A Comparison of Anomaly Detection Algorithms with applications on Recoater Streaking in an Additive Manufacturing Process.

To consistently produce high quality parts in additive manufacturing remains challenging. The most occurring defect affecting the output quality during the printing process is re-coater streaking. While different detection models have been proposed in the literature, a thorough comparison of these models is lacking. Moreover, every model is only tested and tailored to their own specific data sets. In this research, these different detection models have been implemented and compared against each other to get a better overview of the advantages and disadvantages of each model. Furthermore, an existing method has been improved to make it more general applicable and a tried and tested pre-processing step has been introduced to this application.

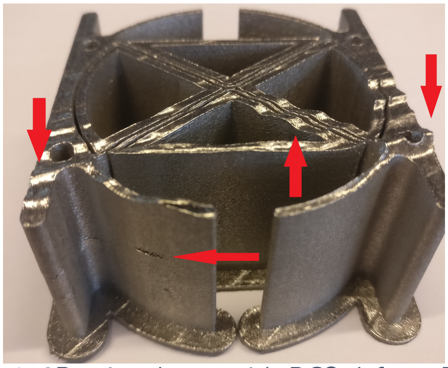

Figure 1: 3D printed part with RCS defect. Red arrows indicate the deterioration.

Introduction

An additive manufacturing process prints a part layer by layer. For each layer, the build area is coated with a metal powder which is melted together to print the part. A defect occurring during this coating often ruins the whole print. Of the metal powder-related defects, recoater streaking (RCS) is the most occurring. RCS is caused by a damaged recoater and increases the surface roughness of a part, rendering it unusable. Figure 1 shows a part with an increased surface roughness caused by RCS.

Detection of RCS has been studied and multiple methods have been proposed in literature. These models however are all tested on, and tailored to their own datasets. A clear overview of the advantages and disadvantages of each model is missing. Furthermore, it is currently unknown how these models react to new machines. The objectives of this research are to create a thorough comparison of different RCS detection models found in literature under the same benchmarks, and test them on a new dataset. Furthermore, the effect of different pre-processing methods are tested.

Methodology

Six algorithms have been proposed by literature to detect RCS. Some are specially designed for this problem while others are tried and tested methods in computer vision. In this study, a novel improvement for one of these algorithms has been introduced to make the model more generally applicable. These algorithms range from Neural Networks and Filter Features to Line Profiles and Local Binary Patterns. Each model has its own benefits and shortcomings.

Before images are processed to search for RCS, some pre-processing takes place. In this study, two different models have been tested. One from literature to enhance RCS in an image [1], and an existing noise reduction by image morphology model has been introduced to this field.

To create the comparison, all models will be combined with both pre-processing steps. For each combination all models will be benchmarked and tested on our dataset. In this factsheet, only the best performing combinations are reported. A variety of metrics have been selected for these benchmarks to establish a detailed representation of the models. The processing speed will be reported for both the training and prediction time, as these differ significantly.

Results

Table 1 shows an overview of all models and their best performing pre-processing method. All models score >96% accuracy and >90% in both recall and precision, with a different model scoring high-

Model	Pre	Acc.	Precision	Recall	AUC	AP	Training	Prediction
LP	[1]	**99.28%**	98.66%	99.41%	0.998	0.998	**287s**	45.74ms
LBP [1]	None	98.95%	**99.13%**	98.10%	**0.999**	**0.999**	330s	75ms
FF [2]	Our	96.06%	97.28%	91.70%	0.970	0.955	386s	10.58s
NN [3]	None	96.11%	92.17%	97.59%	0.983	0.937	>1 hour	6.7s
NN [4]	None	98.47%	98.71%	97.30%	0.995	0.985	>1 hour	34.84ms
NN [5]	None	99.01%	97.64%	**99.70%**	**0.999**	0.998	>1 hour	**31.34ms**

Table 1: Comparison of all models with their best performing pre-processing method. LP: Line Profiles, LBP: Local Binary Pattern, FF: Feature Filters, NN: Neural Network.

est for each metric. Furthermore, all models score >0.930 in AUC and AP. Which pre-processing method results in the highest performance differs per model, but most models perform best without one.

The metrics where the models differ most, are the training and prediction speeds. The three neural networks, [3, 4, 5], take over an hour to train while the other models take around 5-6 minutes, mostly due to training for many epochs. Next to that, [2] and [3] take over six seconds to predict a single image while the other models are all below 100ms.

Conclusion

Determining which detection model performs best all depends on what metrics are deemed most important. As shown in Table 1, LBP [5] has the highest precision while one NN [1] has the highest recall. At the same time, LP always performs better than one of these but never both, and has the highest accuracy of all methods. Therefore, a trade-off has to be made which metric is deemed most important.

This study has created a thorough comparison of six detection models, and shown each model's advantage. Extending this study with different materials or machines, or new models would result in interesting findings. Furthermore, it would be interesting to translate any of these models into a real-time detection application.

References

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