Visualizing a Digital Twin for Operators in High-Mix Low-Volume Manufacturing using Augmented Reality

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Figure 1: AR interface with a highlighted component (left), a colored arrow (center), the on-demand menu, and an informational message. Note: the alignment in this (cropped) device screenshot differs from the viewer's perceived alignment.

Abstract

High-mix low-volume manufacturing relies heavily on human assembly is important. To reduce the effects of human mistakes and to limit training time in a high-employment market, companies are looking into ways to let technology support operators to not only guide assembly but also inspection of work. Inline inspection (with digital guidance) can decrease the costs of rework or scrap production. We evaluate a mostly transparent augmented reality overlay of a product's digital twin to support assembly and inline inspection in a formative within-subjects study with six operators. To isolate interface effects from AI performance, progress tracking and inspection were simulated via a Wizard-of-Oz setup. We discuss the results of the evaluation and present lessons learned.

CCS Concepts

• **Human-centered computing → Empirical studies in visualization**; *Ubiquitous and mobile devices*; **Usability testing**; • **Applied computing → Computer-aided manufacturing**.

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Keywords

Augmented reality, Digital work instructions, Artificial intelligence, HoloLens 2, Information visualization.

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1 Introduction

The manufacturing industry faces several challenges: increasing demand for flexibility, a shrinking and volatile workforce, and the complexity of high-mix, low-volume production (HMLV), all of which make a consistent product quality difficult. Companies are turning to digitization to accelerate operator training and to integrate quality inspection throughout production. Digital work instructions using augmented reality (AR) [18] enable in-context guidance for assembly and inspection tasks, supported by action recognition [22] using artificial intelligence (AI).

This paper presents our approach to designing and evaluating a proof-of-concept AR guidance system, with emphasis on information visualization and the human-computer interface on a head-mounted display. The system leverages AI to automate some tasks, such as basic task completion tracking and correctness checking.

We describe the rationale for our visualization design and report on a formative within-subject study using a Wizard-of-Oz setup. The study examines the role of in-context visualization of a digital twin as the main guidance principle during assembly and inspection of a medium-sized product with standard industrial components.

Our research goal is to explore how in-context visualization of the digital twin — augmenting the workspace with virtual assembly components to indicate product assembly state, and suggesting the next action — can support high-quality assembly.

2 Related Work

Augmented reality interfaces for assembly have been studied for years. In 2023, Tainaka et al. [24] reviewed the literature and established a selection framework for valid AR visualizations for specific cases and provided tool support that is able to offer several valid options for the identified task types. Options range from simple text, images, visualization of 3D models, to video fragments. A software framework guides decisions between different visualizations.

Jasche et al. [11] compared the effects of abstract and concrete visualizations of 3D models on the performance of a complex machine setup. Their abstract visualizations used simplified outlines, while the concrete visualizations were solid. Their results showed that performance was lower with abstract visualization, but could be compensated by using videos for complex tasks. Laviola et al. [13] tried to determine the minimum amount of information that should be conveyed through AR. They conclude that providing excess information does not necessarily improve performance.

Dhiman et al. [5] focused on the effect of different levels of detail in instructions using photos, videos, and rationale in AR to facilitate learning craft in projected AR. While providing additional information did not necessarily improve speed, it did improve quality, as well as competence and intrinsic motivation ratings.

Pietschmann et al. [21] evaluated the performance effects between different forms of visual guidance, showing a significant performance and usability increase at the expense of a higher error rate when avoiding visual occlusion by hiding visual guidance when close to the target. Side-by-side instructions could be an alternative to avoid disappearing guidance close to the target. Khuong et al. [12] concluded that this might outperform in situ visualization. Blattgerste et al. [3] later showed that improved in situ visualizations might lead to better results. These improved visualizations used outlines of blocks. Tang et al. [25] reached similar conclusions in 2003, when comparing solid 3D visualizations (and arrows) to printed instructions. Marino et al. [16] confirmed these findings in a more complex setting with diverse participants.

Less research focused on (inline) quality inspection, based on an analysis of several surveys [6, 27]. Li et al. [14] is an exception that uses color-coded 2D flat shapes to indicate the correctness of pin insertions for aviation connectors. Marino et al. [17] used a tablet to overlay a semi-transparent solid rendering of an assembly to check conformance. Liu et al. [15] used color-coded 3D AR-overlays to oversee machining progress. Alves et al. [1] used green rectangles to support the placement of a measurement device during quality inspection. Dalle Mura [4] used semi-transparent overlays to provide instructions for correcting alignment errors in a car body assembly. Fortuna et al. [7] compared different AR rendering techniques for inspection and concluded that outlines performed best overall, although semi-transparent rendering was more effective for the detection of misoriented components in an assembly.

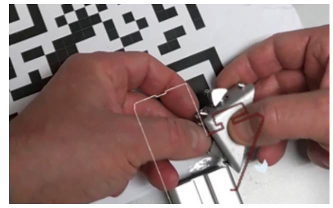

Figure 2: Correcting placement of angular bracket with overlay indicating the expected position using a thinker red line.

3 Augmented Reality Guidance Interface

We implemented an AR head-mounted display (HMD) interface for HoloLens 2 (using Unity 2022.3), designed to minimally interfere with manipulation and to enable in-situ quality checks. We made this choice because this combination offered the best capabilities, and operators were generally positive after receiving a short demo. We know current HMDs do not meet the integration requirements on the shop floor due to concerns about their use for long periods of time [23].

The AR interface (Figure 1) uses four different ways to guide an operator to perform assembly and inspection of a (partial) product:

(1) outlines of assembly components: for picking and inspection, the outline is static; for placing, it is animated. Assembly components can have four colors: white, yellow, green, and red. Reference components are white, components to be inspected are highlighted in yellow. Green is used for components that need to be manipulated, and red for components on which an error is detected. To enhance differentiation, line thickness is increased for red outlines (Figure 2);
(2) a directional (colored) arrow pointing where the next action is to be performed;
(3) two-dimensional graphical user interface (GUI) elements (realized using MRTK3 [20]): on-demand menu that provides access to instructions, notification dialogs that give additional information when deviations from expected behavior are detected, or feedback when an explicit archival action, such as saving a verification picture to a server, is performed;
(4) a virtual camera to explicitly confirm a quality inspection (Figure 3), e.g., when a faulty assembly occurs.

The on-demand menu appears over the open hand of the operator when they look at it. They can reposition it by grabbing and moving it or by re-invoking the gesture. Notification dialogs appear at a central position in the AR area of the HoloLens 2, orthogonal to the viewing direction, to ensure visibility. The arrow appears well within the bounds of the viewing area and is rotated towards the location of the new action. Arrows stay in view until the target component is fully in view.

Most interaction with the GUI is done by pushing a button with a finger, except moving the menu with work instructions and activating the camera.

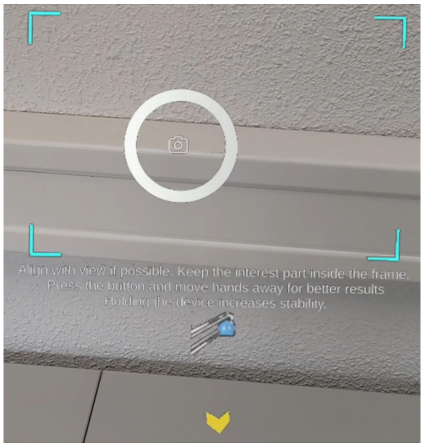

Figure 3: Virtual camera showing a view of the 3D model of the assembly with the component to be inspected highlighted. The yellow arrow indicates the inspection location.

The visual information for the digital twin is generated from a CAD file using CAD2DWI, an extension of [9], which can be used as a basis for automated state estimation [8]. Assembly progress in this version is checked using hand positions, while the correctness of the assembly is validated in separate steps using inspection of the resulting assembly, e.g., presence and position assessments based on (mobile) camera images. Detailed discussion of these components is outside the scope of this paper.

4 User Study

To investigate the effect of in situ guidance, we conducted a comparative, counterbalanced (AB/BA) within-subject user study. In this study, we let participants perform a simplified industry-relevant assembly and inspection task consisting of 10 steps, guided through the application in two conditions: in condition A, they could use the app as described in the previous section, with outlines guiding the assembly. In condition B, they could only use the menu-based interaction and did not see parts (1) and (2), as discussed above. The overall approach was approved by the UHasselt social and societal ethics committee (SMEC).

We did a pre-study with six colleagues before doing the study with professionals from the assembly industry. This approach was discussed with and approved by the project partners.

The procedure starts with an introduction during which the goal, the procedure, as well as privacy-related aspects were explained to the participants. And they could declare their agreement to audio-visual recordings throughout the study and the treatment of the resulting data after the study. The introduction ended with a short demographic questionnaire.

After this, the participants could familiarize themselves with the assembly actions and components. They then performed an assembly task in both conditions. Before each condition, they received an explanation of the functioning of the HoloLens 2 app. The researcher explained that the app would automatically progress if an assembly was deemed correct by the app. It was also explained that this was not guaranteed to be detected correctly. During the experiment, the progress was ensured by a researcher seated near the participant using the Wizard-of-Oz test. The researcher operated a Wizard-of-Oz interface similar to NexOz [19], but with more fine-grained controls to guide the AR visualizations with separate visualizations for picking and placing (within a single step), inspection, and deviations (Figure 4). This way, the app would work similarly for each participant. The resulting reaction time was similar to that of the actual AI components. Each assembly was stopped by a guiding researcher at the same step in the process. When the assembly was ended, the participants filled out a SUS and a NASA-TLX questionnaire.

At the end of the study, the results and experiences were discussed with the participant in a semi-structured interview. Overall, the study took about 30 minutes per participant.

5 Results

We conducted a within-subject study with six employees from a manufacturing company. All had experience with both assembly tasks (1 participant had less than one year of experience, while over half of them had over 15 years of experience) and inspection tasks (2 had between 1 and 5 years of experience, half of them had over 10 years), although the actual assembly tasks differed significantly from the tasks in the study. All participants were male and had an age varying between 24 and 55. Some also had experience with other assembly tasks in their spare time; none of them had experience with augmented reality.

The mean raw TLX scores were low, although slightly higher (worse) for condition B without outlines; 36 versus 38. This indicates that the task load was low for both conditions. The mean SUS scores for conditions A and B were 69 and 54, respectively, corresponding to high (69) and low marginal (54) acceptance [2]. Figure 5 shows overall scores for raw TLX and SUS per condition, including mean and IQR. Figure 6 shows means and IQR per SUS subscore and per condition. This visualization reveals that *support needed* and *a lot to learn* were the main aspects that negatively impacted the score in condition A for some participants. For condition B, cumbersome also had a high agreement.

While most of the assemblies in condition A conformed to the model, some of the assemblies in condition B had significant deviations, ranging from wrong spacing to components assembled in the wrong place. Some participants explicitly mentioned liking the guidance offered in condition A, one participant even mentioned wanting to use it every day for his car tinkering hobby, if it were available for that purpose. Other participants mentioned that they

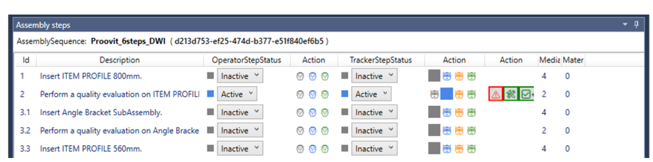

Figure 4: Selected assembly and inspection steps from the assembly used in the study. Direct actions are provided to generate deviation messages and action and step progress. For each step, the user interface state and system state are indicated.

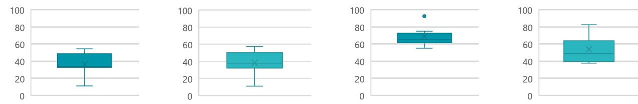

Figure 5: Mean and IQR scores of, from left to right, raw TLX (A and B) and SUS (A and B). Raw TLX scores are low and similar, SUS is higher for A than B.

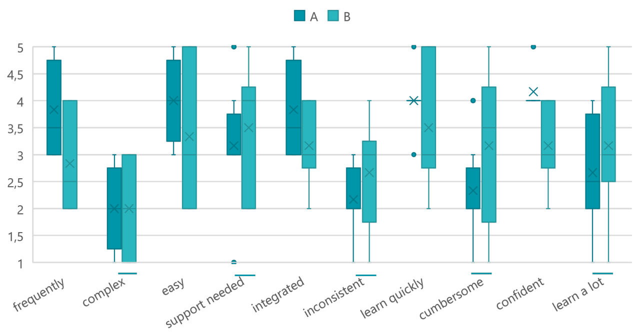

Figure 6: Subscores of SUS. Subscores alternate between higher is better and lower is better (line just above subscore name). Subscores are better for condition A and generally more consistent across participants.

would primarily like to use it for new assemblies, after receiving some training. Some participants were hesitant to manually move to the next step, despite explicitly having been told that the system trying to do this automatically was not perfect. Others were quick to move to the next step and even missed some key parts of the instructions, leading to wrong assemblies in condition B. One participant created a separate method that didn't follow the exact instruction order as provided through the interface, but he achieved a good end result.

The interviews at the end of each session provided explanations for differences or even relative corrections in subscores for individual participants. E.g., P1 stated that (slight) variations in some subscores did not accurately reflect how he experienced mental load, which was effectively higher in condition B. Several participants noted order effects. The first time, the system was completely new, and the second time, they were already more familiar. Others explicitly referred to the guidance offered in condition A, which positively impacted their scoring either through arrows or through the outlines. P4 mentioned that his 3 score for *need an expert* was based on the initial experience, but that it was already better towards the end. One participant explicitly mentioned confusion because the orientation differed between the outline and the menu.

6 Discussion and conclusion

We built a minimal proof-of-concept AR interface that exploits state tracking of an assembly and interleaved inspection tasks. Despite having no experience with AI and just a brief oral discussion and a 2-page explanation of the interface, most participants were able to successfully use the interface.

The results indicate that minimal guidance during assembly and inspection, in combination with artificial intelligence, can effectively guide operators and that operators are willing to use these systems. The direct visualization of the digital twin using color-coded outlines on top of the assembly had a clear positive impact on the impressions of operators and their performance. This study contributes to existing research by providing additional evidence that in situ outlines can effectively support assembly and gives a first indication that this can be extended to inspection tasks. This evidence is preliminary. Further studies with a more complex industrial assembly and a larger, more diverse sample are advised.

For an effective roll-out, there should be minimal training, and use cases should take into account limitations of current technology, such as the limited area in which overlays can be presented and other technical limitations, such as limited battery life. Permanently wearing an HMD is not an option at this point, neither for operators nor for operational reasons. For inspections or new aspects of assembly, which frequently occur in HMLV manufacturing, the usage of a mobile guidance system on a tablet might be useful.

With respect to the AR user interface, outlines allow for maintaining a clear view of the assembly, while still giving in-context information, although care should be taken not to disturb fine-grained actions. Some operators work around this limitation by viewing under the HMD glasses of the HoloLens 2. Inspection during assembly can be valuable, although it shouldn't be done too frequently, as (experienced) operators can deviate from the chosen work instructions while still being effective in the overall assembly. Using a flexible guidance system and logging might enable the detection of specific operators' skills. Using visualizations of a digital twin can be useful to operators, but care should be taken that these visualizations align with the operator's viewpoint. This may impact automation of digital work instruction generation [9].

Allowing the interface to be developed and tested separately from the AI components can be valuable, e.g., using a Wizard-of-Oz. Early testing of communication and clear specification of protocols, including message frequency and filtering, are advised.

Based on the *preliminary* results during this *formative* research, we believe that sharing in-context digital twin information with operators in an accessible format as color-coded component outlines for assembly and inspection (with digital work instruction as backup), and combining it with smartly deployed automation through AI can benefit both human and business value. To do this, apps given to operators should guide when needed, not enforce detailed procedures, giving them the freedom to locally deviate from established procedures, while ensuring quality where and when needed. Further research is needed to come to more definitive results. Integrating the app in an overall quality process, such as pFMEA2 [26], an extension of pFMEA [10], incorporating human and artificial intelligence, is an interesting direction for future work.

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