ZenRobotics Recycler – Robotic Sorting using Machine Learning

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1 Abstract

In this paper, we present the ZenRobotics Recycler, a system that sorts construction and demolition (CND) waste by picking valuable objects from a conveyor belt using robotic hands. It is the first CND recycling system that reaches a useful purity of wood, stone, and metal without resorting to human sorters. We describe how we applied machine learning to solve some of the key problems such as recognizing materials and grasping irregular objects from a waste stream on a conveyor.

2 Introduction

Construction, renovation, and demolition projects produce large amounts of construction and demolition (CND) waste that is costly to dispose. Waste processing plants extract useful materials from unsorted waste to reduce these costs. For example, minerals extracted from waste are often used as fill material, e.g., in road construction. The remaining waste is usually converted into refuse-derived fuel and burned for energy. Sorting processes typically aim to minimize leftover unsorted material (refuse/reject), but the extracted material fractions have to have high purity in order to be disposable without cost or to be sellable for profit.

A waste processing plant that processes CND waste can also accept commercial and industrial waste that contains, for example, packaging materials and furniture. Materials extracted from mixed waste include, for example, wood, minerals, ferrous and non-ferrous metal, and hard plastics. The waste goes through multiple mechanical stages that usually start with waste resizing by crushing or shredding. Next, the objects are sorted by size using screening, and by density and area using centrifuges. Later processing stages can include flotation, magnets, optical separators, and manual sorting.

The fractions produced by mechanical sorting processes usually require manual quality control to reach a useful purity of raw materials. In the final sorting stage, human sorters usually pick desired materials or remove undesired materials from a conveyor carrying an output fraction of the mechanical sorting stage. Manual sorting is dangerous and the workers suffer from exposure to hazardous elements, such as dust, mold, and asbestos, in the waste stream. Attempts at automating

this stage have been unsuccessful thus far. In the following sections, we describe in detail how the ZenRobotics Recycler solves these problems.

3 ZenRobotics Recycler

The ZenRobotics Recycler (ZRR) is a system comprising a set of sensors, a control system, and industrial robots. The sensors and control system control industrial robots to pick selected materials from a waste stream on a conveyor into multiple chutes. ZRR uses machine learning for object and material recognition and object manipulation and can replace manual sorters in the final stages of waste sorting. It can also sort waste streams that omit the initial energy-consuming resizing step (non-destructive recycling), because the robot can manipulate objects of varying sizes and shapes.

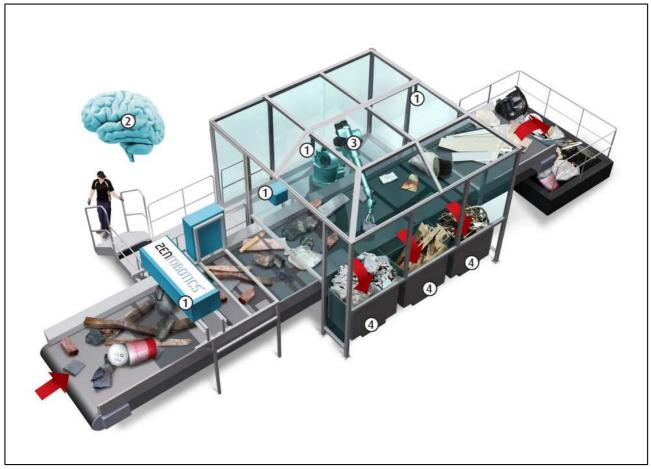


Figure 1: ZenRobotics Recycler. 1. Sensors 2. Control system ZenRobotics Brain 3. Industrial robot 4. Recovered fractions. (Image © ZenRobotics Ltd 2014. Used with permission.)

A ZRR installation consists of a sensor module on top of a conveyor, followed by one or more robot manipulators that move objects of different fractions from the belt to chutes, see Figure 1. Inputs

from multiple sensors are combined to identify objects and recognize their materials using sensor fusion and machine learning algorithms.

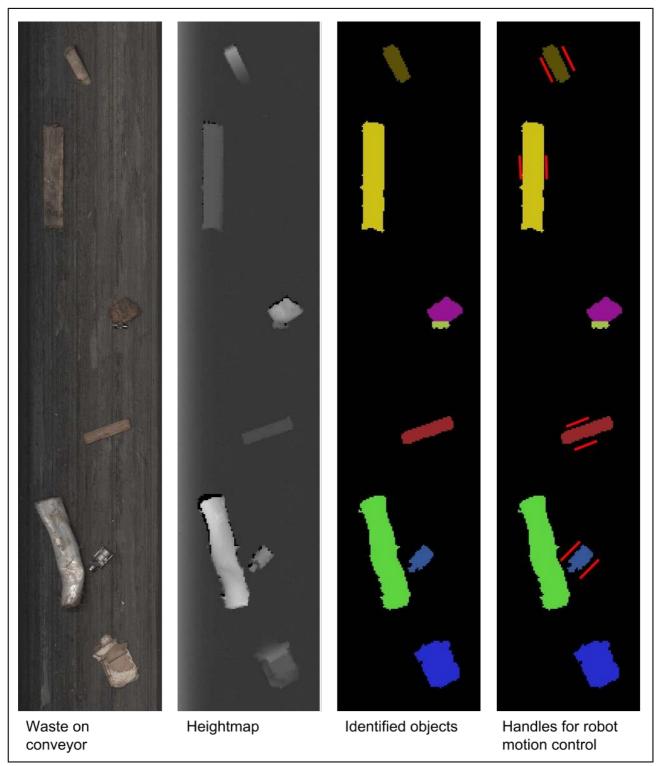


Figure 2: Illustrations of the ZenRobotics Recycler data flow. The identified objects are shown with different colors.

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The first step in the data flow is a high-resolution 3D sensor based on a laser line. This sensor gives an isometric 2D height map of the conveyor. The height map is used as the primary input for segmentation, that is, identifying individual *objects* on the belt (for an overview of segmentation methods, see [1, Chapter 5]). In addition, several sensors sensitive from visual wavelengths to near infrared as well as a metal detector are used for determining the materials of the identified objects. In addition to material recognition, high resolution RGB cameras also offer a visual view to the waste stream for annotation.

Given the identified objects and their materials, the system optimizes a picking sequence maximizing the monetary value of the recovered objects. For deciding where to grasp, we use a concept that we call *a handle*. A handle contains information on from where and how the robot could potentially grasp: the X, Y and Z coordinates, rotation, opening, and possibly other degrees of freedom. Adaptive algorithms are used to optimize the handles for estimating and maximizing the picking success for each object. We generate and prune many potential handles, and then evaluate the remaining top candidates with a more complicated model, much like the approach described in [2]. For handle selection, the height map produced by the 3D sensor is the most essential input. Figure 2 shows the RGB view, heightmap, identified objects, and handles.

A pneumatic gripper (Figure 3) attached to an industrial robot arm picks objects of desired fractions and throws them to corresponding chutes in a ballistic trajectory. The system is far more versatile than purely mechanical sorting as it can be trained to pick virtually any solid objects recognizable by the sensors, assuming the objects are in a suitable size range for the robot to manipulate. Also, using robots to pick objects makes it possible to handle overlapping objects.

The system can replace manual sorters, either in new production lines or retrofitted to existing ones. A retrofit system is shown in Figure 4.

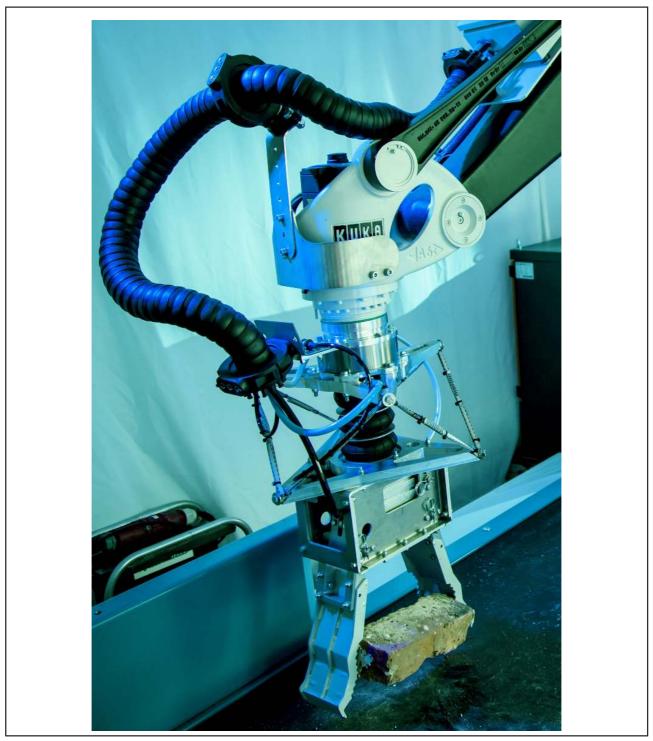


Figure 3: Pneumatic gripper of the ZenRobotics Recycler. Since the system operates in an unstructured environment, it has to tolerate occasional collisions, due to, for example, objects moving. Our solution to this problem (shown in the middle of the picture) is a 6-degree-of-freedom suspension pre-tensioned with a pneumatic spring. (Image © ZenRobotics Ltd 2014. Used with permission.)



Figure 4: Retrofit ZRR Fast Picker system installation. (Image © ZenRobotics Ltd 2014. Used with permission.)

Figure 5 shows a block diagram of the overall data processing steps in the ZenRobotics Recycler. Two important machine learning problems involved in these steps are the material classification of the identified objects and choosing how to grasp irregular objects. Material classification is a supervised learning problem and the grasping task is a reinforcement learning problem [3, p. 3], while both involve sensor fusion and computer vision. We continuously enhance the performance of our system by manually annotating mistakes done by the system. These include (1) classification errors causing contaminants in the recovered fractions or missing valuable objects, (2) failed grasping causing either missing an object or causing contaminants, and (3) collisions while throwing the grasped objects. Most often, the manual annotation can be done based on collected offline data, but in some cases the materials are either unrecognizable based on the sensor images or are too rare that sampling the waste stream is insufficient. In those cases, we also involve humans sorting actual waste into desired fractions which are fed one at a time through the system to provide training samples of known materials.

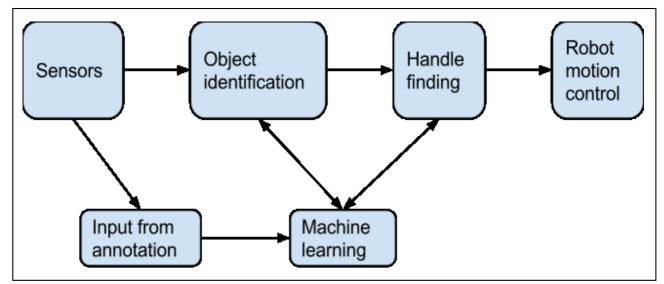


Figure 5: Block diagram of the overall ZenRobotics Recycler data processing steps

4 Discussion

Developing the ZenRobotics Recycler has required a joint effort on robot control, mechanical design, sensor technology, machine learning, software development, and others. With the development team growing, and the product prototypes changing, keeping the right balance between rapid development and quality control has been an important point.

One of our key design choices has been the use of the modern programming language Clojure [4] for software development. As a functional programming language, the code is relatively dense, and language features such as immutable objects avoid many problems inherent in parallelization, and help to produce testable and bug-free code.

The deployment of the first ZRR has proved that robotic sorting of construction and demolition waste is feasible. This might impact the waste industry as a whole. For instance, compared to hand-sorting, salary costs per working shift may diminish radically, so it makes sense to move from one or two shifts to three shifts. Once robotic sorting has been well established, the rest of the recycling plant can be further optimized for robotic sorting, for instance by changing the preprocessing to produce heavier objects that human sorters could not handle. New plants can also be built from scratch around the robotic system, as was done for the first time in SITA Viikki [5].

Machine learning approach helps in automating the fine-tuning of the system. For instance, the waste feed might differ on each site, and the definitions of the recycled fractions might vary as well.

We maintain multiple sites by producing data logs on site and transfering them to the main office for automatic analysis and storage. If some detail is changed (like adding a new fraction for sorting), the machine learning algorithms can re-analyse the stored data for a quick response.

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5 References

- [1] RICHARD SZELISKI (2011): Computer Vision: Algorithms and Applications. Springer.
- [2] IAN LENZ, HONGLAK LEE, ASHUTOSH SAXENA (2013): Deep Learning for Detecting Robotic Grasps. arXiv preprint arXiv:1301.3592.
- [3] CHRISTOPHER M. BISHOP (2006): Pattern Recognition and Machine Learning. Springer.
- [4] Clojure programming language (2007): http://clojure.org/
- [5] SITA Finland (2013): Viikissä huhkivat robotit, http://sitaatti.sita.fi/viikin-robotit/