A Human-Inspired Linear Scoop Gripper and Grasping Framework for Manipulation of Thin Deformable Food Products

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***Abstract*—Handling raw products in supermarkets is still nowadays a typically manual task. First steps toward automation of these actions are being taken, typically for large production volumes with tailored solutions in well controlled environment. This paper presents a parallel mechanism robotic gripper capable of gripping by scooping and caging deformable fresh-produce like fish and meat as part of an automated logistic delivery chain with high mix low volume. The design motivation has been derived from human pick and place strategies to achieve flexible and robust capabilities in an unstructured environment. The gripper is designed using a variable stiffness actuator, to provide the delicacy required to handle the products without damaging them. Human experiments also provide input to a grasp planning framework to pick the best suited grasp strategy and position for a given object in a given surrounding. Finally, extensive testing of the gripper and grasping framework in lab and industrial conditions demonstrate its suitability for production in the real world setting.**

I. Introduction

As the global population and consumer demand for diverse and highly personalized food products rise, food manufacturing is adopting new strategies to meet the challenges. Automation in the food industry is being integrated to boost production rates and enhance food quality and hygiene [1]. Globally, 70% of organizations are piloting these technologies, accelerated by COVID-19 to improve business processes and customer experiences. Operations at manual service counters and in small-scale food production environments are typically labour-intensive and physically demanding. It involves precise cutting or slicing, quality control, picking, packing and labelling. The tasks performed by a worker demand great attention to detail, as companies prioritise the quality of their products [2]. The daily output of a meat packer varies based on factors such as the type of meat, the packing facility's efficiency, and the company's production targets. However, the repetitive nature of the work can contribute to mental fatigue, which in turn may reduce attentional control and increase the likelihood of mistakes, such as inaccurate labelling or inconsistent portion sizes. Additionally, the environmental factors, such as cold environment can potentially lead to the reduced dexterity [3], [4]. Therefore, the introduction of automation to support workers with physically demanding and repetitive tasks can deliver significant benefits to the process as well as to enhance product quality.

Fresh fish and meat handling with robotic automation, enhance precision and efficiency. Fresh fish are slippery, deformable, and fragile, presenting significant challenges for robotic manipulation. Unilateral gripping technologies are widely used for fresh products [5]. More specifically, air-based (Coanda, Bernoulli and Vacuum) unilateral grippers are preferred while magnetic, needle, and adhesive based are not suitable for food products. Fresh products can have two or more mediums (e.g., skin, fat tissue) within the same product. Therefore, gripper material and design is not generic to many products and is always customized for a specific product surface to exert the required lift force. Soft robotic grippers are also widely used [6]. Large adoption remains challenging due to assumptions on fragility of the food product and inertial implications while manipulating. Moreover, they are also usually customized for a product as shown in [7] for sushi handling.

The market currently offers various grippers for packaging activities, such as mGripAI's two, four, or six-fingered rubber-tipped gripper [8], RoboBatcher Flex 3's new gripper [9], and RightPick's 3-fingered gripper [10]. However, most of the solutions are built to handle specific types of meat or fish as part of the large scale production system in combination with other automation mechanisms in a controlled environment. There is a lack of grippers designed for general manipulation of flexible fresh products that are also suitable for small-scale production and retail environments such as fresh-produce counters.

In this paper, we present a novel gripper and grasping pipeline for picking different types of fresh fish and meat in unstructured environment and packaging. We introduce a gripper capable of scooping under the object or grasping on the sides while caging them with a soft palm from the top. The use of variable stiffness actuators for gentle interaction, in combination with linear closing on the same plane, actuated scoopers at the distal link, wide opening, and sensing makes this gripper applicable for a wide variety of objects. The gripper design and the grasping framework has been optimized based on human grasping strategies. These properties differentiate our work in comparison to other scooping based gripper designs [11], [12] found in the scientific literature.

In Section II, we present the human experiments conducted to analyze the different grasping strategies used to pick a fish or meat and derive requirements for a robotic gripper. The designed robotic gripper is presented in Section III. In

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Section IV, a grasp planning framework is introduced to pick the optimal grasp strategy. The performance and experimental validation of the gripper and the grasp planning framework in lab and industrial settings is presented in Section V. Finally, concluding remarks are provided in Section VI.

II. Human Experiments

In this work, we demonstrate that the understanding of human manipulation strategies can provide valuable insights for improving robotic handling of delicate and deformable objects, including in food processing and retail industries. This study, conducted as part of the SoftEnable Horizon Europe project, investigates how humans manipulate fresh sea bass fillets through a structured pick-and-place task.

The primary aim of this study is to analyse human manipulation strategies when handling fresh sea bass fillets to inform the development of robotic grasping systems. By capturing and evaluating human grasping and placing behaviours, the study seeks to identify natural, efficient, and precise handling techniques that can be replicated in automated systems. Our aim is to use the findings to design dexterous, adaptable robotic grippers capable of handling delicate and deformable objects.

The experiments take place in a walk-in fridge (3m × 3m) to maintain the freshness of the fish and simulate realistic industrial conditions. This setup ensures that the handling of fresh produce is representative of real-world food processing environments, where temperature variations could impact the mechanical properties of the fish fillets. The study involves eight participants performing a structured pick-and-place task with fresh sea bass fillets to analyse human manipulation strategies. Each participant completes 16 trials, picking a fish from a cluttered container, weighing it on a scale, and placing it into a packing tray according to predefined rules using only the dominant hand (Fig. 1). Participants must follow a structured sequence when placing fish in the packing tray: the first fish is placed skin down, the second fish is positioned on top with the skin facing up, the third fish is placed next to the first fish with the skin down, and the fourth fish is placed on top of the third fish with the skin facing up. This alternating orientation standardises packing across trials and preserves product quality by preventing direct skin-to-flesh contact between adjacent fish, reducing the risk of cross-contamination.

The data collection system (Fig. 2) captures both motion and visual data. Motion tracking is performed using five OptiTrack cameras to monitor wrist movement, while a Rokoko SmartGlove records IMU data from the wrist and fingers. Video recording is achieved through three Realsense RGB-D cameras (D435i) that capture depth and RGB video along with a high-resolution camera (1920×1080 @ 60fps). ArUco markers are placed on the table to aid post-processing, enabling accurate tracking of the trays and scales.

The collected data was analysed to identify patterns in human manipulation strategies, focusing on both picking and placing actions. The results of the study reveal four distinct human manipulation strategies. The analysis of picking strategies indicates that all four identified approaches -grasping from the head, grasping from the tail, grasping from the top middle, and scooping from underneath—are used with varying frequencies (Fig. 4). The most common strategy across participants is grasping from the tail, while grasping from the top middle is the least used. Participants tend to prefer consistent picking strategies across trials, with only minor variations when transitioning from cluttered picking to single-item picking from the scales. However, no statistical significance was found between participants and the applied strategy.

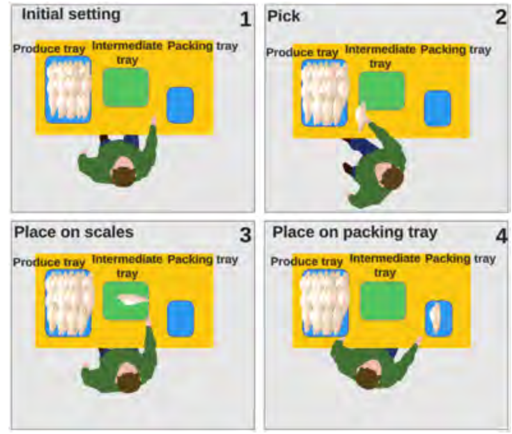

Fig. 1: Experimental sequence for fish pick and place experiments in a walk-in fridge.

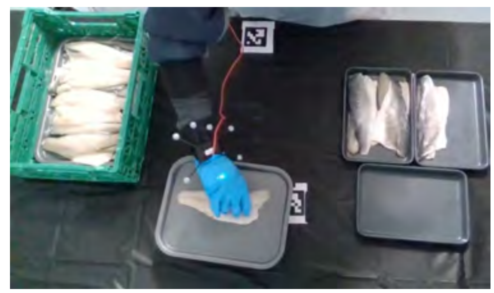

Fig. 2: Data collection in the fish experiments: Rokoko SmartGlove, OptiTrack motion tracking, and Aruco markers.

We can observe that the *Tail First* and *Head First* strategies are mostly similarly distributed between participants over the two scenarios. *The slide hand from underneath strategy* is only used by four participants when placed on the packing tray, with less than five occurrences for each participant. It is particularly notable for participants 5 and 8, who both used the strategy twelve times for placing on the scales, dropping down the usage to three and five respectively for the second scenario.

A Chi-Squared test confirms a significant correlation (*p-value* < 0.05) between picking and placing strategies (Fig. 3). Specifically, participants who pick a fish from the tail are more likely to place it head first, while those who pick from the head tend to place it tail first. Additionally, those who scoop from underneath or grasp from the top middle often favour sliding the fish into place rather than using a direct placement

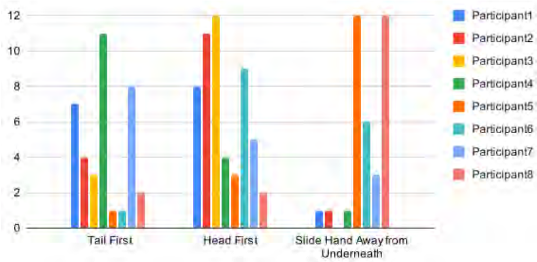

Fig. 3: Placement strategy across participants.

technique.

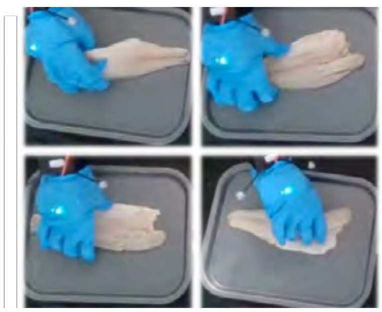

Fig. 4: Human grasping strategies: grasping from the head, grasping from the tail, grasping from the top middle, and scooping from underneath.

Based on the observations described above, we can conclude that there exists specific range of manipulation strategies specifically suitable to manipulate soft and flexible items. Thus, we can formulate the design requirements for robotic grippers and similar hardware designed for flexible, soft and delicate object manipulation.

III. Linear Scoop Gripper

The human studies described in Section II provided valuable insights and requirements for the gripper design: soft, gentle grasping; the ability to open wide and scoop thin objects; active use of soft fixtures in the hand to cage and constrain deformation; and appropriate sensing. Moreover, the ability to function in a walk-in-fridge-like environment and include food safety-related aspects was also important. Out of this requirements we take this ones for the design of the gripper:

- Handling delicate fish and meat products without damaging them
- Handle soft object of up to 1 kg
- Include mechanism to securing the product during transportation
- Flexible design of the gripper to implementation of different manipulation strategies
- The gripper should offer possibility to include shielding to protect mechatronic from aggressive disinfect and cleaning products, which are needed to keep the hygiene standards of the production chain

Fig. 5: Linear Scoop Gripper developed by DLR - left scooper actuation by servo over lever - ratio 1:1.2

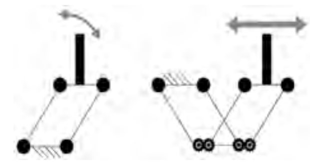

Fig. 6: Parallel (left) and double parallel (right) mechanism

The Linear Scoop Gripper (LSG, see Fig. 5) was developed using the qbmove Advanced [13], a variable stiffness actuator. It not only provides robustness but also helps reduce contact forces during grasping, compared to rigid grippers. It has a maximum torque of 5.6 Nm , a motion range of $+/-170°$ and a stiffness range of 0.5 to $83.5 Nm/rad$. The finger kinematics consists of two parallelogram mechanisms and closes linearly. A parallel mechanism, such as that used in the Robotiq 2F-85 and many other parallel jaw grippers, does not close linearly on a same plane, i.e., the fingers tend to come forward when they close. This requires significant equalizing motion from the robot to maintain finger contact with the object. Another disadvantage of this approach is the increased distance of the object from the wrist for smaller objects when the gripper is in a grasping configuration, which reduces the robot's workspace. Consequently, the goal for LSG was to develop a parallel closing mechanism for the gripper that does not require equalizing motion from the robot. Fig. 6 illustrates the function of the double parallel mechanism. Unlike the parallel mechanism shown in the left, the design on the right consists of two parallelograms arranged behind each other and interconnected via spur gears. The inner parallelogram is pulled outward by a return spring, and the second parallelogram follows at the same angle due to a coupling. A tendon, connected to the actuator via a pulley system, pulls the two fingers in parallel and close on the same plane when actuated. The movement is reset via four torsion springs on the inner levers. The double parallelogram mechanism achieves a much larger opening width with the same space requirement and is bendable at right angles to the closing direction. This reduces the interaction forces between the end effector and the object. Two mounting points for the fingers are provided on the screw-on plates to enable further adaptation to the object. The modularity at the finger base,

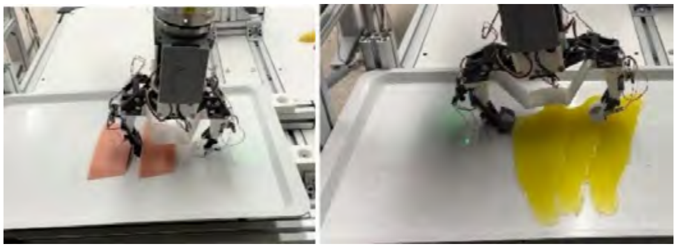

Fig. 7: Use of actuated scoopers for grasping in medium (left) and high (right) clutter scenarios.

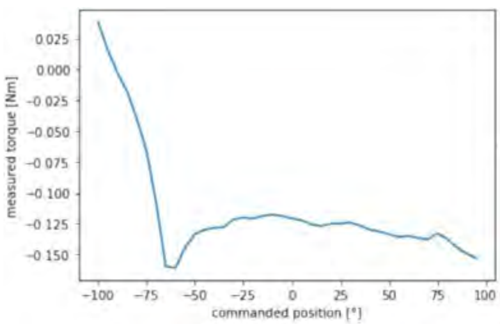

Fig. 8: Friction curve for stop condition based on commanded gripper position vs measured actuator torque.

allows easy maintenance and fast replacement.

The most gentle grasp of a fish is to scoop and grasp from under. The linear closing of the LSG make this feasible. By additionally including a scooper at each fingertip actuated by a small servo mounted directly in the finger and connected through a lever, this grasp is made further easy to execute. The independent operation of the scooper allows for better control and new grasping strategies in medium or high clutter environments as shown in Fig. 7. One scooper can remain vertical, allowing it to fit between objects, while the other stays flat to push the fish onto the scooper. Additionally, combined motion from the arm and gripper enables the gripper to start the grasp using vertical scooper. During this process, the gripper closes and rotates the fingertips simultaneously, while the robot performs compensatory movements to maintain the scoop tip's contact with the surface. In a high clutter scenario, the scooper can also slide under a single fish fillet and grasp it, provided other software components such as vision has the capability to precisely segment individual objects.

Thin and deformable objects can easily slip from the fingers without counter-pressure. Increasing the finger contact force will only damage or squeeze the object. Therefore, a soft palm was developed and is attached to the base of the fingers. It can adapt to the object shape and only provides the minium counter-pressure required to stabilize the object in the gripper. While grasping heavy objects, the palm easily deforms and do not introduce any noticeable external disturbance for the grasp.

A stop condition was implemented in the grasp controller based on the torque measurement of the actuator to control

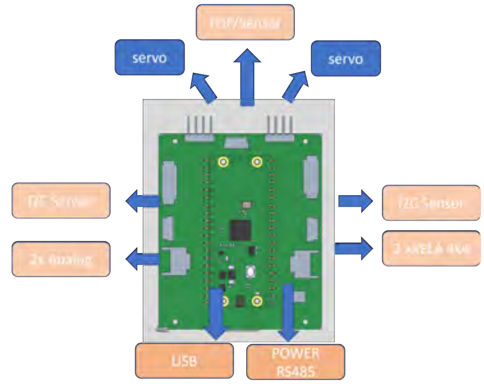

Fig. 9: Softenable sensorboard based on Raspberry Pico

contact force. The controller closes the gripper by commanding linear interpolation to the goal position and getting meanwhile the torque of the gripper as feedback. If the torque reaches the threshold, the controller stops the gripper in this position. A first implementation shows that without a friction observer the torque threshold is always above $0.15Nm$, which is equal to a grasp force of 600 grams. To achieve a lower threshold for stop condition values, the friction in the gripper mechanism was analysed. The reset spring together with friction in the levers lead to position dependent friction torque. This has been calibrated to achieve low contact forces during object grasping. Fig. 8 shows the curve mapping commanded position and measured torque, which is utilized by the controller for soft stop conditions. The controller is now subtracting the friction torque from the actual measured torque and can achieve 10 times lower contact forces. By comparing with a force gauge calibrated for weight, the gripper is shown to stop at 60 grams when closing a $6mm/s$ speed and 150 grams when closing at $30mm/s$ speed.

To integrate different additional sensors and actuators, we develop a PCB called sensorboard (see Fig. 9), which uses the same interface as the qbrobotic cube actuator. A Raspberry Pico is used as microcontroller due to the dual core design and the rich IO interfaces, e.g. PIO. To read different sensors, the board offers two ADC for analog sensors like force resitive sensors (FSR), eleven I2C ports to read for example two tactile sensors, e.g. two XELA 4x4 or time of flight sensors like VLX6180. Three of the I2C connectors are QWIIC standard to easliy integrate sensors from Adafruit or Sparkfun. Two of the QWIIC can be used over PIO as UART ports to integrate tactile sensors like tacterion sensors. Two RC servo can be connected to the board to handle the scoops. The current for both servos can be read by a sensor on the board. Two small 3D hall sensor board were developed based on the Allegro A31301 and the Melexis 90395 to be used as encoder or for tactile sensing.

IV. Grasping Framework

This section presents the proposed grasping framework designed for handling thin deformable food products. The

Algorithm 1 Grasp Planner

Require: 6D object poses $\mathcal{O} = \{O_1, O_2, ..., O_n\}$, collision meshes, sorted grasping strategies $\mathcal{S}$ = [ScoopUnder, TopSide, Head, Tail]
Ensure: Optimal grasp pose g^* for target object O_t
Digital simulation with bin and objects $\mathcal{O}$
for each object O_i in $\mathcal{O}$ **do**
  Define grasping region R_i
  Compute collision with neighboring objects $C_{\text{neighbors}}(O_i)$ for R_i
end for
for strategy s in $\mathcal{S}$ **do**
  if s is ScoopUnder **or** TopSide **then**
    Grasp axis $\hat{g}$ = object major axis $\hat{a}_{major}$
  else
    $\hat{g}$ = object minor axis $\hat{a}_{minor}$
  end if
  for candidate grasp positions along $\hat{g}$ (center $\rightarrow$ ends) **do**
    if grasp g is collision-free **then**
      Compute score $S(g) = S_{\text{strategy}}(g) - \lambda \cdot C_{\text{neighbors}}(g)$
      Store g and $S(g)$
    end if
  end for
end for
Select $g^* = \arg\max_g S(g)$
return g^*

framework integrates perception, digital scene reproduction, and grasp planning that encodes human-inspired strategies.

The framework receives as input an RGB-D scene containing a bin of objects. The bin location is identified using two *AprilTag* markers. Objects inside the bin are detected using a YOLOv5 model [14] trained on a combination of synthetic data (generated using BlenderProc [15]) and real images of fish and meat products. The 6D poses of the detected objects are then estimated using a dense correspondence-based approach [16]. Fig. 13 and Fig. 14 show the vision performance in different scenes. Although alternative vision pipelines (e.g., SAM [17] in combination with Any6D [18]) can handle unknown object models, the current work focuses on the grasp planner and assumes known objects to simplify the vision pipeline.

The grasp planner reproduces the perceived scene in a digital simulation environment. Each object is surrounded by a grasping region that defines where the gripper needs to interact to execute the grasp. The planner evaluates candidate grasps according to human-inspired strategies and geometric constraints grasp constraints of LSG. Based on experimental validation of grasp stability for LSG, the grasp strategies are prioritized in the following order:

1) Scoop from under
2) Grasp from top on both or single side
3) Grasp from head
4) Grasp from tail

For each object, the planner begins evaluating grasps from the center of the object and extends toward both ends until a collision-free grasp with neighboring objects is found. The gripper collision mesh is included in the simulation to ensure feasibility. The planner computes a grasp score $S(g)$ for each candidate grasp g as:

$$S(g) = S_{\text{strategy}}(g) - \lambda \cdot C_{\text{neighbors}}(g), \tag{1}$$

where: $S_{\text{strategy}}(g)$ is the priority score of the grasp strategy (i.e., Scoop under to grasp $>$ grasp on top-side $>$ grasp on head $>$ grasp on tail), $C_{\text{neighbors}}(g)$ is the total collision volume between the gripper and neighboring objects, λ is a penalty weighting factor.

The optimal grasp g^* is then selected as:

$$g^* = \arg\max_{g} S(g). \tag{2}$$

Once a collision-free grasp g^* is selected, the gripper executes the motion using compliant joint impedance controller. The computed grasp scores can be used to rank objects in the bin from easiest to most difficult to grasp. This ranking enables the system to first pick the easier objects, thereby creating free space and improving grasp planning for the remaining objects [19]. The pseudo-code for the grasp planner is presented in Algorithm 1. Grasp failure is detected using the vision system and force sensors onboard the LSG. This ensures a regrasp in case of failures.

V. Experimental Evaluation

In this section, we present different experimental validation of LSG and the grasping framework. We also discuss the performance of the gripper in realistic cold environment.

A. Human Grasp Strategy Replication

The LSG has been qualitatively evaluated to reproduce the four grasp strategies performed by the humans: grasping from the head, tail, top, and scooping from under. Fig. 10 shows the LSG executing different grasps similar to as shown in Fig. 4 by the human participants.

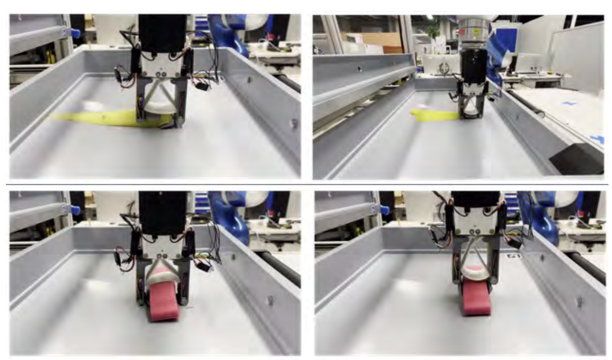

Fig. 10: LSG grasping a fish phantom. Clockwise from top left to bottom left: Grasping from the head, tail, top middle, and scooping from under.

B. Validation in Industry-Representative Conditions

Robotic end-effectors must be engineered to support cold operating conditions and hygienic design principles to ensure regulatory compliance. Particular consideration must be given to operation in refrigerated conditions, where temperature control and material durability directly affect food safety and product quality.

The LSG was operated in a cold chamber for eight hours to observe the gripper behavior under stringent environmental conditions. The temperature was set to $5°$, and the humidity to 80%, replicating the environment of the walk-in fridge. The gripper was mounted on an aluminium profile simulating the robot arm and was commanded to grasp a silicon phantom every minute. After the test run, the recorded grasp force and temperature from the scooper encoder were similar for each grasp. A further seven day test was performed. The gripper stayed powered in the cold chamber for the entire duration, but was only grasping during working hours for safety reasons. The fish was grasped around 1000 times during the seven hour interval every day. The standard deviation for the grasp force was $0.047N$ at a given goal force of $28N$. The temperature was stable for the whole test at $3.6°$. The scooper was also tested for durability by performing a motion after every grasp. These tests showed continued performance of the gripper in a cold environment as needed to handle fresh produce. Fig. 11 shows the gripper inside the cold chamber and the plot highlights grasp force and scooper encoder temperature over time.

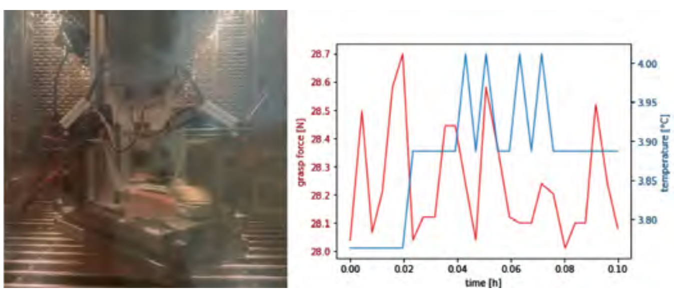

Fig. 11: LSG grasping a fish phantom inside a cold chamber and the measurements recorded overtime for temperature and grasp force.

To maintain food hygiene, all equipment should have smooth, cleanable surfaces, sealed sensing components, and resistance to aggressive cleaning agents typically used in meat and fish processing environments. Alternatively, we apply single-use food-safe disposable plastic cover tailored for the robot and LSG gripper manufactured from 500 gauge low-density polyethylene. Fig. 12 shows this setup while grasping a real fish. The supplementary video demonstrates LSG grasping real fish with a protective cover, without disturbing the operation or movement of its different links.

C. Grasp Planning

To validate the grasp planner in different scenarios, we tested it with four carefully chosen object placements in the bin. These scenarios (A to D) are shown in Fig. 13. We used three objects: two sea bass and one salmon fillet. The results from the vision pipeline, presented in Section IV, are shown in the top row, with the object model (based on its 6D pose) overlaid on the RGB image. The planner's results are shown in the bottom row, where the black-filled block represents the gripper's optimal grasping pose, as calculated in Algorithm 1 in Section IV. Each object's grasp region is highlighted with a unique colored grid; filled grids indicate collisions with neighboring objects or the bin.

Fig. 12: Experiments with real fish, using food safe disposable protective cover for the gripper and the robot.

The goal in all scenarios is to grasp the bottom sea bass fillet. In scenario A, the target object is surrounded by two objects, leaving only the tail region free. The planner selects a scoop from under grasp, which is the most stable and generates the least force. In scenario B, one side of the target object is blocked by another object, while the other side is free. The planner chooses a grasp from top on one side on the free side at the object center. In scenario C, the target's grasping region is partially blocked by the salmon fillet. The planner again selects a grasp from top on one side, but slightly away from the center, where the region is free of collisions. In scenario D, the grasping region is fully covered on both sides, so the planner opts for a grasp from the head. These scenarios validate the grasp ranking, considering both strategy and grasp position.

The grasp planner was also tested in a cluttered scenario, where more than two-thirds of the bin was occupied by eight different objects. This scenario is shown in Fig. 14. The object pose estimation is displayed as an overlay in the left image, while the right image shows the digital simulation of the detected environment, which serves as the planning scene. It includes the computed grasp region, with collisions highlighted as solid grids and free areas as empty grids. The planner's results for picking different objects are shown in Fig. 15, with objects sorted (1 to 8) from the least to most collisions in the grasping region. Notably, in all cases, the planner selects different grasp strategies at positions as close as possible to the object center. The gripper's position is marked with a black solid block. This experiment demonstrates that the planner can effectively handle complex cluttered scenarios.

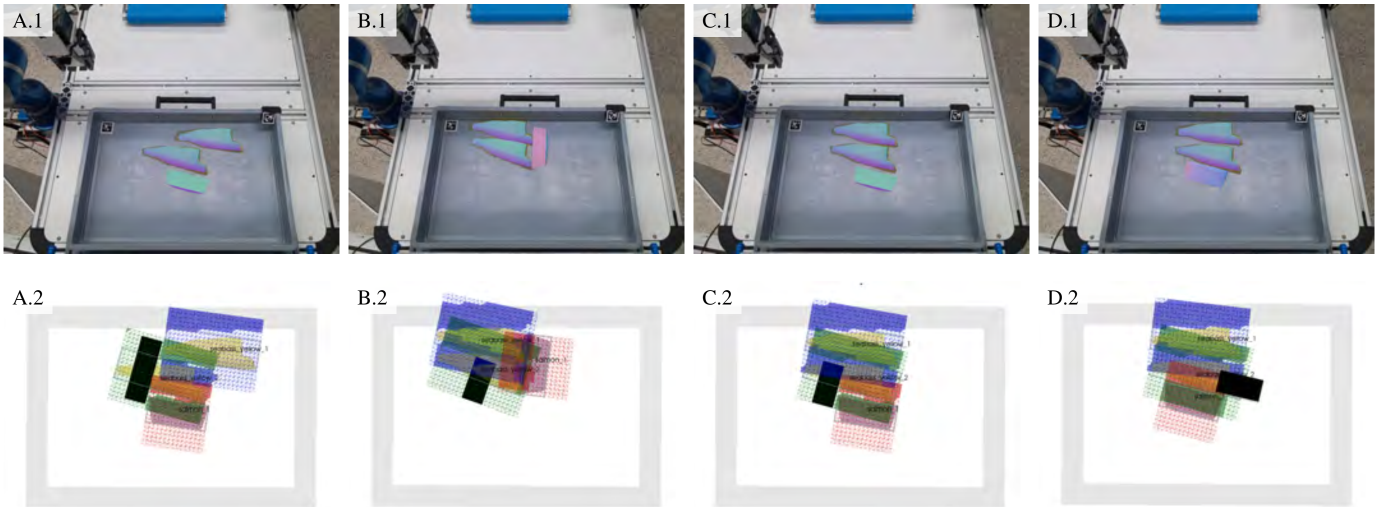

Fig. 13: Evaluation of the grasp planner in scenarios A to D for grasping the bottom seabass fish. Row 1 shows object pose estimation with an overlayed mask on the RGB input. Row 2 highlights the suitable grasp with a black rectangle representing the gripper, and colored grids indicate the grasping regions, with filled grids showing collision areas with neighboring objects.

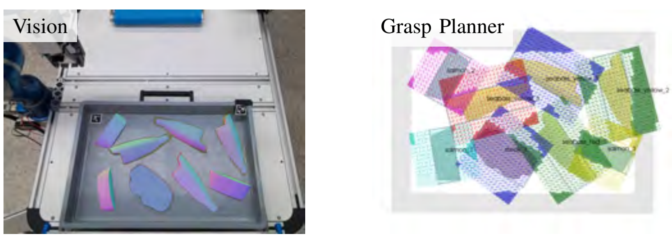

Fig. 14: Evaluation of the grasp planner in a cluttered scenario with eight objects occupying over two-thirds of the bin. The object pose estimation with overlayed masks and grasp regions (grids), including collision areas (filled grids), are shown.

D. Benchmarking

To avoid any food spillage during the benchmarking process, we created fish and meat phantoms that mimic the look and feel of the intended fish. The material is a type of silicon that offers similar mass-to-volume ratio for the fish. The slippery nature of the fish can be mimicked by using silicon oil on the fish before the experiments. We reproduced a steak and three types of fish fillets: salmon (pink), seabasss (yellow) and thin seabass (pink).

A simple experimental benchmark was conducted to measure the gripper performance. The object was always placed in the middle of the bin with collision free regions around it. To run this experiment in an automated fashion, the following sequence was performed. First, the different objects and their pose in the scene was detected using the vision pipeline (Fig. 14). The robot then grasps a random object using an appropriate strategy. The object is then transported away from the grasping region. Again, the vision pipeline is triggered to check the current remaining objects and compare it against the status before grasping to determine grasp success. The grasp success and time taken is recorded. The object is again placed in a random position in the grasping region and the process is repeated. The system stops after ten trials. Table I shows the result for three types of fish and meat. In this validation, the time taken is not optimal as the robot path was not optimized and the joint velocity was under 50 percent of the maximum for safety reasons.

Item	Total time (s)	Grasp time (s)	Picks per hour	Success rate (%)
Salmon	17.9	6.3	200.7	100
Steak	16.6	3.3	217.3	100
Seabass	17.5	6.4	206.2	70

TABLE I: Benchmark result for grasping three deformable objects in a low clutter scenario.

Finally, the LSG gripper and the grasp planning framework was demonstrated extensively during the Automatica 2025 trade fair in Munich. The objects were always placed in random configurations and varying clutter. The supplementary video highlights this demonstration in detail. LSG has also been employed for other research on deformable object manipulaiton, for instance, imitation learning to place deformables [20] and co-design of kinematics for different tasks [21].

VI. Conclusion

This paper introduces the linear scoop gripper, which enables a variety of gripping strategies for grasping thin, flexible food items. A user study shows the various strategies that participants use to grasp fish fillets. These movement sequences were transferred to the gripper design to achieve optimal performance with a simple design and minimal active degrees of freedom. Subsequently, a grasping framework was developed to enable objects to be grasped in clutter. The gripper was then tested in realistic conditions like low temperature, hygiene, and real fish. Further experiments were conducted

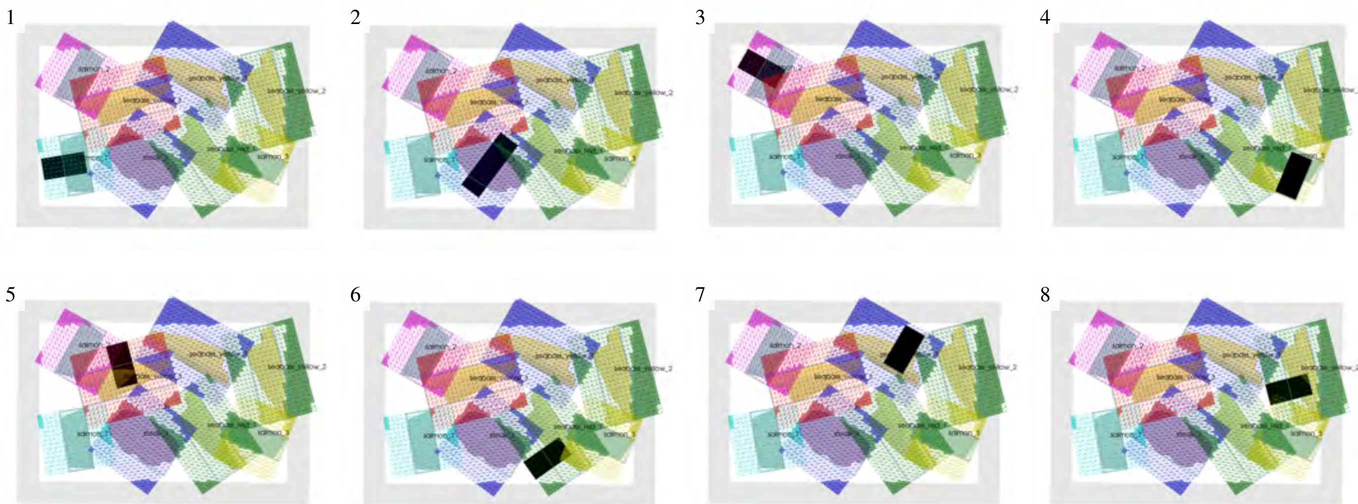

Fig. 15: Best generated grasps for all objects in the scene (Fig. 14), sorted from least (1) to most (8) grasp collision regions. The black rectangle represents the gripper in the optimal grasp pose.

in lab conditions with silicon phantoms to benchmark the performance. In future, studying FDA materials will enable changes to improve the cleaning process. Another important step will be to fully integrate tactile sensing into the scoops in order to detect grasping failures and slipping.

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