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A deep learning-based worker assistance system for error prevention: Case study in a real-world manual assembly

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ABSTRACT

Modern assembly systems adapt to the requirements of customised and short-lived products. As assembly tasks become increasingly complex and change rapidly, the cognitive load on employees increases. This leads to the use of assistance systems for manual assembly to detect and avoid human errors and thus ensure consistent product quality. Most of these systems promise to improve the production environment but have hardly been studied quantitatively so far. Recent advances in deep learning-based computer vision have also not yet been fully exploited. This study aims to provide architectural, and implementational details of a state-of-the-art assembly assistance system based on an object detection model. The proposed architecture is intended to be representative of modern assistance systems. The error prevention potential is determined in a case study in which test subjects manually assemble a complex explosion-proof tubular lamp. The results show 51 % fewer assembly errors compared to a control group without assistance. Three of the four considered types of error classes have been reduced by at least 42 %. In particular, errors by omission are most likely to be prevented by the system. The reduction in the error rate is observed over the entire period of 30 consecutive product assemblies, comparing assisted and unassisted assembly. Furthermore, the recorded assembly data are found to be valuable regarding traceability and production improvement processes.

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