Picking a Conveyor Clean by an Autonomously Learning Robot

Janne V. Kujala, Tuomas J. Lukka and Harri Holopainen

Abstract—We present a research picking prototype related to our company’s industrial waste sorting application. The goal of the prototype is to be as autonomous as possible and it both calibrates itself and improves its picking with minimal human intervention.

The system learns to pick objects better based on a feedback sensor in its gripper and uses machine learning to choosing the best proposal from a random sample produced by simple hard-coded geometric models.

We show experimentally the system improving its picking autonomously by measuring the pick success rate as function of time.

We also show how this system can pick a conveyor belt clean, depositing 70 out of 80 objects in a difficult to manipulate pile of novel objects into the correct chute.

We discuss potential improvements and next steps in this direction.

I. INTRODUCTION

In this article, we describe our research prototype system that can pick piled waste from a conveyor belt. The motivation for this prototype is grounded in the existing industrial robotic application of our company: robotic waste sorting.

ZenRobotics’ robots have been sorting waste on industrial waste processing sites since 2014. At one of our sites, 4200 tons of construction and demolition waste has been processed. Of that waste, 2300 tons of metal, wood, stone and concrete objects have been picked up from the conveyor by our sorting robots. Performance of the robot in this environment is critical for paying back the investment. Currently the robots are able to identify, pick and throw objects of up to 20 kg in less than 1.8 seconds, 24/7. The current generation robot was taught to grasp objects using human annotations and a reinforcement learning algorithm as mentioned in [1].

Robotic recycling is rapidly growing, and is already transforming the recycling industry. Robots’ ability to recognize, grasp and manipulate an extremely wide variety of objects is crucial. In order to provide this ability in a cost-effective way, new training methods which do not rely on hardcoding or human annotation will therefore be required. For example, changing the shape of the gripper or adding degrees of freedom might require all picking logic to be rewritten or at least labor-intensive retraining unless the system is able to learn to use the new gripper or degrees of freedom by itself.

We have chosen to tackle a small subproblem of the whole sorting problem: learning to pick objects autonomously. This problem differs from the more studied problems of "cleaning a table by grasping" [2] and bin picking [3], [4].

[5] in several ways: 1) The objects are novel and there is a large selection of different objects. Objects can be broken irregularly. In effect, anything can (and probably will) appear on the conveyor eventually. 2) The objects are placed on the conveyor belt by a random process and easily form random piles. 3) On the other hand, this problem is made slightly easier by the fact that it is not necessary to be gentle to the objects; fragile objects will likely have been broken by previous processes already. Scratching or colliding with objects does not cause problems as long as the robot itself can tolerate it (see Fig. 2).

Our solution starts with no knowledge of the objects and works completely autonomously to learn how to make better pickups using feedback, for example from sensors in the gripper like opening or force feedback. In the following sections, we will first describe the system in detail, describe our experiments with the system and conclude.

II. DESCRIPTION OF THE SYSTEM

In this section we describe our prototype system in detail.

A. Hardware

The hardware of our system consists of a waste merry-go-around (Fig. 1), a 3D camera (Asus Xtion), and a gantry type robot (a prototype version of our product model). The gantry robot includes a wide-opening gripper and a large-angle compliance system (Fig. 2). The gripper has evolved in previous versions of our product step by step to be morphologically well-adapted to the task.

Fig. 1. The waste merry-go-around used in the experiments to keep the material loop closed. The picked objects slide to the same conveyor as the other objects and all are brought back to the picking area with one more conveyor (occluded in this picture).

The gripper is position-controllable and has a sensor giving its current opening. In addition to the gripper opening, the robot has four degrees of freedom, the \((x, y, z)\) coordinates...
and rotation around the vertical axis (i.e., the gripper always faces down).

B. SOFTWARE

In our prototype system, we make use of our product’s existing software modules that handle conveyor tracking and motion planning to execute a pick for a given handle, a data structure similar to the rectangle representation of Jiang et al. [6] containing gripper \((x, y, z)\) coordinates, gripper angle, and gripper opening for grasping an object. In our prototype, we replace those modules of our product that use information from line cameras to decide where to grip.

1) Automatic calibration: Recently several methods have been developed (see [7] and the references therein) for calibrating sensors to robots. For the present prototype, we use a simplified automatic procedure for calibrating the 3D camera’s \((x', y', z')\) coordinates to the gantry \((x, y, z)\) coordinates (Fig. 3). The gripper’s angle and opening parameters are calibrated separately using known gripper geometry parameters.

2) Heightmap generation: The 3D camera image\(^1\) is projected using GPU into an isometric heightmap defined on gantry \((x, y)\) coordinates (Fig. 4). The projection code marks pixels that are occluded by objects to their maximum possible heights and additionally generates a mask indicating such unknown pixels.

3) Handle generation: The handle generation happens in two stages: first, we exhaustively search through all closed handles, that is, gripper configurations where each finger of the gripper touches the heightmap and the heightmap rises between the two points (Fig. 5). The full set of closed handles are weighted by the sum

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[h(s_0 + 1 \text{ pixel}) - h(s_0)] + [h(s_1 - 1 \text{ pixel}) - h(s_1)]
\]

of height differences at the gripper contact points shown in Fig. 5. A sample of 200 handles is generated using probabilities proportional to the weights. After this, each handle in the sample is duplicated for all possible extra-openings allowed by the heightmap (taking into account the nonlinear movement of the gripper as it opens and closes) and the maximum opening of the gripper. This completes the hard-coded stage of handle generation.

For every handle of the first stage, features are generated from the heightmap around the handle. The features are based on

- 80 \(\times\) 39 pixel \((40 \times 19.5 \text{ cm})\) slices of the heightmap aligned at the left finger, center, and right finger of the gripper (including a margin of 4 cm around the rectangle inside the gripper fingers),
- the opening of the handle and extra opening to be applied when grasping, and
- the height of the handle (which is subtracted from the heightmap slices so as to yield translation invariant features).

Of these, the image features are further downsampled and transformed by a dual-tree complex wavelet transform [8] to yield the inputs for a random forest that is trained to

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\(^1\)Figures 4, 5, and 6 show depth images from an earlier version of our prototype using a higher resolution industrial Ensenso N20 depth sensor instead of the Asus Xtion that was used in the experiments reported here.
classify the handles into those that succeed and those that fail. The handle that gets the best score (most votes from the random forest) is chosen for picking (except when its score is below 0.1 in which case it is only attempted with a 5% probability in order to avoid picking the empty belt for aesthetic reasons). When there is no trained model available, a random handle from the output of the first stage is chosen for picking.

4) **Feedback for autonomous training:** During each picking attempt, the system monitors the gripper opening and if the gripper closes (almost) completely before completing the throw, it is determined that the object has slipped and the pick is aborted. This post-verification signal yields the necessary feedback for training.

The features and result of each pick attempt are stored and a background process reads these training samples periodically and trains a new handle model based on all collected data. When a new model is trained, the system starts using it on the next pick attempt.

The immediate feedback from failed and successful attempts allows the system to learn quickly and autonomously and to adapt to novel objects.

### III. EXPERIMENTS

#### A. Autonomously learning to pick

In this experiment, the conveyor under the system was cleared for calibration, the calibration was run, and the conveyor was started at a slow constant speed. When there were objects coming under the robot, the picking software was started. The system started picking with just the hard-coded first stage model. After every 100 pick attempts, the system trained the second-stage model using data from all pick attempts from the beginning and started using the newly trained model on subsequent picks. For technical reasons related to data collection, the system was paused briefly every 15 minutes.

The results of this experiment are shown in Fig. 7a. The same experiment was repeated running the training every 10 seconds. The results are shown in Fig. 7b. From these results, it is clear that the immediate feedback from post-verification allows autonomous learning that can be very fast.

#### B. Picking the conveyor clean

In this experiment, the conveyor under the system was cleared for calibration, the calibration was run, and after moving the conveyor until there were objects in the working area, the picking software was started. Then, the conveyor
Fig. 6. Handles are generated in two stages: first, all closed handles are enumerated and a sample of size 200 is generated using probabilities proportional to the sum of the slopes at the finger contact points (a sample of size 10 is shown in the figure). Then, based on a trained model and features calculated from the heightmap around the handle, each handle in the sample is evaluated for all possible extra openings. The figure shows the estimated success probability (proportion of “success” votes from the random forest) for certain handles. The best handle is chosen for picking (except when its score is below 0.1 in which case it is only attempted with a 5% probability).

IV. CONCLUSION AND FUTURE WORK

We have demonstrated a prototype system that is able to pick a pile of novel waste objects from a conveyor and which has autonomously learned to select better points to pick from. We have shown that performing this task with a 4 dof robot with a single camera not on top of the system is possible.

It is easy to think of several ways to improve the performance of the system. For the picking the conveyor clean task, simply adding better edges to the conveyor and making the working area slightly larger would help - currently the working area is very limited due to the 3D camera used. The machine learning algorithm used is very simple. Enlarging the set of candidate handles could boost performance significantly and would be easy to parallelize on the GPU. It would also be possible to make the hard-coded first stage less conservative regarding shadows.

On the other hand, it would be possible to address some of the specific types of errors that were observed:

- grasping shadow: our current handle model does not make use of the mask indicating areas with unknown height (i.e., areas occluded by objects from the 3D camera’s point of view); using this information in the features would allow learning to better handle the shadows; alternatively two 3D cameras could be used to reduce shadows
- grasping at object (corner) that just came in range: this could be improved by additional logic to avoid handles at the edge
- grasping at empty belt: when there are no objects, small variations of the conveyor height, small particles, or sensor noise may yield handles; we have reduced such pick attempts by avoiding picking (except by small

movement was controlled manually, moving it short distances at a time, so as to let the robot pick the conveyor clean. The system started picking using just the hard-coded first stage model and the second stage model was trained on data from all picking attempts from the beginning every 10 seconds. The picking performance improved during the experiment as in the other experiments. Although somewhat more pick attempts will fail than on a constantly moving conveyor, the system will retry picking any objects left on the working area until it succeeds. The accompanying video shows how, after some training, the system clears a large pile from the conveyor (Fig. 8).
Fig. 8. Picking the conveyor clean. Some shots from the accompanying video, after an initial learning period. By our count from the video of the experiment, 70 out of 80 objects were correctly deposited in the right chute. The third frame shows on the right one of the objects that slipped beyond the working area by failed pickup attempts.

probability) when the score of the best handle is below certain threshold

- thin objects: the postverification may yield incorrect failure signal when grasping a thin object and the system may learn to avoid picking thin objects; this shows the importance of the feedback signal
- heavy stones slipping: could use slower throw, adding throw acceleration as another degree of freedom for the generated handles.

On the other hand, with this system, the point of diminishing returns is quickly reached because the system can retry picks that failed. The difference between an 80% success rate and 90% success rate is relatively minor, as opposed to the same difference in a line scanning system where 80% would mean double the number of unpicked objects from 90%.

At the moment, the cycle time of the prototype, around 6 seconds, is a far cry from our production system’s 1.8 s cycle time. However, there is no fundamental reason why such a cycle time could not be reached by this type of system; the difference is mostly caused by the prototype being very conservative about when the images are taken and not being yet optimized.

More interesting extensions of the systems in terms of practical applicability would be, e.g., learning to control the conveyor in order to maximize some function of the amount of picked material and the percentage of objects that get picked; sorting objects by some characteristic while picking, and learning to carefully pick one object at a time. In the current setup, the last one was not a problem; two-or-more-object picks were rare but this may be more related to the size of the objects and the gripper.

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