Increasing Reliability in FDM Manufacturing

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Abstract: Additive Manufacturing machines following the Fused Deposition Modelling process can rapidly produce wide varieties of parts. A 3D computer model is divided into instructions the FDM machine uses to produce the part layer by layer. Numerous parameters can be modified to improve the instructions generated and extensive research is being performed into determining optimal parameters. Due to the complexity of the process and limited available data about influence factors, that might change over the duration of manufacturing, some produced parts have subpar quality or fail to be produced at all. An early automated detection that the resulting part will not be inside the preset quality tolerances could save substantial resources by not finishing production on those parts. Furthermore it might be possible to utilise machine learning techniques such as XCS to adaptively change instructions during printing as to return the part into the accepted parameter range.

Keywords: Additive Manufacturing, Machine Learning, Quality Control

1 Introduction

Additive Manufacturing (AM, often referred to as *3D printing*) techniques such as the Fused Deposition Modelling (FDM) process offer a large diversity of rapidly producible parts. While this versatility allows to produce small batches or even unique parts in a rapid and cost efficient manner, it complicates automated quality control. It is no longer feasible to specificly develop measures to ensure production within tolerances for a given part as could be done in a traditional production line, e.g. to ensure a hole has been drilled at the desired position. It also becomes harder to predict the quality of the resulting part or occurrence of complications during the process. Manufacturing machines following the FDM process (henceforth referred to as *printers*) receive a material (typically in form of a cable on a spool), heat it up and extrude it through a nozzle to lay it down in a layer-wise fashion, gradually building up the part [GRS15]. Specifics in achievable outcome are often highly dependent on the printer and its production environment. However all printers share a basic set of instruction they receive to construct a part. Instructions include, but are not limited to: Movement of the print head on given paths, retraction/extrusion of material and temperature modifications. It should be possible to evaluate and grade the quality of each instruction in a given situation. Quality in this context would describe the resemblance of the printed part to the to be printed computer generated 3D model. Assigning a quality to a sequence of

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multiple instructions is also possible and likely much more feasible as positive quality most of the time only becomes distinguishable after a few layers. Negative quality on the other hand could easily be produced by a single instruction, for example when knocking a part over. It is quite obviously impossible to print a new layer on top of a part no longer in the correct position.

This work focuses on hobby market grade printers, that gained widespread popularity in recent years as printers became more affordable than in the early years of commercial additive manufacturing [WG14]. The typical workflow for producing a part is to model it using computer aided design (CAD), convert the model into instructions the printers firmware understands and then to perform post-processing if needed. While there is usually some degree of monitoring by a human user, automated monitoring solutions are rare.

Research in optimising FDM manufacturing is focused on the described workflow and to pro-actively influence the quality outcome through parameter selection. An overview over the state of the art in research since the commercial introduction of FDM in the early 1990s is given by Mohamed et al. [MMB15]. Kim et al. [KSA16] analysed the effect of build orientation on mechanical properties of the finished part under different environmental conditions. Lieneke et al. [Li16] experimentally determined dimensional tolerances in FDM manufacturing. Kozior and Kundera [KK17] focused on the impact of parameters on mechanical properties, while using ABS plastic. Alafaghani et al. [Al17] gave an experimental approach to parameter selection and evaluated the results by comparing detailed part measurements to the original 3D CAD model. Syed et al. [To18] identify several of the key challenges for AM, such as the need for real time quality assurance and monitoring and control towards optimisation.

Section 2 motivates a setup to detect unsatisfactory prints by introducing some of the possible issues that can lead to failed or poor quality prints and how they manifest. In section 3 an Observer/Controller setup utilising an XCS based controller is introduced. This controller will be able to diverge from the pre-planned instructions and enable the system to either execute an early stop of the manufacturing process to save resources or to perform instructions that reduce the deviation from the model to fit given tolerances. An issue that will serve as a first performance test is introduced in section 4.

2 Detection of Quality Impairments and Failures

During 3D printing some instructions performed by the printer can fail to have the expected outcome. In this section two different sets of problems and a system to detect those issues as early as possible during the manufacturing process will be introduced. At first, faults that mirror negative quality but mostly correct production will be described. The second section focuses on failed prints and the detection of likely future failures after more instructions will have been performed.

2.1 Quality Impairments

3D printed parts can have numerous, quite different, faults that make them unsuitable for usage and/or sale. Important quality features are dimensional accuracy, completeness, stability and visible texture. While quality reducing faults might be remedied by post processing, the goal should always be to keep additional (semi-)manual manufacturing steps as minimal as possible. Post processing can for example include sanding, painting and assembling separately printed parts. Painted parts do not rely on a perfect (in terms of visual examination) surface structure but missing dimensional accuracy (e.g. 15% to large) is obviously not desired and can, for most parts, not be fixed by cutting or sanding.

However, it is rather easy to evaluate if a whole print is too large/small in comparison to the model by a significant factor. Ideally such dimensional discrepancies would be detected soon after the print has started to ensure minimal material waste. Doing so in a fully automated, rather than manual, fashion requires a well calibrated (optical) sensor and a known frame of reference. The easiest solution consists of a simple camera placed in a fixed position on or next to the printer. Other techniques such as radas or lidar scanning could be used to increase the discernible dimensional deviation but for most applications the degree of detail offered by a camera is sufficient. As soon as the sensor setup picks up on deviations outside of the desired tolerances the print can usually be aborted.

Issues in completeness can have three origins. Either the features got lost during the transformation (*slicing*) of the 3D model into instructions for the printer, the feature broke off the part as adhesion forces were too weak or they were not printed at all because material could not be extruded. The latter increases with higher print speeds as the motors controlling filament extrusion can not perform fast/cleanly enough. Detecting completeness issues can most of the time be done during or after slicing before the printing process has actually started. Given a sensor setup as described above, it becomes possible to detect missing features during the manufacturing itself. When the absence of a feature can be detected, a prediction be made for the quality of this part, of future parts with similar features during this print and following that also future prints. Whether or not the absence of a feature should result in print abortion highly depends on acceptance tolerances, where missing visual feature might be acceptable, but the absence of a screw thread will likely result in the part being unusable . Ideally, the missing feature could be put in place retroactively avoiding abortion or lower quality altogether.

Stability and visible textures of the part relate to the movement of the print head and the amount of materials extruded. If one layer is not printed as intended the next layer will likely also follow the same slightly-off form.

A constant comparison of the part in print with its 3D model utilizing one or more cameras can lead to detecting various quality issues during print, which might result in the part having to be discarded. For comparing model and result multiple approaches will be investigated. It is not feasible to perform high quality 3D scanning during production, which will make direct comparison of a scan of the part with the original mode impossible during runtime. Machine learning techniques such as deep convolutional neural networks will likely be able to transform the RGB-images from a video stream of the part into a representation that can more easily be compared to the same representation of the desired model. Running a simulation of the ideal printing process in parallel to the actual print could allow the detection of deviations.

Another indicator of faults can be the movement of a segment of the part. Segments that typically show this issue are small and tall structures (*towers*). If, during the deployment of the next layer on top of an existing tower, said tower moves along with the print head, this new layer will not be in the exact position, it was meant to be deployed in. The error accumulates further with height and might even lead to the separation of the part from the print bed resulting in a failed print as outlined in section 2.2. Figure 1 gives an example, where the part lost partial adhesion resulting in movement of the two towers to the sides. The expected result was two identical smooth towers. The earlier these faults can be detected, the more time, energy and material can be saved and, as outlined in section 3, the more likely it will be possible to reduce faults to a stage were tolerances are met again.

Fig. 1: A structure with two identical towers. During printing the tower base loosened from the print bed with the middle connecting structure remaining connected to the bed. The movement of the sides resulted in very inaccurate albeit finishing printing.

2.2 Failed Prints

While prints resulting in parts outside of set tolerances produce potentially salvageable wastage, a printing process can also fail completely. A failure usually entails that the part deviates substantially from the model in terms of completeness. A typical scenario is that the adhesion between part and print bed fails and the print head either knocks over the part or picks it up from the bed dragging it along. Obviously it becomes impossible to finish the print correctly. The printer continues to execute the instructions that should follow on. This can either result in just extruding material mid air or in clogging of the nozzle pushing subsequently extruded material upwards around the nozzle or build up pressure inside the extruder. This can, in worst case scenarios, permanently damage the print head and extruder by clogging, blocking of joints and sensors or even overheating. Especially overheating is quite dangerous as it quickly creates fire hazards, which is intensified as hobby market FDM printers often (all printers used in our research project [No19]) lack sufficient overheating/thermal runaway protection out of the box. Detecting adhesion failures can be done reactively with the same camera setup as described in section 2.1. If the comparison of model and part returns enough deviation, which will always be the case, when the part is not in the position/orientation it should be in, an error can be raised aborting the print. Another approach would be to use image recognition systems to try to scan for the issues as both build up around the nozzle and printing in mid air have a very specific visual appearance. Although, detecting build up would require a camera angle, that also has the nozzle in view and will likely take some amount of build up to trigger. Yet, is in not likely that this amount would be too dangerous in terms of fire hazards. Mid air prints result in small strands of material that randomly accumulate into balls, also sometimes dubbed *spaghetti*. Jiang and Rybnikov developed an open source image recognition system, called "The Spaghetti Detective" [JR19], that actively scans for the issue occurring and notifies the user.

Fig. 2: A benchmark print that lost adhesion due to warping and then got dragged along until the human operator detected the issue. The warping is best visible to the lower left. The spaghetti print failure is visible to the top right where the print should have continued.

Ideally one would want to detect an adhesion failure that will occur in the future (proactively), rather than only being able to detect an already happened one. As this is a rather complex physical problem with numerous unknown variables, the following focuses on observing signs of (gradually) failing adhesion rather than precomputing whether and when it might fail. Many times quality issues might be visible before the print actually fails. Warping, the deformation of material due to non-uniform cooling, occurs from the lower layers upwards, especially in corners of the part, that loosen from the build plate. Figure 2 shows a part that got dragged along after bed adhesion was lost partially due to warping visible to the lower left, where the edge is warped rather than straight. The other common sign is part movement in towers or small segments as introduced in section 2.1 and figure 1.

3 Learning Countermeasures

There are two general approaches to prevent the occurrence of quality impairments and failed prints: Pre-emptively selecting parameters (that modify the instruction generation process) that facilitate a more optimal print process and to reactively modify future instructions (in the same print) to remedy the negative impact of an instruction that did not have the expected outcome. The former approach is currently under active research by Nordsieck et al. [No19]. The project aims to develop an abstract architecture to automatically optimise the parameters of producing machines to reduce commissioning times by persisting existing expert knowledge and combining it with machine learning approaches. This development is performed on hobby market grade FDM printers and aims to take environmental factors into account, while maintaining a wide variety of printed parts and materials. Although a sophisticated parametrisation is certainly beneficial and the basis for effectively utilising additive manufacturing, failed prints and subpar quality can still occur. The FDM process is highly dependant on environmental conditions, like temperature and humidity, as well as the properties of the extruded material. For the context of this work the material will be PLA, ABS and PETG plastics by various brands in multiple colours. The material is a mixture of the base plastic as well as colouring material and other additives to enhance mechanical/physical properties and comes as a single strand of normed width (e.g. 1.75mm) on a spool. From there it is pushed into the extruder by a grinding wheel. Slight irregularities in the material are to be expected and hard or impossible to evaluate beforehand. The impact varies with deviation, but can ultimately lead to print issues, especially when very small parts are printed and material has to be frequently retracted, increasing grinding marks in the filament. Depending on size and desired quality print durations can range from several minutes to multiple days, which can lead to surrounding temperature and humidity changes during the duration if the printer is not placed in a climate controlled environment. The typically used systems, like the popular slicing software Cura [Ul19], do not accommodate for that.

A reactive approach could recover into acceptance space mid production by selecting parameters for the remainder of the instructions that offset the change in outside factors, or extruding more/less material in a segment where previously too few/much material has been extruded. This approach would first need to observe an issue occurring (see also section 2). Ideally, the detection of an issue would happen even before it would actually manifest irreversibly and result in a change in behaviour by modifying instructions. This forms a rudimentary Observer/Controller architecture [To11]. To develop such a system, an algorithm that allows the easy incorporation of existing knowledge will be employed. The classifier system XCS [BW02; Wi95], a derivative of Learning Classifier Systems (LCS) [Ho76], was developed by Wilson in 1995. While standard XCS takes binary inputs, this problem is easier modelled using continuous (e.g. for temperatures or speeds) or other (e.g. class based) non binary inputs. The XCS extension XCSR allows real value inputs [Wi00]. In XCSR IF-THEN rules with an assigned quality, that describes the accuracy of predicting a reward, are used. While these rules are typically generated and then optimised by a steady-state niche genetic algorithm (GA), they can also be created by humans to incorporate existing knowledge. Those rules can then be further optimised by the XCSR just like artificially generated rules can. Some generated rules could damage the system if executed directly on the machine without prior offline testing in a simulation or evaluation by a knowledgeable expert beforehand. Simple sanity checks could avoid the output of print head positions that lead to collisions with the bearing, the bed or the print itself, but there are likely rules having impacts harder to discern. In addition, rules exploration on the live system could produce a lot of resource wastage until good rules are found. This is especially apparent when rules for edge cases that occur very rarely are searched. An accurate simulation of the system would therefore be desired to allow offline learning and rules exploration before deployment on the real world system and online learning to improve the rules set even further.

4 Conclusion and Future Work

Additive Manufacturing allows a great flexibility in part production, but is influenced by numerous parameters. While static approaches can try to optimise the parameter selection, they are unable to accommodate for environmental or material changes throughout the process. This work introduces the concept of a system that bases on the statically optimised instructions and makes adjustments whenever necessary. Observing deviations of the expected current state lead to slightly modified instructions that try to recover the print, so that the processes do not have to be aborted. If recovery was impossible, this would be detected and the print would be stopped. The initial steps towards creating the described system will involve detection of issues in the printing process.

A first, performance test will be to retroactively fill gaps between the walls and the roof of a print in the topmost layer. This is an often occurring quality impairment in larger flat parts. Current post-processing workflows are painting the part, smoothing the surface in an acetone bath or to fill the gaps by manually controlling the printer. The go-to pre-emptive solutions are to reduce top layer speeds and to perform *ironing* with slight material extrusion. Ironing is a process performed on the top layer that is meant to smooth out the surface and make the lines, in which filament has been layed out, less visible. During ironing the heated nozzle grazes the top most layer multiple times without actually printing, which forms a more uniform surface. If some material is extruded the gaps can be filled. The downside is that this substantially increases the printing duration. The algorithm proposed in this work will have to decide after the top layer is printed whether or not performing ironing will increase quality and then execute accordingly.

The principles developed on the domain of FDM 3D printing will be applicable to other similar manufacturing tasks and thus also improve the state of the art outside of the domain.

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