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Product- and Process-related Influencing Factors for Computer-Vision based Tracing in Additive Manufacturing

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Zusammenfassung Die additive Fertigung (AM) erfährt in verschiedenen Branchen, darunter die Automobilindustrie, die Luft- und Raumfahrtindustrie sowie die Dentalindustrie, eine steigende Bedeutung. Die Unternehmen setzen unterschiedliche AM-Technologien mit spezifischen Nachbearbeitungsanforderungen ein, was zu einer erhöhten Prozesskomplexität führt. Das Produktportfolio erstreckt sich von Prototypen bis hin zu mittelgroßen Serienprodukten, was eine gesteigerte Produktionskomplexität zur Folge hat. Die manuelle Produktverfolgung in der AM-Produktion ist mit hohen Kosten verbunden und weist eine hohe Fehlerquote auf. Computer Vision stellt eine mögliche Lösung für die Auftragsverfolgung in der AM-Produktion dar, die zu einer Reduktion der Produktionskosten und der Komplexität führen könnte. Die Faktoren, die die Anwendbarkeit von Computer Vision in AM-Produktionsumgebungen beeinflussen, sind jedoch noch nicht Gegenstand der Forschung. Im Rahmen dieser Arbeit erfolgt eine Untersuchung produkt- und prozessbezogener Faktoren, die für die Anwendbarkeit von Computer Vision für die Auftragsverfolgung in der AM von Relevanz sind.

Abstract Additive manufacturing (AM) is gaining importance in diverse sectors like automotive, aerospace, and dental. Companies use various AM technologies with unique post-processing requirements, leading to increased process complexity. The product portfolio ranges from prototypes to mid-volume series products, resulting in increased production complexity. Manual product tracking in AM production is costly and has a high error rate. Computer vision is a potential solution for order tracking in AM, which could reduce production cost and complexity. However, the factors affecting the applicability of computer vision in AM production environments are yet to be addressed by research. This work examines product- and process-related relevant to the applicability of computer vision for order tracking in AM.

Introduction

The market for additive manufacturing (AM) is in a state of constant growth and acceleration. Additive technologies are used in various industries, with the automotive industry being the largest in terms of revenue. For instance, the BMW Group has consistently increased its volume of additive manufacturing, producing over 430,000 parts in 2022. [1] There are many applications for AM parts, the most common being end-use parts, prototypes, and tooling [1, 2, 3]. Additionally, there are numerous AM technologies available today, including often specific processing steps [2]. The production of a large number of different AM parts within a single production environment has led to high production complexity in so-called additive production systems. The general AM process chain consists of a digital layer and a physical layer and can be divided into three fundamental steps pre-processing, manufacturing, and post-processing [2, 4]. AM always begins with a 3D model in the digital space. After planning and scheduling production as well as setting up the AM machine, the part is manufactured layer by layer. The process chain then splits into two streams: a digital stream and a physical one. Due to the high geometrical variance within AM product portfolios, it is often challenging to map physically produced parts to digital information, such as the next processing steps. Currently, there are numerous post-processing technologies available in additive production systems [2, 5]. The specific process chain for each part depends on the AM technology used and the customer's requirements, such as surface properties. Consequently, post-processing often presents challenges, such as extended lead times, production bottlenecks, and manual labor used for non-value-added operations [5]. Furthermore, post-processing accounts for approximately 30% of part costs, with a growing trend [1].

Due to the broad product range in combination with a high process variance, it is challenging to keep track of parts in AM production systems. In practice, there is a disconnection between digital and physical processing chains after the AM manufacturing process itself. Order tracking is often done manually, resulting in low process performance [6]. Computer Vision (CV) is an emerging technology that could help streamline the process of part identification and next-step scheduling, as previous research has already shown [6, 7]. However, there are technical limitations of the CV technology that have not been thoroughly examined. Within the following research approach, product- as well as process-related influencing factors on part tracking by CV in AM production systems are further investigated and main technical challenges are derived.

Background

Nowadays, the manufacturing industry is undergoing significant changes during the Fourth Industrial Revolution. The so-called Industry 4.0 represents the convergence of information technology and industrial production, blurring the lines between the digital and the physical worlds [8]. In this context, the integrated use and analysis of data is a core capability, which enables data exchange throughout the value chain, which in turn allows dynamic control of the production system based on real-time data [9]. Beyond the technological aspects, the organizational aspects of an enterprise may also be transformed by the Fourth Industrial Revolution. For this reason, Schuh et al. developed an Industry 4.0 maturity index as a framework for implementing Industry 4.0 [10]. According to this, Industry 4.0 comprises the following four stages: visibility, transparency, forecasting ability, and adaptability, as shown in Figure 1.

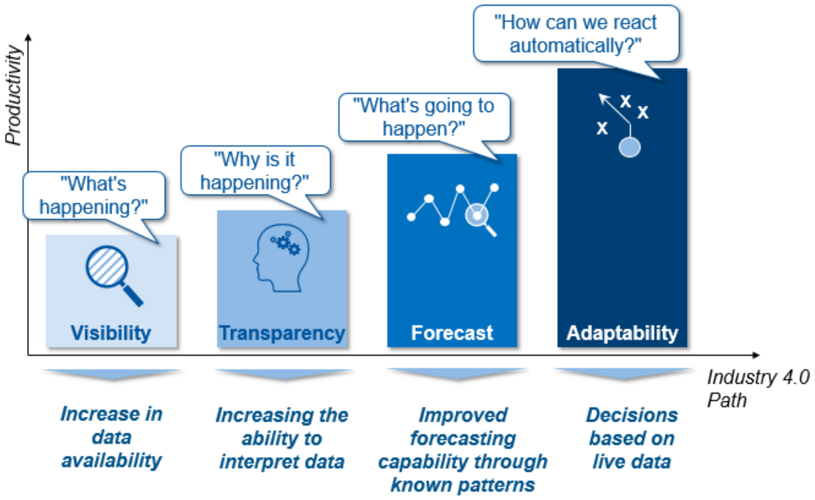

Figure 1: Development Path of Industry 4.0 according to Schuh et al. [10]

The initial stage of Industry 4.0, called visibility, involves creating a digital shadow of the current production environment. The main challenges include decentralized data storage and limited function-specific data capture. Organizations must focus on maintaining an up-to-date enterprise-wide digital representation to increase the visibility of the current running operations. Integrating existing systems, such as product lifecycle management (PLM), enterprise resource planning (ERP), and manufacturing execution system (MES), as well as sensor data from the shop floor plays a key role in creating a reliable single source of truth for effective decision-making. The next step, called transparency, focuses on understanding root causes through data analysis and integrating specific engineering knowledge. Analyzing the digital shadow for rapid decision-making involves semantic linking, data aggregation, and contextualization. Data analytics can process extensive datasets together with business systems facilitating comprehensive stochastic analysis. Based on the first and second phases of the Industry 4.0 framework, predictive capabilities can be established by simulating the overall production environment. For instance, simulating occurring errors within the production environments enables the identification of preventative measures. After establishing the third phase, organizations can implement automated decision-making systems. It is crucial to carefully consider which processes should be designed autonomously, taking into account the risks associated with automating customer approvals. The aim of adaptability is achieved when a company uses data from its digital shadow to make fast decisions and implement measures automatically, without requiring human assistance.

Traceability is the ability to trace information about a product along its process chain, including part-related information such as material, processing history, application, and location [11]. In the context of Industry 4.0, traceability can be considered a subset of the first two phases: visibility and transparency. To ensure traceability in a quality management system according to DIN EN ISO 9000, several requirements must be met. To ensure traceability and maintain product conformity, manufacturers must implement appropriate identification methods for their products. These methods should enable manufacturers to uniquely identify each output of the production, so that its characteristics and measurement requirements can be tracked and verified throughout the whole product lifecycle, including engineering, production, and usage phases. Despite the different realizations nowadays, a general distinction can be made between internal and external traceability. External traceability refers to traceability throughout the supply chain. This means ensuring that the product's history can be documented throughout the entire value chain, from the procurement of materials and parts to their processing, assembly, distribution, and sale. Internal traceability, on the other hand, refers to tracking a part within a defined section of the value chain, such as a production environment. [12, 13] Traceability includes maintaining the necessary documentation, such as production records, test results, and supplier information. Such practices establish transparent links between inputs, processes, and outputs, facilitating effective quality control. [14] Traceability systems can be implemented in various ways, but product identification is a crucial element in all of them [15]. It describes the identification of a specific part instance within batches of parts using part-specific labels. Hereby, labels often can be unique part characteristics, such as their unique geometrical shape [16].

The field of artificial intelligence (AI) has made significant progress in recent years due to the increase in computing power and data availability. AI is now being used in the production sector for tasks such as scheduling, production management, and predictive maintenance [17, 18]. There are also initial attempts to use AI in AM e.g., for in-situ process monitoring or manufacturability analysis [19, 20]. Computer vision (CV) is a technological subset that is growing with the progress in AI. It focuses on the development of systems and algorithms that enable computers to process and interpret visual information [21]. CV enables machines to capture, analyze, and respond to images and videos, mirroring the capabilities of humans. There are already numerous CV applications in various fields and industries, including autonomous driving, warehouse logistics, medical imaging, and surveillance, and their number is increasing [22]. However, CV encounters several challenges. To achieve high accuracy, it is necessary to implement the appropriate CV algorithm, fine-tune its parameters, and train it on a vast amount of annotated data [23]. Moreover, CV faces challenges in dynamic environments where various process parameters, such as camera positioning, lighting, equipment, and image quality, vary widely [24].

Today, AM has become increasingly important for the production of individualized parts [25], agile prototyping [26], and fast spare part supply [27]. Therefore, the AM technology itself is often applied in so-called AM production systems, which host multiple manufacturing technologies next to each other in workshop-like production layouts. These production systems can either exist as a single company, called AM-Supplier, or be integrated into a larger organization, where often the term AM-competence center is used. [28] They can produce up to half a million parts [1], which equates to over 2200 parts in a single business day. Within an AM production system, there are often multiple available in-process and post-processing technologies. This increases production complexity but also enables a wide range of producible products. The product portfolio of AM production systems can be divided into two main dimensions according to the literature: product width and product depth [29]. Product width refers to the range of producible products, whereas product depth refers to the different variants of a base product, such as the same base geometry with different individualized features. As AM is used in a wide range of applications nowadays, suppliers often must cover this wide product width to become economically successful [30]. Figure 2 shows some examples of typical products offered by an AM supplier.

Figure 2: AM product portfolio and examples [31, 32, 33, 34]

To be able to produce many different products within the same production system, the flexibility of the production system itself must be ensured. This can typically be achieved by increasing the number of hosted processing steps. [35] Hence, AM production systems often cover over 30 different manufacturing technologies and over 50 different post-processing treatment steps [36]. Post-processing, in particular, can increase throughput times by 53%, cause bottlenecks, and often also damage [5]. Due to the variety of AM technologies and post-processing steps, additive production systems have a high level of production complexity [7]. Furthermore, many AM technologies produce parts in batches to reduce manufacturing costs and production time. Once a geometrical base part has been produced, individual post-processing steps are often required. Thus, after production, it is crucial to correctly identify and schedule parts for their associated post-processing steps to meet final product requirements. Currently, this identification and sorting task is primarily performed manually [6]. A wrong identification can result in improper post-processing, which can lead to part damage and the need to produce the part again. To achieve an economical operation of a production system, it is essential to synchronize both the physical material and the digital information flow seamlessly synchronized. Previous research has outlined different approaches to accomplish this task.

Traceability in Additive Manufacturing

Due to the increasing production throughput of AM in recent years, tracing for AM has become more important. Hence, tracing has been the subject of multiple research approaches already. Overall, these approaches can be divided into two main areas. The first area focused on reviewing existing tagging strategies and partly deriving rules for the design of tags for AM [37, 38]. Besides that, more recent approaches outlined the utilization of computer vision as a promising solution for tracing products in AM production systems [6, 7]. The most relevant approaches will be introduced below. Beginning with the first area of approaches, Sola et al. [37] outlined the state-of-the-art tagging strategies in AM, categorized by the base material used - plastics and metals. Here, Sola et al. concluded that external tags should fulfill a list of requirements based on a literature review. Sola et al. investigated existing tagging strategies, including QR codes and embedded tagging by varying local part densities, based on this list. In conclusion, Sola. Et al. stated that that each part should be evaluated individually to determine the appropriate tagging strategy, since the tagging itself could influence the inner characteristics of the part, such as mechanical strength. Differentiating from Sola et al., Jahnke et al. [38] investigated the tagging of power-based AM parts by using data matrix codes based on the GS1 standard. Here, Jahnke et al. first outlined different possibilities for tagging a part including a qualitative evaluation of benefits and threads. Afterwards, the authors defined a generic test specimen to physically evaluate different parameters that influence the recognition process. They concluded with best practices based on the experimental insights. The authors' key findings indicate that tag size has an enormous influence on recognition accuracy. Even for tags integrated under the surface, reliable identification was only possible when using the largest chosen test specimen.

The potential of using CV to identify parts on the shopfloor of additive production systems was outlined by Obst et al. [6] and Schuh et al. [7] Both publications suggest that utilizing CV can reduce costs and improve the quality of the identification process. Obst et al. compared different object identification using a comparative expert evaluation based on three dimensions: differentiation ability, processing speed, and reduced cost for identification per part. Based on the key result, that CV has a huge potential for the identification of AM parts on the shop floor, Obst et al. investigated product-related influencing factors on the recognition accuracy. The authors defined common geometries, component positioning, format, dimension, and similarity as drivers for complexity in the application of CV for AM-part recognition. At the end of their research, Obst et al. conducted a dynamic cost calculation, comparing an available CV system for part identification to the state-of-the-art manual process. The results showed that using CV for part identification within additive production systems can save around half of the cost. On the other hand, Schuh et al. investigated a concept for part recognition using a common CV algorithm called MVCNN (multi-view convolutional neural network), which was implemented into a smartphone application. Schuh et al. examined influencing factors and their effects on recognition accuracy during neural network training in a series of experiments. The results indicate that an augmentation of the virtual part pictures has the greatest influence on recognition accuracy. The app itself has been implemented as a prototype and initial tests suggest that it can save even more costs compared to the stationary approach examined by Obst et al.

In conclusion, previous research has addressed tracing solutions for additive production systems. Besides using external tags for each part, which would increase costs, researchers have identified CV as a potential technology for seamless identification of parts on the shop floor by their unique shape. However, there is currently no dedicated approach investigating the product- and process-related requirements that are relevant for the utilization of CV for tracing in AM. Thus, within the following section, product- and process-related requirements are derived from previously conducted research and supplemented by the author's latest findings.

Requirements for the application of Computer Vision

As previously mentioned, the identification of AM parts within additive production systems is a topic of interest for both the industry and research. For instance, AM-Flow, a Netherlands-based company, has developed the first industrial system for this purpose.

Their approach has already been evaluated economically by Obst et al. [6]. The system is stationary and parts move on a conveyor belt through a photo chamber. Schuh et al. [7] presented an app-based approach for part recognition using a convolutional neural network to classify smartphone photos. While a stationary system allows for a more automated part identification process, the app is more suitable for complex production systems, such as those in the AM sector, due to its flexibility. Although AM parts are typically produced in batches, they often do not share the same process chain and therefore need to be identified multiple times during the overall process on the shop floor. Regardless of the specific CV solution used, the generic process of part identification using CV throughout the additive process chain is illustrated in Figure 3. The process starts with a CAD part in the digital space. As all processes are entirely digital until part production itself, tracing can be easily ensured by connecting different digital data sources. When a part is ready for production, a data and training pipeline is typically triggered, which trains a CV algorithm on rendered images of the later physically produced part. After an AM technology produces a part, it must be identified on the shop floor to schedule subsequent post-processing steps. Depending on the product requirements, this identification may need to happen multiple times, as batching is also used in some post-processing steps to reduce manufacturing costs. At the end of the process chain, it is necessary to identify a part in logistics to assign it to the correct customer and order.

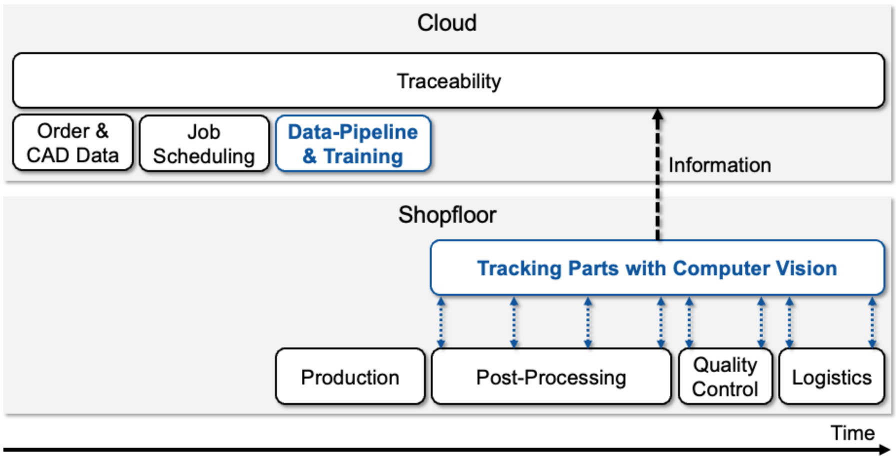

Figure 3: Tracking parts throughout the additive process chain

Regardless of individual part or process-related influencing that may affect the suitability of CV for the identification of parts in AM, there are several factors related to the CV algorithm itself. In addition to selecting an appropriate base algorithm for CV tasks, such as the MVCNN, competitive data and training methods also play a crucial role. The main challenge of these deep learning applications in AM is that only the CAD data of the parts to be manufactured are available for training. As examined by Schuh et al. [7] and Nickchen et al. [39], there are several possibilities for optimizing the training dataset to better adapt to the subsequent real-world identification. They found that big improvements in recognition accuracy can be achieved by rendering only physically stable orientations of the 3D models. Furthermore, the augmentation of the dataset through a visual filter like Random-Brightness-Contrast can prepare the algorithm for real-world application and reduce overfitting. There are several other factors regarding the CV algorithm itself and its training pipeline, which will not be further examined within this publication. Instead, process- and part-specific influencing factors to the suitability of CV for part identification are outlined in the following section.

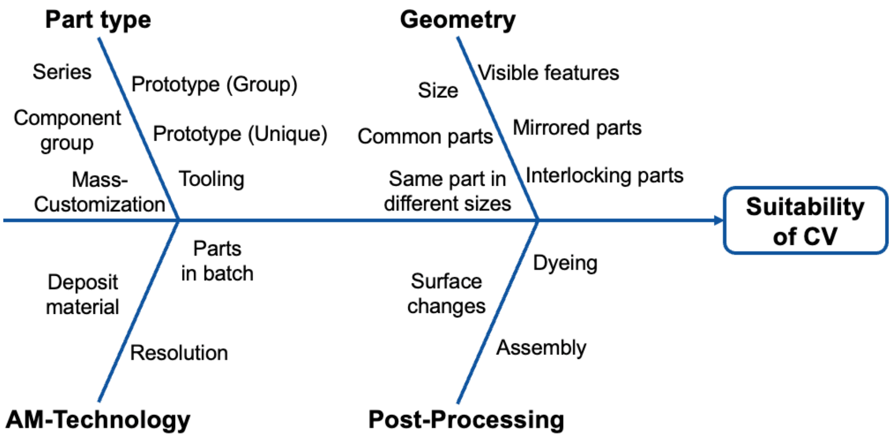

Figure 4: Ishikawa diagram of part- and process-specific factors

Process-related influencing factors

Process-related influencing factors refer to the factors, which arise from the overall material flow between AM part manufacturing and the finished product. Parts must be identified multiple times within the process to schedule them for the next processing steps. The underlying fundamental technical problem is illustrated in Figure 5, where a part P must be identified within a batch of several parts B.

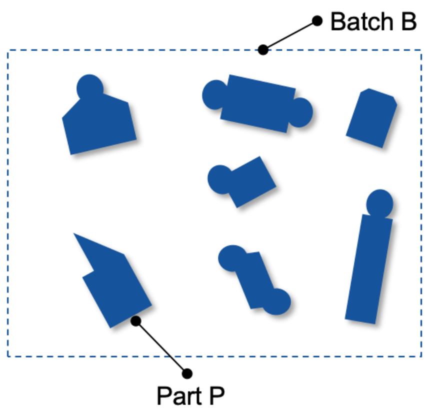

Figure 5: Fundamental Technical Problem for Part Identification of a Part P out of a Batch B

Part identification may occur multiple times within the process chain, depending on the required post-processing approach. However, it must occur at least once for every part [6]. For the identification of a part P within a batch B, the main influencing factors are the quantity of parts included in batch B and the geometrical variance of the parts within the batch. A larger quantity of parts leads to technical challenges when using CV. This is because algorithms must be trained on a larger set of parts, which requires more effort during the training and evaluation phases. Additionally, a higher number of parts increases the statistical probability of part similarity and hence reduces the geometrical variance, which affects the applicability of CV for part identification. If the geometrical shape does not vary significantly within a batch, algorithms must be trained for a longer period of time, and more attention to part specifics among each part must be paid. On the other hand, if the geometrical shapes vary greatly within a batch, such as in the case of prototyping parts, it is typically easier and requires less effort to train a suitable algorithm. As illustrated by Figure 3, the identification of parts out of a batch may occur multiple times within a part-specific process chain. To produce parts in an economical manner, parts are often processed in batches, as in process steps like blasting, surface treatment, or packaging [40]. Batching multiple parts in post-processing repeats the fundamental technical problem shown in Figure 5 with a different set of parts various times during the process chain. Furthermore, another distinction can be made according to the process phase the part is in. The primal identification after the AM process is dependent on the specific technology used. For instance, the accuracy of identification may be affected by deposit material that may adhere to the part, as algorithms are trained on optimal CAD data. The more excess material is sticking to a part, the more the geometrical shape varies from its 3D model, resulting in lower CV recognition accuracy. During post-processing, process-related influencing factors, such as the change of the surface of a part, can occur. If those changes are not considered within the CV training phase, lower accuracies of the algorithms are expected.

Part-related influencing factors

Independent of the AM technology and process chain, certain factors determine the success of CV for the given task, which are solely part-specific. They can be divided into two categories: the part type and the part-specific properties. The part type strongly influences the suitability of CV for part identification. If a part is a unique prototype and is only produced once (or once in the given batch), it positively affects the applicability of CV. On the other hand, in a prototype group, which describes a prototype that is produced several times with small differences in its geometry or size, it is challenging for CV to correctly identify a single part due to the similarities in the batch resulting from the missing unique geometrical features. Another widely applied part type is end-use parts produced in series. To evaluate the suitability of CV for series parts, it is necessary to differentiate the application. If only the fundamental part needs to be identified, it all comes down to geometry-specific factors. To identify the exact instance of the series part with CV, visible markings on the part are necessary. If these markings cannot be implemented in the geometry due to product requirements, CV is not suitable for this application. Additive manufacturing is also used for rapid tooling. These tools have good conditions for a high CV performance due to their unique geometry and typically one-time production. Additionally, AM allows for mass customization, where the design can be partially open to the customer. As these designs vary from part to part, CV is also well-suited for these components.

Part-specific influencing factors can be derived from CV algorithms themselves. As deep learning classifiers, they perform better when instances are more diverse [39]. Therefore, the number and nature of unique features are the most influential factors in the geometry of a part. The more distinct the features, the better the CV accuracy can perform. Part size also matters, but only to the extent that the part should not be too small for the CV system to capture the unique geometrical features. On the other hand, performance can deteriorate significantly if the same part is produced in different sizes [6]. However, this factor is also application-dependent. In stationary CV systems where there is a constant distance to the parts, its influence is less significant than in flexible systems like part identification app mentioned earlier. Furthermore, there are some edge cases in part geometry where CV performance decreases. For instance, mirrored parts, which are common in symmetric products, have a very similar geometrical shape and can be difficult to distinguish [6]. Another example is interlocking parts, which can be produced in a single step with additive manufacturing. The challenge lies in the fact that the appearance of the part during identification is fundamentally different from its CAD model. Besides the basic geometry, surface properties also affect the performance of CV identification. A smoother surface reduces the difference between the real part and the CAD model. However, surfaces that are too smooth may reflect lighting and be more sensitive to changes in the environment. Since the rendering of the CAD model can be programmed to fit the real part, the color of the material and part does not significantly affect CV performance, unless it changes during the process chain on the shop floor through post-processing such as dyeing.

In conclusion, when using CV for part identification in AM, it is important to consider not only CV algorithm-specific influencing factors but also part- and process-related factors. Beforehand, the fundamental problem of identifying a part P out of a batch B has been introduced and factors that influence this identification process have been outlined. To validate these influencing factors in real-world examples, a case study will be conducted in the next step.

Case Study

Within the last section, three real-world example case studies of part-process chain combinations are introduced and evaluated in terms of CV algorithm applicability, based on the key results of chapter 4. All those examples must be understood in the context of an additive production system, whereas many different technologies and post-processing options are available.

The first example is a metal end-use-part produced in a small series. AM enables huge geometric freedom in designing a part [41]. Hence parts can be topologically optimized to have the same mechanical properties but less weight, or multiple parts can be joined together to simplify assembly or reduce local stress peaks in welds [42]. These design advantages have led to many applications in the aerospace and automotive industries. The typical process chain on the shop floor starts with the production by a powder bed fusion process. Since the part usually is relatively small, it gets produced multiple times in one batch, as shown in Figure 6. After printing, the parts must be separated from the base plate and each other. Subsequent, support material must be removed. Depending on the application of the part, it must go through post-processing steps like grinding or heat treatment. Since the part is produced in series, the whole batch shares the same process chain. Thereby, an identification code is used on the surface of the part, which can be directly manufactured within the AM process itself.

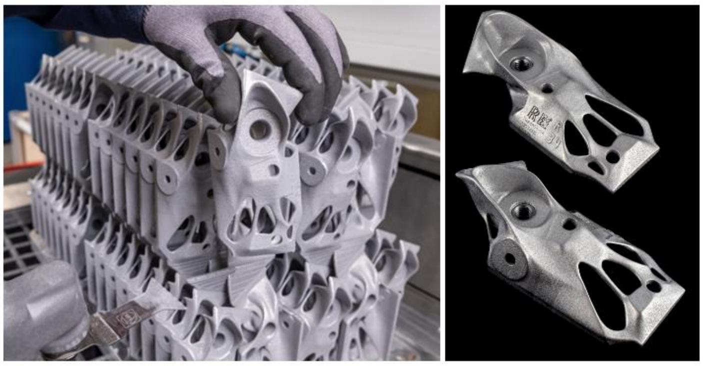

Figure 6: Metal part in series production (source: [30])

For the before outlined example of a small series part, the identification must be done by the part's unique geometrical features, which is the identification code on the part surface, since the geometrical base shape for every part within the batch is the same. This unique code must be included in the CAD files of the later-on physically produced part, which often is an additional process step within the pre-processing and subsequent increase in part cost. However, for example, Additive Marking is offering already software solutions, that automate this task [41]. Hence the post-process chain is also the same for the whole batch, further identifications during the operations might not be necessary. A major challenge for the example part is the good image quality of a relatively small area of the part itself. According to the industry, this is typically solvable by special camera equipment as well as part-specific fixtures, which perfectly position the part. If those circumstances are taken into consideration, the identification by CV is applicable.

Another use case in AM is mass customization. It is popular for consumer parts, but automotive OEMs also already offer customized aftermarket products [32]. With mass customization, only the general geometry of the part is given by the manufacturer. The customer then can design sections of the part by himself- or herself, typically the surface structure, choosing between multiple colors or customizing the part with a personal text. In this case study, we will consider a part that is built into a car's interior. It is produced in plastics by a powder bed fusion process. After printing, the batch gets automatically unpacked and blasted. Then the parts get smoothed. In the last step, the parts get dyed in different colors.

Figure 7: Customized interior part (source: [32])

As described above, all parts share the same process chain in the beginning. Only the final post-processing steps, such as dyeing, differ from part to part, so the parts must be identified there besides the usual identifications at quality control and logistics. In mass customization, the basic geometry of all parts is the same. The unique features of each part are given in the customer-made design. In this use case, these designs are the main influencing factor for the applicability of CV for identification. The greater the portion of the part that is adjustable, the greater the variability in the batch and therefore the performance of the CV. Furthermore, the CV training algorithm must be adapted to the color changing of the parts and a focus on the varying designs must be made in training data generation. If these requirements are fulfilled, CV can be used to identify customized parts. Manual CV applications, such as the Part-ID app may perform better than automated systems because the user can lay the focus on these part-defining features.

The third and last typical AM use case is the production of prototypes. Since it was the leading application in AM for so long, the technology often got called Rapid Prototyping [44]. Until today, technological advantages such as geometric freedom or the low part cost for small volumes led to many AM-produced prototypes. When functional prototypes and cosmetical models are considered together, they account for the largest share of AM applications [1]. Although orders in this application typically consist of only one or a few parts, they are mixed with other orders and produced in batches for economic reasons. Most prototypes are produced in plastics [45]. Typically, because the surface quality and color do not matter as much as in other applications, their process chain is not as long. However, after printing the batch must at least be unpacked and blasted.

Figure 8: Prototypes – unique and in group
(sources: left [34], right [46])

To evaluate the suitability of CV for identifying prototypes, a distinction must be made between unique prototypes and prototype groups. Because the part must fit perfectly in the first run or the final product design is not determined yet, prototypes may be produced several times with small variations in size and design, as shown in Figure 8. Depending on the extent of the differences between the individual parts, this can have a severe impact on CV performance. Unique prototypes, on the other hand, are produced only once, so the features of the basic geometry are easily distinguishable from the batch. However, both types of prototypes share some characteristics in terms of CV applicability. The surfaces of prototypes usually do not get processed too much, leading to good, non-reflecting surface properties for CV capture. The parts often do not share the same process chain and because of that, identification on the shop floor is needed multiple times in different basic sets. Hence, CV is well-suited to identify prototypes but there are aggravating factors if they are produced multiple times with small geometrical differences.

Conclusion

Nowadays, AM is becoming increasingly important within multiple sectors such as the automotive or aviation industry. This can be supported by the increasing amount of AM applications outlined by the Wohler's report over the last decade. [1] Today, AM suppliers face the challenge of producing a great number of parts within so-called AM production systems, which include often multiple AM technologies as well as post-processing steps. Taking into consideration the wide application of AM, the main challenge for suppliers is the economic production of a huge number of AM parts within a complex production environment. Hereby, parts often need a unique process chain to fulfill final product requirements, such as mechanical strength or surface roughness. To reach those requirements, AM parts must be seamlessly tracked within the production environment by means of identification and scheduling of parts to their related next process steps. Therefore, CV has been identified before as an emerging technology. However, previous approaches not systematically analyse part as well as process-related influencing factors on that identification. Thus, our approach deeply investigated the fundamental problem of the identification of a single part out of a batch, listing all relevant influencing factors on the CV applicability. Findings have been structured using an Ishikawa diagram. Key findings are that the individual geometrical features as well as the geometrical variance within a batch play an important role. Besides, AM process specifics, such as surface roughness or sticking powder to the part can play a role. Depending on the product requirements, parts must be identified multiple times throughout the overall process chain, changing each time the characteristics of the fundamental technical challenge, as shown in Figure 5. In conclusion, this paper examines the first step in the investigation of part and process-specific influencing factors. Future research should deeper investigate a methodical approach, how to apply CV for part identification and scheduling within AM production systems. By that methodology, combining CV-related as well as part- and process-related influencing factors, a holistic picture can be drawn on how to optimize CV for this task.

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