Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 00 (2022) 000–000

www.elsevier.com/locate/procedia

12th CIRP Conference on Photonic Technologies [LANE 2022], 4-8 September 2022, Fürth, Germany

A deep learning approach for real time process monitoring and curling defect detection in selective laser sintering by infrared thermography and convolutional neural networks

Victor Klamert[a], Matthias Schmid-Kietreiber[a], Mugdim Bublin[a,*]

[a]*FH Campus Wien, Favoritenstrasse 226, Wien 1100, Östereich*

* Mugdim Bublin. Tel.: +43 1 606 68 77-2133. *E-mail address:* Mugdim.bublinqfh-campuswien.ac.at

Abstract

Selective Laser Sintering (SLS) of polyamide powders is one of the most prevalent additive manufacturing (AM) processes. Failures induced by curling and other process irregularities affect mechanical properties and part quality. In order to improve cost- and resource-efficiency, flexibility and sustainability of SLS, a real time and in-situ quality control of the whole SLS process chain is needed. Machine learning (ML) and especially deep learning (DL) is increasingly used for SLS quality control in recent time. In this approach, we investigated applications of DL to implement an in-situ quality control of the SLS process. Especially convolutional neural networks (CNN) have been used to classify infrared thermography recordings containing artificially induced defects. Using VGG16 CNN with the thermal recordings as the input data, we achieved 99,1 % accuracy and 97,2 % F1 score in curling defect detection. These results encourage the deployment of DL for non-destructive, in-situ quality control of SLS processes.

Keywords: Additive Manufacturing; Deep Learning; Quality control; Selective Laser Sintering

1. Introduction

The technology of additive manufacturing (AM) improved from every point of view over the past few years is firmly rooted in advanced production [1]. Using AM large numbers of deployable end parts is manufactured in significant production areas like automotive, aviation, aerospace and medical engineering. New challenges appear to utilize the full potential of AM, especially the sustainable exploitation of resources. Selective Laser Sintering (SLS) of polyamide powders is one of the most popular AM processes well suited for the production of individual, complex and topology-optimized parts for various industrial sectors [1]. This paper aims to investigate detection of curling failures of SLS process by modern deep learning (DL) networks using thermal infrared imaging as input data. Deep neural network architectures, with more hidden layers and automatic feature extraction, has enormously expanded the ability of image, speech and language recognition by computers [2]. Especially in computer vision, revolutionary results have been achieved by using convolutional neural networks (CNN) [2].

The deployment of DL enables also an efficient and sustainable real time process monitoring to predict failures [2-4]. Previous approaches from Baumgartl et al. [3] confirmed the effective deployment of thermal imaging and CNN to detect delamination and splatters in selective laser melting images with an average balanced accuracy of 96.80%. Westphal and Seitz [4] revealed a method to caption anomalies and powder bed defects using a HD webcam and a VGG-16 CNN architecture.

2. Methods

The experimental setup was applied on the EOS Formiga P110 SLS machine for polyamide powders (PA12 was used in this case). A FLIR T420 thermal infrared camera was installed at the top window of the machine to record the temperature distribution at the surface of the powder bed. The camera system has 320 x 240 pixels and 30 frames per second. As seen on Fig. 1 and 2, a calcium fluoride optical window was used to separate the camera system from the actual installation space. Calcium fluoride has a very low refraction index of 1,434 (no anti reflection is necessary) and a transmittance of more than 90% at the spectral range. First test runs revealed a slightly coating at the optical window, caused by vaporization during the sinter process. This indicates that installed nitrogen flushing had to be revised in further iterations [5].

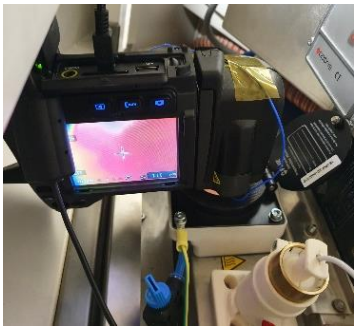

Fig. 1. FLIR camera setup

Fig. 2. Calcium fluoride window

A test run was implemented to set all necessary parameters (as the emissivity had to be calibrated) and get the first data set visualizing an accurate SLS process. To get the data set of a defective process caused by artificially created curling, the process temperature was manually lowered from 167°C to 162°C. A few iterations had to be implemented to get suitable results without any termination. A total process time of 80 minutes was continuously recorded in both cases (accurate and failure). Curling as seen on Fig. 3 is caused by initial stress through uneven solidification of the top and bottom side of the part related to uneven or defective temperature distribution. Additional factors like laser power, layer cooling time, part location/orientation, part dimensions and the number of layers will also affect the phenomenon of curling [6].

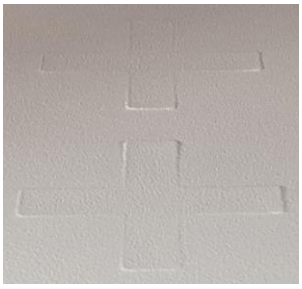

Fig. 3. Curling at powder bed

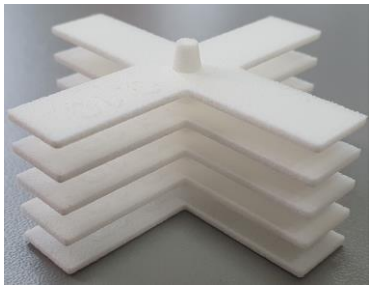

Fig. 4. Calibration part

Standard calibration parts where used throughout the whole project. These parts contain five stacked cross sections by the dimensions of 50 mm x 50 mm as seen on Fig. 4. The cross sections are connected by conical structures with a total height of 14,5 mm. The components are usually used to verify default parameters of the sintering process. The temperature settings of each of the four powder bed sections are calibrated manually. Therefore, the distance between the cross sections of the calibration parts are evaluated to detect any deviations like curling.

Fig. 5 shows the outline laser exposure of the test parts. As seen on Fig. 6, there is a significant temperature difference between the powder bed and the literal part after leaser exposure. Towards the next applied layer and cooling time, the temperature distribution at the powder bed surface was nearly homogenously.

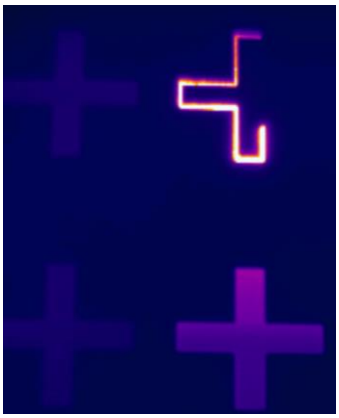

Fig. 5. Outline laser exposure

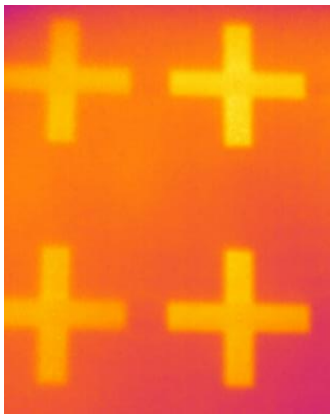

Fig. 6. Layer cooling down

The experimental trials were continued until total process abortion to show maximum possible impact of failures. By increasing curling effect and applying a new layer of powder, the coater ripped out some parts of the powder bed and got stuck as seen on Fig. 7. In cases like this, a complete restart of the process is required. All parts at the surface are defective and have to be removed including non-used polyamide powder. Beside increasing cost factor, a massive delay will result due to cleaning and pre-heating the machine.

Fig. 7. Increasing curling and movement of the coater led to total process abortion

3. Thermal imaging of artificially created curling

Beside the main purpose of this paper, to reveal an innovative and sustainable possibility of monitoring and evaluating the SLS process, one of the most important issues to be discussed and examined was the visibility of curling at the thermal recordings. Our expectations were that neural networks could detect failures visible by humans.

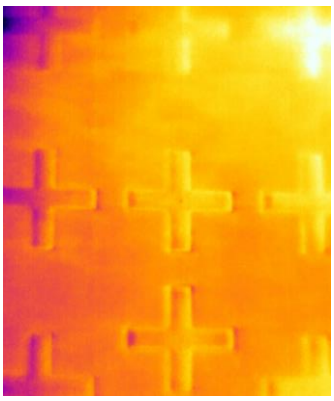

Fig. 8. Visible curling after coating

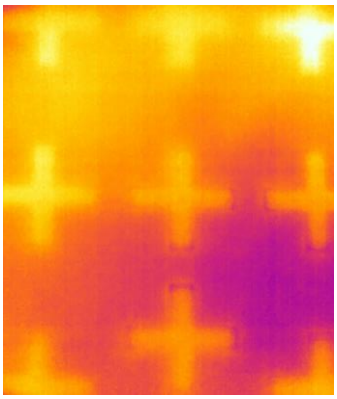

Fig. 9. Visible curling after layer cooling time

The frames of the thermal recordings where extracted, compared and evaluated to get first impressions about the depiction of curling. Due to the high amount of data (>140.000 frames per process where rendered), samples where used every 1000 frames. First considerations revealed the expected results: even immediately after coating of a new layer of polyamide, the effects of curling appears clearly at the thermal images as shown on Fig.8. Towards the layer cooling time, the effects where still verifiable as shown on Fig. 9. They appear only in certain spots, also shown on Fig. 9, due to an uneven temperature distribution, caused by manually adjusting the process temperature.

4. Processing the data with convolutional neural networks

The extracted frames where manually classified in accurate and defective parts to train the algorithm. After correcting some imbalance in the amount of data, both classes where split into a ratio of 80% training, 10% evaluation and 10% test data. A total amount of 100.000 frames was processed. A VGG-16 (Visual Geometry Group) Convolutional Neural Network (CNN) architecture was implemented to predict failures at the thermal recordings [8].

The input frames are converted into 224 x 224 pixels with (RGB) channels. Subsequently a variety of convolutional layers is deployed. These convolutions have a kernel size of 3x3 and 1x1 to apply a linear transformation of the output channels. After the convolutions max pooling and padding are used to preserve spatial resolution. The last three layers are fully connected and the output layer is composed of 1000 units (1000 capable classes) including a soft-max activation function [7].

5. Results and discussion

VGG-16 network was iterative trained using the following hyperparameters: binary cross-entropy cost function, 10-3 learning rate, Adam optimizer (ß1=0.9, ß2=0.999), 100 epochs and early stopping with patience=20. The network performed quiet good during training as seen on Fig. 10. The training stopped after 59 epochs revealing an remarkable accuracy of 99,1 % and F1 score of 97,2 % as seen in Table 1 [8].

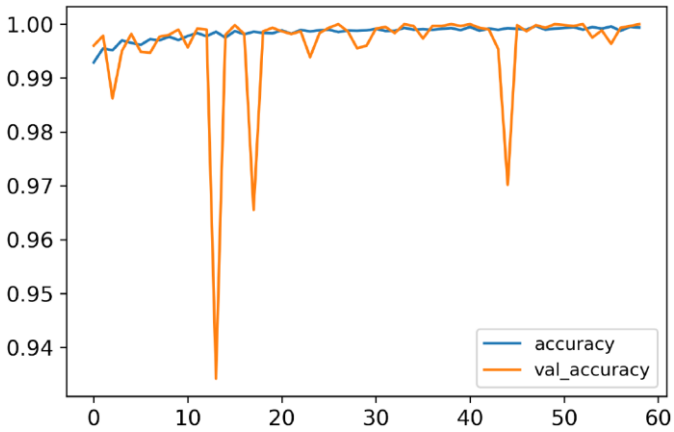

Fig. 10. Accuracy behavior during the training epochs on train and validation data [8]

Table 1. Result comparison of different CNN [8]

	VGG-16	Xception	ResNet50
Loss	2.6955	6676.5933	1943.556
Accuracy	0.9909	0.1658	0.1658
Recall	0.9530	1.0	1.0
Precision	0.9916	0.1658	0.1658
AUC	0.9768	0.5	0.5
F1	0.9720	0.2845	0.2845
Epochs	59	49	55
Sec/epoch	540	1170	530

As can be seen in Table 1 other CNN networks like Xception and ResNet50 also performed very well on the training data but poorly on the test set with accuracy of 16,6% and F1 score of 28,5 %. This indicates overfitting the training data, since Xception and ResNet50 use larger networks with more parameters than VGG-16.

To evaluate the predictions made by the VGG-16, the Grad-CAM heat map was rendered from every frame. The gradient-weighted class activation mapping uses the gradients as weights during backpropagation and highlights important areas related to the predictions made by the network [9], which helps interpreting and explaining deep neural networks results.

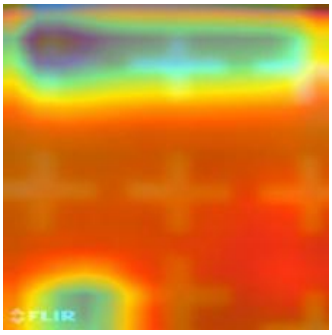

Fig. 11. Grad-CAM heat map correct process

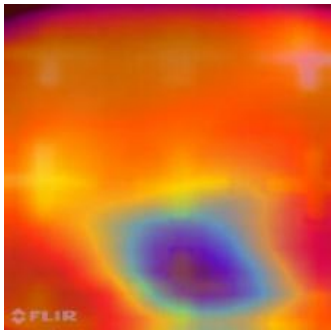

Fig. 12. Grad-CAM heat map defective process

A clear difference is visible between the heat maps of correct and defective processes as shown on Fig. 11 and 12. There were no significant variations of the heat maps during the correct process (see Figure 11), but in the case of the defective process, the heat map revealed distinct changes as seen on Figure 12. This corresponds to thermal images of the defect process (see Figure 7), the more the failure occurred, the more the "hot spot" moved to the centre of curling as seen on Figure 12 (right bottom corner).
The above results indicates that the VGG-16 network is able to detect the process with curling defects with high accuracy, and that the network decisions are explainable using Grad-CAM.

6. Conclusion

This work investigated an approach for real time monitoring the SLS process and in situ curling failure detection. CNN networks where used as cost-effective and sustainable SLS quality monitoring method to prevent defective parts and process terminations. Using extracted thermal images as input data, CNN proved to be an expedient and effective way for detecting errors visible by humans during SLS processes. As a result, the VGG-16 network achieved a failure detecting accuracy of more than 99 %. In addition, evaluating the Grad-CAM heat maps approved and explained the predictions made by the DL. These results encourage usage of DL for non-destructive, in-situ quality control of the SLS processes.

In future, we plan to use more data and tune hyperparameters to improve the network performance. We will also try to detect different kinds of defects and perform online SLS process parameters optimization by deep neural networks.

Furthermore, a concept for data-fusion based on combining thermal imaging data, deep learning and additional sensor concepts will be implemented. The aim will be expansion from achieved 2D imaging to 3D structural data. Previous approaches confirmed the effective deployment of fringe projection and enhanced phase measuring profilometry (EPMP) to monitor the 3D surface topography of the powder bed surface [10-12]. Our approach will be linear movement of laser triangulation to scan the powder bed and compile 3D data.

Acknowledgement

The research leading to these results have been funded under the cooperative doctoral program "Digiphot" between FH Campus Wien and TU Wien.

References

[1] M. Srivastava, S. Rathee, "Additive manufacturing: recent trends, applications and future outlooks", Springer Online, 25. Oktober 2021, https://doi.org/10.1007/s40964-021-00229-8

[2] A. Geron, „Hands-On Machine Learning with Scikit Learn and Tensorflow", O'Reilly UK Ltd.; 2nd ed Edition, 11. Oktober 2019, ISBN-10: 1492032646

[3] H. Baumgartl, J. Tomas, R. Buettner, M. Merkel, "A deep learning-based model for defect detection in laser-powder bed fusion using in-situ thermographic monitoring,", Progress in Additive Manufacturing 5, pp. 277–285, 2020, https://doi.org/10.1007/s40964-019-00108-3

[4] E. Westphal, H. Seitz, "A machine learning method for defect detection and visualization in selective laser sintering based on convolutional neural networks", Additive Manufacturing, vol. 41, 2021, https://doi.org/10.1016/j.addma.2021.101965

[5] J. Picker, „Aufnehmen und Auswerten der Temperaturverteilung im Bauraum einer SLS-Anlage ", FH Campus Wien, High Tech Manufacturing, 22.08.2021

[6] A. Almabrouk Mousa, "Experimental investigations of curling phenomenon in selective laser sintering process", Rapid Prototyping Journal, Vol. 22 No. 2, https://doi.org/10.1108/RPJ-12-2013-0132

[7] K. Simonyan, A. Zisserman, "Very deep convolutional networks for large-scale image Recognition", Visual Geometry Group, Department of Engineering Science, University of Oxford, ICLR 2015, https://arxiv.org/pdf/1409.1556.pdf

[8] M. Schmid-Kietreiber, „In-situ detection of printing defects during SLS using Convolutional Neural Networks", FH Campus Wien, Computer Science and Digital Communications, 01.01.2022

[9] R. R. Selvaraju, M. Cogswell, A. Das, R. Vedantam, D. Parikh, D. Batra, "Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization", In Proceedings of the IEEE international conference on computer vision, pp. 618-626. 2017

[10] Z. Li, X. Liu 1, S. Wen, P. He, K Zhong, Q. Wei, Y. Shi, S. Liu, "In Situ 3D Monitoring of Geometric Signatures in the Powder-Bed-Fusion Additive Manufacturing Process via Vision Sensing Methods", MDPI Journal Sensors, 2018, 04.2018, doi:10.3390/s18041180

[11] B. Zhang, J. Ziegert, F. Farahi, A. Davies, „In situ surface topography of laser powder bed fusion using fringe projection", Additive Manufacturing, vol. 12, 2016, https://doi.org/10.1016/j.addma.2016.08.001

[12] N. Southon, P. Stavroulakis, R. Goodridge, R. Leach, „In process measurement and monitoring of a polymer laser sintering powder bed with fringe projection", Materials and Design, vol. 157, 2018, https://doi.org/10.1016/j.matdes.2018.07.053