Real-Time In-Situ Process Error Detection in Additive Manufacturing

P. Becker N. Spielbauer A. Roennau R. Dillmann
Department of Interactive Diagnosis and Service Systems (IDS),
FZI Research Center for Information Technology,
Haid-und-Neu-Strasse 10–14, 76131 Karlsruhe, Germany
{pbecker, spielbauer, roennau, dillmann}@fzi.de

***Abstract*—The economic importance of additive manufacturing utilizing Fused Deposition Modeling (FDM) 3D-printers has been on the rise since key patents on crucial parts of the technology ran out in the early 2000s. Altough there have been major improvements in the materials and print quality of the printers used, the process is still prone towards various errors. At the same time almost none of the printers available use build in sensors to detect errors and react to their occurrence.**

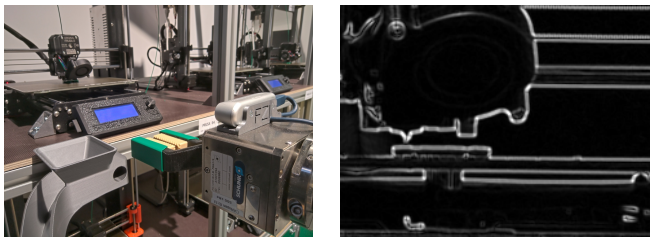
This work outlines a monitoring system for FDM 3D-printers that is able to detect a multitude of severe and common errors through the use of optical consumer sensors. The system is able to detect layer shifts and stopped extrusion with a high accuracy. Furthermore additional sensors and error detection methods can be easily integrated through the modular structure of the presented system. To be able to handle multiple printer without the same amount of sensors, the sensor was added to the tool center point (TCP) of a robot.

I. Introduction

Since its introduction, 3D printing has increasingly become an everyday and proven alternative in the additive manufacturing of components in virtually all areas of engineering. The additive manufacturing processes represent a subgroup of the original forming processes that generate finished components from raw material [1].

Probably the best known method of 3D printing is the so-called fused layer process, also known as Fused Deposition Modeling (FDM) or Fused Filament Fabrication (FFF). In this manufacturing process, the model is extruded layer by layer from heated filament. The materials used were traditionally thermoplastics that were easy to process. Despite constant development and improvement, printing with the melt-layer process is relatively error-prone compared to traditional primary forming processes, since in addition to the choice of material and extruding temperature, as well as other process variables, factors that are difficult to influence, such as humidity and age of the material, make the process uncontrollable [2], [3].

The occurring defects can be functional as well as purely aesthetic. While a missing extrusion, which for example can be caused by a clogged nozzle or missing filament supplies, inevitably leads to a uselessness of the component. The print must be aborted. Other serious defects are, for example, misalignment in the component, a lift-off of print layers due to insufficient adhesion or volumetric deviations caused by incorrect pre-processing of the print file.



(a) To check errors during the printing process at multiple 3d printers a light-weight robot is carrying a camera.

(b) Example image when a clogged nozzle error was detected.

Fig. 1. An image of the general set-up to the left and a detailed view of one processing step in the computer vision pipeline to the right.

Particularly when producing large objects, it can therefore happen that both material and printing time can be saved if errors are detected in time and countermeasures are taken. The necessity of permanent process monitoring currently means high personnel and time expenditure, which can be minimized by a sensor-based solution.

To implement such a solution, various concepts for several additive manufacturing processes have been developed and investigated in recent years, including visual error detection using a camera mounted in front of the printer and spatial monitoring of printing processes using several cameras for FDM printing, or thermal monitoring of selected processes.

II. Related Work

As the number of companies and service providers is increasing, initiatives such as the RepRap project [4] enable hobbyists worldwide to build and improve 3D printers themselves for low entry prices [5], [6].

The necessity of process automation is further underlined by a study published in 2018 by the Federal Environment Agency [7]. Since some harmful substances can evaporate during the printing process and manual monitoring of the process, even for small batch sizes, is not only time-consuming, but can even pose a health risk for the operators.

For desktop FDM printers, Jeremy Straub presented in 2015 a proposal for a system with multiple cameras around the installation space that could be used for complete process monitoring [8]. In 2016, Baumann and Roller at the University

of Stuttgart developed a single camera system to detect a detached print and extrusion is stopped [9]. In 2017 Nuchitprasitchai et al. developed a monitoring system with two cameras and investigated the detection of a print stop error with different geometries and filament colors [10].

III. Approach

In this paper we present an approach to automatically detect errors in-situ in FDM processes with multiple printers. It is able to detect layershifts and nozzle clogging at this first stage.

A standard consumer camera is mounted at the tool center point of a robot. While the printers are printing, the robot checks all printers for errors one after each other. The recorded image is processed with OpenCV, an open source image processing library. Several stages of image processing provide a robust approach even when there are changes in the filament color or the illumination.

At the beginning the image is smoothed with a Gaussian filter which reduces the noise of the image and eliminates occuring pixel errors and generally suppresses small structures in the image [11]. After smoothing, the image is converted into a grayscale image. This is a done to reduce the influence of colors and illumination. The next step consists of applying a Sobel filter to emphasize the edges of the object under surveillance.

As the software structure is lightweight, modular and flexible, further error detection algorithms can be implemented easily.

IV. Evaluation

To evaluate this approach a set-up of in total six Prusa MK3S FDM printer were used. A central management software coordinated the prints of the printers. While a printer was printing the robot was used to inspect it regulary for those two implemented error cases. When a error was detected the software stack called the user to let her check the print and confirm or decline this error.

To evaluate the performance of the both algorithms for detecting layer shifts and nozzle clogging in total 1367 measurements have been taken. 715 for the nozzle error and 652 measurements for the layer shift.

Printing errors are hard to repeat so the actual error was added to the G-code of the printed object. Both errors were added at around 39% of the printing process.

Figure 2 shows the printing progress at which point an error was detected and the print cancelled. As the layer shift algorithm needs some printed layers after the error occured the detection needs more time in which the object proceeds. This leads to an mean cancel progress of 77 %. The nozzle clogging algorithm is based on the distance between the nozzle and the object. As soon as the error occurs a detection is possible so the mean cancel progress is around 60 % and is therefore earlier detected than layer shifts.

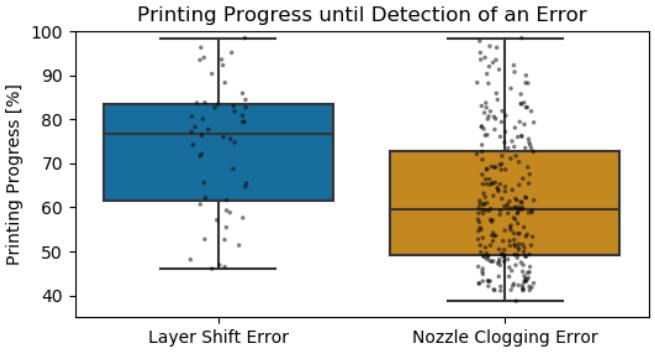


Fig. 2. Both errors can be detected within the print process. The layer shift takes longer to be detected in average as the algorithm needs multiple shifted layers to detect an error. There is no detection earlier than 40% as both errors were firstly detectable after 39% print process.

V. Conclusion

In this work an approach is proposed to detect errors in additive manufacturing while the print is in progress. An early detection can save valuable resources like time and material. A robot was used to be able to monitor more then one printer at once. This reduces workload on human workers in industry that don't have to check the printers manually anymore. Especially in regards to future production possibilities with huge printer farms this approach can be necessary to make it profitable. Also there exist more error that are common in 3d printing like warping, layer separation or lost objects. These errors shall be detected in future approaches but also in combination with the proposed one.

References

[1] F. Klocke, *Fertigungsverfahren 5: Gießen, Pulvermetallurgie, Additive Manufacturing*, ser. VDI-Buch. Springer Berlin Heidelberg, 2015. [Online]. Available: https://books.google.de/books?id=Z5_DCgAAQBAJ

[2] L. Bochmann, C. Bayley, M. Helu, R. Transchel, K. Wegener, and D. Dornfeld, "Understanding error generation in fused deposition modeling," *Surface Topography: Metrology and Properties*, vol. 3, no. 1, p. 014002, 2015.

[3] R. Anitha, S. Arunachalam, and P. Radhakrishnan, "Critical parameters influencing the quality of prototypes in fused deposition modelling," *Journal of Materials Processing Technology*, vol. 118, no. 1-3, pp. 385–388, 2001.

[4] RepRap, online, accessed 20.Oktober 2018. [Online]. Available: https://reprap.org/wiki/RepRap

[5] R. Jones, P. Haufe, E. Sells, P. Iravani, V. Olliver, C. Palmer, and A. Bowyer, "Reprap the replicating rapid prototyper," *Robotica*, vol. 29, no. 1, p. 177191, 2011.

[6] A. Bowyer, "3d printing and humanity's first imperfect replicator," *3D printing and additive manufacturing*, vol. 1, no. 1, pp. 4–5, 2014.

[7] Keppner, Kahlenborn, Richter, Jetzke, Lessmann, and Bovenschulte, *Die Zukunft im Blick: 3D-Druck*, 2018.

[8] J. Straub, "Initial work on the characterization of additive manufacturing (3d printing) using software image analysis," *Machines*, vol. 3, no. 2, pp. 55–71, 2015.

[9] F. Baumann and D. Roller, "Vision based error detection for 3d printing processes," in *MATEC web of conferences*, vol. 59. EDP Sciences, 2016, p. 06003.

[10] S. Nuchitprasitchai, M. Roggemann, and J. M. Pearce, "Factors effecting real-time optical monitoring of fused filament 3d printing," *Progress in Additive Manufacturing*, vol. 2, no. 3, pp. 133–149, 2017.

[11] E. R. Davies, *Computer and machine vision: theory, algorithms, practicalities*. Elsevier, 2012.