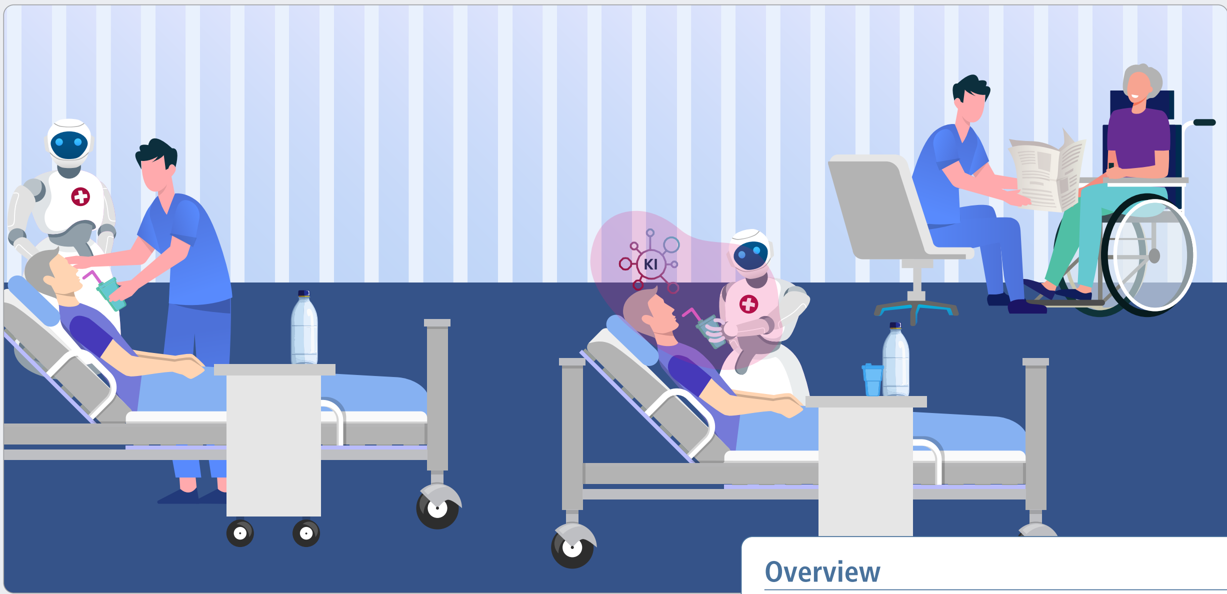
Lernende Systeme

GERMANY'S PLATFORM FOR ARTIFICIAL INTELLIGENCE

USE CASE

LEARNING FROM INTERACTION

Care-supporting robotics: Individual care and assistance



Overview

Industry: Care sector

Task: Alleviate the workload of caregivers to enhance their focus on core tasks and interactions with care recipients

Method: Learning from demonstration, reinforcement learning, etc.

General information

Robotics can be utilized in a variety of ways in the care sector. Thus, the research area is correspondingly broad, encompassing robotic systems that perform tasks removed from direct human interaction (e.g., transporting laundry), as well as systems designed for close or direct engagement with individuals (e.g., offering beverages). Additionally, it includes so-called social bots, which aim to provide companionship to those in need of care and/or maintain social connections. The focus here is on care-supporting robotics that relieve caregivers so they can devote more attention to their core tasks and interactions with those requiring care. For instance, robots could assist in the future by fetching and offering drinks to individuals who often drink too little, opening water bottles, or even aiding drinking when necessary. The integration of robotics into care is therefore expected to achieve high levels of acceptance. This is grounded in the consensus within the care sector that human attention and connection must not be replaced, hindered, or compromised by robots (German Ethics Council 2020, p. 7).

Status quo

There are already robotic systems for fetching and delivering objects, but these are still in the pilot phase. These systems rely on predefined and preprogrammed tasks. For example, a robot can transport medication along a programmed path from point A to point B and use navigation algorithms to avoid obstacles along the way. Interaction is often limited to sending the robot back to point A. Control of the system is typically carried out via devices like tablets. The robot's manipulation capabilities (e.g., gripping) are constrained by its hardware and are further limited in practice for safety reasons. Fully adaptive, learning-capable robotic systems are not yet in widespread use for care assistance. This is because the requirements for interaction with individuals in need of care are exceptionally high.

Future perspectives with AI

In the medium term, it will become possible to personalize predefined skills (such as actions or perception) on site through interaction. For instance, the parameters of a skill could be refined during interaction, such as learning the weight of a water bottle through handling it. Another example would be adapting pre-trained models for object recognition, activity detection, and implicit feedback interpretation (e.g., gestures, facial expressions) to care-specific contexts. This could include distinguishing between caregivers and care recipients or recognizing typical caregiving tasks.

In the medium to long term, robots could also learn new tasks through interaction. The ultimate vision is the autonomous learning of entirely new tasks, a significant challenge for research and development. This requires robots to acquire specific behaviors and skills as well as sequences of actions. A modular set of high- and low-level capabilities could then be rearranged to perform tasks. For example, a robot might learn from caregivers the layout of spaces and storage locations and from care recipients their individual preferences (e.g., drinking schedules, preferred beverages, or comfort zones). The robot could then execute corresponding actions, such as retrieving and serving a favorite beverage at the right time and distance or providing tailored assistance for drinking adapted to individual impairments.

Sources of learning

- Developers during offline phases, including learning foundational skills and knowledge in simulations, equipping the robot with a basic vision system for object recognition, and integrating pre-trained (multimodal) general models (foundation models)
- Interaction with caregivers, such as learning about routes, tasks, and the locations of objects
- Interaction with care recipients, gaining insights into individual preferences
- Self-observation by the robotic system, for instance, learning how to handle objects through direct interaction

Required data

Environmental data collection using multimodal sensors

- LiDAR for optical distance and speed measurements, such as serving as a basis for path planning
- General feedback from data derived from explicit or implicit, conscious or unconscious human feedback
- Camera data for capturing facial expressions to appropriately position drinking aids
- Audio data including linguistic and paralinguistic information, such as spoken instructions and intonation
- Interaction data, such as whether a water bottle was successfully handed over or fell over, demonstrations of actions, or pointing out a route

Learning methods

- Active learning through human demonstrations and imitation, such as when a person brings a drink to the mouth in a specific way or when the robot is guided and repeats the movement through teach-in methods
- Reinforcement learning, e.g. learning individual preferences based on positive and negative feedback
- Few-shot learning, e.g. using pre-trained general models for object recognition that are fine-tuned for care-relevant objects
- Pre-trained general behavioral models

Quality assurance

When robotic systems are used close to people, functional safety is crucial. Machine learning processes should always be supervised by individuals, who are not in need of care ("human-in-the-loop"-approuch). Newly learned skills or tasks must be reviewed and authorized by these individuals. Additionally, systems require robust control measures for safety, including features like complete system shutdown, mechanical constraints, and defining adaptability limits for parametric AI models. Testing in real-world care environments is essential for systems nearing market readiness.

System requirements

To manipulate their environment, such as grasping a drink, robots require appropriate hardware. The location of computation for robotic actions and the training and inference of AI components play a significant role. While on-device computing resources (edge computing) are limited, centralized data centers (cloud computing) can provide greater computational power and should ensure security. Robots must also have sufficient strength to hold and carry intended objects, along with complementary and parallel systems using multimodal sensors with multiple redundancy levels. Furthermore, the knowledge base of the robotic system must be designed to be expandable from the outset.

Further requirements

- **General considerations:** Robotic systems in caregiving must be simple, safe, fast, and affordable to ensure practical adoption. It is essential to define how such systems can be integrated into daily care routines, identify key considerations, and assess actual on-site needs. The specific characteristics of potential interaction partners in caregiving, such as dementia or varying levels of care dependency, should also be accounted for. Furthermore, the deployment must be acceptable and transparent for both caregivers and care recipients. Training and ongoing education for caregivers should also be planned.

- **Legal regulations:** Compliance with applicable laws is mandatory, including regulations such as the AI Act and General Data Protection Regulation (GDPR). For example, GDPR must be adhered to when dealing with audiovisual recordings and preference profiles of individuals. Implementing Edge AI solutions can enhance data protection by keeping sensitive processing localized (cf. Ecker Houdeau et al. 2024).

- **Recommendations from the German Ethics Council:** The integration and implementation of robotics in caregiving should follow the recommendations of the German Ethics Council (2020). These include incorporating ethical principles from the outset of development (ethics-by-design) with values such as autonomy, identity, and privacy. The early involvement of caregivers and care recipients in the development process (participatory design) is also recommended.

Realization and possible obstacles

The use case of fetching beverages is generally achievable within a manageable timeframe if limited to simple, parameterizable tasks within specific constraints. These include actions such as navigating paths to glasses and bottles, moving and opening bottles, and similar straightforward operations. However, caregiving robotics systems capable of learning through interaction with caregivers and care recipients are unlikely to be feasible for another decade. This is due to the high variability of scenarios and the sensitivity to errors in the learning process. A significant technical challenge is the lack of sufficient data for model training. Currently, there is a shortage of freely available behavioral and 3D data from diverse real-world applications, particularly covering various demographics. This issue is especially pronounced in caregiving, where data on different levels of care dependency. Caregiving-specific action sets are also missing. Open questions also remain regarding regulatory aspects, such as compliance with the AI Act (e.g., risk classification) and authorisation processes. Key issues include determining who the system is permitted to learn from and how: Should it only learn from caregivers or from care recipients, too? Should learning approaches differ based on care levels?

(Evaluation I Status 2024-10)

This use case was developed with expertise from the working groups "Learning Robotic Systems", "Future of Work and Human-Machine Interaction" and "Health Care, Medical Technology, Care" of the Plattform Lernende Systeme – Germany's Platform for Artificial Intelligence, particularly by Prof. Dr. Elsa Kirchner (University of Duisburg-Essen, DFKI), Dr. Dorothea Koert (Technical University of Darmstadt), Prof. Dr. Oskar von Stryk (Technical University of Darmstadt), Prof. Dr. Elisabeth André (University of Augsburg), Prof. Dr. Karin Wolf-Ostermann (University of Bremen) and Martin Zimmermann (imsimity gmbh).

USE CASE

Additional information on robotics projects in care

- Community Innovative Pflege (CIP)
- Funding projects by the Federal Ministry of Education and Research (BMBF), including:
  - Robotic systems for care (RoboPflege)
  - Autonomous robots for assistance functions: interactive basic skills
- Robotic Assistant GARMI
- JuBot Project: Staying young with robots
- KoBo34: Intuitive interaction with cooperative assistance robots for the third and fourth stages of life
- TCALL Initiative: Transfer cluster of academic teaching care facilities in long-term care

Sources

German Ethics Council (2022): Robotik für gute Pflege. Stellungnahme. 2020.
Ecker, W., Houdeau, D. et al. (2024): Edge AI: AI close to the device (Executive Summary) based on the White Paper: Edge AI: KI nahe am Endgerät. Technologie für mehr Datenschutz, Energieeffizienz und Anwendungen in Echtzeit. White paper by the Plattform Lernende Systeme, Munich. https://doi.org/10.48669/pls_2024-4
Plattform Lernende Systeme (2023): AI at a glance: Hybrid AI. Combined use of knowledge and data (publication series).