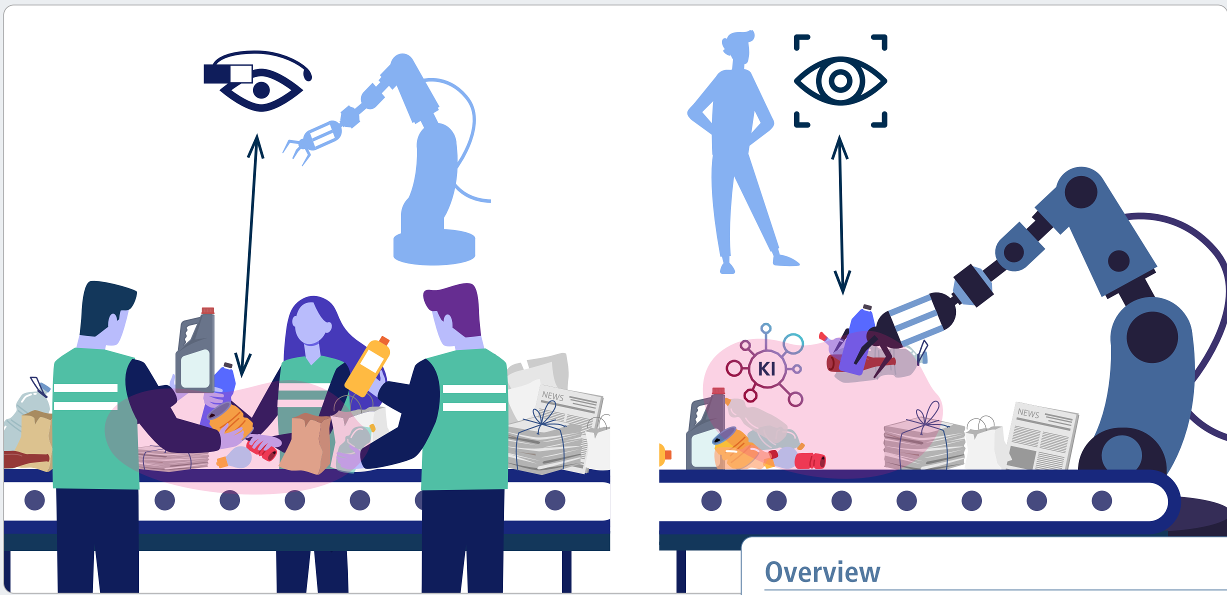
USE CASE

LEARNING FROM INTERACTION

Effective circular economy: Robots for more efficent sorting of recyclable materials



Overview

Industry: Waste management/recycling sector

Task: Use of pick-and-place robots to precisely sort recyclable materials and remove specific or problematic objects

Method: Reinforcement learning, ensemble learning, transfer learning, and others

General information

An efficient circular economy is crucial for achieving the EU-wide environmental and climate goals as well as the United Nations' sustainable development goals (Agenda 2023) (Circular Economy Initiative Deutschland 2020). Increased automation in recycling is also important to enhance both precision and cost/resource efficiency. Additionally, automation addresses labor shortages and transfers unpleasant or even hazardous tasks to machines. Intelligent robotics, especially learning from human-machine or robot-robot interactions, can contribute to these goals. Classical pick-and-place robots are used in this context to precisely sort recyclable materials and remove specific or problematic objects on conveyor belts, such as electronics, batteries, or hazardous substances.

Status quo

There are already well-functioning technical solutions for waste sorting. However, people still often need to assist, which is usually physically demanding, sometimes harmful to health, or even dangerous. Waste sorting often fails to achieve the desired quality and frequently reaches capacity limits. Thus, further reducing the quality of waste separation. Pick-and-place robots are already widely used today and are relatively inexpensive. In combination with appropriate sensors, they could automate the manual picking of objects in sorting facilities.

Future perspectives with AI

Interactive robot learning can help to achieve higher levels of autonomy in recycling via intermediate steps of partial automation (keyword: variable autonomy), while gradually increasing the robustness of the necessary AI models with each interaction. Improved recycling through these means can become a key component of a circular economy, especially with multimodal sensors that are able to detect hidden objects or objects that can be dismantled. It is also a preliminary stage to other operating stations, such as those that dismantle sorted recyclable materials or break them down to recover raw materials. Within existing plants that use conventional waste sorting methods, robotic systems with learning capabilities can be used in a complementary way (e.g., to enhance and ensure quality).

This approach unlocks potential in several ways:

- Release of labor for tasks with higher value creation through the streamlining of unattractive, unpleasant, or potentially hazardous processes
- Increased safety for workers by protecting them from hazardous substances and dangerous objects
- Economic advantages with the prospect of full automation: lower operating costs and the potential redundancy of human-oriented (safety) requirements, such as ventilation, workspace, accident prevention, etc.

Sources of learning

- Observation of human activities, e.g., learning by demonstration (What does the human pick up and how?)
- Human cues for distant objects to be sorted, e.g., pointing with a laser pointer or marking on transmitted camera images of the conveyor belt
- Human verbal feedback during the learning phase, e.g., naming objects and materials
- Human (verbal) feedback or instruction to learn affordances (object is graspable, liftable, etc.) or grasping capabilities
- Robot learning from all human instructors at once, across multiple conveyor belts. This allows each robot to benefit from the capabilities learned by others, such as recognising objects or executing grasps

Required data

In real environments, data can be collected from built-in sensors and involved robots (e.g., data on learned movements). Additionally, there may be data from (previous) recycling tasks or from the preparation and training for these tasks. The sensors are also used to observe objects and materials that go far beyond human perception, which is a significant advantage. Examples include 3D cameras, radar, THz, IR sensors, multi- and hyperspectral cameras, magnetic sensors, barcode and matrix code readers for object identification or symbol scanning. The collected sensor data is systematically gathered and combined (data fusion) to accurately detect objects, even when materials overlap. This process also creates valuable datasets for learning, including metadata. Comprehensive documentation is also established for assessing quality.

Learning methods

- Reinforcement learning
- Ensemble learning (collective learning, e.g., boosting, federated learning)
- Few-shot learning (developing AI models with limited data)
- Team learning (among multiple robots)
- Transfer learning (across different domains, e.g., between geographically separated recycling facilities)
- Self-learning/continuous learning, when a robot operations reach a certain threshold of quality.

Quality assurance

- (Statistical) analysis by qualified instructors, other team members, and/or external technical means (subsequent laboratory investigations): comparison of the results of robot actions and procedures (especially interactions) with objectives and efforts, as well as losses
- Existing technologies for quality control in recycling
- Learned procedures could be executed and evaluated under the same or different (real or virtual) conditions for quality assessment
- Verification of sorting results during a learning phase to collect feedback (e.g., false or correct classification) for reinforcement learning (batch input of feedback in so-called batches)
- Evaluation of the documentation of data collection

System requirements

- Commercially available fast pick-and-place robots can be used, with sensors and machine intelligence potentially being separated and distributed.
- The robots and sensors can be synchronized with the movement of the conveyor belt. This separation allows human instructors to work independently from robots, ensuring safety.
- Robots or the entire system must be capable of applying different learning methods to act intelligently, enabling smooth communication and interaction among the robots and with humans in both real and simulated environments.
- The system must have appropriate sensors, actuators, and AI models. It needs to be capable of learning purposefully from just a few repetitions (cf. few-shot learning), similar to humans. This may require virtual environments (including necessary interfaces) to implement interactive learning.
- Learned skills must be executed at the required speed, with sufficiently accurate localization and grasp estimation ensured.

- In addition to machine learning, other AI methods will also be employed, such as rule-based systems to safeguard robots. AI models should also be monitored (model monitoring) to adjust them to changes in the real environment, thus maintaining the robustness of the AI models.
- Finally, evaluation algorithms and systems are needed, as well as a maintenance infrastructure (e.g., repairs and cleaning of robots and sensors, software updates).

Further requirements

To promote societal understanding of the opportunities, challenges, and background of AI-supported waste sorting, it is essential to involve the directly affected individuals and their representatives, as well as other stakeholders (e.g., waste recovery companies, employee representatives, unions, and occupational health associations), from the development phase onward. Instructors also need the necessary skills to train the robots. During implementation, the legal framework, particularly the General Data Protection Regulation (GDPR), must be observed and complied with. Furthermore, scenarios (e.g., use cases in specific companies) are needed. Overall, the implementation effort must remain reasonable to ensure that the transfer to practice represents a realistic endeavor.

Realization and possible obstacles

Demonstrators with a Technology Readiness Level (TRL) of 5 already exist, for example, for sorting batteries (see: Competence Center ROBDEKON). A system prototype with a TRL of 6 or 7, representing a functioning system in a real operational environment, should be technically feasible within one to two years as part of a corresponding development pilot project, given the available components. There is a need to demonstrate the feasibility of the use case and to improve communication about the benefits for stakeholders (win-win situation). Additionally, the systematic, human-centered integration of (partially) autonomous robotic systems into operational practice presents a challenge (see Sascha Stowasser & Oliver Suchy et al. 2020).

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