RoboToy Demoulding: Robotic Demoulding System for Toy Manufacturing Industry

Daniel Sánchez-Martínez[1][a], Carlos A. Jara[1] and Francisco Gomez-Donoso[2][b]

[1]*Human Robotics, University of Alicante, Alicante, Spain*

[2]*University Institute for Computer Research, University of Alicante, Alicante, Spain*

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Abstract: Industrial environments and product manufacturing processes are currently being automated and robotized. Nowadays, it is common to have robots integrated in the automotive industry, robots palletizing in the food industry and robots performing welding tasks in the metal industry. However, there are many traditional and manual sectors out of date with technology, such as the toy manufacturing industry. This work describes a new robotic system able to perform the demoulding task in a toy manufacturing process, which is a tedious labor-intensive and potentially hazardous task for human operators. The system is composed of specialised machinery about the rotational moulding manufacturing process, cameras, actuators, and a collaborative robot. A vision-based algorithm makes this system capable of handling soft plastic pieces which are deformable and flexible during demoulding. The system reduces the stress and potential injuries to human operators, allowing them to perform other tasks with higher dexterity requirements or relocate to other sub-tasks of the process where the physical effort is minor.

1 INTRODUCTION

Nowadays, there is a growing trend towards the automation and robotization of industrial processes. The automotive industry, for example, has embraced the use of assembly line robots to streamline their manufacturing processes. Similarly, production factories have integrated industrial robots to handle palletizing tasks efficiently. Moreover, various other robotized industrial applications, including welding, painting, inspection, and quality control, have become increasingly common. This technological progress has replaced human operator of the line production process. However, the toy manufacturing sector is completely manual, making the operators to carry out high-effort demanding tasks such as demoulding of hot plastic pieces of dolls and managing ovens at elevated temperatures. This manual process consists of the following steps. First, the operators fill a mould with liquid plastic material. Then, they introduce it into the oven at more than 250 degrees Celsius; once the oven has finalized rotating, operators move the mould to an air cooler; finally, they place the mould in the demoulding zone to extract all the soft pieces.

This work presents a novel robotic approach for the demoulding task in the toy manufacturing process using a vision-based algorithm and force control to avoid damaging or breaking parts. Furthermore, this system is collaborative, so as not to replace the human factor in the process but to relocate it. The robot performs the demoulding task which requires both high force and dexterity, while the operator is still required for the other steps mentioned above, reducing the possibility of injury or stress in the human operator.

The main contribution of this work is the development of a robotic system able to perform the demoulding of plastic and soft pieces, which manual performance requires the operators to apply high forces in short cycle times. In addition, a vision-based algorithm has been developed to improve the accuracy and repeatability of the task execution, which is an important fact in industrial tasks. Finally, this collaborative system allows the operators to perform other dexterous tasks instead of this physical demanding one.

This document is structured as follows. First, in Section 2 some related works with similar contributions are presented. In Section 3 the manual and traditional manufacturing process of the toy sector are explained and detailed. In Section 4, the developments

[a] https://orcid.org/0009-0008-2279-3503

[b] https://orcid.org/0000-0002-7830-2661

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and contributions of this work are presented. Then, in Section 5 different experiments of the approach are exposed. Finally, in Section 6, some conclusions are described.

2 RELATED WORKS

Nowadays, the manipulation of soft and flexible pieces is a common research field which covers many different kind of objects, as described in (Lahoud et al., 2021), where authors developed a robotic system to manipulate fabric clothes to perform the stitching task. Similarities can be observed in relation to the demoulding task, given that the precision required for its execution must be exceptionally elevated. However, the stitching task does not require high forces and it is more difficult to damage or to break the object, in contrast to the demoulding task.

In (Navarro-Alarcon et al., 2016), it is presented an automatic method to compute the parameters of the deformation model of the soft object in real time with an external camera. They prepared a clear setup where the piece is always visible. However, in our use case, the soft piece is inside the mould and when the robot is demoulding it, the piece is occluding all possible views, so it is needed to estimate the applied force before the performance of the task. In (Ubeda et al., 2021), authors present a development based on a collaborative robotic system able to perform sanding tasks using a force control loop with the feedback of a force sensor. Force control is an important fact when manipulating soft objects, but they applied the sanding task to rigid materials, so they had not to worry about deformations. In (Ortenzi et al., 2018), a vision-based manipulation system of plastic objects was developed. In that paper, it is summarized clearly the challenges of the manipulation of soft pieces: the lack of deformation models for the pieces, the difficulty to perform a visual tracking, and the drawbacks to generate inputs and outputs for the visual error obtained. In addition, the paper describes how to handle kinetic sand whose dynamic model is unknown. However, they manipulate the material in the same temperature conditions, which makes easier the estimation of the deformation model. In the case of our approach, the deformation level depends on the temperature of the pieces which varies a lot during the extraction.

Regarding the manipulation of soft objects, there are many different applications. In (Herguedas et al., 2019), authors classify soft objects in groups depending on the deformation model used, dimension of the object, the control strategy followed, perception-based classification and predominant actions they deal with. In this description, the use case faced in this paper is classified in some of the most complicated groups because we are handling 3D shaped objects with no previous deformation model and the perception system is only about the feedback force of the own robot due to the occlusions during the task. To solve problems related to the lack of knowledge about the deformation model, in (Navarro-Alarcón et al., 2013), authors propose a vision-based method to servo control the deformation of a deformable object applying a model-free method that estimates the object's deformation Jacobian matrix in real time. They detect some points of interest of the piece to carry out the manipulation. However, this work presents the same drawback regarding the field of view and the approach does not face the problem of partially occluded objects as in this case, and it is necessary to control the force without any visual feedback.

In contrast to the classic control methods to apply force during the robot manipulation, in (Lin et al., 2019) authors present a safe control system based on Reinforcement Learning and force sensors to improve the control and to avoid dangerous and unpredictable situations, especially in the simulation - real world transition. Implementing this kind of algorithms is really useful to obtain general solutions; however, stability and reliability are not usually guaranteed. The problem of this work is clearly delimited, so the accuracy, stability and repeatability of the trajectories are priority. Another similar case is explained in (Huang et al., 2019), where authors apply Deep Reinforcement Learning to improve the interaction between the robot and fragile objects based on curiosity (rewarding the robot the exploring actions) in pushing tasks. The main disadvantage of the possible application of this system in our work is the penalization of large forces its algorithm uses to learn, because the availability of huge forces are really important for us, as will be explained in the following sections. Main disadvantage is the penalization of large forces, which are important parameters to consider for the development of this work.

In conclusion, nowadays there are many contributions related to the manipulation of deformable objects, integration of collaborative robots in industrial environments and force controllers. However, currently, there is not any significant advance in a real industrial case which involves the robotic manipulation of soft pieces with high force requirements in collaborative tasks of the toy manufacturing process. This work aims to fill this gap and brings about a relevant improvement in this sector.

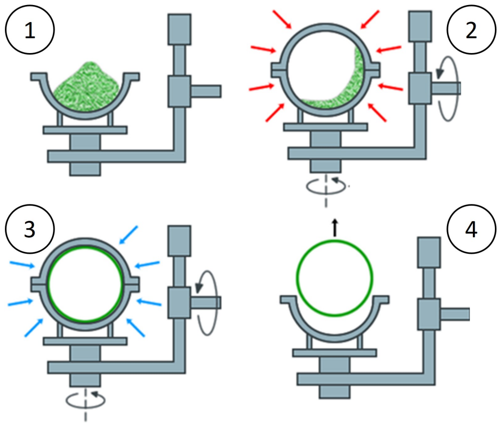

Figure 1: Rotomoulding manufacturing process.

3 MANUAL TASK

Toy industry is a really manual sector which involves several tasks such as the demoulding of plastic pieces, painting, assembly, packaging and many others. In this case, the project is focused on the demoulding task which is the most physically demanding one.

The extraction of the pieces is just one task of the complete process shown in Figure 1 and explained as follows.

- **1. Substance Pouring:** the process begins with carefully pouring the desired substance into the mould. The amount of liquid plastic material depends on the specific kind of manufactured piece.
- **2. Sealing, Placement and Rotational Heating:** once the mould is filled, this is tightly closed to avoid any leakage or escape of the substance. Then, the operator places the mould inside a rotomoulding oven. The rotomoulding oven is specially designed to facilitate rotational movement along two distinct axes. Once the mould is placed inside the oven, the rotation starts. This rotational movement serves for two purposes; firstly, it ensures the uniform distribution of the material across the entire inner surface of the mould, eliminating any inconsistencies or air pockets. Secondly, the rotation helps in heating the mould, allowing the substance to melt, fuse, and adhere to the mould's inner surface. The heating temperature and duration vary depending on the material being processed.
- **3. Air Cooling:** after finishing the heating process, the operator moves the mould to an air cooling system. This system helps to rapidly decrease the temperature of the mould by the circulation of ambient or chilled air around the mould surface.

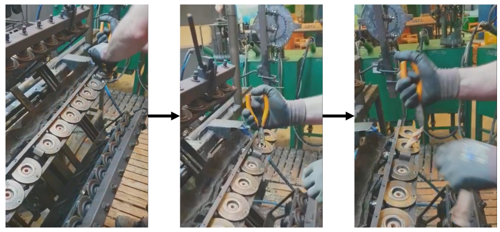

Figure 2: Manual demoulding task.

The cooling process is carefully controlled to solidify the substance within the mould.

- **4. Mould Unsealing and Extraction of Pieces:** once the substance has solidified (the piece is not rigid and it stills soft) and reached the desired temperature, the seal on the mould is carefully removed. Special attention is given to avoid any damage to the mould or the formed pieces. With the mould unsealed, the resulting pieces are extracted.

By following these steps, the rotomoulding process ensures the creation of uniformly distributed and accurately formed objects with desirable properties. Distinctive types of pieces necessitate varying quantities of material, distinct heating and cooling duration, as well as different demoulding forces. As illustrated in Figure 2, skilled operators use pliers to extract the components since both the pieces and the mould retain elevated temperatures. Prompt demoulding is essential to prevent the pieces from an excessive cooling, because prolonged cooling compromises their malleability and complicates the extraction process.

4 ROBOTIC SYSTEM

In order to develop a robotic cell with all the needed capabilities, the first step is to design and simulate the mock-up, in order to set the layout of the elements. In Figure 3, it is shown the distribution of the different elements of the robotic cell: the rotomoulding oven is marked as the red area, the air cooler is marked as the green area, the demoulding zone is marked in yellow, and finally, the robot (UR10e) is marked in blue.

From the simulation, the developed mock-up was developed and it is illustrated in Figure 4 where color areas show the different elements mentioned above.

Finally, the robot was integrated in order to finalize the construction of the robotic cell as shown in Figure 5. This configuration enables the robot only to access the demoulding area in order to execute the extraction using the robotic gripper equipped with customized fingers and an integrated vacuum system.

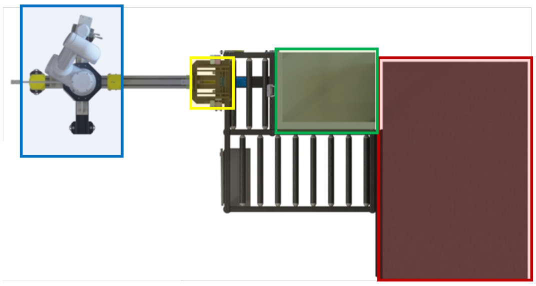

Figure 3: Layout of the simulated robotic cell with marked elements.

Figure 4: Real developed mock-up.

Figure 5: Final robotic cell.

Once the hardware of the robotic cell has been integrated, the developed software of the system must ensure the safety of the operators and achieve the demoulding without damaging the pieces. In Figure 6, it is explained the workflow of the system.

First of all, the system is initialized and the robot is stopped until its action is required, so the operator carries out the other tasks of the process (filling the mould, putting in the oven, insertion in the cooler and placing the mould in the demoulding zone) safely and securely. Then, the operator goes out the robotic cell and presses an external button to send the confirmation to the robot in order to start the program. Next, four pneumatic actuators fix the mould and the inte-

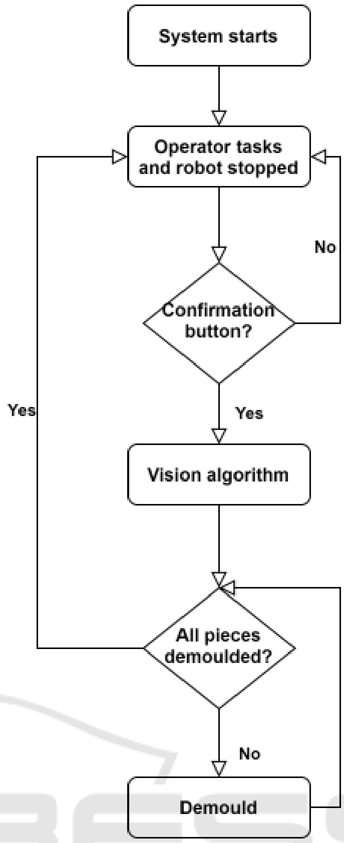

Figure 6: Automatic demoulding pipeline.

grated camera (Real Sense d435i) of the robot gripper detects the pieces. The computer vision algorithm computes the grasping point to perform the demoulding. Then, the robot starts the demoulding trajectory as shown in Figure 7. It introduces the vacuum system equipped finger of the gripper into the detected extraction point, closes the gripper and the air inside the piece is removed to make easier the extraction. After demoulding all the pieces from the mould, the robot moves to the initial position and the cycle of the system starts again. These steps ensure the operator will be out of the robotic cell during the robot performance, avoiding risk of injuries. Nevertheless, a pair of laser scanners have been integrated around the robotic cell to slow down or stop the robot in any unforeseen situation. The security insurance and the removal of the direct physical effort of the task reduce the stress of the operators.

4.1 Vision Algorithm

As explained previously, the operator places the mould in the demoulding zone and four pneumatic actuators fix it. However, the human error when placing

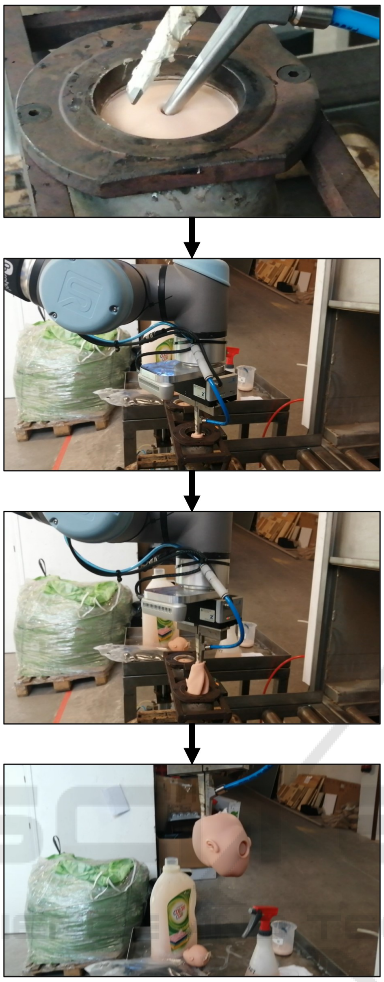

Figure 7: Demoulding process.

the mould produces small variations in the positions. The vision algorithm has been developed in order to detect the extraction point of the pieces before the demoulding and to correct these small variations.

Figure 8 provides a comprehensive overview of the entire algorithmic process, encompassing the acquisition of the initial image to the detection of hole coordinates. The process unfolds as follows.

- **1:** in the initial step, the camera captures both the initial RGB image and the point cloud of the environment.
- **2:** next stage involves the removal of background points from the point cloud to optimize computational efficiency and eliminate non-relevant data for the algorithm. A defined threshold will eliminate points that are outside, in order to minimize the area of interest for detection.
- **3:** after reducing the point cloud, the target is to detect the top of the mould, where pieces are located. In order to achieve it, RANSAC algorithm is employed to identify the best-fitting plane, which corresponds to the top surface of the mould. RANSAC is an iterative method for estimating the parameters of a mathematical model of an observed data set containing outliers. In this case, the observed data set is the point cloud, the estimated model a plane (top of the mould) and removed outliers are the points out of that plane.
- **4:** subsequently, any data outside the bounding box of the identified plane is discarded from the initial image. This step changes the data managed from 3D to 2D to improve computational cost.
- **5:** by narrowing down the focus to the region of interest, the center of the piece can be readily detected (green circles at the center of the pieces).
- **6:** finally, the robot moves towards these coordinates and introduces the vacuum finger into the identified extraction hole. Then, the robot follows the demoulding process shown in Figure 7.

This sequence of steps ensures a comprehensive and accurate algorithmic process for the detection of the extraction hole, facilitating the subsequent robotic manipulation.

The accuracy of the vision algorithm is crucial in identifying the extraction hole of the pieces since it closely matches the dimensions of the gripper's finger. This gripper incorporates a vacuum system which removes the air from inside the piece, facilitating the demoulding process. Additionally, these holes enable us to securely grasp the piece from its interior, preventing any damage to the external surface of the piece. Another important feature is the scalability of this algorithm, which is easily modifiable to detect other kind of pieces such as legs, bodies and arms, instead of just doll heads.

5 EXPERIMENTATION AND RESULTS

This work aims to achieve industrial production requirements, which do not allow many failures during the process and need really accurate actions. In order to test the repeatability and performance level, several tests have been carried out.

The primary parameters to evaluate in this application are the accuracy of the vision algorithm and the applied force of the robot. A substantial level of repeatability is essential to consistently identify the identical center point of the pieces, which has been achieved optimizing parameters of the vision algorithm explained previously. Moreover, it is crucial to

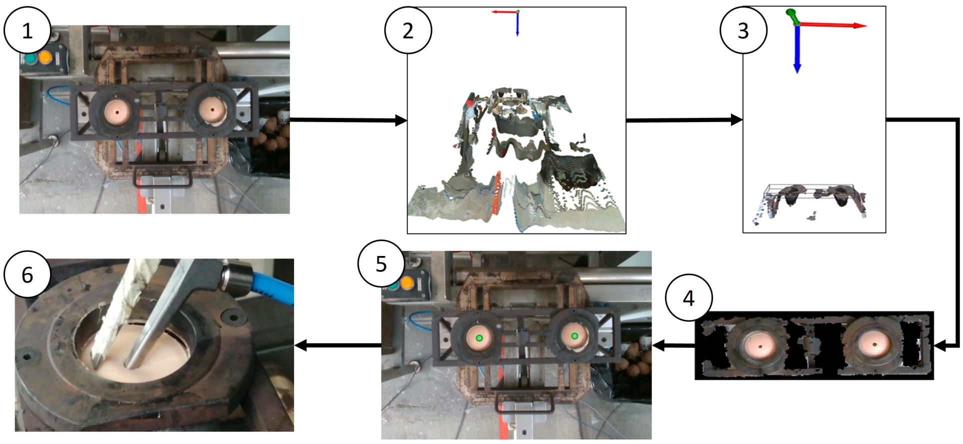

Figure 8: Vision-based algorithm process for extraction point detection.

appropriately define the force, ensuring it is sufficient for demoulding without causing any damage. The robot force limit is 150 Newtons (N); however, it is possible to disable restrictions and set the maximum force to 225N. This test is based on good accuracy of the algorithm to carry out 30 cycles of the complete process using the ”head” pieces mould (2 pieces per mould), and divide the results in different situations which depend of the temperature of the pieces and the force applied. Possible situations to appear during the experiments are explained below:

- **Stuck:** when the robot tries to demould the parts by applying force but the part does not come off the mould, the robot enters an elastic loop with no end. This usually occurs when it has taken a long time for the robot to grip the part and the part has cooled down.
- **Slip:** this situation is similar to the previous one. The robot tries to demould the piece, but it does not come off the mould. However, in this case, the gripping force is lower and the piece slips.
- **Damaged:** in this case, the robot has demoulded the part, but has scratched it during removal, so although the part has been demoulded, the result is not good. This usually happens when the force applied is sufficient to demould the piece, but it is not very high and the robot spends a lot of time doing it.
- **Broken:** when the robot applies too much force, the soft piece breaks.
- **Demoulded:** if the force applied is correct, the piece is demoulded.

As explained previously, the robot will perform the demoulding task 30 times, which corresponds to 60 possible pieces to extract. In Table 1 results are shown for three different force limits:

Table 1: Demoulding success rate with different forces.

	Forces (N)		
	150	**190**	**225**
Stuck (%)	43	22	0
Slip (%)	17	12	6
Damaged (%)	0	7	3
Broken (%)	0	3	11
Demoulded (%)	40	56	80

The results lead to the conclusion that the more force is applied, the more successful the demoulding. The following figures explain each result according to the situation.

5.1 Stuck Results

As explained previously, if the robot is not applying enough force to demould the piece, it cools, and consequently the robot tries to demould it in an infinite loop. Figure 9 shows the results obtained and the trend of the percentage of times this situation will occur according to the force applied.

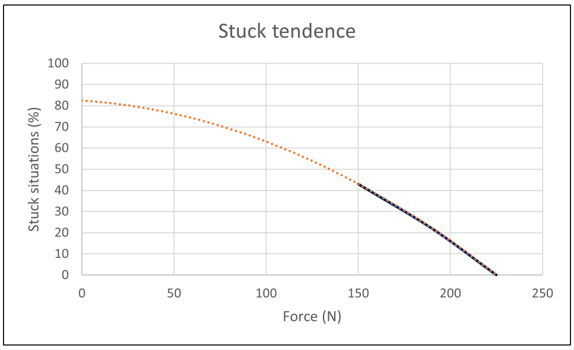

Figure 9: Trend of stuck situations as a function of the force applied by the robot.

It is noticeable that when the forces are high, the parts do not get stuck, whereas when the forces are reduced, this situation becomes more frequent because the robot does not manage to dislodge the parts from the mould.

5.2 Slip Results

The piece slips from the robot during the demoulding task due to the lack of applied force. Slip and stuck situations are the most repeated ones when the robot applies low forces. Figure 10 shows the results of the test and the trend of the slip situation according to the force applied.

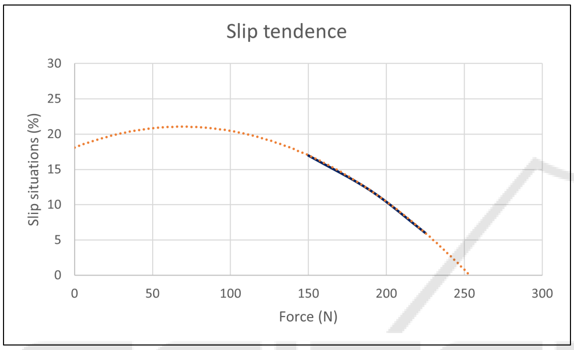

Figure 10: Trend of slip situations as a function of the force applied by the robot.

The results obtained show the relation between low forces and slippage produced in the pieces during demoulding task.

5.3 Damage Results

Causing harm to the pieces is a frequent occurrence when dealing with moderate levels of force, as the robot managed to remove the piece but encountered challenges in doing so, resulting in damage to the piece during the procedure. Figure 11 represents the trend of the damage situations from the obtained data of the tests.

By contrasting the preceding graphics, it is possible to infer that when subjected to lower forces, the piece remains undamaged due to its inability to be removed from the mould. Conversely, at higher forces there is no damage because the robot successfully accomplishes the demoulding of the piece.

5.4 Broken Results

As mentioned previously, the pieces are highly soft and malleable, which poses challenges for manipulating this material as the robot runs the risk of either

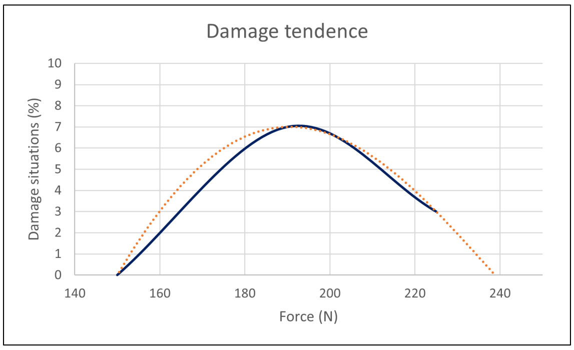

Figure 11: Trend of Damage situations as a function of the force applied by the robot.

deforming or breaking it. Figure 12 shows the tendency for part breakage situations to occur.

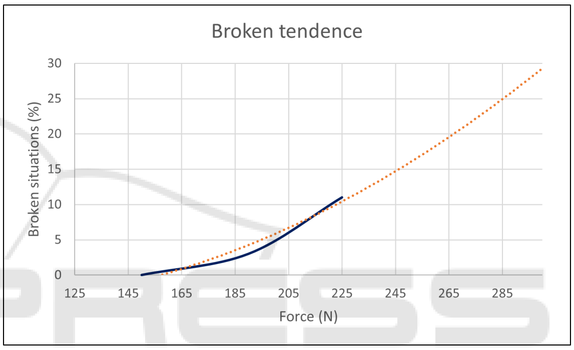

Figure 12: Trend of Break situations as a function of the force applied by the robot.

These situations occur when the demoulding task is performed with relatively higher forces. It can be observed that with an increase in force, the probability of breakage also tends to rise.

5.5 Demoulded Results

This situation measures the number of demoulded pieces, which means the absolute success rate of the task. Figure 13 represents the trend of the demoulding success rate.

In conclusion, the results obtained indicate that as the force increases, the probability of successful demolding of the part also increases. However, as mentioned in the previous graphics, if the force is increased, the probability of breaking the piece rises too.

To sum up, considering the three distinct forces applied (150N for low, 190N for intermediate, 225N for high), the potential scenarios can be categorized as follows. At low forces, there are instances of slips and pieces getting stuck. At intermediate forces, the robot tend to damage the pieces. And at high forces,

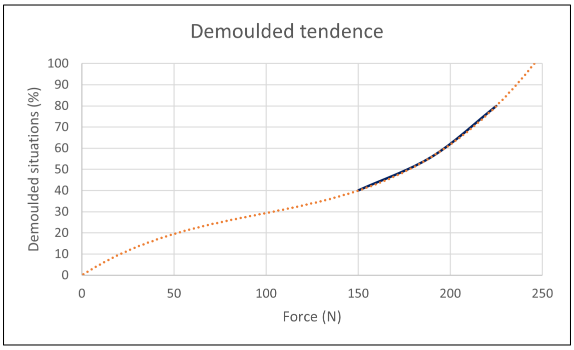

Figure 13: Trend of Demoulded situations as a function of the force applied by the robot.

the pieces can either break or demould successfully.

Target forces to achieve a successful task performance are elevated. Indeed, it is important to consider that the rise in the rate of broken pieces could have an impact on the overall results. This is the reason for research into new gripper finger designs to achieve demoulding of pieces at medium forces or to define new demoulding paths to avoid part breakage.

6 CONCLUSION

This paper has presented a new robotic system able to perform the traditional demoulding task of the rotomoulding manufacturing process of plastic toys. An accurate vision-based algorithm detects the extraction hole of the pieces, where the robot grasps them. The first step to achieve this performance level was to develop the accurate vision algorithm. Then, the definition of effective demoulding trajectories to achieve the extraction of the pieces.

The results obtained allow us to understand the direct relationship between the force applied and the number of successful demouldings. However, this fact increases the possibility of breaking the pieces during the process. As future work, in order to improve the system and to avoid failed extractions, the fingers of the gripper could be redesigned to increase the grasped area of the piece, to reduce the possibility of leaving marks or to break it.

Finally, a more exhaustive study will be carried out on the trajectories the operators make during the manual process in order to define similar ones to the robot. Furthermore, as this system is easily scalable, the number of parts to be demoulded will be increased to cover all the parts that a normal toy doll has. Instead of only demoulding heads, the system will also be able to extract bodies, legs and arms. In addition, this work has the potential to be completely adapted to cover all the different models of toys the factory produces; however, when the need arises to extract larger pieces, it becomes evident that the collaborative robot may fall short in terms of force capacity. In such situations, it would be necessary to resort to an industrial robot, which offers greater force and performance capabilities. However, making this switch would entail losing the collaborative nature of the task since industrial robots often operate in more controlled environments and are not safe for direct interaction with humans. Therefore, a balance must be struck between the size of the pieces and the robot's capacity to maintain safe and efficient collaboration.

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