Abstract

The ongoing transition toward Industry 4.0 and Industry 5.0 is driven by the increasing demand for high-variety, low-batch production, as well as the need to preserve the central role of humans within manufacturing systems. Recent industrial revolutions have marked a paradigm shift from rigid, standardized automation toward flexible and intelligent solutions capable of rapidly adapting to frequent production changes. Within this context, Human-Robot Collaboration (HRC), supported by Artificial Intelligence (AI), has emerged as a promising technology to achieve the necessary scalability and adaptability, while simultaneously improving human working conditions and ergonomics.

Despite its strong potential, the practical deployment of HRC in industrial assembly lines remains limited. Although collaboration allows task parallelization between humans and robots, potentially reducing overall process times, achieving these benefits in practice requires effective coordination and synchronization between the two agents. Actual efficiency improvements depend on the robot's ability to adapt its behavior to the operator's location, actions, and task progression, enabling timely, complementary interaction. Limited awareness of human behavior often leads to suboptimal task allocation and poor temporal coordination, resulting in idle times and increased overall execution time. As a result, when working alongside humans, robots operate at reduced speeds compared to traditional automation to minimize the risk of injury and ensure human safety. The trade-off between efficiency and safety makes collaborative systems economically less competitive than traditional fully automated production lines. The primary bottleneck lies in the lack of solutions that enable robots to replicate human cognitive capabilities, such as situation awareness, intention understanding, and adaptive decision-making. AI-based methods, which actually allow robots to reason and adapt their behavior in dynamic environments, are therefore essential to promote the flexibility required by modern manufacturing.

This thesis addresses these challenges by developing AI-based methods to improve

the operational efficiency and flexibility of HRC systems, as key enablers for their economic viability and practical deployment in real-world assembly lines. Since assembly cycle time and resource utilization are primary drivers of production cost, improvements in execution-time efficiency directly contribute to enhancing the economic competitiveness of collaborative systems. To this end, the work proposes a set of methods for efficient and flexible coordination of human and robot activities, covering the entire human-robot collaboration pipeline. First, an easy and rapidly deployable solution for recognizing lastly performed human assembly operations and detecting execution errors is developed. The proposed recognition framework classifies previously unseen assembly steps without requiring application-specific training, significantly reducing deployment time compared to classical supervised learning approaches. Then, both motion-level and task-level human behavior prediction strategies are introduced to anticipate future human actions and movements. By predicting the operator behavior, the robot can proactively adapt its actions accordingly, minimizing idle times and enabling collision avoidance, thereby improving both productivity and safety. Finally, learning-based robot decision-making strategies are proposed to optimally select robot tasks and motions based on the observed human behavior. The developed approaches are specifically designed to maximize the assembly process efficiency while preserving the full human decisional autonomy, maintaining the central role of workers in the production process in accordance with the human-centric principles of Industry 5.0.
The overall collaborative system is structured into three modules, namely Human Activity Recognition, Human Behavior Prediction, and Robot-Decision Making, enhancing system flexibility and facilitating integration and validation of each module. All proposed methods are tested both through extensive simulations and real-world experiments involving human participants, demonstrating their applicability to heterogeneous assembly scenarios and improved performance compared to baseline approaches in terms of efficiency, generalizability, and human-centered collaboration.