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Voxel-based description model of quality-related data for a holistic quality assurance in additive manufacturing

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Abstract

Additive Manufacturing has opened new possibilities for products in industries such as aerospace, healthcare, and automotive, especially with its ability to create complex geometries and customized shapes. Nevertheless, there are still some challenges to overcome for large-scale industrial production. One barrier to adopt Additive Manufacturing for a large-scale production is the uncertainty about the quality of the final product. Therefore, quality assurance represents a major challenge for Additive Manufacturing. On the one hand, conventional standards are unsuitable for a holistic quality assurance, due to the complex designs made possible by Additive Manufacturing. For geometric inspection those standards are not able to adequately address freeform surfaces of additively manufactured products. On the other hand, the variety of possible defect types occurring at different stages in the Additive Manufacturing process chain require complementary quality control strategies that are currently operated isolated from each other. Therefore, cross-process chain linkage of the measurement data is hampered, and quality-relevant process interaction cannot be considered.

This work presents a voxel model that is able to incorporate multiple defect types and deviations at once and can represent tolerances and deviations of freeform surfaces. This voxel model can therefore act as a quality model for the quality assurance of the component. For this purpose, the data points acquired in the measurements must be registered in a first step. Thereby, different data structures, which can be, for example, volume data or surface data, must be merged without a loss of information. To facilitate this data fusion, a 3D model (nominal model) of the component can be transformed into a structured voxel model, in which each voxel represents a measurement point. The measurement data (actual model), which in this work will be in-situ profile data of each layer acquired by a laser line sensor, is stored in this model. Through this, each nominal voxel can be compared with a corresponding actual voxel, regarding internal defects and geometrical deviations. In addition, tolerances for different defect types can be defined in each voxel, which allows for a statement on the quality of the component.

Geometric modelling, Model, Quality assurance

1. Introduction

With the ability to manufacture components with almost no constraints, Additive Manufacturing (AM) is often referred to as a disruptive technology. Novel applications such as highly functional components for high-tech products that cannot be produced with conventional manufacturing products are enabled through AM.[1] In addition, the possibility to manufacture topologically optimized components offers a high potential for lightweight applications and thus, contributes to more resource-efficient product lifecycles [2]. Nevertheless, AM is still a relatively young manufacturing process, and there are still some challenges to overcome for widespread adoption [1, 3]. One of these challenges is the build-up of process knowledge to ensure a stable manufacturing process and a minimal development time for the qualification of new components and materials [1, 4, 5]. Due to the complexity of the AM processes and the multitude of influencing parameters, it is challenging to link occurring defects to the associated process parameters, which can be monitored by sensors or can be retrieved from the machine [6, 7]. An advantage of AM is that there is the possibility to have a process parallel generation of a quality model through in-situ measurements of different sensors. For in-situ quality assurance, however, it must be possible to assign the defects to corresponding sensor data. For this to be achieved, the sensor data and a nominal model must be transformed into the same coordinate system. Especially for multimodal sensor data, registration requires considerable effort. Since the acquired sensor data sets usually have different resolutions, not every data point of a sensor can be linked to a corresponding data point from another sensor. As a result, information is either lost or additional uncertainty is added to the data set due to the interpolation of data points. [8, 9] In the process chain of additively manufactured products, the AM process is often followed by additional process steps in which also measurements are done. In order to enable traceability of the data to any defects or irregularities that have occurred, cross-process chain linkage of this acquired measurement data must be ensured. However, conventional quality models do not offer the possibility to represent different component states in one model. [10, 11] Since AM components are usually used for high-end products, they must meet high-quality requirements, which, in most cases, means no occurrence of defects. [12] Nevertheless, even with a complete digitization of the components, holistic quality assurance cannot be guaranteed. Especially for topology-optimized components tolerances and deviations cannot be properly treated by existing norms. This is mainly because corresponding norms work with regular geometries that cannot be applied to topology-optimized surfaces and volumes. [13–15] According to the deficits identified, the following requirements for a holistic quality assurance arise:

- *Mapping of different sensor data, machine data, and defect types in one model*
- *Mapping of different component states in one model*
- *Process parallel generation of model for in-situ quality assurance*
- *Efficient evaluation of freeform surfaces*

In this paper, a Voxel-based Quality Assurance approach is presented, which addresses the described requirements. In the first step, the state of the art is summarized and evaluated to which degree it can tackle these requirements. Subsequently, the Voxel-based Quality Assurance is presented and discussed. Finally, a summary and an outlook follow.

2. Related Work and state of the art

2.1. Modelling of geometrical deviations in Additive Manufacturing

Additive Manufacturing and the associated possibility of manufacturing components with complex geometries result in corresponding challenges for geometric quality assurance. In general, geometric quality assurance, i.e., the determination of geometric deviations and their comparison with the tolerances, is carried out based on GPS standards. Thereby, the deviations are determined based on standard geometries. Irregular geometries are tolerated by defining a tolerance zone around the corresponding geometry. [16, 17] Nevertheless, there are also some limitations regarding the GPS standard. On the one hand, there are no methods for the efficient tolerancing of complex structures such as grids or topology-optimized surfaces. On the other hand, it must be possible to define adaptive tolerance zones that take into account the measurement method used and the measurement uncertainty. [15] Despite these disadvantages, which are primarily referred to as the GPS standard, there are some approaches in the literature to define tolerance zones adaptively. Pagani et al. [18] presented an adaptive tolerancing algorithm. They were able to divide complex structures into multiple tolerance zones based on local curvature. However, only transitions and no sharp boundaries between different tolerance zones can be defined. Since the GPS-based approaches primarily work with surface data, they are unsuitable for storing various sensor data and component states, and for a process-parallel generation.

Other promising approaches are voxel-based approaches for determining deviations and tolerancing free-form surfaces. The voxel structure of this geometrical voxel model makes it predestined for in-process generation. [19–21]. Petrò et al. [21] described a method for voxel-based geometrical tolerancing of additively manufactured components. Tolerances could be defined in accordance with the GPS standard. In addition, the authors were able to define much more precise tolerance zones than with previous standards. Nevertheless, defining a tolerance zone makes the model unnecessarily large. This is not conducive to efficient evaluation of the geometry. Another disadvantage of this geometric voxel-based approach is that only the information whether material is present in the voxel or not can be stored. This allows only data from 3D measurement systems to be integrated into the model.

2.2. Data fusion approaches in Additive Manufacturing

To be able to interpret the sensor data in the sense of the AM process, this multimodal data must first be put into context. In the literature, there are several data fusion approaches for AM. Many data fusion approaches are primarily about merging in-situ sensor data. This means that the data is recorded and merged layer by layer. Accordingly, a merged data set is usually stored for each layer. In most cases, thermographic data is merged with 2D camera data and the process parameters. In some cases, acoustic emissions and surface profiles are also considered in the data fusion. [22, 23] In addition to pure in-situ approaches, there are also data fusion approaches that allow the fusion of the acquired data along the process chain [9, 25]. Donegan et al. [9] presented a method to merge volumetric in-situ and CT data and then compare it to the nominal in the form of surface data. Although this work is promising the fused data set is transformed into surface data (STL) for evaluation. Accordingly, the volumetric data is lost, and the method is primarily suitable for the monitoring of geometric quality. Due to the transformation into surface data, the data fusion approaches according to the GPS approaches are rather unsuitable for an efficient evaluation of freeform surfaces.

2.3. Intermediate Results

Table 1 summarizes the methods of the state of the art and evaluates the degree of fulfillment to address the described requirements.

	GPS Standard [15-17]	Extensions of the GPS standard [18]	Geometrical voxel-based evaluation [19-21]	Data fusion approaches [9, 25]
Mapping of different sensor data, machine data and defect types in one model	○	○	◔	◕
Mapping of different component states in one model	◔	◔	◔	◕
Process parallel generation of model for in-situ quality assurance	○	○	●	◕
Efficient evaluation of freeform-surfaces	◔	◑	◕	◔

Table 1. Ability of the methods available in the prior art to address the requirements described.

3. Voxel-based Quality Assurance

3.1. Model Structure

The basic idea behind Voxel-based Quality Assurance is to store sensor and machine data in voxels, where a voxel represents a data point on a regularly spaced, three-dimensional grid (volumetric pixel). The model can be successively expanded in the process and in the entire process chain. On the one hand, this should allow different component states to be described and, on the other hand, defects to be traced back to their cause even over whole process chains. Figure 1 illustrates the general structure of a voxel. In this example, the part is digitized by a laser line sensor during the AM process. The final component is checked in the final quality assurance process using a high-resolution surface scan and a CT volume scan in this example. Because each voxel is stored with sensor data and it is also possible to process this data, the quality of the component can be determined in each voxel at any time in the process chain.

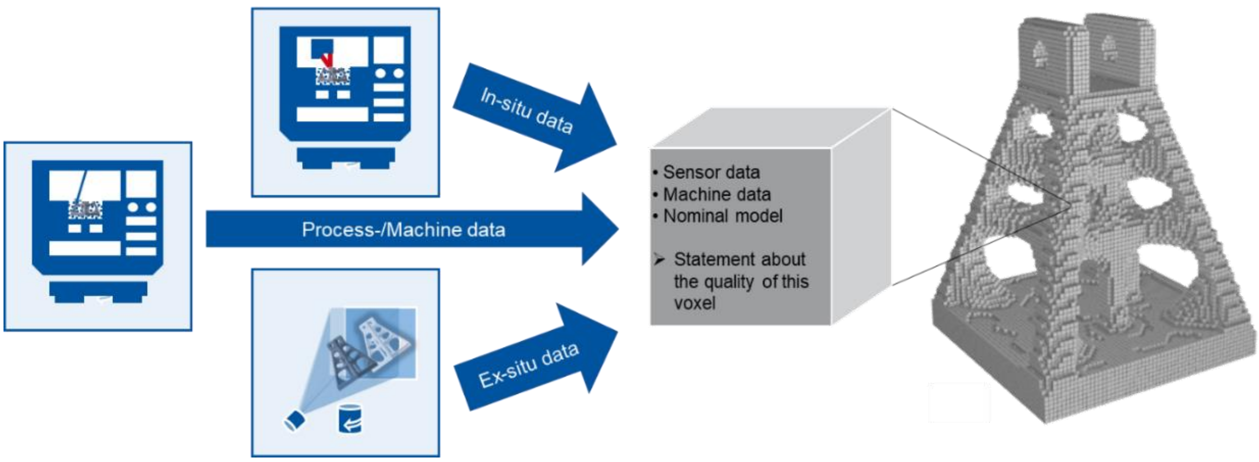

Figure 1. Conceptional design of voxel model with data inputs and the general content of a voxel. Different sensor data, machine data, and the nominal model is voxelized and merged into separated voxels.

3.2. Implementation

To create the voxel model, several steps have to be carried out. In general, these steps are shown in Figure 2. First, the nominal model of the component is created. For this purpose, a point cloud is simulated based on the sliced CAD model and the AM process used. Depending on the lowest defined tolerance, the voxel size is defined. Then, the point cloud is transformed into a voxel model (voxelization). The previously defined tolerances are set according to the GPS standard. In addition, tolerance zones are set for free-form surfaces. The next step is to add the measurement data and machine data, which will be referred to as actual data in the following, to the model. In our example, this is the data generated in each layer during an FDM AM process by a laser light section sensor. The generated point cloud is then voxelized and registered with the corresponding layer of the nominal model. The CT and FLP data generated in the downstream quality assurance processes are also transformed into voxel data and registered with the nominal model. In the resulting voxel model, the quality can finally be determined by comparing the nominal model in combination with the tolerances and the actual data.

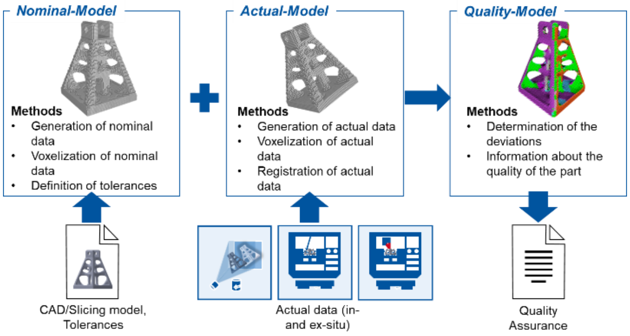

Figure 2. Conceptional implementation of Voxel-based Quality Assurance

3.3. Voxel-based Quality Determination

As mentioned before, sensor data is stored in each voxel. This data can now be used to evaluate the quality of the investigated part on a voxel basis. A geometric approach to evaluate the geometric deviation and the accordance with the tolerances can greatly increase the memory requirements of the voxel model. Therefore, a novel data-based voxel-based approach is proposed for evaluation (see Figure 3). The tolerances are transformed into data-based tolerances. That means tolerances are stored in nominal voxels only. This ensures that the size of the voxel model is kept to a minimum. In the following, all considered voxels $V = \{v_1, \dots, v_j\}$ are distinguished between nominal voxels $N = \{n_1, \dots, n_k\}$ and actual voxels $A = \{a_1, \dots, a_l\}$. A nominal voxel $n_i \in N$ is a voxel in which material should be present according to the nominal model. An actual voxel $a_i \in A$ is a voxel in which material is present according to the acquired data. The desired state for each component is that both nominal material and actual material are present in a voxel $v_i = n_i + a_i$, which is represented by a green voxel in Figure 3.

To determine the tolerance, a distinction is made between two cases. In the first case, which is represented by a yellow voxel in Figure 3, a voxel contains actual material but no nominal material $v_i = a_i$. In the first step, the nearest nominal edge voxel is determined, and the distance is calculated. This nominal voxel contains an array of outer tolerance voxels $T_{out} = \{t_1, \dots, t_m\}$ which acts as a voxel individual tolerance zone. In the next step, the tolerance voxel closest to the considered actual voxel is determined $t_{closest} = \min_{t \in T} ||t - a_i||$. Now the distance from the tolerance voxel to the nominal voxel $d_t = ||t - n_i||$ and the distance from the actual voxel to the nominal voxel $d_a = ||a_i - n_i||$ are compared. If $d_t > d_a$, a_i is inside the tolerance zone. If $d_t \leq d_a$, a_i is not in the tolerance zone. In the second case, which is in Figure 3 represented by a blue voxel, there is only nominal material present $v_i = n_i$. The tolerance is determined almost analogously to the first case. The difference is that now an array of inner tolerance voxels $T_{in} = \{t_1, \dots, t_m\}$ is considered. In addition, thresholds can be set for the number of voxels that are adjacent to each other. This means that the irregularities are only counted if a certain number of missing voxels is given. In this way, inaccuracies due to measurement errors can be reduced. Internal defects such as pores are determined analogously.

This allows for efficient mapping of positive and negative deviation of geometry and tolerance conformance. The model can solve the requirements described above. Due to the voxel structure, the model can store different sensor and machine data, as well as nominal data voxel-based. At the same time, different component states can be represented in the voxels and accordingly in the model. Since the voxel model is a volumetric model, it can be built up successively by adding voxels and is therefore predestined for in-situ quality assurance. Since any type of information can be stored in the data-based voxel model, any type of error can also be represented in the voxel. In addition, the presented approach allows efficient modeling of tolerance zones for complex geometries. Since the tolerances are represented in the nominal voxel the memory requirements of the model can be kept low.

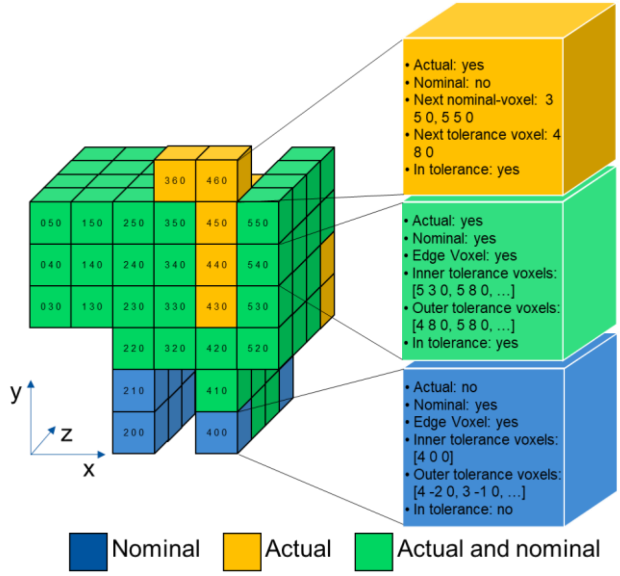

Figure 3. Voxel-based geometric Quality Determination

4. Conclusion and future work

In this work, a Voxel-based model is presented, which can be used for the quality assurance of additively manufactured components. Existing requirements of the industry are presented and the deficits of existing standards and solutions from the state of the art are identified. The presented model provides the ability to combine different sensor and machine data at different stages in the process chain. Additionally, it can implement existing standards in geometric quality assurance and can even overcome the limitations of these standards. This allows the model to be used for real-time quality assurance. The purpose of this work is to introduce the Voxel-based Quality Assurance concept. An implementation, respective validation, and examination of the practical applicability are part of future work. Thereby the steps must be carried out according to the previously described implementation. First, a nominal voxel model must be initiated. In the next step, the acquired in-situ data is registered in the model. Finally, the quality is determined by the processing of the data. Furthermore, the model can create a link between defects and machine data, enabling root-cause analysis and creating additional process knowledge.

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