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Automated Generation of a Digital Twin of a Manufacturing System by Using Scan and Convolutional Neural Networks

Markus SOMMER[a], Josip STJEPANDIĆ[b1], Sebastian STOBRAWA[c] and Moritz von SODEN[d]
[a]*isb - innovative software business GmbH, Germany*
[b]*PROSTEP AG, Germany*
[c]*Leibniz University Hannover, Institute of Production Engineering and Machine Tools, Germany*
[d]*Bornemann Gewindetechnik GmbH & Co. KG, Germany*

Abstract. The simulation of production processes using a Digital Twin is a promising means for prospective planning, analysis of existing systems or process-parallel monitoring. 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. This obstacle can be removed by a novel approach to generate a Digital Twin using fast scans of the shop floor and subsequent object recognition in the point cloud. We describe how parameters and data should be acquired in order to generate a Digital Twin automatically. An overview of the entire process chain is given. A particular attention is given to the automatic object recognition and its integration into Digital Twin.

Keywords. Digital Twin, Digital Factory, Object Recognition, Indoor Object Acquisition, Simulation

Introduction

The Digital Factory has already been recognised as a strategically competitive advantage by the industry and is closely linked to the company's overall business strategy, that can be implemented throughout the organization. The results of a survey show that 91percent of industrial companies are investing in digital factories and only six percent of respondents describe their factories as being fully digitized yet [1]. Many fields of application exist today for digital models of a production system in a discrete event simulation (DES), e. g. planning of factories, layout optimization in the shop floor, approval processes in the area of reconstruction and fire protection, or optimization of production processes. 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 [2]. Nevertheless, current studies prove that the use of simulation models for production systems (hereinafter also referred as "Digital Twin in manufacturing") in small and medium-sized enterprises is still not standard [3]. The main reasons for this are [4][5]:

[1] Corresponding Author, Mail: josip.stjepandic@prostep.com.

Non-transparent procurement costs, required IT expertise (e. g. due to inefficient or overly expensive services), non predictable operating costs (e. g. owing to manual or inefficient adaptation of the Digital Twin), and 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. A preliminary report has been presented [6]. Deep product semantic as well as high quality CAD data of all geometrical objects in all stages of planning process are the pre-requisite for seamless downstream processes [7]. With fast scans of the shop floor and subsequent object recognition, the production layout (e. g. size and location of the objects) and the production semantic (e. g. machine types, transport routes) can be recorded as automated as possible and visualized true to scale in digital models [8][9] [10]. The identification of CAD models from a reference library and the transfer of geometry and other object data (e. g. machine types) as modular objects directly from the library significantly reduce the scan times for a first rough "prescan" of the production [11]. At the same time, database reconciliation enables the use of simpler and cheaper scanning methods [12]. The definition of suitable interfaces enables the transfer of information into a program for simulation of production systems and a precisely fitting Digital Twin of the manufacturing can be generated - almost without manual interventions [13][14].

The remainder of this paper is structured as follows: In Section 1 the solution concept and demonstration of the use cases are presented with the related discussion in Section 2. Finally, Section 3 summarizes the conclusions and outlook.

1. Solution concept

1.1. *General approach*

The general approach for an automatic generation of a Digital Twin is given in source [6]. Starting from the existing production system, it consists of three fundamental steps:

1. Scanning the production system to obtain a point cloud (section 1.2),
2. Modelling with the objective of creating a mock-up a as CAD model (section 1.3), and
3. Simulation modelling for the generation of a Digital Twin (section 1.4).

Scanning is conducted by using either high-resolution video camera for prescan standard terrestric scanner (Zoller + Fröhlich, FARO, Leica or similar) or a mobile high-resolution camera. Modeling need to be heavily supported by object recognition to save time, which would be spent in the step of manual remastering. The object parameter (e. g. machine characteristics) are stored in the CAD library and additionally linked with an external database. Scalability is an important requirement for this approach because theoretically each of the infinite built objects need to be recognized. The expert knowledge of the built environment need to be acquired by forms or expert interviews and also inserted in the simulation process. Provision of adequate 3D models and additional specific information of the factory equipment by their manufacturer is standard at this time. Usually, models are delivered in neutral and native formats. For the intended purpose, cooperation with the manufacturers of the machine tools has been established to get appropriate and accurate 3D models. For older objects which does not have 3D documentation, an alternative approach need to be developed to derive a feature-based model, e. g. by recognition of singular features.

1.2. *Scanning the production system to obtain a point cloud*

The scanning of production layouts is largely done with a laser scanner. The single scans are connected with each other via registration. If High Dynamic Range (HDR) images are taken in addition to the laser scan with a standard triggering, a maximum of eight scans can be performed per hour. If the factory is filled with a lot of machines, a large number of single scans are required to avoid the shadowing. During the scan, no further information about specific machines can be included in the 3D point cloud. Alternatively, the shop floor is filmed with a camera and depth image or a stereoscopic camera [9]. It is possible to include information about QR code, language, etc. during the recording in the 3D point cloud. The camera can be mounted on a drone, tripod or held in the hand.

During the scanning process the user is shown the progress via a 3D mesh. The 3D mesh is faded into the filmed image. Due to the color change between scanned and not scanned, the user is able to follow the progress. The 3D mesh is built up based on feature recognition. In the case of structurally weak areas, the user must film more intensively, so thatmore images of the area are saved. The individual images are streamed to a central system via WLAN. The generation of the 3D point cloud is done in the following step. With the offline generation of the 3D point cloud it it is also possible to carry out further optimization over the complete 3D point cloud and thus further increase the accuracy.

It is also planned to integrate mobile phones with a depth image. These mobile phones provide a color and depth image. With this procedure the user is able to scan a layout of the shop floor with a mobile phone at any time. Furthermore, the investment in such mobile phones is manageable at about 800 €. The accuracy is currently around two centimeters and is therefore sufficient for the specifications (Figure 1).

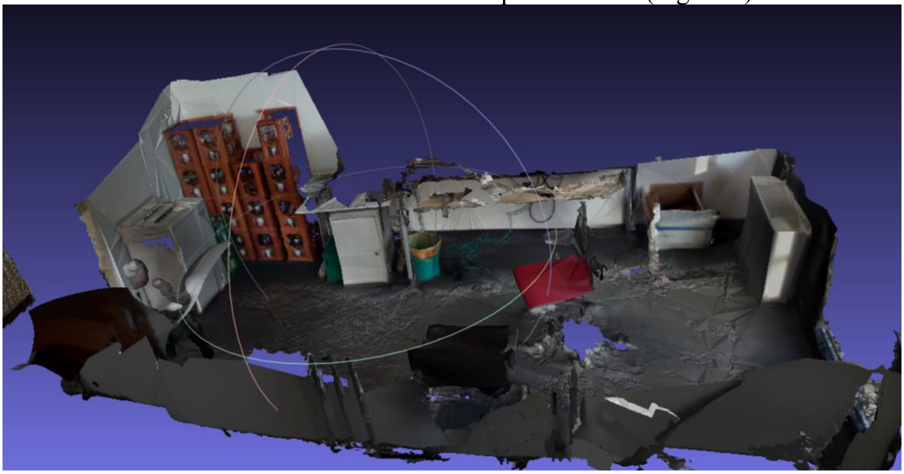

Figure 1. 3D Reconstruction with film.

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 for object recognotion. 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.

1.3. *Modelling with the objective of generating a mock-up*

Object recognition based on the point cloud from scanner was taken as a basis procedure for generating a mock-up. The approach is to set up a library with all relevant objects as parametric models and recognize them in any point cloud as often as it occurs. Subsequently, the generation of a mock-up would be reduced to recognition of already known objects and minimal manual rework. For this purpose, an automated object recognition workflow was built up with a modular structure to consider different recognition approaches, based on previous comparison of publicly available frameworks [7][15]. This workflow provides the possibility to embedd different recognition algoritms. Based on previous research [15], three popular algorithms were taken in the shortlist: VoxNet [16], VoxelNet [17] and G3DNet [18].

VoxNet and VoxelNet transform the point cloud into voxels that each contain a small amount of points. It produces bounding boxes based on the features of the voxels. G3DNet, as a point based method, is a DL architecture that is used in 3D object classification and segmentation. It attempts to semantically segment each point in the data by learning the local and global features of the points and classifying each of them. Clusters of points with the same labels can be detected as objects.

A basic amount of relevant objects was selected and transformed from SolidWorks into point cloud using a virtual scanner (Helios). Augmentation of data has been done with 24 rotations (Figure 2). This data set was used for training of a Convolutional Neural Network (CNN). For testing (e. g. object recognition in practical sense) several measures were necessary. The large amount of data (approx. 6 GB for area of 1.000 m^2) causes the data processing to be slow and time-consuming. This would not be acceptable in term of a smooth and fast workflow. Furthermore, each data set must be checked and adjusted manually, because during the scanning procedure undesired reflections, in particular on glass surface, occur, which must be removed as "false data" by using a point cloud editor.

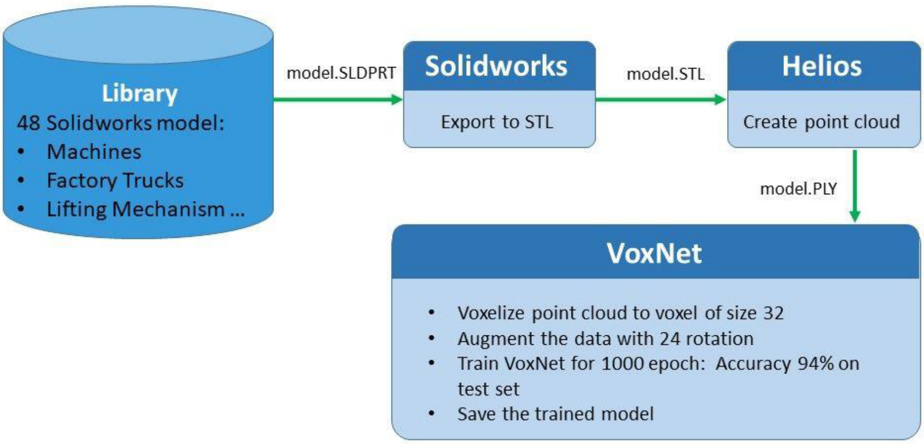

Figure 2. Training procedure, (e.g. based on VoxNet [16]).

Additional methods were developed to simplify object recognition. Although object recognition algoritms are capable to search for objects in each space, for an intended industrial explotation some preprocessing and adjustment in sense of subdivision (segmentation) of huge spaces (and data volumes vice versa) look promising. First issue was a preselection of smaller agglomerations in the entire point cloud which are assumed to contain an object, by using a Point Cloud Library (PCL) module [19]. PCL presents an approach to the subject of 3D perception of point coulds and it is meant to provide support for all the common 3D building blocks that applications require. The library contains state-of-the art algorithms for: filtering, feature estimation, surface reconstruction, registration, model fitting and segmentation. PCL is supported by an international community of robotics and perception researchers. In particular, the functions for filtering and segmentation of a point cloud were applied.

Cluster extraction in the point cloud of a hall proceeds in three steps (Figure 3). At first, the point could is reduced (sparsed) by using a voxel grid filter. Subsequently some unnecessary objects (floor, walls and the roof points) are removed by using the normal segmenter. Finally, all existing clusters in the hall are extracted by using the Euclidean Cluster Extraction. The result of this module consists of different clusters, which then are used for object prediction in order to determinewhich objects contain the corresponding point cluster.

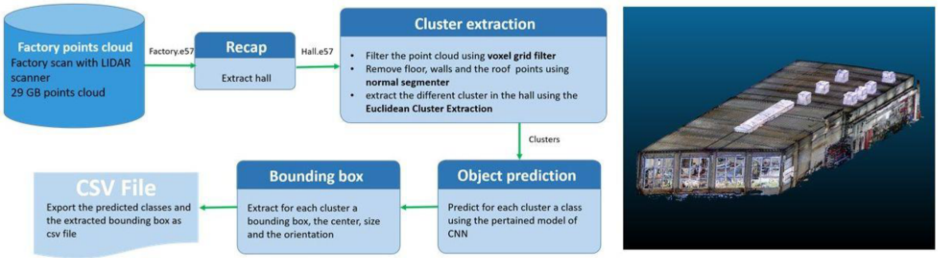

Figure 3. Testing workflow.

To conclude this process chain, two final steps are necessary. At first, for each cluster a bounding box is created to (a) visualize the search space and (b) facilitate the result check and remodeling process, if the recognition is not successful. For an experienced user, it is quite easy to visually check wheter an object is covered by an appropriate bounding box. Furthermore, the bounding box allow a simple check of proper orientation of the recognized object in space. Finally, the collection of clusters, recognized objects and corresponding bounding boxes can be understood as an assembly with singular parts represented either by a model or by a bounding box. Therefore, the framework creates an assembly structure, where singular object are considered as parts of such an assembly. This structure makes the check, modification, repair and extension of such mock-ups much easier [20].

The result of this process chain consists of a CSV file, which works as a steering part, with corresponding objects and bounding boxes as secondary result. Such a structure can easily be imported into, for example, SolidWorks and enhanced with original and parametric SolidWorks parts from the model library. In case of not successful recognition, the user receives a hint for a repair operation. The procedure is repeated until a desired result is achieved. The remaining not properly recognized objects should be processed using the CAD functions of SolidWorks preferrably embedded in macros.

1.4. *Simulation modelling for the generation of a Digital Twin*

In the following the process of simulation modeling is presented in more detail. As mentioned, the representation of the production system generated by the scan and subsequent object recognition is provided as a CAD model. A tree structure is used to arrange and correlate different objects of the production system. The upstream process was therefore designed in such a way that the tree structure distinguishes objects that must also be distinguished for the simulation model, e. g. machines, conveyors or transport equipment.

The export of the model operates as follows: The tree structure of the model is looped through by a macro in SolidWorks. The structure is transferred to an XML file. Since the XML structure can adopt the tree structure of the model, the method mainly adopts the data that is stored in the model and inserts it into the interface [21]. Here, a distinction is made between the input parameters already described, such as machines, conveyors or transport equipment. Every item is assigned attributes. These attributes can be different for various objects, depending on the properties of the objects. For example, processing time can be stored for machines, while for a conveyor belt the length is stored in the XML file. However, it is also possible to store the same attributes for both example objects mentioned. For example, the locations in the model are transferred here in X and Y coordinates. The method then finally generates an XML file that must be saved locally.

Next it is shown how this XML file can be imported into the simulation software and how the model setup is carried out afterwards. The import of the XML file to the simulation software is structured in such a way that all values from the XML file are first written into an internal table of the simulation software. This procedure is useful because it reduces the calculation time. The simulation software gets access to the XML file only once and reads out all data, which leads to a performance advantage. In the program code, this import is therefore autarkic to the model generation. Furthermore, the import is simple, since the structured design of the XML file means that no further adjustments to the data are necessary. For example, the data type, such as string or integer, is transferred and stored accordingly in the simulation software. A further processing of the data is hereby directly feasible. The internal table in the simulation software corresponds to the structure of the XML file, i. e. all attributes correspond to columns and the single objects are listed line by line.

The model construction is carried out by an autarkic method, too. For this, the internal table created by the import is step by step run through. Each line corresponds to an object of the model, so that a simulation module is generated here in each case. In the first step, a case analysis is carried out, which depends on which object type is given. This means that a different generation process is carried out for a machine object type than for a means of conveyor, for example. This corresponds to the differently stored parameters, as mentioned above. In a second step, a part of the model is then generated for each object. For this purpose, the item data is first used to place the object. This data must be scaled to the size of the simulation model surface. Then the specific data is added to the generated module. These differ depending on the type of object. Once the method has been completed, a rudimentary model is obtained. This concludes the automated part of the method. User input is required for further automated generation steps. An additional method has been developed that implements predecessor and successor relationships in the model based on the production schedule. For this the production schedule is required first, which cannot be determined by the scan and the subsequent object recognition. In order to design this process as efficiently as possible, predefined tables have been stored in the model, which can be filled either with minimum effort by experts of the production system or by a defined export, for example from a manufacturing execution system

(MES). By the end of the method or the connected methods after user input, a conditionally operable simulation model is obtained, which can be extended to a Digital Twin. To process the above-mentioned use cases is still missing [22][23]:

- if necessary, further user inputs that lead to a correct representation of the real system in a company-specific manner, such as linking logics,
- an update process that includes current states or input parameters into the system,
- a validation of the model to verify that the generated model correctly represents the processes and
- a connection of the simulation model to the real production control, in order to be able to use the Digital Twin as a support tool.

2. Results and Discussion

The testfield for the approach presented consists of a mid-size factory with three halls and a stockroom. Objects are known from the inventary list, but mostly not documented in CAD. First attempt has been conducted for an overall factory planning scenario which comprises all object types given, but pipelines. The developed framework has been tested using real-life data. The overall recognition rate is high, although the environmental impact is quite negative. More than 66 procent of all object can be trully recognized. However, the recognition procedure is sensitive. It comprises significant issues which need to be resolved. At general: objects with a unique shape like a hanging crane can be recognized easily (Figure 4). During the analysis of the outliers (objects which were either not recognized or recognized false) three main challenges became apparent, which cause the failure of recognition: occlusion, small test base and overfitting.

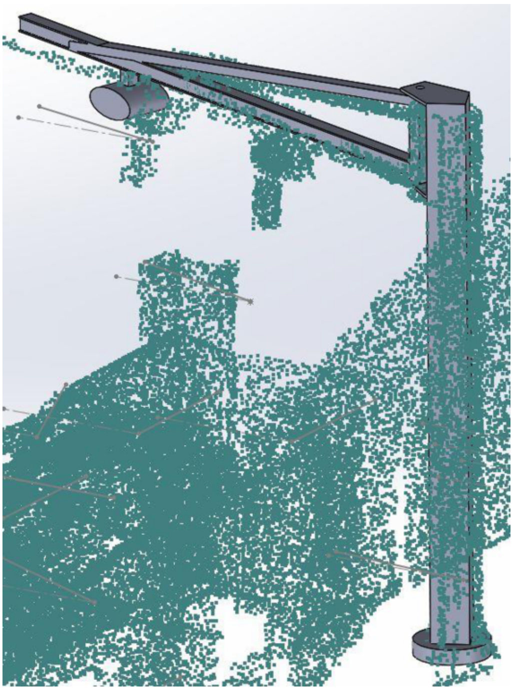

Figure 4. Recognized object: hanging crane.

A single part based algorithm fails completely in case of a significant occlusion. This becomes clear when two or more objects are assumed as one cluster (Figure 5). Although this case does not rarely occur in a factory, it will not be investigated further, but resolved by an additional loop, where clusters which contain more than one object are subdivided manually and then processed separately.

Scanning with a scanner device in the height of approximately one meter above the ground of the factory has a basic drawback that the top area, especially the roof, of these large objects, which are mostly machines, can not be acquired properly. In order to create a closed geometrical object, the top is being approximated by a plane. That is not only a dimensional deviation, but also reduces a possible distinctive characteristics of the object. This drawback is enforced by a basical structural difference between the test object, which is derived from a CAD model by using a virtual scanner and the scanned object.

Overfitting is not obvious, but its impact is ubiquitous. All three used CNN frameworks provide similar results and are sensitive on changes (e. g. input data quality). This implies a strong overfitting. The attempts to reduce overfitting lie in the extension of test base by more model variants.

Figure 5. Impact of occlusion.

This approach has weakness due to the small test base. Here, verification in larger space with more complicated scenes and different types of repetitive objects is needed. A collection like ModelNet for objects in a factory would be supporting. Like for similar studies with a different solution approach [24], some other limitations of this study should be clarified for future research:

1. Utilizing architectural domain knowledge to prevent acquisition of huge unnecessary data. A prescan which identifies the object and its bounding box would be helpful. Furthermore, the identification and evaluation of labels could reduce time for recognition. Prevention of outliers, likeundesired reflexion, would reduce the amount of data.
2. Improve the robustness of recognition methods by better training and continuous learning. Combination of a primar and a secundar recognition algorithm would be a solution,e. g. in case of occlusion [25][26].
3. Better integration of singular steps. Basically, it is about reverse engineering, which was included in leading CAD systems a decade ago. Assuming a fast and reliable

recognition algorithm, it could be implemented as a module in a CAD system and integrated into PLM as an object recognition module.

3. Conclusions and outlook

This paper advances the realm of generation of a Digital Twin in the most automated way in a built environment with complicated scenes (e. g. indoor environments with repetitive, irregular-shaped objects, and noisy measurement data as input). With this, the Digital Twin and the use of discrete event simulation provide manufacturing companies improvement potential for production systems leading to cost savings. It was shown how the overall procedure for the automated generation of a Digital Twin can take shape, which information is required and how it is stored in a useful and process-oriented way.

Future research can be conducted in four directions. First, the effectiveness of the proposed approach should be tested on other complicated cases with less obvious repetitions to make the procedure more stable [24]. Secondly, although the results of the laser scanning are promising, this way of shape acquisition is expensive and, therefore, it must be investigated which alternatives, e. g. photogrammetry, can be useful in term of accuracy and data volume [27]. The usage of video camera looks promising, but does not fulfil the accuracy requirements at this time. Thirdly, more advanced object recognition or computer vision methods can be selected to improve the semi-automatic or manual object generation [28]. The object recognition can be improved in multiple ways. Expanding model library would improve the training procedure and reliability of results. Fourthly, the process chain as such contains of several step and can be improved in term of performance and stability. Further simplification can be achieved by using intelligent templates [29] ensuring a deeper modularity [11]. Use of an alternative recognition method with multiple representations can be taken into account too [30].

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