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An Approach For Analysis Of Human Interaction With Worker Assistance Systems Based On Eye Tracking And Motion Capturing

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Abstract

Human behavior in production systems influences productivity, product quality, work safety and overall process performance. To guide human behavior, digital worker assistance systems can be used to support cognitive decision tasks and sensory perception tasks. In doing so, the design of the assistance systems affects user experience and work results. To optimize and develop human-centric productions systems, data on human behavior and interaction with manufacturing equipment must be collected and analyzed. This analysis is expected to yield benefits regarding process monitoring, quality assurance, user experience and ergonomics. In addition, the results could be used for training purposes to monitor skill improvements.

This paper presents a framework for data acquisition and analysis of human interaction with digital worker assistance systems. In addition to the overall system architecture, the individual development steps are discussed. An eye tracking device and a motion capturing camera are used for data collection and provide live information about human behavior in conjunction with a digital worker assistance system. The data is stored in a database and analyzed by custom analysis algorithms. The results are displayed in a dashboard application and show that the presented framework with eye tracking and motion capturing is suitable for the analysis of human interaction with worker assistance systems.

Keywords

Human; Interaction; Data Acquisition; Data Analysis; Framework; Worker Assistance Systems; Eye Tracking; Motion Capturing; Assembly; Dashboard; Cyber-physical Production Systems

1. Introduction

Human behavior in production systems affects productivity, quality and flexibility [1]. However, training of workers is not always possible, because companies often rely on temporary employment, which may lead to a decrease in productivity [2]. Furthermore, customization and multiple product variants pose additional challenges [3]. One solution to provide support are digital worker assistance systems that help with cognitive decision tasks (e.g., assembly sequence) and sensory perception tasks (e.g., torques) [4]. Keller found that digital worker assistance systems increase productivity for untrained assembly workers, but the changes in human behavior which lead to the improvements were not monitored [5]. There is a lack in knowledge about the interaction between humans and worker assistance systems, which conceals optimization opportunities.

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The analysis of human behavior at digital worker assistance systems is motivated to support research similar to the use cases in the annotated references:

- Determine maturity level of lean production and worker movements [8,6,9,7,10].
- Discover inefficient hand movements and optimize assembly station layout [8,6,9,10].
- Monitor standard conformance, ergonomics and safety [8,6,10,11].
- Discover poorly understandable instructions and optimize texts, images and videos [8,9,11].
- Competency measurement before and after training sessions [8,10,11].
- Analyze usage of worker assistance systems to determine necessity after training period [8,10,11].
- Anomaly detection and process locking to support quality assurance [6,10].
- Create instructions automatically from captured behavior of expert worker [10].

To increase transparency and allow for improvements of digital worker assistance systems according to the listed use cases, this paper presents a framework for data acquisition and analysis based on an existing digital worker assistance system [12], an eye tracking device [13] and a motion capturing camera [14] as data sources. While the data sources already come with dedicated software tools, the authors identified the following issues, which lead to the development of the presented framework:

- Lack of standardized communication interfaces across data sources.
- No merging of multiple data sources across software tools.
- Implementation of custom analysis algorithms not possible.
- Not suitable for live data analysis and dashboard generation.
- Insufficient documentation about database structure of existing worker assistance system.
- Analysis software for eye tracking device is expensive [15].

The developed framework eliminates these issues. The communication is based on the open platforms communication unified architecture (OPC UA) and allows the connection of multiple data sources. In addition, the framework supports the implementation of custom analysis algorithms. The analysis runs on live data and the results are displayed in a dashboard application. The database and dashboard applications are based on free open-source software. Due to the implementation of custom analysis algorithms, there is no need for expensive proprietary software. The next sections provide information about the background of this work, the framework development and implementation as well as a conclusion of the results.

2. Background

A survey on digitization shows that 86 % of the participating companies want to increase efficiency through digitization, which is the highest rating category. The second most important request is an increase in transparency at 75 % [16]. To gain insights and find optimization potentials, the lean philosophy already introduces “Standing in the circle” also known as “Go & See” where shop floor managers observe workers in the factory [7]. Hofmann et. al. found that the visualization of live process information along with Go & See allows for better bottleneck identification [8]. In addition, the analysis of human interaction with manufacturing unveils optimization possibilities beyond productivity improvements. For example, Lange et. al. conducted interviews on the operability of tooling machines and identified multiple design dimensions which all affect user experience [9]. Regarding sensor technology for the analysis of human-machine interaction, Zheng et. al. present how eye tracking information can yield benefits regarding process performance, human performance, work environment and safety [11]. Their work also includes selected eye tracking measures to be used in various manufacturing and logistics areas. For analysis of worker movements, Jathe et. al. present an exemplary use case of motion capturing to identify work activities in the car industry [6]. Peruzzini et. al. combine multiple human factors to analyze user experience, but their implementation only targets data post-processing and does not support live analysis of streamed data [17].

3. Methodology and Framework

The presented data acquisition and analysis framework is developed based on the methodology "Development of mechatronic and cyber-physical systems", as presented in VDI/VDE 2206:2021-11 [18]. The methodology – also known as the V-model – proposes five major steps for system development, which are shown in Figure 1. The next five sections of this paper show the application of the V-model to the development of the presented framework.

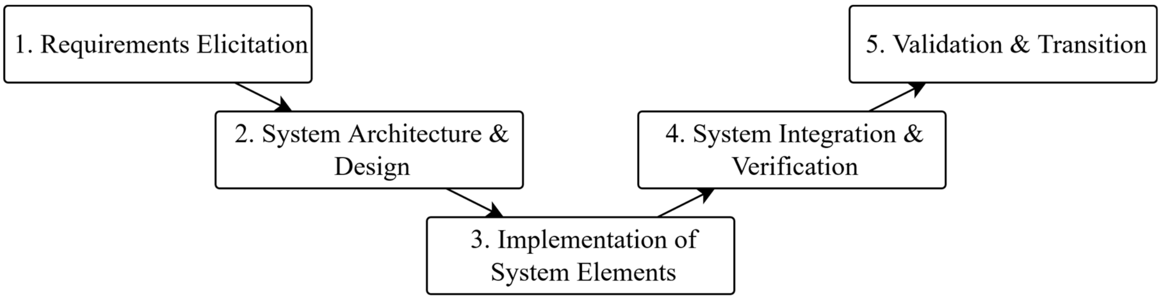

Figure 1: Methodology for Development of presented Framework according to VDI/VDE 2206:2021-11 [18]

3.1 Requirements Elicitation

The first step towards system development according to the V-model is the elicitation of requirements. The requirements for the presented framework are based on the use cases and issues with existing solutions as presented in the introduction of this paper. Figure 2 shows the use cases and derived requirements. There are use cases which share essential requirements and were merged into the groups A and B to reduce the number of connection lines. At the worker assistance system, the worker's gaze on the instructions (R1.1) and movements (R1.2) must be tracked to collect data about human behavior according to the intended use cases.

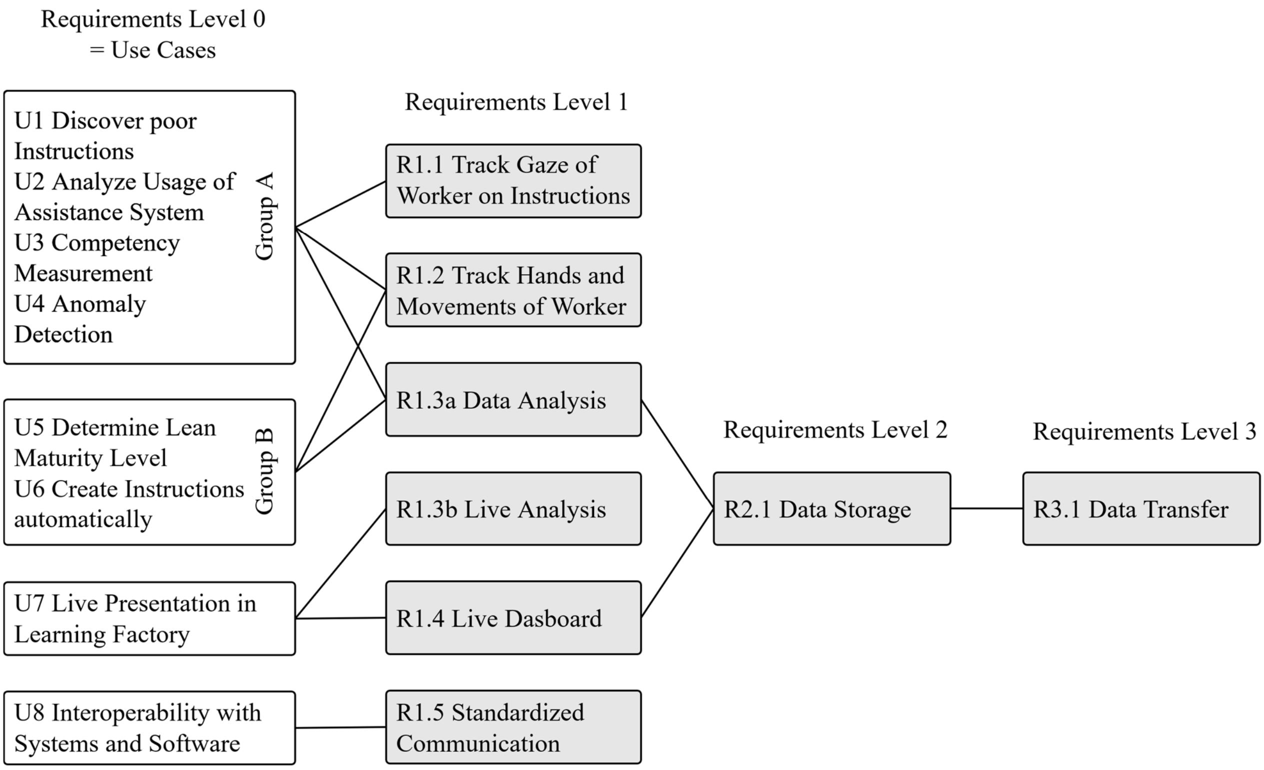

Figure 2: Requirements Elicitation for Data-driven Analysis of Human Interaction with Digital Worker Assistance Systems based on Use Cases

Use case U7 extends the data analysis requirement to also support live analysis of data. From the requirements of data analysis (R1.3a) and the integration of a dashboard (R1.4), the requirement for data storage (R2.1) is derived on the second requirements level. The data storage then requires data transfer software (R3.1) to save the live information into the data storage, which is displayed requirements level three. The next section discusses the system architecture of the framework based on the requirements.

3.2 System Architecture & Design

Figure 3 shows the system architecture of the framework which is tailored to the identified requirements. The chosen architecture was designed based on the guidelines for event-driven processing [19] and cyber-physical production systems [20]. At the bottom of figure 3, there is the data source layer, which consists of a worker assistance system, an eye tracking device and a motion capturing camera according to the requirements R1.1 and R1.2. Following the guidelines for event-driven processing, the information flow between the components is realized using a publish and subscribe paradigm [21]. OPC UA is the preferred communication standard for production systems and was chosen for the framework [22]. The provided information is available in the form of standardized OPC UA data streams, which satisfies requirement R1.5. For debugging purposes, free OPC UA clients can be used to view the data streams [23].

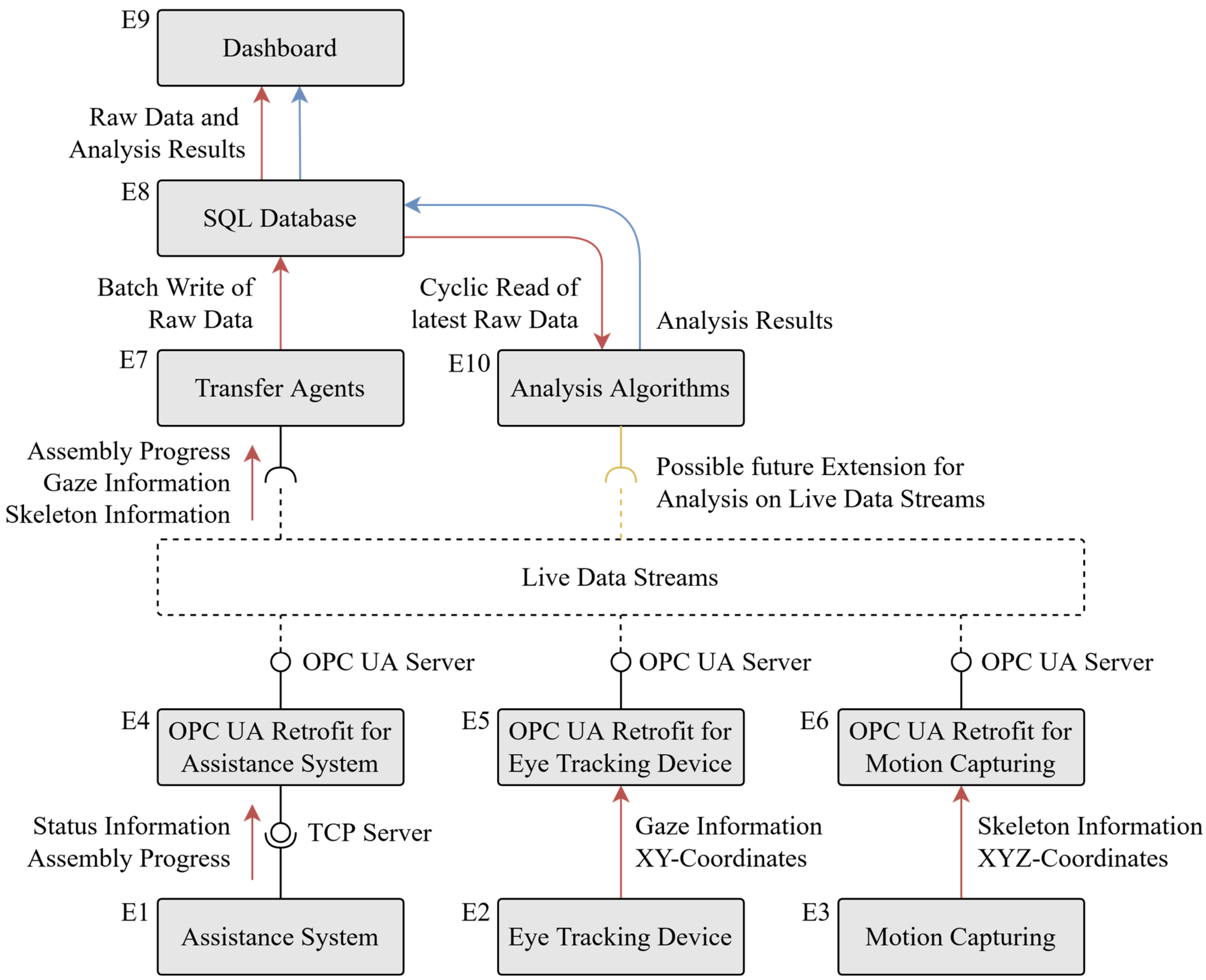

Figure 3: System Architecture of Framework for Data-driven Analysis of
Human Interaction with Digital Worker Assistance Systems

Above the data stream layer, there are transfer agents that write into a database, which supports the Standard Query Language (SQL), satisfying the requirements R1.5, R2.1 and R3.1. The analysis algorithms consume the latest batches of stored data, satisfying requirements 1.3a and 1.3b. To provide a visualization and to satisfy requirement 1.4, there is a dashboard application, which is customized to show the raw data and analysis results. The next section presents the implementation of the individual system elements, which are numbered as E1 – E10.

3.3 Implementation of System Elements

After the specification of the system architecture and design, the individual system elements are implemented. As proposed in the V-model, the implementation involves multiple disciplines for hardware and software. The framework consists of ten system elements according to figure 3. The system elements can be distinguished into three types: standard components (T1), standard components with custom configuration (T2) and fully custom components (T3). Table 1 shows an overview of the system elements and states information on their implementation. The framework includes four custom software components written in Python [24]. For the OPC UA retrofit on the motion capturing camera, the original body tracking library by Microsoft was incorporated, which is written for C++. The library takes the RGB-color and depth images from the camera and uses artificial intelligence and computer vision algorithms for motion capturing.

Table 1: System Elements and Implementation Information

ID	Type	Implementation	Comments
E1	T2	Desoutter Pivotware V7	Configured to send TCP messages to OPC UA retrofit.
E2	T1	Tobii Pro Nano	Provides XY-coordinates of the worker's gaze at 60 Hz.
E3	T1	Microsoft Azure Kinect DK	RGB+D camera, comes with library for motion capturing.
E4	T3	Python Application	Forwards information from TCP to OPC UA server.
E5	T3	Python Application	Fetches eye tracking data, forwards to OPC UA server.
E6	T3	C++ Application	Fetches motion data and forwards to OPC UA server.
E7	T3	Python Application	Subscribes to OPC UA servers and batch writes every 5 s.
E8	T1	PostgreSQL Database	Hosts database for raw data and analysis results.
E9	T2	Grafana Dashboard	Plots raw data and analysis results.
E10	T3	Python Applications	Read from database every 5 s for analysis, write results.

3.4 System Integration & Verification

The framework is integrated at one of three assembly stations for assembly of an electric motor replica. The chosen assembly station involves 19 assembly steps. Figure 4a shows the setup for integration and verification of the framework. The eye tracking device is mounted below the screen of the assistance system at an assembly station. Based on the included calibration software, the position of the worker's head is within the best range for tracking when standing straight in front of the assembly station. The motion capturing camera is mounted at the top of the assembly station. The settings of the camera allow for a wide and narrow field of view, where the narrow option has proven to be more accurate for motion capturing.

Figure 4b shows the image of the motion capturing camera with visualization of the skeleton joints. The viewport includes the relevant desk area. The boxes for material supply are not visible on the camera image but when the worker grabs material, the motion capturing algorithm still provides XYZ-coordinates at the positions of the boxes. Figure 4c shows a closeup of the screen of the assistance system and a scatter plot of the XY-coordinates for the worker's gaze at the screen.

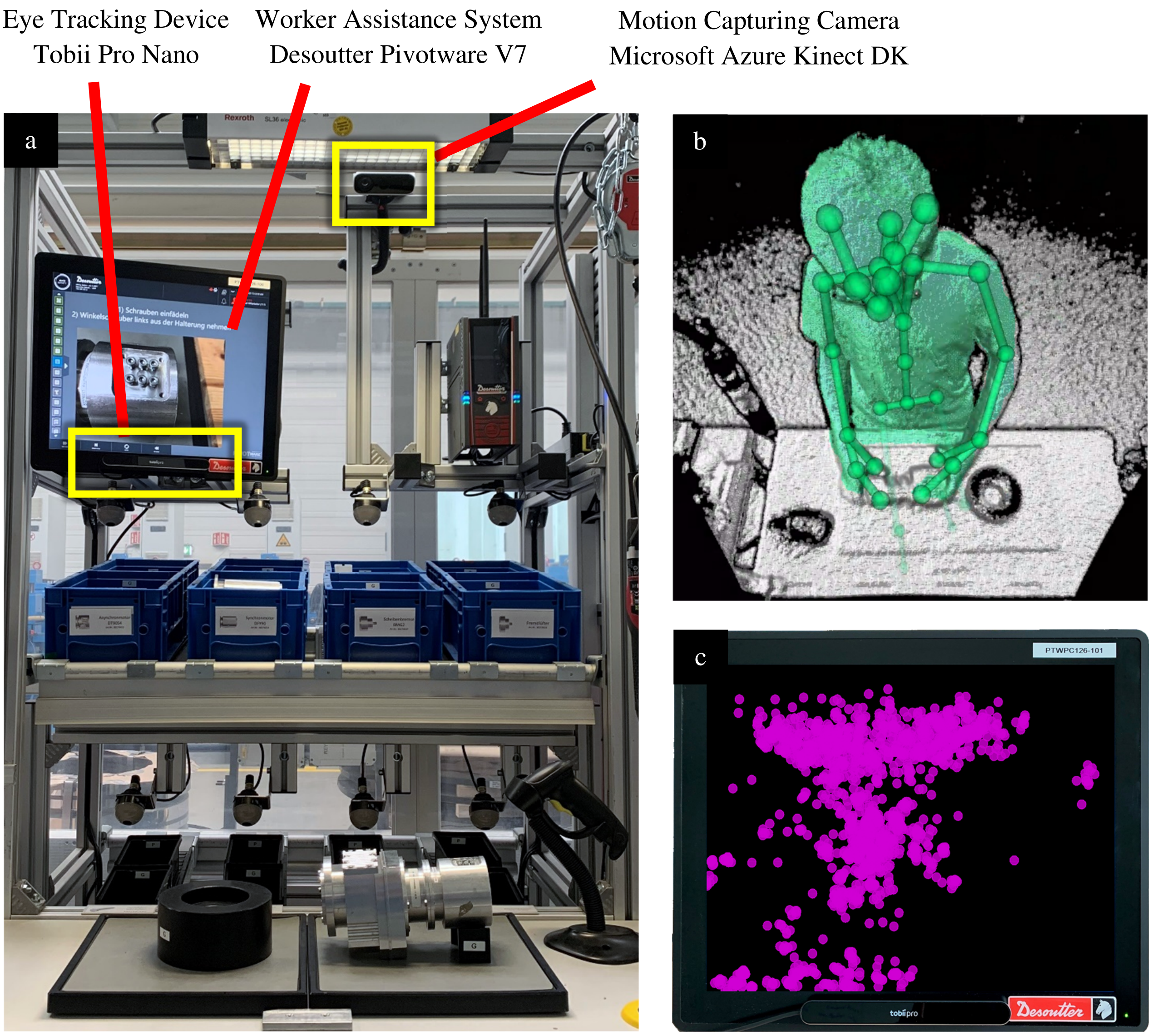

Figure 4: Setup with Integration of Framework for Data-driven Analysis of
Human Interaction with Digital Worker Assistance Systems

To verify that the developed framework behaves according to specifications, all 19 assembly steps were carried out by unexperienced worker. Figure 5 shows the dashboard application with visualization of raw data and analysis results with annotations which are discussed in the validation section of this paper. The first plot shows the assembly progress. The eye tracking section shows when the worker looked at the screen, but there is no information about the tracking algorithm detecting head or eyes. The XY-coordinates of the worker's gaze are not shown as time series but as a scatter plot in figure 4c and focus on the instruction text and image area. The motion capturing section of figure 5 shows the detected person count and indicates that the motion capturing algorithm only lost tracking a few times. The Z-coordinates of the right hand are at about 1000 mm distance from the camera, which is reasonable based on the setup shown in figure 4a. The XY-coordinates of the right hand move around the center of the assembly station as expected.

Figure 5: Dashboard with Visualization of Raw Data and Analysis Results

The dashboard refreshes every five seconds and shows the history of data recorded during the assembly process. Due to the batch write logic of the transfer agents (E7) and the cyclic read logic of the analysis algorithms (E10), the dashboard is lacking a few seconds behind real-time. The data is still perceived as live generated for demonstration purposes. A detailed investigation of the data shows some anomalies, which are discussed in the following validation section, highlighting the links to the worker's activities.

3.5 Validation and Transition

The final step of the V-model is to validate that the developed framework is suitable for the intended analysis of human interaction with worker assistance systems. The initial analysis results include the timewise percentage of the worker looking at the screen of the assistance system for each assembly step. In addition, the distance between the right hand and the top right material box D2 is monitored to incorporate the motion capturing data. In the following, the link between work activities and anomalies in the collected data are discussed based on figure 5.

Assembly step six takes the longest to complete and starts at around 15:16:45 h. During most of the time of the sixth step, the worker does not look at the screen, but the right hand shows minor movements. This correlates with the fact that small hard to mount screws are attached during this step. The analysis results for the percentage of the worker looking at the screen is also the lowest of all major assembly steps.

Furthermore, there are two very short assembly steps in the recordings that are related to minor tool handling activities. These steps are separated from the adjacent activities by the assistance system but do not yield conclusive analysis results for the looking at screen value, because the time durations are too small.

Another observation shows a correlation between the motion capturing losing tracking of the worker and the position data of the right hand, e.g., at around 15:17:50 h. The tracking fails to detect the worker when there are peaks in the X-coordinate of the right hand and the worker moves towards the edges of the tracking area.

According to the instructions, material should be taken from box D2 only once. However, the distance measurement between the right hand and material box D2 indicates that the worker has reached three times into the box towards the end of the assembly process. This correlates with a confusion that the worker experienced because the provided parts did not look like the ones on the instruction image.

Besides the instruction text and image area, the eye tracking data in figure 4c shows a cumulation at the lower left part of the screen. This is where multiple buttons are placed on the user interface of the assistance system to skip or retry steps. Although the buttons were not pressed during assembly, the worker's gaze moved around the area several times.

4. Conclusion and Outlook

After motivating the analysis of human interaction with production systems, the requirements of the presented framework are derived from research use cases and issues with existing tools. The chosen system architecture follows guidelines for event-driven processing and cyber-physical production systems. The data sources are equipped with OPC UA interfaces to provide standardized publish and subscribe communication. For data storage and visualization, the framework relies on free open-source software. For future improvements in performance and query logic, the database will be replaced by a time-series database. The data analysis is performed by custom algorithms. For verification, the developed framework is implemented at an assembly station with a worker assistance system. The motion capturing algorithm only lost tracking a few times. The eye tracking data must be investigated further as by now, there is no distinction between the worker not looking at the screen and the worker not being in the tracking range. Regarding the analysis results, the first algorithm successfully merges signals from the worker assistance system and eye tracking device. The initial motion capturing analysis is kept simple but could be extended in the future. To minimize the lag between data acquisition and display of analysis results, the algorithms will be connected to the live data streams instead of the database in the future as indicated in figure 3. The validation shows links between the worker’s activities and analysis results but must be extended to more detailed statistics in the future.

Further research will include the application to more use cases as listed in the introduction of this paper. After developing additional analysis algorithms, the authors plan to record and analyze multiple datasets. The findings are expected to reveal optimization possibilities for the design of worker assistance systems.

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Biography

Fabian Hock, M.Eng. (*1997) has been a research associate and PhD student at the Institute for Production Management, Technology and Machine Tools (PTW) at the Technical University of Darmstadt since 2022. His research interests include human-centric assistance systems in cyber-physical production systems.

Prof. Dr.-Ing. Joachim Metternich (*1968) has been head of the Institute for Production Management, Technology and Machine Tools (PTW) at the Technical University of Darmstadt since 2012. He is also the spokesman for the Center of Excellence for Medium-Sized Businesses in Darmstadt and was president of the International Association of Learning Factories (IALF).