the end-effectors. For each of the phases, the kinematic feasibility of the planned trajectory is checked (block ”Feasible” in Fig. 6(a)). In this block, the generation of a path for the joints of the robot is performed using the reverse priority algorithm. If the desired motion is not feasible because, e.g., of the constraints on the joint ranges, the task is aborted, allowing the intervention of a human operator. The transition between a phase and the following is triggered online based on the information coming from the force/torque sensors and the joint position sensors of the robot. This information can be used to detect two possible events (block ”Event” in Fig. 6(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 is a critical step of the manipulation process, since an incorrect positioning of the end-effector w.r.t. the object, possibly due to errors on the estimate of the object pose, could cause the picking failure. Hence the end-effector starts moving towards the object along a specified direction until contact is detected. Then, it stops, and the end-effector position at the contact is 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.



(a) Horizontal Rotation Primitive.

(b) Cylindrical objects being picked using the *horizontal rotation* strategy.

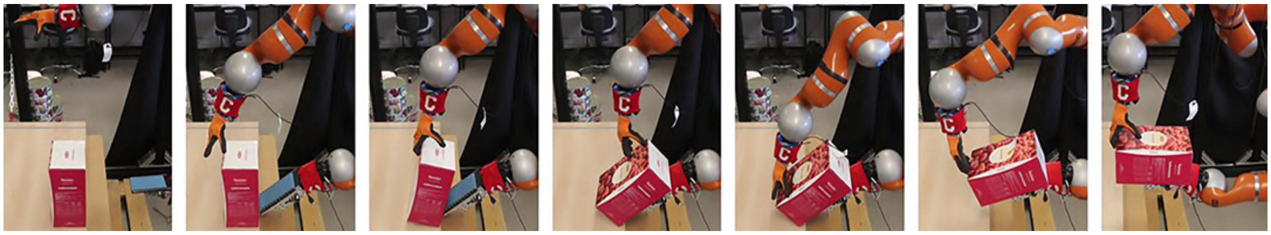
Fig. 7. WRAPP-up picking cylindrical objects.

An example of the described reactive approach is reported in Fig. 6(c) and 6(b), where the states of an example trajectory and the corresponding force sensor readings are shown. For this example, we considered a worst-case scenario where the uncertainties on the pose estimate are such that require additional pose refinement steps. Indeed, in phase (A) the hand is approaching the object laterally to refine its pose. As reported in Fig. 6(b), when contact is correctly detected (the magnitude of the force F_x along the contact direction exceeds the threshold set at 10N), the pose along this direction is updated, and the hand is placed front to the object and starts moving towards 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 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) (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.

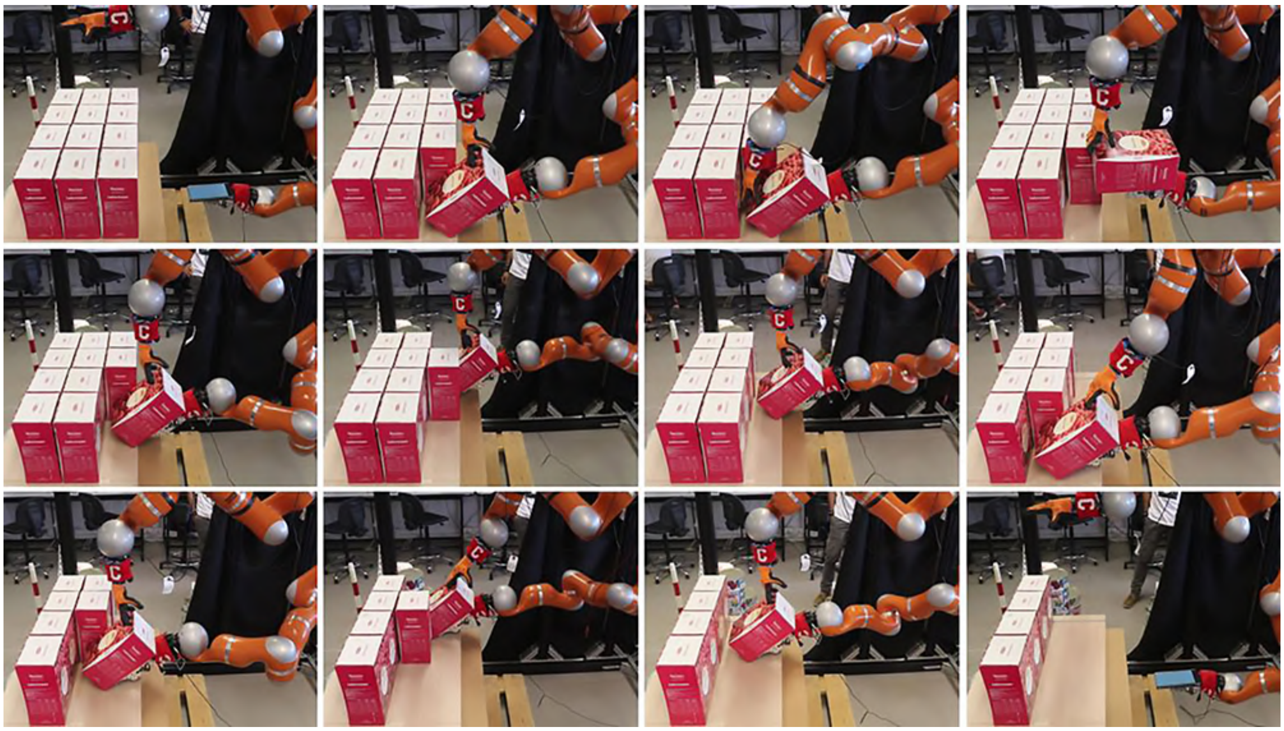
As said, the example shows the effectiveness of the reactive approach even in case of a not precise knowledge of the pose, which although requires the execution of the redundant and time-consuming lateral approach (phase (A)). Depending on the level of uncertainties on the pose estimated by the perception system, such redundant steps could be not necessary.

VII. Experimental Validation

In this section, the preliminary experimental validation of WRAPP-up is reported. The picking capabilities of the system are shown on a representative set of objects from the ones in Tab. II. Indeed, the objects used for the tests allow us to cover the two main shapes we have identified to be relevant for logistics, i.e., cuboids and cylinders. Furthermore, they allow us to test all the four motion primitives we presented



(a) Horizontal Rotation Primitive.



(b) Two rows (8 pieces) of thin boxes being picked using the *horizontal rotation* strategy.

Fig. 8. WRAPP-up picking thin boxes.

and validate the platform's performance in different picking scenarios.

Fig. 7(a) shows the strategy used to manipulate objects which 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 allows the 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 Fig. 7(a), and the tray is used to collect and deploy the bucket. In this case, the hand can be employed 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 shown in Fig. 7(b).

The *horizontal rotation* strategy is also effective to pick thin boxes, see Fig. 8(b).

In this case, the hand is placed behind the box and tilts it until the box lays 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 tray while the latter is returning parallel to the horizontal plane. The former approach has been tested to successfully pick 8 boxes close to each other, as in Fig. 8(b), showing the robustness of the designed strategy even in the presence of other objects behind the handled box.

The best picking strategy is not chosen solely based on the object's shape, but it also depends on the location of the object on the pallet and the position of the other possible items. To show this concept, two different picking tests have been performed on the same object (with a box-like shape) depending on its different orientation, see Fig. 9 and Fig. VII.

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 towards 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 degrees around the vertical axis w.r.t. the previous case, and they are compactly packed, as shown in Fig. VII.

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.

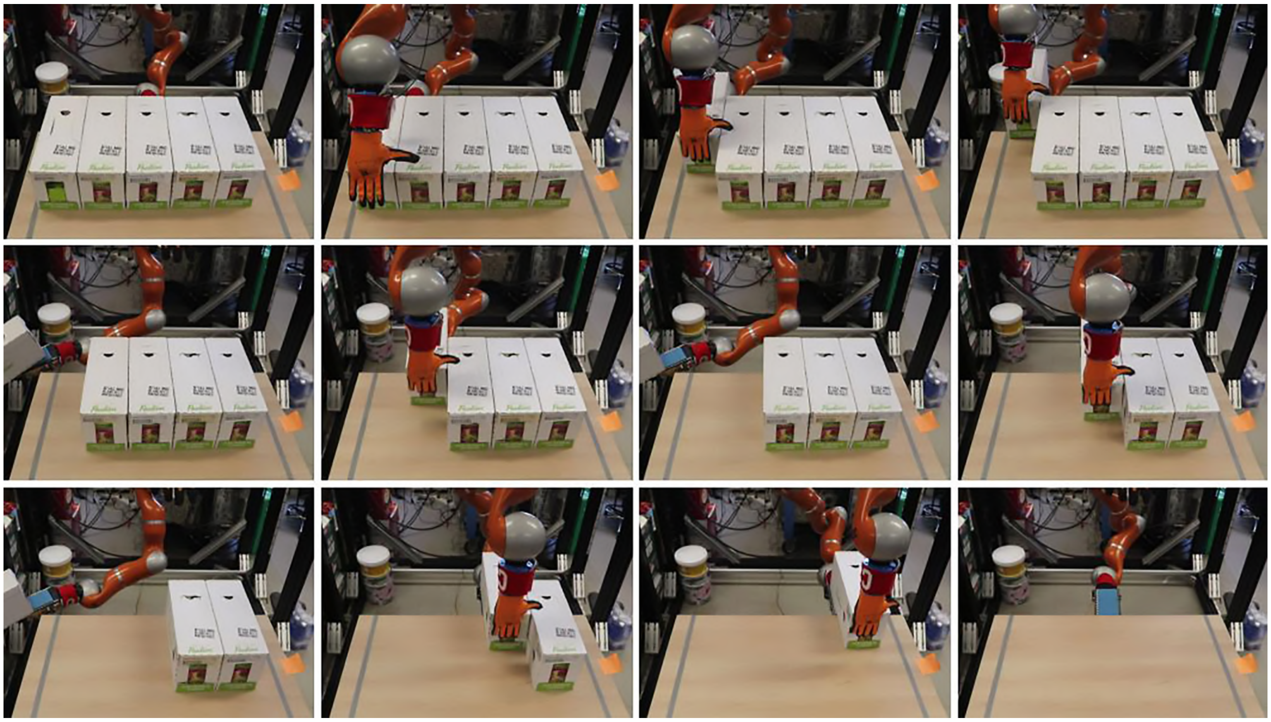


Fig. 9. WRAPP-up picking thick boxes using sliding primitive.

Then, the hand slides inside the created gap and proceeds to slide the box towards the tray.

Table IV shows the time for picking every single 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 that are contained in the pallet, the standard EU Pallet dimensions have been considered for the base of the pallet, and a full pallet has been considered to be 1.5 meters height. To compute the number of objects that can be contained in such a pallet, the dimensions of the objects have been taken into account. A pallet of thin boxes contains thus 192 items, a pallet of cylinders 360 items, one of the thick boxes 176 items in the first case, and 165 items in the other. Hence, the time to empty a pallet has been estimated, multiplying the average time to pick an object for the number of objects in the full pallet. Table V reports the global performance indicators we obtained for the picking task. The time to empty a pallet has been computed as the average of the values reported in Table IV. Fifty picking actions have been performed for each case in order to test the system and estimate the values of the performance indicators. The success rate is the average of the four cases.

A. Discussion

This set of experiments was aimed at verifying the effectiveness of the hardware and the picking strategies in an unloading simulation of goods on a pallet. These experiments demonstrated 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 Tab. I, 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 Tab. V are 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 has to 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 as, with the current setup, some of the more burdensome objects in Tab. II could result in being difficult to handle because they exceed the nominal payload of the arms. Strategies and solutions to effectively handle those objects will be investigated. A more specific study on the robustness of the platform for different objects and setups, to evaluate how different friction forces could impact the reliability of our manipulations that involve the exploitation of environmental constraints, will be subjects for future works.

VIII. Conclusions and Future Works

In this work, 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

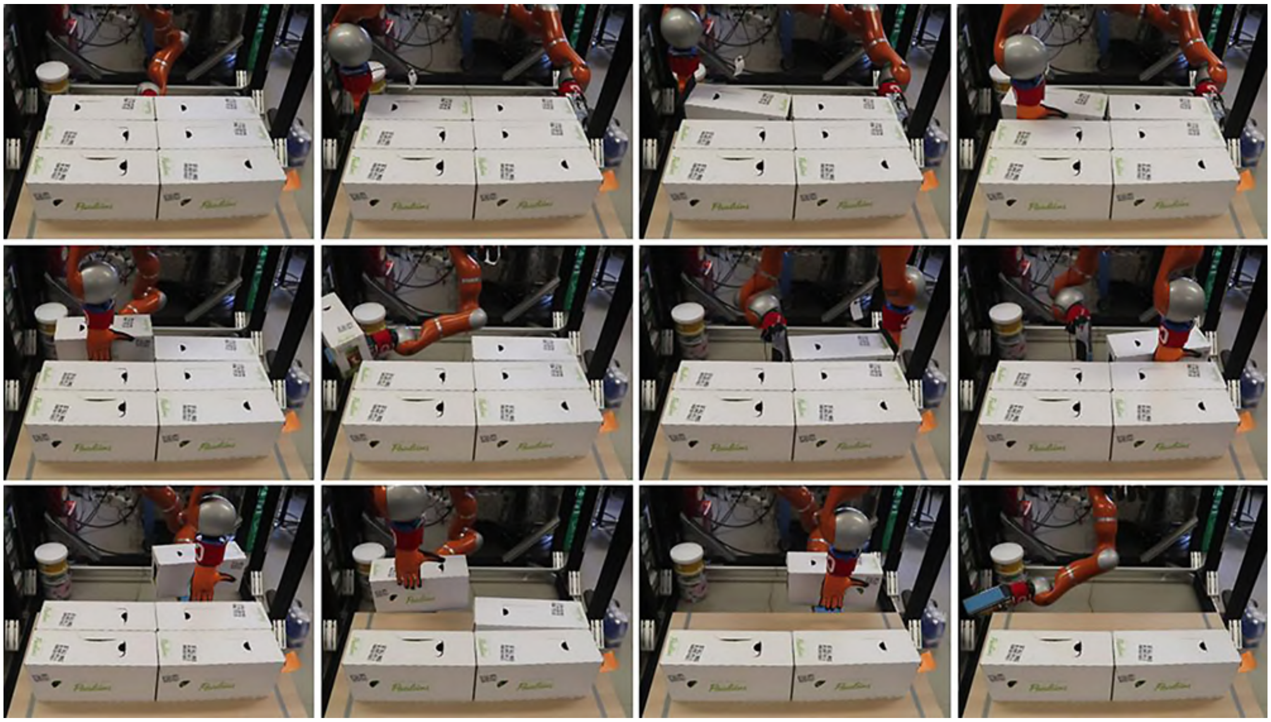


Fig. 10. WRAPP-up picking thick boxes using the *vertical rotation* primitive.

TABLE IV

PICKING PERFORMANCE INDICATORS FOR THE FOUR SCENARIOS.

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

TABLE V

PICKING PERFORMANCE INDICATORS

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

dual arm robot provided with a Pisa/IIT SoftHand and a Velvet Tray. The first end-effector is adaptable; hence it is used to establish stable grasps to rotate and slide goods with various shapes, while the second end-effector is mainly used to support the weight of the objects. The robot has been experimentally validated in multiple picking actions on a set of four different representative objects. Future works will include, on one side, to 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. On the other, to adopt suitable feedback strategies based on vision, force feedback, and tactile feedback in order 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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