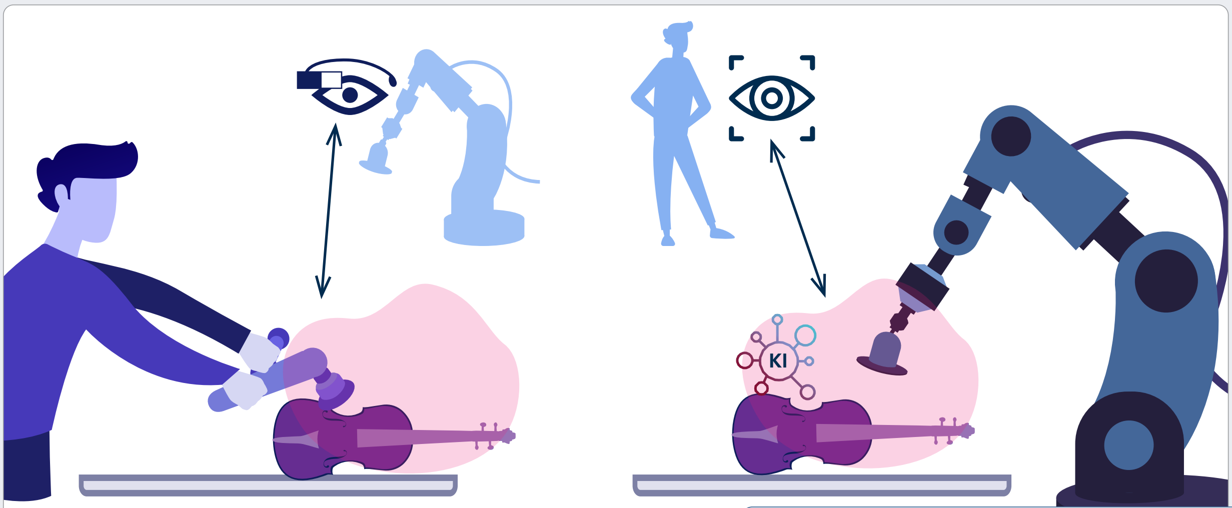
Lernende Systeme
GERMANY'S PLATFORM FOR ARTIFICIAL INTELLIGENCE

USE CASE

LEARNING FROM INTERACTION

Sanding, polishing, varnishing: Personal robots for craftspeople



Overview

Industry: Craft

Task: (Partially) automated sanding work in one-off and small series production to minimize health hazards, increase the efficiency of production processes and the attractiveness of the crafts industry

Method: Learning from demonstration, reinforcement learning, etc.

General information

The (semi-)automated surface treatment for one-off and small series production with robots is an area that can reduce the health strain on craftspeople, while also increasing the efficiency of manufacturing processes and the attractiveness of the crafts industry. Essentially, surface treatment can include both subtractive tasks (sanding) and additive tasks (varnishing). The use case focuses on sanding tasks, such as those encountered in the production of cello bodies or in model construction.

Status quo

In contrast to the use of robots in mass production (e.g., pick and place), surface treatment in one-off and small series production receives little attention. However, there are already simple solutions for geometry-based path planning and control using force-sensitive end effectors (e.g., devices at the end of a robotic arm for sanding or gripping). For automated offline path planning, 3D scanning, or optical systems are sometimes already used as a standard. Additionally, there are initial solutions for human-robot interaction (HRI) with industrial robots or cobots: robot movements can be programmed one-to-one and motion-by-motion through manual guidance of the arm (kinesthetic teaching) or achieved via infrared-positioning devices. Despite these low-threshold methods, the potential of machine learning is not fully utilized in this area. Teach-in is still based on control engineering. However, application-oriented researchers already develop systems that use machine learning to equip robots with sanding skills.

Future perspectives with AI

Through learning from interaction, robotic skills for surface treatment can be developed, transferred, and improved. Craftspeople can specialize and optimize robotic systems for suitable tasks by using the appropriate software, without requiring special programming skills or AI knowledge. In the crafts sector, the cost of robot programming is often not feasible, making no-code solutions essential to boost productivity. The vision: a shift in perspective from expert technology to the user, similar to the transition from mainframe computers to personal computers (PCs). The goal is a „personal robot" for craftspeople: a craftsperson should be able to train the robot in craft skills, much like a master teaches an apprentice. In the context of variable autonomy, robots could, in the future, gain more skills and higher degrees of autonomy through interaction with humans. For instance, the robot could recognize which tasks need to be done directly on the object and consult the craftsperson for approval or in case of uncertainty. The focus here is not on (partial) automation, but on providing robotic tools that, due to their flexibility and low barrier to entry, allow room for creativity. This aims to enable a more productive manufacturing of single items and small series capable of creating a wide variety of different, sometimes unique and complex products (high mix, low volume). This would make it attractive to specialize in fields that are currently considered unprofitable, opening up new business models.

Sources of learning

- Experience and feedback from users/experts
- Human-robot interaction (HRI)
- Observation of the environment and self-observation during surface processing
- Learning skills that other robots have already learnt (see learning methods: transfer learning)

Required data

A multisensory perception of the environment is necessary, both with and without contact with the component, as well as the recognition of processing classes, such as sequences of movements for specific tasks.

The following data are important:

- Capturing position and force, acoustics, acceleration, speed, etc., with sensors and the integration of such data (data fusion)
- Collection of process and interaction data (data gathered during task execution or via teach-in)
- Visual perception, e.g., the properties of the object to be processed (such as edge detection) via a vision system
- Speech data, manual corrections, or other human feedback

Learning methods

- Learning from demonstration (LfD), supervised learning (SL), reinforcement learning (RL), or interactive imitation learning (IIL)
- Active training of basic skills and processing strategies (general and later task-specific), as well as optimization during application through additional one-on-one demonstrations or strategies for RL
- Transfer learning to transfer skills to other contexts or adapt them for different tasks

Quality assurance

- Exclusion of potentially faulty data sources or learning outcomes
- Validation of learning outcomes through human feedback
- Comparison with predefined quality standards

System requirements

Partially mobile or adaptive workspaces are required to adjust to the physical limitations of the robot. A key factor for robot learning is the multisensory online evaluation of environmental and process data (learning on device). To be able to recall and combine simple to complex learned skills (e.g., stopping at an edge) later, these skills must be collected and stored in skill libraries. For the retrieval of such skills, processing classes, or training modes (e.g., LfD, IIL, etc.), users will need a powerful yet simple user interface for human-robot interaction (HRI), for which safety concepts are a critical requirement (e.g., real-time responsiveness and continuous collision control, safeguarding of the system with control engineering).

Further requirements

Humans need a general willingness to interact with robots. Users must be capable of training robotic systems. For efficiency reasons, the range of tasks assigned to the robots should be of low complexity.

Realization and possible obstacles

In some cases, foundational research is still required; however, the greatest effort lies in system development. On one hand, these systems are still too complex for users, and on the other hand, the integration of various system components (robots, tools, control, actuators, sensors, etc.) presents a challenge. While the fundamentals for a robotic system that can be trained by users should largely be clarified in about two years, users are likely to be able to utilize this technology in practice only in about five years due to the necessary reduction in system complexity.

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This use case was developed with expertise from the working group „Learning Robotic Systems" of the Plattform Lernende Systeme - Germany's Platform for Artificial Intelligence, particularly by Gunnar Bloss (werk5 GmbH).