

use cases were covered in the literature, such as the prototyping of low-cost automation solutions [4], and AR maintenance scenarios with or without an established connection to machine control [5]. The use of AR assistance systems supports users during their day-to-day work, which can reduce execution time and error occurrences without added cognitive load [6]. Despite their value for certain use cases, AR assistance systems also come with drawbacks such as high development costs for the AR solution [7] as well as their authoring tools [8], and the risk of adding cognitive load to workers, if not designed from a user-centric perspective [9], [10]. Furthermore, current AR solutions are implemented with differing hardware components, ranging from handheld devices to projectors, and therefore don't cover all requirements of individual workplaces [11], [12]. Existing AR assistance systems are therefore tailored to one specific, previously defined use case, which makes them rigid and leads to new costs whenever the production processes are changed.

A possible solution to these problems is the development of adaptable assistance systems [12], which can be supported by functionality that understands user cognition [8], and automation for authoring tools [13]. While some adaptable assistance systems have been developed [14], they can lack generalisation and applicability because they are developed and tested in strict laboratory scenarios and are therefore not close enough to actual industrial conditions [15].

This paper describes a framework that enables the creation of adaptable AR assistance systems by using a condition-based approach. It offers building blocks which describe the assembly scene, including individual assembly steps and components, and augments visual guidance accordingly. Further enhancements to analyse user cognition and automation of authoring tools are discussed.

2. Related work

2.1 AR Assistance Systems for Manual Assembly

Up until now, many different AR assistance systems to guide manual assembly were developed and are still in development, as each individual industry use case has its specific requirements that need to be met by the solution [7]. One example is the modernization of a control cabinet production process by Khokhlovsky et al. [16] in which a process prone to human error was improved by utilising AR technology as well as an assistant robot to improve assembly time and allow for better focus during the process. Another example was published by Mura et al. in 2016 [13]. Their optical see-through solution uses sensor data to provide visual guidance for correct component assembly, detecting mistakes and assisting operators. However, the complex setup and testing is time-consuming. A proposed solution is a self-learning procedure that analyses sensor data to automatically deduce assembly sequences.

Wang et al. [8] identify high time expenditure as a key disadvantage in AR assembly research, categorizing it into AR assembly guidance, training, and simulation/design. They focus on guidance and assistance systems, concluding that authoring processes and integration into enterprise workflows for AR guidance in complex assemblies are time-consuming. They suggest developing more intelligent AR assembly systems that adapt to the operator's cognitive status as a solution. Additionally, a user study comparing three different AR assistance methods for assembly guidance [7] concluded that there is not one best method for all factors but instead outlines advantages of each method depending on the individual use case it's being used for. The aim of the study was to assess the impact of the three AR assistance methods, namely a Head-Mounted Display, a smartphone, and a wristband with an external monitor, on performance, mental and physical workload, and acceptance.

As there is not one AR solution that fits every use case, the authors of this paper assume that further systems will be developed in the future and existing ones will be adapted, leading to new costs every time the production processes are changed, or the product is modified. This could indicate a need for frameworks for assistance systems, which are designed with adaptability in mind, which is discussed in this paper.

2.2 Adaptable Assistance Systems

Adaptable assistance systems can reduce development costs by responding to context-specific information, such as user actions or errors. This is done by gathering context-based data—such as visual feeds, location data, or user posture—and comparing it to the planned assembly sequence. The results can then be used to implement adaptive system behaviours. In a survey of context-aware frameworks, Baldauf et al. [14] noticed their similarity regarding their layered structure, which separates the data acquisition from its use. This approach makes context sources reusable in varying scenarios. Standardised formats and protocols further improve context-aware systems, as resources can be focused on the development of the context service itself and not on the integration of the data.

Various approaches have been used to recognize user intentions. As early as 1990, a method was developed using postconditions and preconditions to define user actions, detailing the status before and after tasks along with action-specific parameters [17]. By analysing these parameters, the framework aimed to understand the context and generate context-sensitive instructions. The authors find this approach valuable as it breaks down assembly tasks in a machine-readable format, but it requires time-consuming, unique, hand-crafted conditions. Similar approaches to interpret human

behaviour in virtual space were presented in later years which either check if previously defined conditions, which can be stored as a Boolean operator are met [18], such as “is leg moving”, or use checks for key poses of individual action sequences that define user actions [19]. In addition to these approaches, however, there are others that use AI to recognize user intention. In 2019, Qu et al. [20] used machine learning (ML) to extract service requesters’ intentions from their text by analysing their sentence structure and keywords to make it easier for service staff to provide assistance. Although the feature extraction and performance analysis procedures depend on large datasets and focus on service requests for computer problems, they could be conceptually transferable to assembly tasks. One year earlier Ramamurthy et al. [21] performed a survey that investigated ML techniques for human activity recognition. They observed the trend to use deep learning architecture to mitigate traditional ML algorithm limitations. The approach could be adapted to industry use cases to enable comparison of current user action and the planned assembly sequence.

The adaptability of systems has also long been a topic of research. An approach to generate User Interfaces (UI) for assistance purposes based on virtual context was presented by Macik et al. in 2014 [22]. They distinguished between more and less experienced users, varying the level of visual assistance accordingly. This approach utilised a data structure that controlled elements of generated content, such as Input, Output, and action triggers. While the adaptable assistance system appears promising, the maintenance and development costs of the adaptive UI are significant, and the practical benefits seem insufficient. Recent approaches exhibit similar limitations. In 2023 Fisher and Fu [15] analysed object-related user intention in collaborative situations through line of sight. The proposed UI is adapted according to the recognized user intention with the goal of improving the efficiency of collaboration. Despite the innovative approach, the strict laboratory scenario leads to a lack of generalisation, which reflects the missing applicability for industry scenarios and illustrates the state of research in this domain. Work has also been done in the overlapping field of AI for Extended Reality (XR) applications. A literature review by Reiners et al. in 2021 [23] shows that AI has been leveraged in multiple areas, such as trainings, robotics and autonomous driving and concludes its increasing relevance. Its overlapping use has been classified into three main groups: interpretation of XR generated data, conferring intelligence on XR and Training AI. They propose guidelines to distinguish between two main objectives, one in which AI is serving and assisting XR, through pattern detection or improvement of XR user experience, or one in which XR is serving and assisting AI, through generating AI-ready data or to improve AI performance.

In conclusion, many approaches to use AI to understand user actions and improve assistance systems have been developed. Despite the amount of research in this field, the authors are not aware of current industry solutions, that offer these functionalities and are integrated into modern assembly lines. This paper further investigates current obstacles that hinder industry adaption of such systems.

2.3 *Current Obstacles in the industry*

Although the use of AR offers great potential for many assembly work situations, so far existing AR assistance systems have mostly been isolated solutions, each tailored to a specific use case; hence its integration into industry processes often fails to be realised. In a survey of 2020 Souza Cardoso et al. [12] investigated AR approaches across multiple domains, their use cases as well as used AR devices. They summarise the main challenges for AR technology in a production environment to be hardware concerns, which include the user’s mobility and necessity to not occupy their hands, unfeasible tracking methods and low projection quality. They further found that of 120 studied AR applications, only 5% were implemented in a production environment and concluded that the industry does not prioritise developing their own applications but rather prefers to use a standard application that they can integrate into already existing processes. Adaptable systems that are tested in a production environment are one proposed solution to increase industry adaptation.

After reviewing recent research projects that focus on digital assistance systems, Apt et al. [7] summarise the reasons for the non-commissioning of such systems are the investment costs, legal framework conditions, context-related user-friendliness and ergonomics. They also mention the specific corporate culture and the associated expectations in terms of productivity increases, cost reductions or product and process innovations. In addition to functionality, it must be ensured that the capabilities of the system meet the requirements of the workplace and its environment. Utilising AR solutions on a day-to-day basis poses the risk of increasing cognitive load on operators and therefore worsens their performance instead of improving it [9]. For this reason, ease of use is of utmost importance to limit potential negative effects on user performance and health [10]. Even after initial development, using a system in ongoing operations incurs further costs due to the need to adapt functionality whenever production processes or products change. While incorporating AI into assistance systems could enhance adaptability and reduce some of these costs, it also presents an additional challenge. Despite growing interest in AI in the industry, there is reluctance to implement it in industrial operations, as developed solutions are often only tested in laboratory settings due to high integration costs [24]. AI has often not been incorporated into future corporate strategies, which is also due to a lack of suitable frameworks that support integration into existing business models [25]. Other reasons include the lack of suitable data preparation and the retrievability and reusability of developed digital models, which would support the development of frameworks [26].

3. Framework for adaptable AR Assistance Systems

The authors of this paper propose a framework that supports the implementation of adaptable AR assistance systems. In previous research the authors of this paper have conducted expert interviews to assess the requirements of such assistance systems [27]. They found that the experts expressed a need for informative and cognitive assistance features, which focus on the analysis of user action and usability improvements. The system should further be easily adaptable and cater to users' requirements without making the workers dependent on the system. The following concept deduces the experts' feedback, regarding the assistance systems' requirements.

3.1 Concept

After evaluating the work that has been done in the field, and considering current industry needs, the authors conclude that a framework for adaptable AR assistance systems must take the following points into account:

1. Adaptability through generalisation:

Virtual content should be easily replaceable to keep maintenance costs low and enable a setup with many different use cases and engineering tasks in mind. It should promote versatility and ease of use, so the development costs can be kept low, and the setup can be adjusted to changes in production processes. It further enables the adaptation of the visual assistance to cater to the users' requirements.

2. Interchangeability of hardware:

The framework should not be dependent on proprietary AR-technology, such as Eye Tracking or LIDAR sensors. By not relying on those, but rather by offering optional means of integration for them, the framework is compatible with more devices and therefore has a lower barrier of entry.

3. Automation through process integration:

The framework needs to offer interfaces to standard industrial environments to ensure data flow and decrease time spent on data preparation. Providing means for process integration increases the acceptance of the solution across various industry use cases.

The designed assistance system framework consists of multiple components that support the setup process: a workflow, actions, conditions, and assistance features. Figure 1 visualises their structure and relation. A workflow is the sum of several actions and describes the assembly sequence. It describes the assembly process as accurately as possible with the data known to the maintainer of the software, with context that is perceivable by the sensor of the AR device. This is essential, as the system needs to be context-aware to check given conditions during the use of the application. Actions are a subset of a workflow and are defined by a set of conditions. Conditions are defined as preconditions and postconditions and are made of attributes that can be either a Boolean value or a numerical probability value.

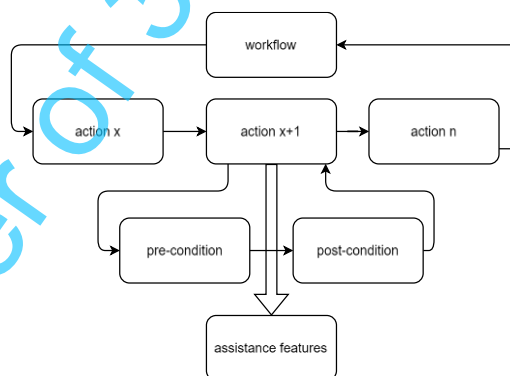


Fig. 1. Visualisation of assistance system framework

A precondition describes the status before its parent action is performed whereas a postcondition describes the status during the task. Any condition can be part of any action, but no two different actions may have identical conditions. For example, condition A may be a simple check to determine whether the user is interacting with a screwdriver, while another condition B could be whether the screwdriver is in contact with a specific screw. An action, "screwing" can now be defined with the two conditions A and B. Actions need to be unambiguous, so no further action can be defined by using only the conditions A and B. The final component is the assistance feature itself, which could be any information that guides the user, such as the description of the current task or the location of the components. It can be attached to a workflow, a task, or a condition, and therefore be adapted to user behaviour. It is necessary to provide the framework with a clear set of conditions that describe all relevant interactions within a given workflow. Conditions are set up by the

software maintainer and can be implemented either manually or via automated processes. As an example, the generic action of movement can be described by the transition of a component, such as a tool, from a fixed coordinate in an environment to another. This behaviour can be described by a single condition checking if the component has moved over time by monitoring its velocity. However, assembly tasks include complex actions that imply specific attributes and may require many conditions to be unique to the system. Examples of conditions can include the number of hands in motion, the velocity of an assembly component or the position of individual components during an assembly sequence.

3.2 Demonstrator

To evaluate the efficacy of the proposed concept, the authors developed an exemplary AR assistance system for manual assembly tasks for inline assembly of electric motor components. The development of the demonstrator is part of a publicly funded research project, which provides the industry use case, realistic components, and feedback of core users. A HoloLens 2 was used as an AR device. The framework itself and its virtual environment were developed using the real-time engine, Unity. All mentioned building blocks, such as the workflow, actions, conditions, and assistance features, were prepared as Prefabs, which are Unity components, and their logic was programmed with C#.

To set up the scene for the manual assembly task, the authors used a textual description of the assembly process, which was provided by the process designers of their research partners. The thereby deduced assembly task workflow consists of the following actions: 1. placing the lower lid, 2. fitting an inner ring, 3. placing a set of coils, 4. fitting an outer ring and 5. placing an upper lid. Figure 2 visualises the example workflow and action elements.

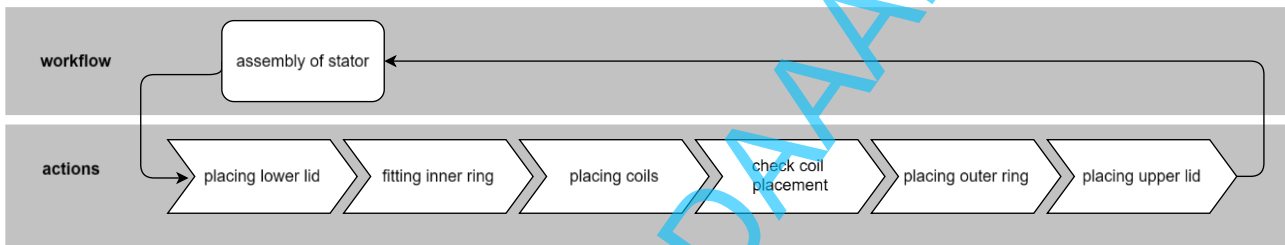


Fig. 2. Example workflow and actions

For each individual action, a set of simple conditions was defined. Once every action has been performed, the system expects the assembly process to start from the beginning. Figure 3 shows some exemplary conditions that were defined for the action “placing coils” and its attached assistance features. The following conditions were designed: 1. Coil was grabbed, 2. Coil is in the final assembly location, 3. A number of required coils have been placed. When the performance of the action is recognized by the system, the corresponding assistance features are shown to the user, which include a textual description of the current task, visual guidance on the coil storage location and visual guidance on coil assembly location.

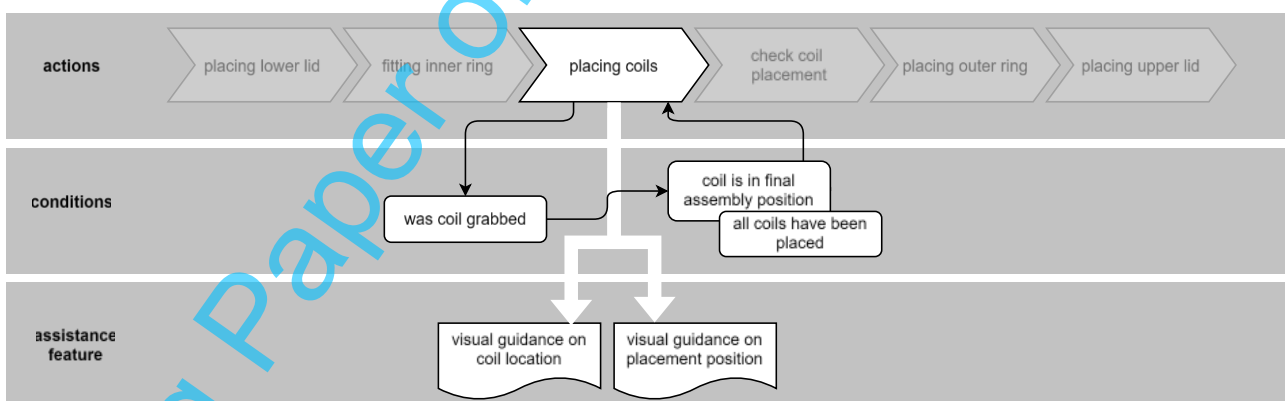


Fig. 3. Example conditions and assistance features

The AR application needs to be able to check whether the described conditions are true. To check if the user grabbed the coil or if the coil is in its assembly position, it is necessary to integrate some form of contextualisation. To achieve this, the authors used a combination of geometry tracking by using VisionLib¹ and QR code tracking that's natively supported by HoloLens 2. The demonstration is shown on a workbench that simulates the inline assembly environment,

¹ <https://visionlib.com/>

as shown in Figure 4. The assembly components are a simplified version of the real use case components and were 3D printed (see Figure 4, green box). As soon as the application runs, its assistance features are shown when either the respective QR Code or the assembly components are recognized by the system.



Fig. 4. Demonstrator setup

While the user performs the assembly tasks, assistance features are visualised in their field of view. The following two assistance features were implemented:

1. Textual description of current assembly task and location of components (see Figure 5, left side)
2. Visual augmentation of final position of components (see Figure 5, right side)



Fig. 5. AR Assistance features

4. Discussion

The exemplary use of the framework for the development of the AR demonstrator gave the authors a clear structure on how to set up the virtual scene and how to describe the assembly tasks. The definitions of the conditions for each step of the task need to be set up, such as the placement of the coils shown in the example. In conclusion this indicates that the initial setup time of a virtual environment is currently not significantly decreased. The authors were already able to reuse created conditions within one assembly sequence, such as the storage location of coils, which indicates that future demonstrators can benefit from already created framework-components.

The developed system is a first building block that acts as a foundation for more elaborate and automated approaches to create workflows of complex assembly tasks. One reasonable approach would be to create a library of conditions for common assembly tasks and therefore shorten development times for setups, such as specific hand poses that are related to specific assembly tasks. Another approach could be to simplify or automate the creation of conditions. This could imply that the maintainer of the program performs the assembly tasks using the AR device to record the process. Afterwards, the recorded steps need to be analysed, classified, and integrated into the framework. To achieve this, ML

can be applied in finding definitions for conditions, for example, by analysing user movement to identify the beginning and end of a task or reading sensor data of involved tools. However, this would require a suitable model as well as proper training for the ML model. An alternative solution could be to create an interface to an existing software that describes work processes and use the existing description as content for the assembly task description and condition design.

Further important elements of the assistance system are the assistance features that guide the operator during the use of the application. Features are currently shown, whenever the preconditions of the actions currently performed are met. This simple approach should be enhanced by adding more variables which contextualise the users need for assistance. For example, the time it takes an operator to perform a specific assembly sequence can be compared. In case one task takes comparatively long, the system could suggest assistance that is suitable for the current assembly step. The condition-based approach could be enhanced for the application of assistance features to therefore react to users' requirements at runtime.

5. Next Steps

The authors are going to evaluate the developed AR demonstrator with a user study. During that study, they will evaluate whether the setup of the assembly task is feasible during the procedure by validating if the AR assistance features are shown at the right time. The users' UX and mental load during the use of the assistance system will be focus of the investigation. Based on the results, adjustments to the conditions and assistance features will be made accordingly. Another important step is to discuss the design of the framework with process designers and assistance system experts to assess its impact on their acceptance of AR assistance systems and possibly improve its design.

6. Conclusion

This paper presented the concept of a framework for AR assistance systems and the development of a demonstrator based on this concept that supports the inline assembly of electric motor components as an exemplary manual assembly task. The authors believe the presented approach to be well-suited for repetitive actions such as assembly tasks, as they are well defined by process designers and are often described in text form and therefore in a machine-readable way. The concept presented has the potential to decrease development costs of AR assistance systems for industry use cases, as it offers generalised building blocks and clear structure during the setup of the virtual environment. Its industry acceptance and efficacy remain to be verified.

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