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# An Analysis and Optimization of Surface Quality in Post-processing of 3D Printed Surfaces Using Fluid Jet Polishing

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*Surface defects including Pores, cracks and unmetled powder are commonly found on the surface of most 3D-printed components. This paper attempts to analyse the effect of fluid jet polishing on surface quality after post-process finishing of 3D-printed surfaces. In this paper, the surface defects before and after post-process finishing of the 3D-printed surfaces by FJP were investigated first. The surfaces were then measured while the types and number of defects captured before and after polishing were determined and analyzed by a purpose-built machine-learning algorithm which was built based convolutional neural network. Hence, post-polishing process parameters was optimized by Taguchi Method. The results of the study will gain better scientific understanding of the effectiveness of postprocessing by FJP but also further enhance the surface quality of 3D-printed components.*

## 1. Introduction

With the increasing demand for intricated components or products in various industries, metal additive manufacturing technology is developing at an unstoppable speed. However, the poor surface quality of the 3D-printed metallic workpieces is one of the common and critical barriers to AM industry. That has limited the application of AM in some fields, like the optics industry. The poor and unexpected surface quality is usually due to the complicated physical phenomena of deposition and fusion of materials and the unique layer-by-layer fabrication method of AM [1]. Numerous factors, such as spatters, splashing particles, laser power, and process parameters, affect the surface quality [2-4]. Hence, improving the surface quality of AM fabricated metallic parts through optimising the AM process becomes extremely difficult. Instead, researchers are seeking surface post-treatment. Maleki et al. [5] have reported in detail in their review paper. One of the possible ways is polishing.

In this paper, the authors attempt to analyse the effect of fluid jet polishing (FJP) on surface quality after post-process finishing of 3D-printed surfaces. This study assessed the surface quality by the surface integrity in terms of number of defects and the surface roughness, arithmetical mean height, $Sa$ . Experiments were conducted to examine the effect of FJP process parameters on surface roughness and surface integrity. A novel convolutional neural network, CenterNet-CL, developed by Wang and Cheung [6], was applied to detect, and count the surface of 3D-printed samples before and after FJP.

## 2. Experimental Setup

As shown in Figure 1, selective laser melting (SLM) fabricated 316L stainless steels blocks in a dimension of 10*10*10 mm were prepared for the study.

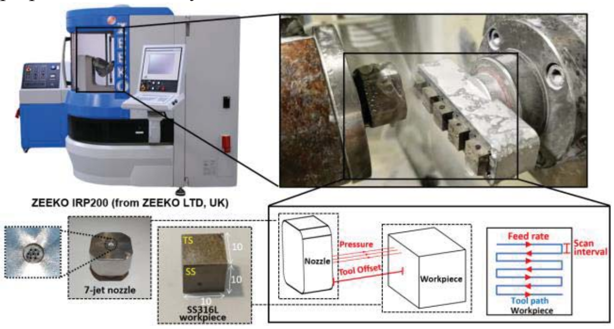


Fig. 1 Experimental setup

The experimented surface is mainly on the top surface, top surface (TS) is the as built surface and bottom surface (BS) is the wire cut base. The FJP equipment was a Zeeko IRP200 and the FJP nozzle is a 7-jet with each orifice of 0.5 mm diameter. Taguchi method was adopted to obtain and verify the optimal parameter settings. Pressure, tool offset, scan interval, and feed rate are the target process parameter to be studied. 10 wt.% #1000 aluminum oxide polishing slurry was used. Measurements of surface roughness, Sa, were taken before and after the polishing experiments with white light interferometer to check the surface roughness. $Sa$ of SLM printed 316L stainless steel's top surface is around 600nm – 800nm. A scanning electron microscope (SEM) was used to observe the defects of the surface before and after polishing. The images were taken by using 200x magnifying ratio. Figure 2 shows the target surface defects that are focused in this paper.

### 2.1 Defect analysis by CenterNet

A convolutional neural network training algorithm (CenterNet) developed by Wang and Cheung [6] was used in the training process of the machine-learning algorithm. CenterNet is a point-based object recognition system that can be effectively generalized to perform a variety of computer vision tasks such as object tracking, human pose prediction, 3D object detection, movement detection, human-object interaction detection, etc. Two corner heatmaps and a center key point heatmap are generated by a convolutional backbone network using cascade corner pooling and center pooling, respectively. A pair of identified corners and matching embeddings are used to detect a possible bounding packet. The final bounding boxes are then determined using the sensed core key points. A labelling software is applied to distinguish and label defects in the training set manually as shown as Figure 2.

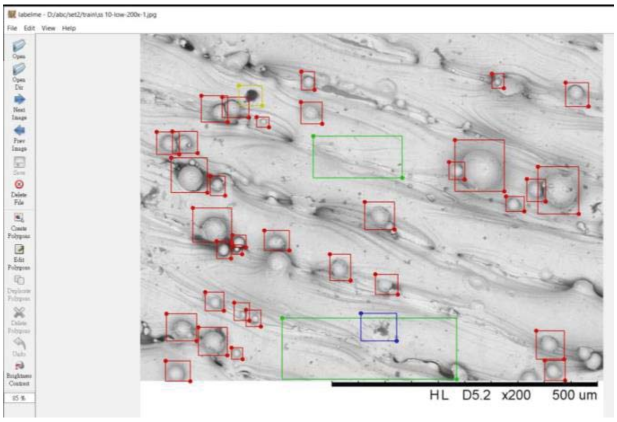


Fig. 2 The process of labelling defects by Labelme

The types and name of defects should be fixed before labelling. Also, the sequence of labelling the objects(defects) types should be in same order. A rectangular tool is used to surround the shape of a defect. Different colors of rectangular tool are employed to label various kinds of defects. The types of defects focused on this project are shown as Figure 3, which are crack, pore, unmelted material, and impurity. After labeling every training and validation set, they are re-examined by expert to validate the accuracy of labels.

### 2.2 Design of experiment by Taguchi Approach

The parameter settings of the Taguchi Method are shown in Table 1. $L_{16}$ orthogonal array was used. The Signal-to-Noise ratio (S/N ratio) characterisitics of "smaller the better" was chosen for the minimal number of surface defects and the lowest surface roughness value.

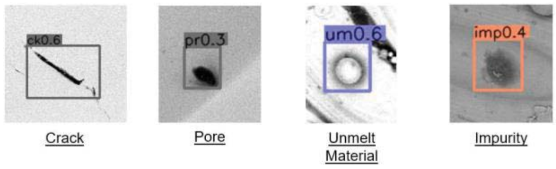


Fig. 3 Type of target defects

Table 1. Factors and Levels selected for polishing SLM SS316L

| Factor / Level | Pressure (bar) | Feed rate (mm/min) | Tool offset (mm) | Scan interval (mm) |
|---|---|---|---|---|
| 1 | 5 | 10 | 2.5 | 0.2 |
| 2 | 6 | 15 | 5 | 0.4 |
| 3 | 7 | 20 | 7.5 | 0.6 |
| 4 | 8 | 25 | 10 | 0.8 |

## 3. Results and discussion

### 3.1 Defect analysis by CenterNet

The surface defects may vary greatly from different manufacturers, in order to enhance the algorithm samples from are two companies (named A and B here) were collected for the training of the algorithm, Figures 4 and 5 shows some sample surfaces. 3 set of data should be separated as they are produced by different companies. 100 pictures for each learning set. The pictures were then further divided into 3 subsets which 80% goes to training set, 10% goes to validation set and the remaining 10% goes to testing set. The training set is a set of data that is used to match the model. The validation dataset is a collection of data that is used to provide an impartial assessment of a model's fit on the training dataset when tuning model hyperparameters. As competence on the validation dataset is integrated into the model configuration, the assessment becomes more biased. The Test Dataset is a subset of data that is used to make an impartial assessment of a final model's fit on the training dataset.

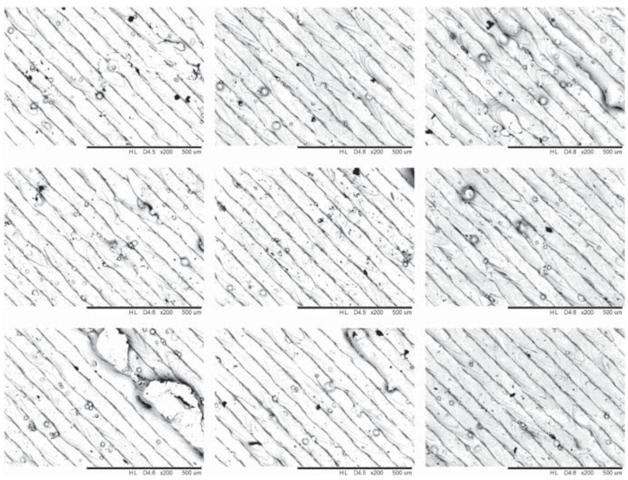

Fig. 4 Some samples from company A

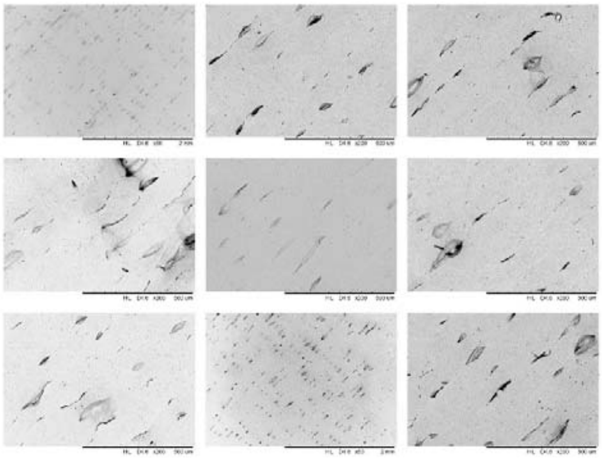

Fig. 5 Some samples from company B

After repeated training, a model of machine learning algorithm was created, and images can be input to obtain an image with labelled defects on it and the number of defects of each image. the number of defects can be obtained. Figure 6 shows an example of images after analyzed by machine learning algorithm

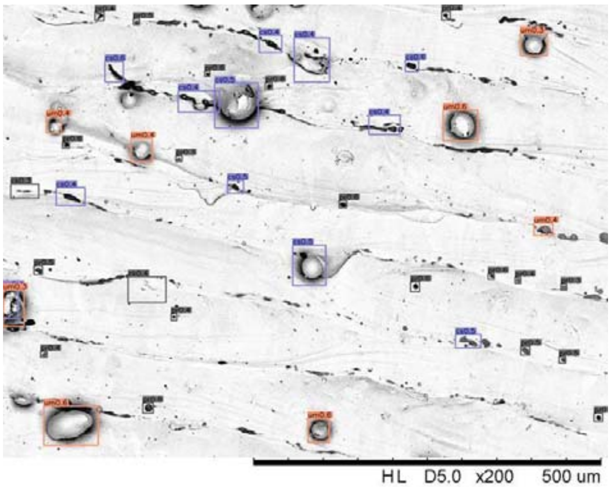


Fig.6 Example of images after analyzed by machine learning algorithm

### 3.2 Optimization of polishing parameter by Taguchi Approach

Two series of experiments were conducted: (1) Set A: 96 samples were polished and measured for the surface defects analysis. There were 16 runs of experiments and 6 samples for each run. Samples were from 2 produced from 2 companies and 3 from each were picked randomly for the experiments. (2) Set B; 16 samples from one single source were polished for the analysis of process parameters affecting surface roughness.

The results of the experiment are shown in table 2. The average S/N ratio of each factor for Set A and Set B was tabulated in Tables 3 and 4. The delta is the value of subtraction of the largest S/N ratio and the smallest one. The larger the value of the delta means the corresponding factor contributes more to the removal of surface defects and the reduction of surface roughness. By ranking the value of delta, the relative magnitude of effects could be compared. The rank shows the rank of contribution of each factor. It is interesting to note that the Scan interval and Feed rate rank 1 and 2 in both set of experiments. They had a larger relative magnitude of effects comparatively. Tool offset contributes more than Pressure in the case of removal surface defect, which conversely in the improvement of surface roughness.

Table 2. Results of the experiments

| Factors / Run | Pressure (bar) | Feed rate (mm/min) | Tool offset (mm) | Scan interval (mm) | Result of Set A (Average number defects) | Result of Set B (Average Sa Values, nm) |
|---|---|---|---|---|---|---|
| 1 | 5 | 10 | 2.5 | 0.2 | 1.11 | 44 |
| 2 | 5 | 15 | 5 | 0.4 | 3.44 | 146 |
| 3 | 5 | 20 | 7.5 | 0.6 | 7.94 | 183 |
| 4 | 5 | 25 | 10 | 0.8 | 7.11 | 229 |
| 5 | 6 | 10 | 5 | 0.6 | 3.11 | 76 |
| 6 | 6 | 15 | 2.5 | 0.8 | 7.00 | 151 |
| 7 | 6 | 20 | 10 | 0.2 | 1.56 | 65 |
| 8 | 6 | 25 | 7.5 | 0.4 | 6.11 | 165 |
| 9 | 7 | 10 | 7.5 | 0.8 | 3.11 | 121 |
| 10 | 7 | 15 | 10 | 0.6 | 4.11 | 111 |
| 11 | 7 | 20 | 2.5 | 0.4 | 5.11 | 86 |
| 12 | 7 | 25 | 5 | 0.2 | 2.50 | 66 |
| 13 | 8 | 10 | 10 | 0.4 | 2.11 | 61 |
| 14 | 8 | 15 | 7.5 | 0.2 | 0.89 | 30 |
| 15 | 8 | 20 | 5 | 0.8 | 9.83 | 133 |
| 16 | 8 | 25 | 2.5 | 0.6 | 6.94 | 144 |

Table 3. Average S/N ratio of each factor for Set A

| Factors / Level | Pressure | Feed rate | Tool offset | Scan interval |
|---|---|---|---|---|
| 1 | -11.668 | -6.776 | -12.201 | -2.929 |
| 2 | -11.585 | -9.724 | -12.099 | -11.777 |
| 3 | -11.065 | -13.970 | -10.640 | -14.239 |
| 4 | -10.538 | -14.386 | -9.916 | -15.911 |
| Delta | 1.130 | 7.610 | 2.285 | 12.983 |
| Rank | 4 | 2 | 3 | 1 |

Table 4. Average S/N ratio of each factor for Set B

| Factors / Level | Pressure | Feed rate | Tool offset | Scan interval |
|---|---|---|---|---|
| 1 | -42.15 | -36.96 | -39.58 | -33.77 |
| 2 | -40.45 | -39.33 | -39.94 | -40.51 |
| 3 | -39.41 | -40.67 | -40.20 | -41.73 |
| 4 | -37.72 | -42.78 | -40.02 | -43.73 |
| Delta | 4.43 | 5.81 | 0.62 | 9.96 |
| Rank | 3 | 2 | 4 | 1 |

Figures 7 and 8 depict the main effect plots of each factor of the two experiments respectively. The effect of Pressure and Tool offset have a proportional relationship with the reduction of number of defects and surface roughness, while that of the other two factors are inversely proportional. The optimal parameter level obtained is Table 5, which are 8 bar Pressure, 10 mm/min Feed rate, 2.5 mm Tool offset, and 0.2 mm Scan interval. An validation experiment was conducted with the optimal parameters and the results are presented in Figure 9. It can be observed both surface defects and surface roughness improved after the polishing process. The surface roughness has decreased from 840 nm to 33 nm, which is a 95% improvement.

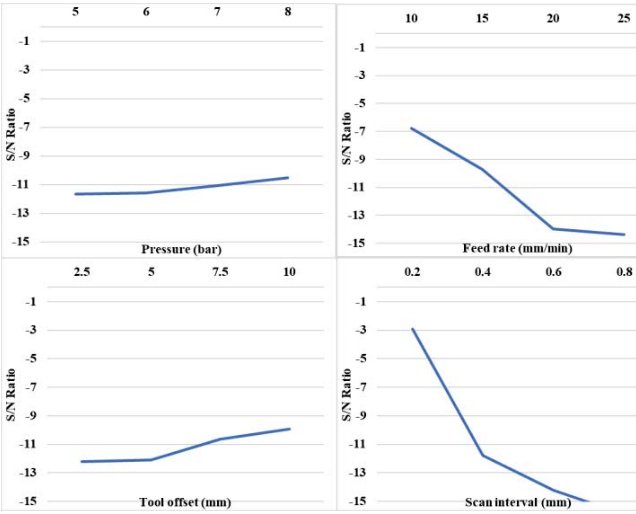


Fig. 7 Main effect plots of each factor for Set A

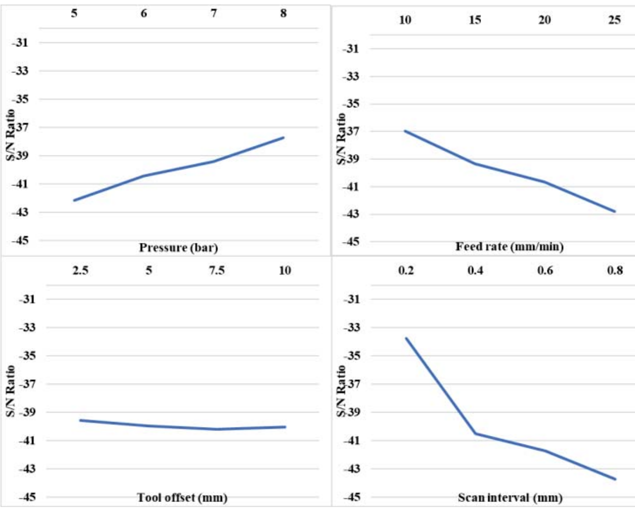


Fig. 8 Main effect plots of each factor for Set B

Table 5 Optimal polishing condition obtained for polishing 316L

| Optimal Condition | |
|---|---|
| Pressure | 8 bars |
| Feed rate | 10 mm/min |
| Tool offset | 2.5 mm |
| Scan interval | 0.2 mm |

## 4. Conclusions

In the current study, the authors have presented the feasibility of FJP technology to the post-processing of 3D Printed surfaces. With the set of parameters, the current study has revealed an encouraging result that the surface integrity and surface roughness of a surface has been improved for more than 90% in only one polishing step. Also, the factors affect the surface have also been analysed. The study presented here provides an effective option to AM industry for the improvement of surface quality.

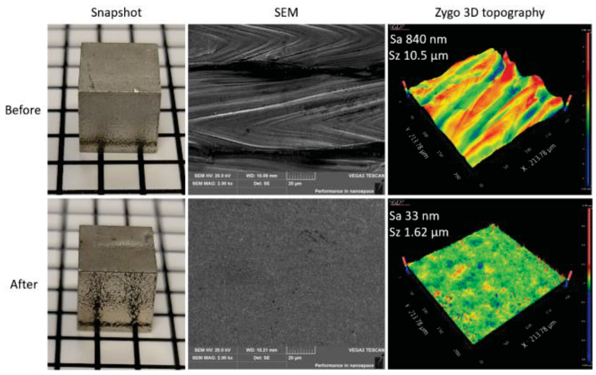


Fig. 9 Snapshots of the 316L sample before and after polishing

## ACKNOWLEDGEMENT

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