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Sensor-driven Analysis of Manual Assembly Systems

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Abstract

A reliable knowledge of processing times and following analysis are the basis for successful production planning. In particular, manual assembly processes are associated with great efforts to get data about processing times. That is why manual assembly processes are often not sufficiently transparent to enable good production planning, scheduling and control. This paper describes a system for automatic analysis and evaluation of manual assembly processes. It is driven by sensor and measurement technology, constructed modularly, and can be used in a wide range of assembly processes.

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1. Introduction

Nowadays companies face the challenging environment of an increasing number of product variants. Furthermore, the trend towards decreasing lot sizes even down to one-piece production continues. [1] In order to meet the challenges of the changing environment and remain competitive, it is necessary to properly plan the production, especially the assembly, in which seventy percent of production costs are incurred [2]. However, there is often still too little transparency within the system. Especially with manual assembly processes, it is difficult to obtain complete transparency due to a lack of standardization and detailed documented assembly instructions. In general, the more time a manual assembly process takes, the lower the transparency becomes. But even with shorter assembly processing times, there often is no complete transparency.

Due to the missing transparency, it is often neither possible to provide specified assembly processes nor assembly instructions in a production with small lot sizes or long assembly process steps.

In more than sixty percent of companies data-driven decisions have a high or very high priority [3]. It is, therefore, crucial to have reliable data. Assembly processes can only be reliably planned, if reliable data are available.

In the field of assembly planning and optimization, the need emerges to simplify the analysis of assembly processes and the acquisition of data.

2. Objective

This paper aims to present an approach to a flexible system that enables automatic analysis and evaluation of manual assembly processes. The system needs to be designed in its hardware, by sensors and measurement technology, as well as in its software. The data create transparency and are the basis for a successful production planning, scheduling and control. The system ensures reliable processing times and allows an analysis of the process steps.

In the following the state of the art and research gaps are presented. Afterwards, the system is introduced especially in its setting, IT-architecture and evaluation. Furthermore, the benefits are shown.
3. State of the art

3.1. Established methods for assembly process monitoring

So far, there are many possibilities to track the time of manual assembly processes, but all are associated with great effort: The determination of actual process times for example, is done by an expert through external recording following a technique developed by the association for work design, industrial organization and company development (REFA) [4]. Before the measurement, the whole assembly process needs to be described step by step. This enables a detailed analysis of the time study [5].

Alternatively to a detailed time study other methods are possible, like self-recording by the assembly operator himself or a time estimation through a survey with the engineering department and shop floor staff. Besides this, the REFA multi-moment observation technique is one more method to minimize the effort of data collection, but it is less precise than an external recording of all process steps [4].

For processes without a detailed assembly plan, an analysis can be made by first observing and recording the process, and separating it afterwards using the video footage. This, however, requires significant effort in post-processing.

Nowadays, the determination of time can be supported by software tools, like apps [6, 7, 8], in which data can be entered. These tools offer assistance in data documentation and evaluation. The main tasks, such as structuring the process into single steps, defining the measuring points, tracking the process variables, for example the weight of the part which is moved, and the measurement effort of the steps itself, still need to be done manually.

Another method to reach target-times without measuring the actual-times are systems of predetermined times. The most common system in Germany is the MTM (Methods-Time-Measurement)-Method [9]. The idea behind MTM is to split every manual movement into a combination of different basic motion types. For the basic motions times are specified by standard values [10]. MTM can be used even before a process is implemented, but needs a lot of personal effort and trained staff.

The following figure shows the relationship between data quality and costs of data generation and processing.

![Diagram showing the relationship between data quality and costs of data generation and processing.](image)

Fig. 1. Data quality and costs of data generating and processing.

All presented state-of-the-art methods to track times of manual assembly processes are not sensor-based. The generation of data is associated with a high effort of manual work. That is why the costs of data generation and processing increase with the quality of the data.

3.2. Sensor-based assembly process monitoring

Because gaining a high data quality with the established methods induce a lot of man power, research in the field of sensor-based systems is on the rise.

In automated production environments, sensor-based applications range from support of production processes to vision-based handling systems and fault detection as well as predictive maintenance. In manual assembly systems the use of sensors to track and support the manufacturing process is less common. As production activities can usually be determined by body posture, arm movements and hand gestures, body-worn sensors are often the most suitable choice for tracking and identifying production activities [11].

There are several approaches that use motion capturing techniques for the ergonomic assessment of assembly operations. Gudehus [12] uses data from a gyroscope-based motion capturing system, worn on the body for semi-automatic identification of postures during assembly operations. The worker positions are then coded in accordance with the Working Posture Analysing System (OWAS) [13] and evaluated with the Lundqvist Index. Bellmann et al. [14] propose to use camera-based recordings for automated analysis, ergonomic assessment and identification of improvement potential of workspaces. The system is supposed to give real-time feedback without the need for the presence of an ergonomics expert. Härtel et al. [15] present a hybrid motion capturing system consisting of a marker-based system and an inertial measurement unit (IMU). The latter is used as redundancy in case the observational methods do not provide applicable data. The workstation is evaluated by the Ergonomic Assessment Worksheet (EAWS).

Numerous studies propose to use devices developed for computer games to collect motion data. Diego-Mas et al. [16] use Microsoft's Kinect™ sensor system consisting of a color camera, an infrared emitter, an infrared depth sensor, a multi-array microphone and a 3-axis accelerometer to record body positions. The collected data is processed to perform an OWAS posture assessment. The comparison of the results with those of human observers leads Diego-Mas et al. to the conclusion that low-cost range sensors provide valuable data in the examined use case, but are not suitable for the application in real work environments, e.g. due to lack of accuracy. A more recent version of the Kinect™ was used by Mgbemena et al. [17] to detect manual handling gestures such as lifting and lowering operations in real-time. While the detection of handling activities in a training environment reached high accuracy, gestures could not be detected at angles below 60° and above 120° in other locations and a different environment.

Schirra [18] reviews the application of motion capture in combination with virtual reality (VR) for ergonomics assessment as well as for validation of assembly activities in
the context of manufacturability of the product and accessibility of the mounting location. An assembly planning system with motion capture and VR techniques is already presented by Bullinger et al. [19]. Electromagnetic sensors track positions of the head, hand and feet for a virtual representation of the operator’s body. Data gloves capture information on the orientation of the hand and fingers to analyze the interaction between the operator and virtual objects. Gestures detected during the virtual assembly and the disassembly of components are set into a relationship to MTM basic movements to calculate planning times for the assembly operation and a logical assembly sequence. A similar approach is carried out by Ma et al. [20]. A hybrid tracking system, including eight CCD cameras for optical motion-tracking and a data glove, collects information on body motion and hand gestures of a worker performing a manual handling task. After performing automatic motion recognition, the operation is evaluated with the Maynard Operation Sequence Technique (MOST), a simplified motion-time evaluation derived from MTM. Both approaches show limitations: [19] is limited to seated operations (see [20] p.341); in [20] not all MOST motions could be recognized automatically. Instead of realizing a fully automated time study Elnekave and Gilad [21] improve the traditional videotape analysis approach. On average, time savings of 43 percent were attained by using enhanced video software during the conduction of MOST analysis for five case studies, compared to a standard video cassette recorder. This software includes advanced playback options, measurement of distances implicated in the tasks executed by the operators and a work sampling module.

Among other approaches, motion capture is also applied to the training of manufacturing personnel. Müller et al. supplement a workplace with a Kinect™ sensor and a learning environment containing computer supported instructions and an e-learning module. An algorithm extracts the position of the worker’s hands from the sensor data, determines the individual operation and informs the operator about the next step of the assembly process. During the study, the initial learning of the given assembly process could not be accelerated compared to the training with paper-based instruction due to – among other things – challenges in hand tracking in different lighting conditions [22]. Stiefmeier et al. [11] choose wearable activity tracking to support the training and work of assembly line operators. The study emphasizes the importance of redundant and diverse sensor systems to ensure reliable tracking of assembly steps. Apart from wearable sensors (Inertial Measurement Unit (IMU), Radio Frequency Identification (RFID) reader, force-sensitive resistors (FSR)) further sensors are placed on tools (IMU, RFID tags) and the main assembly (FSR, magnetic switches) where the sensors on the assembly were most crucial for activity recognition. The task tracking is implemented through with a finite state machine approach that identifies the transition between individual activities by the presence and absence of signal combinations. In the second scenario, which was not conducted in a training environment, 27 sensors were integrated into a jacket, as sensors on assemblies were not applicable. Activity recognition was done through data segmentation and encoding the data into continuous strings which are matched against motion string templates [11]. The approach reached activity recognition rates close to 100 percent in the first scenario and 74 percent in the second setting. In [23] a single wrist-worn IMU is sufficient to distinguish between hammering, screwing with a screwdriver or a power drill, spanner use and null data with an average accuracy of almost 88 percent. The classification was done using features derived from acceleration and angular speed data, as well as input into a nearest neighbor method.

In contrast to the human-centric motion capture approaches [24] focuses on real-time object tracking in a manufacturing environment. Wang et al. propose to attach RFID tags to every object moving along an assembly line and to evenly equip the working area with RFID readers. This allows for real-time object position and movement path prediction and tracking, thereby permitting real-time planning and control of the manufacturing assembly line.

As a result of industry 4.0, the number of assistance systems for biomechanical analyses has increased. Assistance systems can be applied to provide process workflow and assembly support for the operative personnel, using computer vision-based tracking systems such as depth cameras to capture e.g. the withdrawal of material or to recognize parts and their orientation. [25] Parallel in-situ projections or visualizations of workflow and process data with mixed reality systems provide additional support for the targeted and guided production process. Component mix-up can be prevented and the assembly process is less error-prone [26].

4. Research gaps

The state of the art shows that systems for the detection of manual assembly steps already exist. These systems are generally used for quality monitoring or training, for example to recognize whether all the necessary process steps have been taken. The systems normally must be taught in advance: It is usually necessary to define a selection of possible processes or acquire an exact knowledge of the processes. But in particular, when assembling with long processing times, there is no predefined process order or information about individual process steps are missing. Therefore, a more flexible system is necessary. Other limitations of previous approaches using sensors to record manual assembly processes are amongst others:

- Most systems use body-worn sensors: The human-oriented evaluation of work processes is one approach to acquire processing times. This could cause problems in the field of privacy protection and these sensors can handicap the worker.
- The use of systems with motion tracking is often associated with great effort (costs, time). Moreover, the movements of humans are recorded in great detail. In terms of production optimization, however, the process view is more interesting than human movements.
- The assembly detection systems are so far essentially aligned and evaluated in test environments (no real workspace environment, short duration).
To sum up, there was the desire for a solution with maximum flexibility that can be used for production optimization in all manual assemblies and that defines its own processes.

5. Analysis system

This paper presents a system for automatic analysis of manual assembly processes focusing on the assembly process itself. Relevant process data are generated through connecting on-site production equipment with alternative digital sensors and data acquisition systems. Acquired data are used for production optimization, scheduling or control.

The system can be adapted to every assembly process because of its modular and scalable structure. After acquiring the data, algorithms for a data processing and an evaluation are used. Fig. 2 shows the steps from the assembly process to process times and evaluation results.

Fig. 2. Steps to obtain process times and evaluation results.

The system consists of three different layers:

- Setting on the shop floor: The system is based on sensors that are installed directly on the shop floor.
- IT-architecture (interfaces and services): The sensors are then connected to interfaces and services accessing them.
- Evaluation: Finally, at the top level the data are analyzed.

5.1. Setting

Sensors and measurement technologies are installed on parts, products, tools and operation materials. There are no sensors installed on workers. The system uses contacting and non-contacting sensors and the recording is wireless.

To use the system, the sensors have to be positioned and installed. After this, no further intervention by an employee is necessary and the data acquisition runs. The following figure shows tools equipped with sensors.

Fig. 3. Tools with sensors.

A wide range of different sensors is required, because the detection of each different process step needs an individual sensor combination. Which sensors are needed to identify a certain process step depends on the used tools, material, part size, part number and movements. Table 1 shows the selected sensors which are in use today.

Table 1: List of currently used sensors

<table>
<thead>
<tr>
<th>Type of sensor</th>
<th>Task</th>
</tr>
</thead>
<tbody>
<tr>
<td>RFID tags and reader</td>
<td>Localization of part or tool</td>
</tr>
<tr>
<td>Accelerometer</td>
<td>Vibration detection</td>
</tr>
<tr>
<td>Magnetometer</td>
<td>Movement by magnetic field detection</td>
</tr>
<tr>
<td>Gyroscope</td>
<td>Movement detection</td>
</tr>
<tr>
<td>Thermometer and hygrometer</td>
<td>Temperature and humidity measurement</td>
</tr>
<tr>
<td>Ambient light sensor</td>
<td>Movement detection</td>
</tr>
<tr>
<td>Electronic scales</td>
<td>Weight measurement, part extraction check</td>
</tr>
<tr>
<td>Distance sensors (capacitive and inductive)</td>
<td>Part extraction check</td>
</tr>
</tbody>
</table>

This list will be expanded through further research and development. With the final sensor selection, the goal to have a sensor box including all sensors necessary to detect all of the main assembly process steps should be reached. The primary challenges in identifying the right sensors are the size and the sensitivity of the sensors. The sensors ought not interfere with the assembly process by handicapping the workers and have to be resistant to environmental impact.

5.2. IT-architecture

The system is built in Node.js and is responsible for the data acquisition, device management, processing of the data and the understandable visualization of the results as well as the adjustment of the data processing. The goal is to provide the user with high flexibility and high fault tolerance. The presented system uses MongoDB, a NoSQL database.

It obtains all information through external sensors. These sensors are always a part of a device by definition. Only devices are able to communicate directly to the system, in the present case via Wi-Fi and USB. A sketch of the device and the sensors connected to the system is visualized in Fig. 4.
Fig. 4. Device structure.

The user is now able to link the devices and their containing sensors to an entity. This enables to assign every dataset from a sensor to an entity. The entity is a database document which can be any physical object which has to be tracked, for example hammer, drilling machine, workpiece, working desk, etc. Fig. 5 shows an entity and the enclosed devices from a database schema view.

Fig. 5. Entity structure.

Entities can be separated into entity groups, for better structure and to simplify the process of creating context. This is especially useful for detecting connected workpieces in assembly.

Entities as well as entity groups own a set of processes. Processes are templates of calculations or data manipulation algorithms. The combining of a sensor with a process template is called a “processing”. A processing is a unique function with predefined input. The amount of inputs and outputs is not limited. An entity can have more than one processing and the result of each processing is a condition. Fig. 6 shows the connection between entity, device and process templates which lead to a processing.

Fig. 6. Process templates.

To achieve a high level of meaningful conditions, the processing output is taken and used as input for new processing calculations. The higher a processing layer, the more data and information has already been processed.

The first processing layer deals with sensor data, the following processing layers use conditions as input. Conditions are always binary, and the process algorithm is based on simple logical operations. The inputs in the first processing layer are limited by the physical unit like temperature, momentum, density, pressure etc. which are defined by the sensor output. The input of the following processing layers is limited by the condition type. Condition types can vary depending on the entity. Possible condition types could be movement (e.g. ‘part/tool is moving’, ‘part/tool is not moving’), hitting, vibration, spinning, lifting, etc. The following Fig. 7 illustrates the linking between processings.

Fig. 7. Processing.

Due to this standardization of the processing a high degree of reusability is given. The benefits are on the side of the programmer and the user. The programmer has to write the code only once per entity type and the user has to handle just one model to link the processing. The data structure aims to have an impact on the design process experienced by the user. To simplify the data analyzing work even more, the processing can own an interface for different parameters like thresholds and limit values. These parameters have a filter function and an impact on the output of the processing. Fig. 8 shows a simplified sketch of an interface in a processing.

Fig. 8. Interface.

At present, the number of processing layers is still kept to a minimum which is going to be expanded in the future.

5.3. Evaluation

Each attached sensor transmits its measured values to the evaluation system over the course of time. As a result, different sensor values are available for each time stamp. Tests have proven that often several sensors have to be evaluated at the same time in order to come to a conclusion about the process step. As described in chapter 5.2, information is aggregated more and more with increasing processing layer levels and finally transformed into information about the assembly process, e.g. with the help of algorithms and patterns. In the future the system could provide for instance the following evaluation:

- total processing time
- time of each process step (commencement and ending date)
- sequence of assembly processes
- localization
- quality control
- condition monitoring
As soon as the system has recognized which process steps are carried out, optimization methods can work on the data basis.

6. Benefit

The approach presented in this publication provides great benefit: Manual assembly processes can be evaluated and the efficiency and effectiveness of the assembly process can be improved. The system creates transparency, so that manual assembly processes can be planned, scheduled and controlled better. This will save costs and time along with an improvement in quality.

Improved planning leads to superior planning of capacities as there is now transparency on the time individual process steps take. Efficiency will increase and assembly processes can be improved and optimized. In addition, orders can be planned better with reliable information on throughput times.

The system also provides an essential advantage in the flexible analysis: It can be applied in all use cases and high time savings for analysis and further evaluation can be achieved. Moreover, the historical evaluation can be changed by adjusting the limit values and tolerances later on.

Manual assembly processes are automatically and continuously analyzed. This leads to a homogeneous result of all considered processes. Even if several processes are considered on different days, the analysis is always the same. In the long term, a database will be set up with experience data which could then be used for other assembly tasks.

Additionally, the system does not interfere with the process and the process does not have to be interrupted. Further advantages are the choice of sensors, because no sensors are attached to workers and no optical motion detection takes place.

7. Conclusion and outlook

In conclusion, an approach for automated capture and analysis of manual assembly operations has been presented. Manual assembly processes can be recorded and evaluated, saving time and creating new possibilities for evaluation.

Further work will be carried out to improve accuracy and to transfer the prototype to industrial application. With a rising number of implemented use cases the data base is constantly enhanced and due to additional sensors, more and more data will be collected. In addition, the evaluation algorithms are improving. Consequently, the evaluation will be more accurate. In the future, less information will have to be made available to the system. Furthermore, the negative impact of disturbing influences should be investigated. Also, the variable granularity or detailing can still be adjusted; however, more experience in industrial application is necessary. Lastly, the influence on the worker by the system is to be analyzed.

References


