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Automated Generation of a Digital Twin Using Scan and Object Detection for Data Acquisition

Automatisierte Erstellung eines digitalen Zwillings mithilfe von Scans und Objekterkennung

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Abstract: The simulation of production processes using a digital twin can be utilised for prospective planning, analysis of existing systems or process-parallel monitoring. In all cases, the digital twin offers manufacturing companies room for improvement in production and logistics processes leading to cost savings. However, many companies, especially small and medium-sized enterprises, do not apply the technology, because the generation of a digital twin is cost-, time- and resource-intensive and IT expertise is required. These obstacles will be overcome by generating a digital twin using a scan of the shop floor and subsequent object recognition. The following sections describe which parameters and data must be acquired in order to generate a digital twin automatically. It is also shown how the data is processed to generate the digital twin and how object recognition is integrated into it. An overview of the entire process chain is given.

1 Introduction

The digital factory has already been recognised as a strategically competitive advantage by the industry over ten years ago. The results of a study conducted by the Fraunhofer IPA show that more than twenty percent of more than hundred German companies surveyed from small and medium-sized enterprises and large industry successfully used digital factory methods and tools in 2005. Almost ninety percent of the companies surveyed stated that they would like to deal with the topic of the digital factory in the following years (Bierschenk et al. 2005). Many fields of application exist today for digital models of a production system in a discrete event simulation (DES), e. g. planning of factoriess, layout optimization in the shop floor, approval processes in the area of reconstruction and fire protection or optimization of

production processes. According to Wenzel and Peter (2017), simulation in particular is a core element of the digital factory and is becoming increasingly important as a result of developments in the area of digitisation. Simulation in production and logistics has been scientifically investigated and established for a long time - e. g. by Spieckermann (2005), Rabe et al. (2008) or Wenzel et al. (2008). According to Nyhuis and Wiendahl (2012), simulation supports companies in optimising logistical targets, e. g. with regard to adherence to schedules, throughput times, performance, inventory and costs. The benefits in the area of material flow planning are rated by companies as high or very high (Bierschenk et al. 2005).

Nevertheless, current studies prove that the use of simulation models for production systems (hereinafter also referred as "digital twin") in small and medium-sized enterprises is still not standard (Bischoff et al. 2015). The main reasons for this are the following obstacles (Bischoff et al. 2015; Denkena et al. 2016; Weissman and Wegerer 2019):

1. Non-transparent procurement costs (e. g. due to manual or inefficient creation of the digital twin).
2. Required IT expertise (e. g. due to inefficient or overly expensive services).
3. Unpredictable operating expenses (e. g. due to manual or inefficient adaptation of the digital twin).
4. Lack of knowledge regarding available simulation tools and application areas as well as the achievable benefits.

There are various approaches to overcome the described obstacles. The following chapter will first give an overview of existing approaches in literature. Based on this, a novel approach is then presented.

2 State of the Art

Alongside the digital twin addressed in this article, the concept of the digital shadow exists in the literature. The digital twin is characterised by the most accurate physical representation of the manufacturing process in a model. In contrast, according to Schuh et al. (2017), the digital shadow merely represents "a sufficiently accurate representation of the relevant data in production, development, and related areas". The digital shadow therefore only requires data relevant to the process. For about twenty years, approaches to the automated generation of digital production twins in the form of simulation models have been discussed in the literature to eliminate the above-mentioned obstacles. The main approaches are based on the combination of existing technology components. Other approaches, however, follow data-driven model generation (Bergmann 2013). Important research papers, which can be found in the literature, are briefly summarised in Table 1 below:

Table 1: *Distinction from existing research work*

Reference	Summary of key achievements
Lorenz and Schulze (1995)	• Generation of layouts for simulation based on CAD data • Direct user queries or integration of special databases to include information that cannot be derived from the layout

Reference	Summary of key achievements
Selke (2005)	• Filling of a simulation database by filtering, collecting, exporting and manually supplementing operational data • Model generation using predefined strategies for automatic interpretation of operational data • Development of a prototype that is not suitable for productive use
Lindskog et al. (2016)	• Analysis of five studies on 3D modelling of real objects by laser scanning in an industrial environment • Generation of 3D CAD models, but no further processing to a simulation model
Biesinger et al. (2018)	• Description of a case study in which a digital twin in the automotive industry is automatically updated • Various data are automatically read out and the digital twin is updated with this information
Goerzig and Bauernhansl (2018)	• Foundation and first steps aiming at the development of a method for the holistic planning of the digital transformation in small and medium-sized enterprises • Challenges are the complexity of the approaches and their impracticability for rapid implementation
Martínez et al. (2018)	• Automatic generation of a process simulation model from 3D CAD data • The approach describes the generation of the simulation model, but requires that the 3D data is already available

In contrast to the shown approaches in the literature, an efficient procedure for the entire creation process of a digital twin is missing. There is a lack of a comprehensive service, especially for small and medium sized enterprises, with which companies can reduce initial cost.

3 Efficient Generation of a Digital Twin

With this paper, a method is introduced to solve the mentioned obstacles and which, in contrast to the work described in the literature, allows a preferably automated generation of a digital twin. An overall process is aimed at, a service for the generation of a DES. The method was developed within the research project "DigiTwin". The practical relevance of the project will be assessed by the consortium with the German companies isb - innovative software business GmbH, PROSTEP AG and Bornemann Gewindetechnik GmbH & Co. KG. The approach is based on the application of fast scans of the shop floor and a subsequent object recognition. The production layout (e. g. size and location of objects) and production logics, such as machine types and transport routes, are captured as automatically as possible and mapped to scale in

digital simulation models. Figure 1 illustrates this set - up. Three different input sources for the generation of the digital twin are shown.

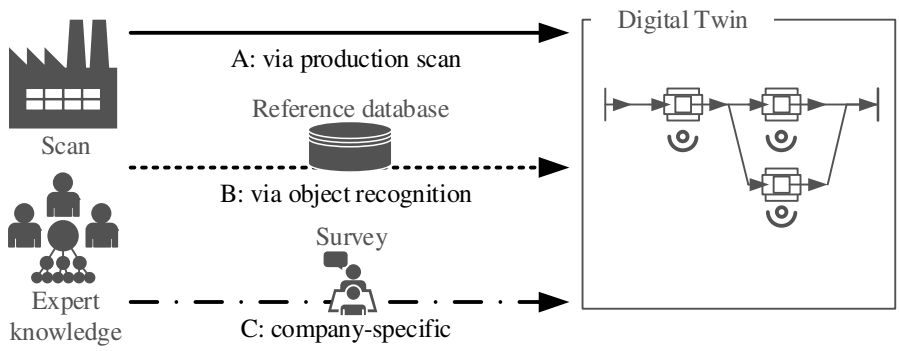

Figure 1: *Mapping of relevant information for the digital twin*

Group A parameters can be obtained directly from a scan (e. g. machine geometries). Different scanning methods, such as laser scanning or photogrammetry, are investigated and the most suitable method will be selected. The parameters of group B (e. g. machine types) require additional object recognition. To record these parameters, a reference database is necessary in addition to the production scan. A matching of the scanned object with the CAD models of the reference database provides the required input parameters for the digital twin. The parameters from groups A and B can therefore be acquired automatically. Finally, the parameters of group C are determined on a company-specific basis, since these company-specific characteristics cannot be captured generically or automatically (e. g. machine ID). For the acquisition of this parameter group, appropriate forms must be developed, so that a survey of typical parameters can be carried out and this process can at least be performed with as little effort as possible.

4 Required Parameters for the Digital Twin

After introducing the parameter groups for efficiently generating a digital twin, the following section gives an overview about the specific data required. The aim at this point is to construe the subsequent DES in such a way that the use cases described below can be simulated. In general, different applications for simulation of production systems are conceivable at this point. For this approach, the plethora of conceivable applications was reduced by selecting prioritised cases by the application partner Bornemann Gewindetechnik GmbH & Co. KG. The selected use cases are briefly presented in the following Table 2:

Table 2: *Selected applications for processing with the digital twin respectively DES*

Use case	Description
Factory planning	Reorganisation of structures based on new concepts (e. g. push or pull), layout planning or material flow analyses

Investment planning	Integration of robotics or new technologies (e. g. 3D print), purchase of new machines
Capacity planning	Trade-off between capacity requirements with actually available capacity to optimise capacity planning
Bottleneck analysis	Identification of workplaces, machines or stations with critical load
Inventory management	Planning and optimising the stocking of products and materials
In-house material transport	Planning and optimisation of the material supply

The selection is wide-ranging and therefore suitable as a basis to determine the required parameters. Thus, long-term planning processes (first three points) and analyses of the existing system (last three points) are both considered. From closer examination of use cases, it becomes clear that the objects shown in Figure 2 must be built into the simulation model. Only with these objects, the mentioned use cases can be executed. Therefore, these objects must be sufficiently recognised and created for the digital twin. This is achieved with the three groups mentioned above.

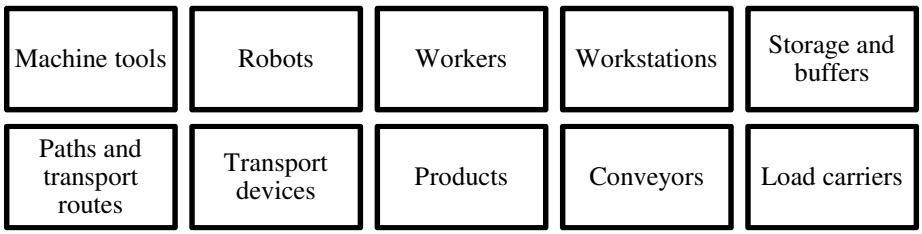

Figure 2: *Objects of a production system required for the use cases*

For each object, there are different parameters that are relevant for the simulation model. This will be exemplary explained in the following by the object "Machine tools”. This approach uses distinct parameter groups. First, for the object type "Machine tools", the parameters that can be obtained directly by the scanning process are determined. These parameters consist mainly of the spatial information, such as length, width and height as well as the location in the factory. The dimensions of the bounding box are used here as an acceptable simplification. Since the simulation model is not able to process exact CAD data, this simplification is useful. Furthermore, machine labels can be determined, if they are visibly attached to the machine. However, experts must validate these in order to exclude incorrect assignments. Further useful parameters are spatial relations to other objects of the production system. For example, it is important for the simulation model to recognise that there is a workstation next to a machine that operates or sets up the machine. Another important parameter of this group is process times.

For the second group of parameters, an object detection is connected upstream. Accordingly, in addition to the spatial information, further information is added to the

model. The crucial step for the object group of the machines is to recognise the concrete machine type. This is achieved by a similarity analysis with an external database. The procedure for this is explained in Section 5. The advantage of this procedure is that any information about a machine type can be stored in the external database. For the research project, many different data for machines, including 3D CAD data, were procured from various machine manufacturers and stored in the database. At this point, it is relevant for the consideration which functions and tasks a machine is able to perform. This can be used to assign production steps in the simulation model. Object recognition thus makes this stored information available for the digital twin. This procedure can also be applied to other objects, such as workstations or means of transport, to store comprehensive information in the external database and thus provide it to the digital twin.

The third group includes company-specific data - especially information that cannot be captured with a scan and subsequent object recognition. Correspondingly, this parameter group for the consideration of machine tools includes: The linking logic to upstream and downstream processes or machines, processing, setup, distribution and recovery times (if not recorded by the scan), setup information, downtimes as well as their distribution and shift calendar and availability periods. In addition, specifics of the respective simulation software may have to be determined, e. g. classifications of the resource type or reference periods for statistical recording. Of course, not all company specifics can be listed generically, but the most common information is stored that way. An additional manual adjustment of the digital twin is still to be expected, but this adjustment effort can be significantly reduced.

A total of 321 parameters for the digital twin were identified in the manner described above. A parameter group was assigned to each of these parameters. In addition, a description of the parameter, a label for the data transmission, whether it is a mandatory entry, a data type, the requirement for updating or continuous recording and an assignment to the described use cases were compiled for documentation purposes. With this, it is possible to develop a data interface to a simulation software to automatically generate a model. The simulation model is constructed at this point by a pre-programmed algorithm, which receives the corresponding data from the interface and then implements this information in a model. In the end, only a little manual effort is required to make the final adjustments.

5 Database Model

The general approach for an automatic generation of a digital twin is roughly depicted in Figure 3. Starting from the existing production system, it consists of three fundamental steps:

1. Scanning the production system to obtain a point cloud,
2. modelling with the objective of creating a mock-up (as CAD model) and
3. simulation modelling for the generation of a digital twin.

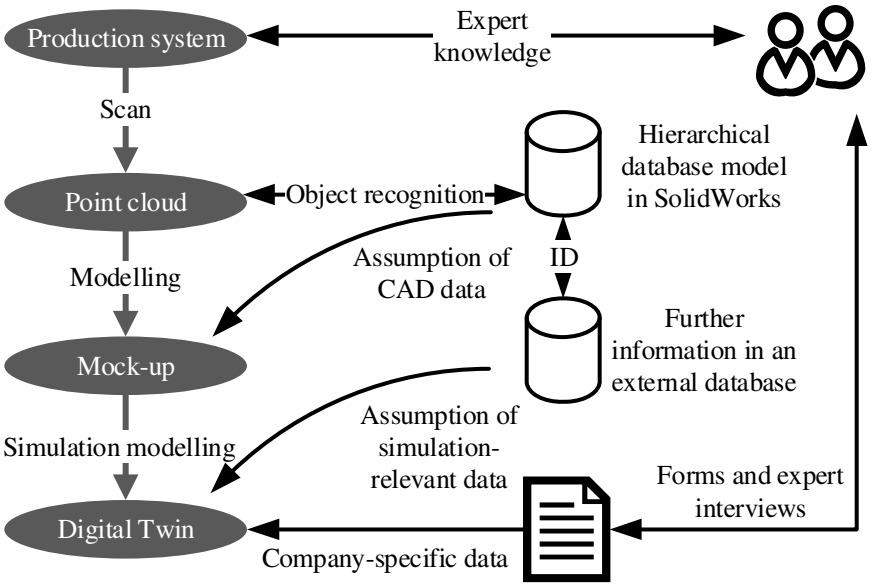

Figure 3: *Schematic representation of the database model*

Step 1 is described in the following Section 6 in detail. Modelling (Step 2) needs to be heavily supported by object recognition to save time and effort. To achieve this, a database is required, in which CAD models of suspected objects, i. e. different machines or comparative images of human beings, are stored. In this case, a hierarchical database in the CAD software SolidWorks is used to not convert the data for object recognition. Scalability is an important requirement for this approach, because theoretically each of the infinite built objects needs to be recognised. Further object parameters are stored in an external database. This information is not necessary for the mock-up, but for the digital twin and therefore for simulation modelling (Step 3). Automation ML is used as an interface between SolidWorks and the simulation software for the digital twin (Siemens Plant Simulation) in order to retain the class structure. The expert knowledge and the company - specific information of the production system need to be acquired by forms or expert interviews and inserted in the simulation modelling process. It is also conceivable that data could be taken directly from IT systems such as from production planning and control systems, workshop control systems or machines (Denkena et al. 2017).

6 Scan Process and Results

In this last content-related section, the scan process performed at the application partner is briefly described. For the scan of a factory, several procedures are generally conceivable. 3D range imaging camera (i. e. stereo triangulation, structured light and time of flight), photogrammetry and laser scanning in particular should be mentioned here (Chen et al. 2017). The following results were reached with laser scanning. However, the use of photogrammetry is currently being examined, as this would simplify the generation of the point cloud and in turn reduce costs. It would also be

feasible to make continuous recording easier, which would allow recording changes over time (such as for determining processing times).

Figure 4 shows a photo of a section of the factory at the application partner Bornemann Gewindetechnik GmbH & Co. KG.

Figure 4: *Photo of the scanned area of the factory*

The photo should serve as a point of comparison to illustrate the quality and level of detail of the resulting point cloud shown in Figure 5. It is also worth mentioning at this point that only the result of one scanning process is shown here. For the scanning of the entire production at the application partner, more than seventy scans were necessary. A scan takes about eight minutes including setting up the scanner. Since approximately forty million points are generated with each scan, the handling of this large amount of data (in this case approximately twenty gigabyte) is another relevant issue for this approach.

From the two figures and their comparison, it becomes clear that a very detailed point cloud can be generated by laser scanning. The further processing through object recognition and the subsequent modelling up to the digital twin gains a sufficient basis. However, challenges for the next steps also emerge. For example, the point cloud represents a section that becomes an overall image by combining it with other point clouds. Furthermore, the resulting overall picture is hardly manageable because the amount of data is too large. Accordingly, a meaningful segmentation into separate objects must take place. This is the only way to achieve useful object recognition. At this point, the question arises whether the degree of detail of the laser scanning is necessary. In addition, the example shown demonstrates that in production, especially when scanning during production times, occlusions and covers need to be handled.

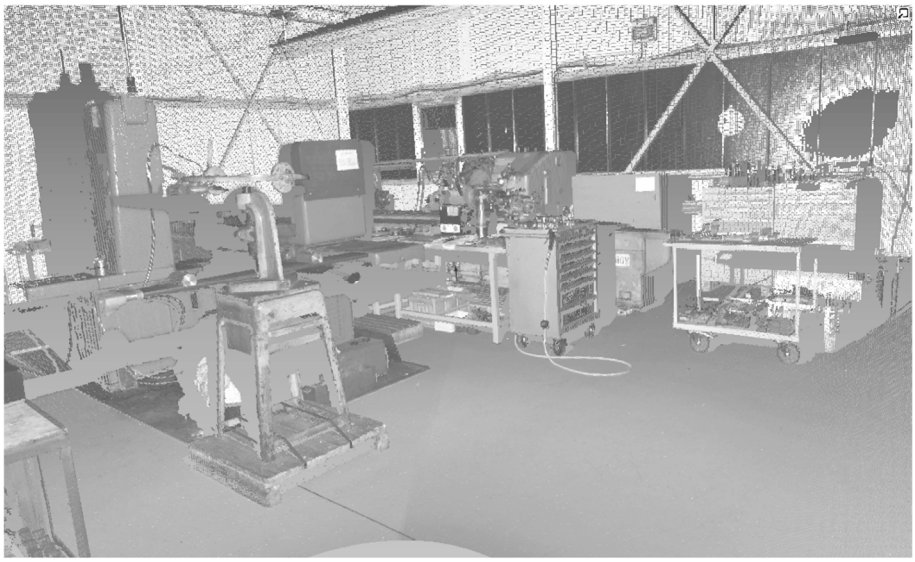

Figure 5: *Exemplary point cloud as a result of the scanning process*

7 Conclusions and Outlook

In the presented paper an approach was introduced, which enabled the generation of a digital twin in the most automated way. With this, the digital twin and the use of DES provide manufacturing companies improvement potential for production systems leading to cost savings. It was demonstrated how the overall procedure for the automated generation of a digital twin can take shape, which data and information is required and how it is stored in a useful and process-oriented way. Finally, first promising results of the laser scanning were shown. However, it must be investigated which alternatives (e. g. photogrammetry) can be useful. Likewise, the overall process must be further expanded and obstacles, such as the occlusion of objects, must be removed. If this is successful, the efficient generation of a digital twin can be provided as a service to companies.

Acknowledgements

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