Concept of a Robotic System for Autonomous Coarse Waste Recycling

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Abstract: The recycling of coarse waste such as construction and demolition waste (CDW), bulky waste, etc., is a process that is currently performed mechanically and manually. Unlike packaging waste, commercial waste and the like, which is usually cut or shredded into small pieces and then automatically separated and sorted on conveyor belt-based systems, coarse waste is separated by specialized personnel using wheel loaders, cranes or excavators. This paper presents the concept of a robotic system designed to autonomously separate recyclable coarse materials from bulky waste, demolition and construction waste, etc. The proposed solution explicitly uses existing heavy equipment (e.g., an excavator currently in use on-site) rather than developing a robot from scratch. A particular focus is set on the sensory system options used to identify and classify waste objects.

1 INTRODUCTION

The waste management and recycling sector can make a significant contribution to reducing climate-damaging emissions. For example, the disposal of municipal waste in a landfill is associated with emissions of approx. 400 g CO_2 equiv./kg of waste, while high-quality energy recovery of the same waste is associated with only approx. -22 g CO_2 equiv./kg of waste (Wittmaier et al., 2009). In Germany, the ban on dumping untreated waste in landfills and the associated requirement for mechanical-biological or thermal waste treatment indicates that the waste- and environmental services industry already plays a significant role in the reduction of climate-damaging emissions. If waste, such as plastics, is recycled materially rather than energetically, climate-damaging emissions can be reduced by 1600 g to 2000 g CO_2 equiv./kg plastic waste (HDPE, LDPE, PET) (Rudolph et al., 2020). Material recycling is an effective form of climate protection and also, naturally, of resource conservation. For this reason, more and more efforts have been made in recent decades to improve material recycling. An essential prerequisite for material recycling is the sorting of materials (paper, cardboard, plastics etc.). In order to obtain sorted materials from mixed waste, conveyor belt-based sorting plants for small-scale waste have been developed since the 1990s. Whereas in the beginning, sorting was exclusively manual and mechanical, AI-assisted robotic systems are now slowly starting to be used for small-scale waste. The technology is continuously improved (Zhang et al., 2019), which makes the sorting process more efficient. However, although efficient sorting techniques are available today specifically for small-sized waste, coarse waste is still sorted using the same technology as in the 1970s and 1980s. As a result, large quantities of principally recyclable materials hidden in coarse waste are lost (coarse waste in Germany: approx. 2.25 million Mg of bulky waste, 197 million Mg of construction and demolition waste etc.) (Federal Statistical Office of Germany (Destatis), 2020). For climate protection and resource conservation purposes, more effective processes for sorting coarse waste by type must be developed to recover recyclable materials from mixed waste.

In this paper, results from investigations into the development of AI-based robotic sorting systems for coarse (bulky waste, construction and demolition waste etc.) are presented. The results show strategies that enable a more efficient sorting of coarse waste. The partial material recycling of mixed waste offers an active contribution to climate protection and resource conservation.

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2 RELATED WORK

2.1 Bulky Waste Sorting Pilot Study

In a pilot study conducted in 2011 (the R&D project ”Efficient Sorting of Bulk Wastes with Robots” (ROSA, 2011)), a system concept for the automatic sorting of bulky wastes was developed. The project evaluated the feasibility of technical solutions for the automated removal of non-recyclable items from large piles of bulky wastes entering the recycling plant. It also looked at options for the automatic extraction of larger items of recyclable material during the final sorting on the conveyor belt. The focus of the project was on the evaluation of sensors and methods for 2D and 3D object recognition. The lack of consistent form features of the often deformed and damaged objects as well as the highly heterogeneous composition of the waste conglomerate were identified as the key challenges for both object recognition and object manipulation.

In support of a theoretical study, lab experiments were conducted to recognize and subsequently manipulate objects within the waste conglomerate using data fusion of different sensors (e.g., cameras, 3D laser scanners, NIR sensors) and standard robotic manipulators (e.g., KUKA). The lab demonstrator was able to prove the basic feasibility of the ROSA concept. However, it was not possible to adapt and test the concept under actual working conditions due to the lack of financial resources and available state-of-the-art equipment at the time.

Nevertheless, the outcome of the ROSA project provides a valuable starting point for more recent efforts to implement a SmartRecycling concept. As described in this paper, new developments in AI-based object recognition, sensor fusion and mobile robotics are the key to solving some of the fundamental problems with the automated extraction of large waste objects from a heterogeneous waste conglomerate ROSA had identified at the time.

2.2 Automation of Large Hydraulic Machines

Standard industrial robots as well as most professional service robots developed for indoor and field applications use electric actuators to grip, hold, and move objects. In these electric-powered systems, several integrated sensors continuously monitor the system-state and thus deliver the information needed to automate the control of manipulators, grippers and other sub-systems.

On the other hand, hydraulic-powered machines, such as cranes and excavators, are more challenging to automate, since they are typically not equipped with the necessary sensors and hydraulic actuators often lack the precision of their electric counterparts.

Despite these shortcomings, large hydraulic-powered machines are prevalent in many industries such as construction, mining, waste sorting, agriculture and forestry, etc. Due to their high performance, robustness, and reliability, they are used in harsh environments and rugged terrain. Also, the deployment of automated hydraulic heavy machinery in construction, mining, and agriculture is increasing. There already exist several automated hydraulic machines, either as commercial products or as research prototypes.

In project ROBDEKON (Kühn et al., 2020), DFKI is part of a consortium that develops solutions for the automation of large hydraulic machines. By retrofitting a M545 excavator, build by the Swiss company Menzi Muck, with sensors and modified actuators, DFKI developed the hydraulic robot ARTER (Automated Rough Terrain Excavator Robot)[1]

With ARTER, ROBDEKON could prove that a large hydraulic excavator can be automated to successfully handle complex tasks, like manipulating barrels filled with hazardous waste, if equipped with sensors that can measure the state and pose of joints, limbs and the like. However, the project also showed that this retrofitting does come at a high cost, limiting the applicability of the concept for many legacy systems. Also, since the robot has to operate in a very unstructured and highly dynamic environment, conventional methods for robot control that cannot react to changes in the environment are only of limited value.

2.3 Sensor Data Processing in Construction Waste Analysis

In different projects, the classification of waste objects based on RGB images was studied. Kim et al. (2019) use a modified LeNet 5 convolutional neural network (CNN) to classify objects by RGB images in carton vs. plastic (Kim et al., 2019). Also, some more applications of neural networks to classify waste objects based on visual image data are presented by Kim et al. (2019). Such an RGB-image-based classification seems to be feasible once objects can be identified within images. In an extreme case, this could be accomplished by scanning a barcode of an object (e.g., when supporting people sorting their waste

[1] https://robotik.dfki-bremen.de/en/research/robot-systems/arter/

(Bonino et al., 2016)). In the use case by Kim et al. (2019) the objects are separated from others before the classification task and solely consumer packaging objects are used (and only two classes need to be distinguished).

Regarding the recycling of construction and demolition waste (CDW) two problems arise that make a classification solely based on RGB images much harder: 1. The objects in CDW are usually broken into several parts and 2. they were often constructed in a unique shape depending on the specific situation and the specific construction. Furthermore, in this use case, objects will cover each other within the heap. All these properties make it hard to classify objects just by RGB image data. A solution could be the use of additional spectra for image classification. Thereby, not just an object classification but a material classification could be feasible.

Linß (2016) presents a thorough review of several methods used to distinguish between different classes of construction waste (Linß, 2016). Discussed are solutions that use sensors of different modalities, e.g., visual RGB cameras, near-infrared (NIR) and short wave infrared (SWIR) imaging for hyperspectral imaging (HSI), as well as methods using x-ray. She concludes that especially the combination of VIS and NIR is of particular interest and will be studied further. Other publications also support these sensor modalities (Anding et al., 2013; Kuritcyn et al., 2015), as well as considered as state-of-the-art in consumer waste recycling utilizing VIS/NIR/SWIR-based classification.

3 THE SmartRecycling CONCEPT

This paper summarizes the results of a study conducted by the authors in 2020 and 2021 (project “SmartRecycling”), with funding from the German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety. The objective of SmartRecycling was to develop a general technical concept for the sorting of coarse and bulky wastes. The implementation and validation of this concept were not within the scope of this study but may be realized in a later project phase.

As the first step in SmartRecycling, the on-site conditions and processes in several recycling plants in Northern Germany were studied, and functional system requirements were developed. A thorough analysis revealed that the process of pre-sorting holds the best potential for automation. Pre-sorting describes the process of removing recyclable items of higher quality and value (e.g., wood, plastics, metals) as well as objects that either contain hazardous materials or are a potential obstruction to the machinery (e.g., mattresses, ropes, nets) from the wastes before shredding and further processing. The items are extracted from the waste conglomerate manually, i.e., by skilled operators with the help of large hydraulic or electro-hydraulic cranes and excavators.

Figure 1: Rail-bound crane from BZ (at ASO, Osterholz.) (Wolff and Wittmaier, 2021, under CC-BY 4.0).

Figure 1 shows a rail-mounted crane from the manufacturer Baljer & Zembrod GmbH & Co. KG that is used in a recycling facility operated by ASO Abfall-Service Osterholz GmbH. The crane is operated manually by an experienced operator. Both the manipulator and the gripper of this machine are actuated hydraulically. The machine itself moves electrically on a rail parallel to the length of the rectangular pit that holds the waste. Other machines typically used in recycling facilities for the pre-sorting of coarse waste are regular diesel-powered mobile hydraulic excavators.

3.1 AI-driven Automation and Actuation

Although the machines used for the pre-sorting of coarse waste can be of different types, they have in common that they are usually not equipped for automation and thus require significant investments in sensors and electronics to make them fit for automated control. The SmartRecycling study postulated the use of state-of-the-art AI and machine learning to develop a solution for the automation of standard off-the-shelf hydraulic and electro-hydraulic machines without the need for significant modifications. Desirable side effects are a reduction in investment and the automated use of legacy machinery in recycling facilities (and other application areas). It needs to be kept in mind that the standard electrical off-the-shelf industry manipulators are usually not suitable for CDW recycling tasks with respect to workspace and payload demands.

The basic idea of this AI-driven automation is to use AI methods such as Reinforcement Learning (RL) to teach an artificial neural network (ANN) how to control a machine by letting it associate observable control inputs, issued through the machine's standard control interface, with the corresponding machine behavior. Motion sensors installed on the ceiling and the walls of the recycling facility track the machine's behavior and record, for example, the movements of the manipulator and gripper. By using markers attached to the gripper, manipulator joints and other critical parts of the machine, each trajectory through 3D space is tracked. Based on that, a 3D motion model of the entire machine is developed. The ANN is then trained with the motion model as output and the corresponding control commands issued by the human operator as input. Using this approach, the ANN can predict the relationship between a control command and the crane's reaction and use this to move the crane precisely to a target position.

Training of the ANN can happen during specific training sessions or during the standard human-controlled operation of the machine. In principle, such an AI-driven control should be largely independent of the machine it is applied to (see also www.smartrecycling-projekt.de).

3.2 System Components

Several AI-based software modules are required to implement the AI-based control and automation outlined above. The SmartRecycling approach proposes four software modules bundled in one unit, dubbed the 'MachineBrain'. The MachineBrain supports the control of the hydraulic manipulator and the hydraulic gripper as well as the detection and classification of objects and materials in the waste conglomerate. The four modules of the MachineBrain are:

- SmartObjectClassifier: The SmartObjectClassifier enables the recognition of individual objects in the waste conglomerate with the help of AI-based object and material classification based on data from infrastructure sensors installed in the facility. In a first step, an object classification and a rough material classification is carried out (see Section 3.3 and Section 3.4). In a second step, the SmartObjectClassifier includes data from the sensors installed in the gripper and the waste pit's walls to further improve the object and/or material classification.
- SmartObjectTracker: This module determines the x-y-z position of the objects recognized by the SmartObjectClassifier. Details are given in Section 3.5.
- SmartMotionController: As described in Section 3.1, the SmartMotionController enables the crane to move independently and approach a specific target position from the SmartObject-Tracker. To achieve this, the AI-driven control software must have learned the relationship between control commands and manipulator and gripper movements. Its motion is calculated using inverse kinematics, considering the precise position and orientation of each manipulator joint, hydraulic cylinders, and such.
- SmartProcessController: The SmartProcessController combines the data on the position and the material class of an object (from ObjectTracker and ObjectClassifier) with the data on the crane's current position and orientation (from the MotionController) and plans the crane's next work steps. External data on the current market situation (Which recyclable materials do currently have the best economic value?) and the overall recycling process (When arrives the next transport? Which materials are potentially harmful to the environment?) can also further optimize the process control regarding ecological and economic aspects.

3.3 Sensory System I: Object Classification

The sensory system's first step is the detection and classification of known objects in the waste heap. If it recognizes known objects or parts of objects, it reads an exact definition of its material(s) from its database. Thus, this is comparable to the approach by Bonino et al. (2016) for consumer waste (Bonino et al., 2016). While Kim et al. (2019) did not explicitly follow this approach, their modified LeNet at least has the chance to identify objects (instead of materials) (Kim et al., 2019). Visual object classification has been well studied for decades. Solutions using different types of machine learning (ML) such as Support Vector Machines (SVM) and deep learning methods such as the well-known convolutional neural networks (CNN) ("one-stage" and "two-stage": e.g., Inception and YOLO variants) were presented (review (Jiao et al., 2019)). These candidate methods will be evaluated and, if necessary, further developed. Sensors usually utilized for this first step are vision (RGB) cameras.

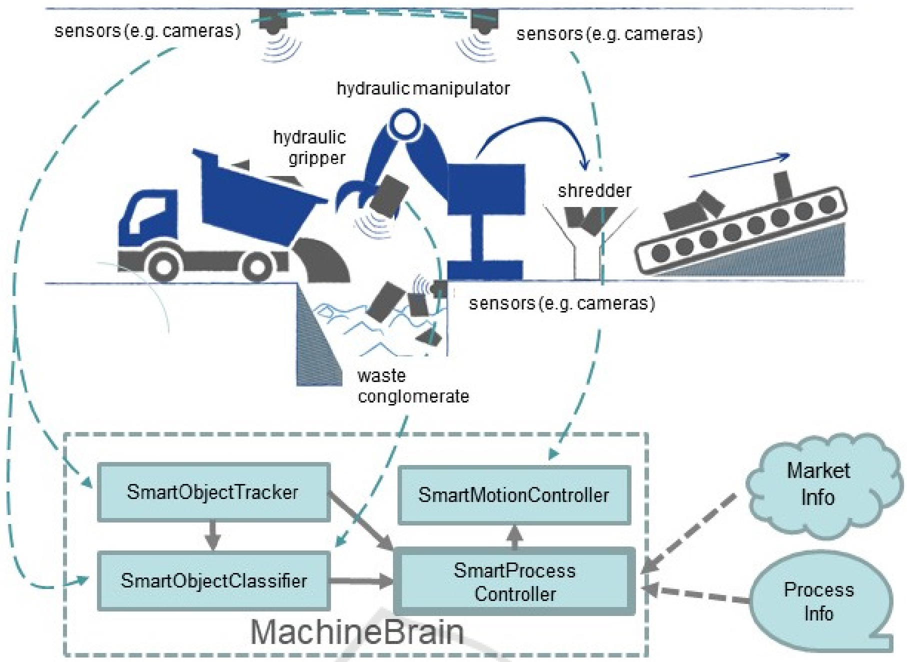

Figure 2: SmartRecycling concept.

3.4 Sensory System II: Material Classification

For unknown and unrecognized objects in the waste heap, a second step is planned in the sensory system: Again, machine learning methods (ML), particularly SVM or CNN, are used to identify the class of material. If this step succeeded, the first step can be triggered again, now in run two, considering the material classification result. For the application of SVM in CDW recycling to classify materials, see (Linß, 2016). As presented within this, the non-visual optical spectra should be taken advantage of, too.

So far, these sensors are used in short distances and with separated objects. Within this project's ongoing work, further research must show whether a material classification is possible in a distance of 15 m to 25 m from sensors at the hall's roof. If only a coarse classification is possible at such distances, additional sensor equipment could be attached to the excavator for a more detailed material classification when grasping.

3.5 Sensory System III: Determination of 3D Position

After the classification of objects and/or materials, the next object targeted to be grasped and sorted can be selected. This could be done using predefined rules, e.g., based on the type of object or its position in the waste heap. To compute the manipulator's path and to perform the grasp, the 3D position of the selected object needs to be known. To this purpose, (1) multiple cameras and triangulation, or (2) other sensors, e.g., LiDAR or time-of-flight (TOF) camera, could be used. As the environment and most sensors are fixed to the infrastructure, a calibration could be carried out to map object positions to an angle in one type of sensors and a 3D position in the position sensors. Here, the solution proposed by Kim et al. (2019) seems to be a very interesting approach (Kim et al., 2019). However, a problem in this use case is supposed to be the large distance between sensors and objects.

4 FIRST SENSOR DATA COLLECTION

In the project's concept phase, the first tests were carried out to reduce the number of potentially usable sensor modalities down to a manageable set. Discussed but not selected were radar sensors due to their coarse spatial resolution and thermal imaging sensors due to the long time constants when the objects' temperatures change. Both sensor types can be added to counter (temporary) poor viewing conditions for the other sensors (due to smoke etc.).

Figure 3: Left column: Sample RGB images in the visual spectrum. Right column: gray images of a spectrum of around 1000 nm. The resolution of the visual spectrum camera is 1920×1200 (FOV 30.4° × 19.0°) and of the SWIR camera 320×256 (FOV 22.9° × 18.3°). The images were taken in a distance of about 15 m (to the plants in the image centers). The second and third row show magnifications of the center of the original images (Kaßmann et al., 2021a, under CC-BY 4.0).

4.1 UV/VIS/NIR/SWIR Sensor Data

Most promising to distinguish different materials seem to be multi-spectral image data in the UV-, visual, and SWIR-spectrum. First sample images were taken in a laboratory environment as depicted in Figure 3. As can be seen in the second row images, the 1,000 nm spectrum (as an example) shows differences that cannot be seen in the RGB image: comparing the two green "plants" in the 1,000 nm spectrum shows that one is a natural plant while the other is made from plastic. Also, the blue vs. the black parts of the chairs can be distinguished more easily in infrared as well as the display frames from the displays.

The third row image shows the problem of the coarse resolution of the SWIR camera's InGaAs sensor: in a distance of 15 m the field of view (FOV) leads to an area that covers a large part of a waste heap, but small objects (like the leaves of the plants) shrink to just a few pixels. Thus, the material classification in a distance of, e.g., 15 m could maybe work for objects of about 10 cm×10 cm but not for small objects in the size of one leaf (≈ 3 cm×5 cm).

Fifty-eight objects of different materials (wood, metal, plastic, stone, paper) were collected at CDW recycling sites and households to generate test image data. For each subset of these objects, images were taken with a visual image camera, a UV camera, and

Figure 4: Left: RGB image of six sample pieces in the visual spectrum. Right: false-color image with the spectra around 880 nm, 1300 nm, and 395 nm (Kaßmann et al., 2021b, under CC-BY 4.0).

a SWIR camera. Multiple bandpass filters of different wavelengths were used (plus one image without filters). Altogether, 14 images of different conditions (wavelengths) were taken for each set of test objects. Sample images of one set of objects are shown in Figure 4. The false-color image shows a more pronounced difference between the two objects on the left and fewer differences within the objects on the right than the image in the visual spectrum. Both are good to distinguish objects of different materials but not to divide objects into image segments.

After the first manual analysis of the sample data, we implemented small scripts to prepare data sets that can be analyzed automatically. Figure 5 (left) shows a tool to select rectangular areas within the test objects. By the script, for each test object, we get a number of pixels in each of the three camera images for each of the different filter conditions. Eventually, each object (rectangle) is represented by sample points in a 14-dimensional space. Figure 5 (right) shows a projection of all selected points (within the rectangles) from the 14-dimensional space to a three-dimensional space.

Each color in the plot represents one rectangle in the camera images. As can be seen, even in such a simple 3D projection, the pixels of the different colors (i.e., different rectangles and different objects) are relatively well separated. As the next step, cluster analysis will be done to check if – for the collected data set – a classification seems to be feasible and what kind of pre-processing should be applied. Afterwards, different classification methods will be tested.

5 CONCLUSIONS

A concept of an autonomous robotic system for sorting construction and demolition waste (CDW) or bulky waste, in general, was proposed. It emphasizes reusing standard presorting equipment typically used in the bulky waste recycling industry, i.e., hydraulic cranes or excavators. The application of a sophisticated and adaptive control system that uses reinforcement learning (RL) methods has been identified as a useful and promising approach. A further advantage of such an ML-based control system is the potential portability to other cranes and applications.

Classifying materials in distances of 15 m to even 25 m is one of the main challenges for such a sensory system. This concept uses a combination of different imaging sensors of spectra in visible and invisible wavelength ranges plus fixed sensors in the infrastructure and mobile sensors at the crane. After the first manual tests have been carried out, automated analyses need to be run on all collected data next. Thereby, the separability of different clusters and the accuracy of the cluster–object assignments can be studied and quantified.

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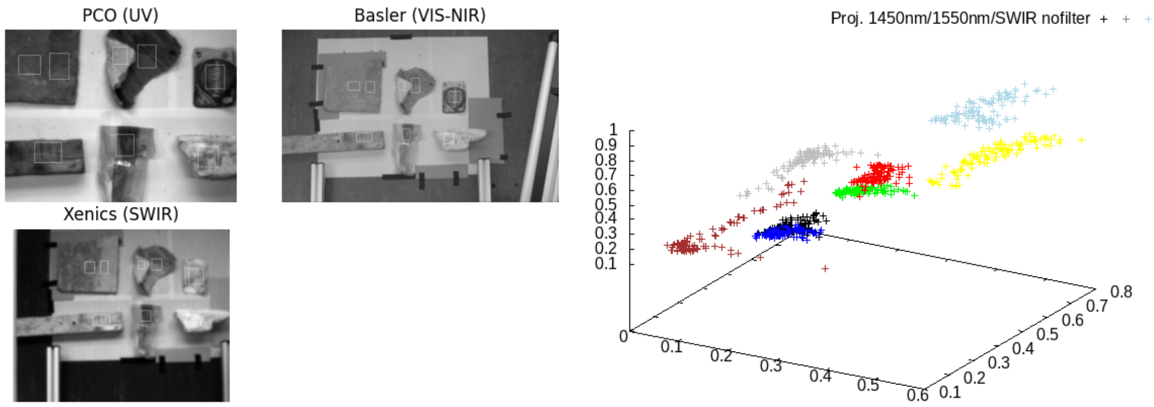

Figure 5: Left: A tool to select sample data of the test objects from all images of a scene. With the rectangles, specific parts (pixels) of the objects can be selected (Keppner and Kaßmann, 2021, under CC-BY 4.0). Right: Three-dimensional projection of the 14-dimensional multi-spectral image data of the objects selected by the rectangles (compare the images on the left). Each color represents pixel data of one rectangle in the three images i.e. of the same object (pixels in rectangle “1” in the UV and in the VIS and in the SWIR image, pixels in rectangle “2” in the UV/VIS/SWIR images etc.).

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