Automated laser polishing for surface finish enhancement of additive manufactured components for the automotive industry

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Abstract

Additive manufactured components require polishing to improve their inherently rough surface finish. In this work, an innovative laser polishing process based on wobbling of the laser beam is proposed for surface finish enhancement of additive manufactured parts made of Cr–Cu precipitation hardening steel, widely employed for mechanical components in the automotive industry. Parts were fabricated by selective laser melting and subjected to the innovative laser polishing under different process conditions. Surface characterization was performed by microstructural analysis and surface roughness measurement. Machine learning-based CNN processing of polished surface images was employed for automatic identification of optimal LP condition.

Keywords Additive manufacturing · Laser polishing · Surface integrity · Machine learning

1 Introduction

Additive manufacturing (AM) is increasingly employed in the automotive and aerospace industry for a growing range of components, including engines and vehicle bodies, due to the high potential for weight reduction and mass customization [1, 2].

However, AM parts are characterised by typically rough surface finish, with arithmetic as-built roughness usually ranging from 8 to 20 μm in case of metals [3]. Many reasons have been given, including the staircase effect due to layer step, the local removal of the supporting structures and the action of surface tension, even when a proper preliminary optimization of the exposure strategy is accomplished [4].

As a consequence, the high-cycle fatigue properties of AM parts are generally lower with respect to their machined counterparts; namely, new failure modes have been identified and their causes have been addressed in the literature [5].

Therefore, in order to improve surface roughness, diverse polishing processes are applied, such as machining, mechanical abrasive or electrochemical polishing methods.

Compared to conventional methods, laser polishing (LP) is an emerging non-contact surface treatment suitable for parts characterised by complex shapes, which are usual in AM, allowing to access any challenging location on the components. In addition, reproducibility, flexibility, reliable monitoring and automation are benefited through LP and different textures can be generated over the same part [6, 7], thus allowing to perform a functional graduation of the surface and specific treatments at fatigue-sensitive locations [5].

The innovation of LP lies in its fundamentally different mode of action on the surface (remelting) compared to conventional polishing (ablation). It is based on tight focusing of laser energy which is effectively delivered where required, thus preventing uncontrolled thermal effects. Surface peaks are melted by the laser to fill the valleys and this redistribution of material results in smoother surfaces, provided that over-melting is avoided [8]. Both continuous- or pulsed-wave emission of the laser beam can be considered for the LP process [9].

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Thanks to these benefits, LP is receiving increasing interest for application on a wide range of metal alloys including steels, Co-, Ni- and Ti-based alloys, and has been investigated to the specific purpose of improving the surface quality of AM parts. Alrbaey et al. [3] investigated the effects of LP parameters for postprocessing the surface texture of selective laser melting (SLM) manufactured parts via a statistical approach, demonstrating that this process has great potential to improve the roughness of AM parts: an average Ra value improvement of up to 80% was obtained in comparison with the original SLM part. By using optimal parameters, the microstructure dendrites (e.g. balling, agglomeration, waviness) and the microstructures of shrinkage cavities (open and closed pores) can be substantially removed. Lamikiz et al. [8] studied a laser-polishing process for metal parts made of AISI 420 stainless steel infiltrated with bronze built-up by selective laser sintering (SLS), showing significant roughness reductions up to 80% in terms of Ra value.

A number of studies are reported to evaluate the impact of the governing factors on surface roughness [9, 10]. Namely, it has been shown that surface roughness can be effectively decreased below 1 μm , thus matching the usual requirements for the automotive and aerospace industry [6, 7, 11], although the initial surface topography is a factor for the overall effectiveness of LP [12]. Zhihao et al. [11] demonstrated the LP process capability of improving the rough surface of additive manufactured Inconel 718 alloy parts, showing that the as-built surface roughness of more than 7 μm could be reduced to less than 0.1 μm through laser polishing process. Mai and Lim [13] achieved a roughness reduction from 195 to 75 nm using LP technology on 304 Stainless Steel. Zhou et al. [6] experimentally investigated LP of titanium alloys determining the polishing parameters on the basis of the energy conservation and they could effectively decrease the surface roughness from 7.3 to approximately 0.6 μm . On the other hand, Yung et al. [7] presented a novel layered LP method to reduce the surface roughness of Cobalt Chromium (CoCr) components with complex surface geometry. The optimized laser polishing parameters were initially obtained from the experimental tests carried out on CoCr alloy planar surfaces. Surface roughness reductions up to 93%, comparable to the results obtained on planar surfaces, were achieved on complex surface geometry. In general, a significant improvement of the fatigue life of AM metal parts is expected after LP.

As a consequence of the LP process, a significant improvement of the fatigue life of AM metal parts is generally expected. Nevertheless, any action on surface roughness via LP affects other properties of the material, such as the micro-hardness [6, 7]. Therefore, proper evaluation of LP must take into account both surface

improvements and microstructural changes, which may lead to new phases in the fusion zone and the heat-affected zone (HAZ) [14].

In this paper, an innovative laser polishing process based on wobbling of the laser beam is applied to AM parts made of Cr–Cu precipitation hardening steel, widely employed for mechanical components in the automotive industry [15]. The driving idea is imported from laser welding, where wobbling of the laser beam along the scanning path is preferred over conventional defocusing of the spot in order to preserve the required irradiance threshold and cover the gap between uneven abutting edges or interlayer addition [16]. Shah et al. [16] experimentally compared conventional laser welding and beam wobbling processes, observing that laser beam wobbling enhances the joint quality and integrity by widening the bond area and mitigating the formation of brittle lower fusion zone in the region. Wobbling has been also suggested to the purpose of fixing welding defects such as undercuts over the surface of the weld bead and incomplete fusion of the parent metal [17]. Kuryntsev and Gilmudinov [17] investigated a laser welding process using a constant laser beam trajectory and a wobbling trajectory. The results showed that after the second welding pass, with wobbling trajectory of the laser beam, middle and cap parts of the seam displayed a lower microhardness with respect to the root part. The laser beam wobbling pass guaranteed less shrinkage and provided greater ductility of the weld metal.

In the case of laser polishing process, compared with traditional laser linear scanning, wobbling provides the concurrent benefits of limited microstructural weakening in the material and increased rate of polishing. Alfieri et al. [10] evaluated the heat effects of post-processing treating via laser beam wobbling on metal parts resulting from SLM of stainless steel in order to improve surface topography, showing that particular advantages are offered when carrying out wobbling of the laser beam compared with traditional linear scanning: heat effects proved to be lower, based on the depth of the fusion zone as well as on the HAZ extent resulting from Vickers microhardness testing.

In this paper, in order to identify the optimal LP conditions in terms of final surface quality, different polishing conditions, all based on wobbling of the laser beam, were applied to the AM parts made of Cr–Cu precipitation hardening steel. Surface integrity characterization was performed through metallurgical analysis and surface roughness measurement. The response of the process was correlated to the governing factors. In addition, machine learning-based image processing was developed in view of on-line real-time automatic identification of laser polished surface quality and integrity, highly functional for mass production automation in the automotive industry.

Table 1 Full-melting processing conditions adopted for additive manufacturing of the samples

Factor	Value
Operating laser power	195 W
Linear speed	1 m/s
Hatch spacing	0.10 mm
Layer thickness	20 μm
Focused spot diameter	90 μm

Fig. 1 Wobbling of the laser beam spot centre along the scanning length

2 Materials and experimental campaign

Square plates of 60 mm side and 3 mm thickness, made of Cr–Cu precipitation hardening steel (with nominal chemical composition matching UNS S17400 steel), were additively manufactured on an EOSINT M270 laser melting machine with Yb-fibre laser source using pre-alloyed, argon-atomized virgin powder of 20 μm mean grain size. Based on previous optimization, the parameters of the part building process were set (Table 1) so as to result in a condition of full-melting of the base material.

LP was performed on the square plates through a scanning head, model ScanFiber, produced by the El.En. company, with a focused spot of 1 mm diameter and an image field of 400 mm $\times$ 400 mm, using a Yb:YAG source by wobbling the laser beam spot centre along the scanning length. The scanning head, relying on galvanometer laser-grade mirrors, allows to benefit from greater accuracy and reduced mass and inertia compared to other systems which mechanically deflect the laser spot by means of a robot, arm, moving or rotating table [18] over a complex scanning path. Indeed, the position (x , y) of the beam spot as a function of time t draws a prolate trochoid (Fig. 1) and depends on the processing speed s , the wobble amplitude A , and the wobble frequency f according to equations:

$$x = st + \frac{A}{2} \cos(2\pi ft) \quad (1)$$

$$y = \frac{A}{2} \sin(2\pi ft) \quad (2)$$

Fig. 2 Laser beam spot wobbling along a single-track scanning: 1 m/min speed, 1 mm amplitude, 200 Hz wobble frequency

Fig. 3 Laser beam spot wobbling along a single-track scanning: 20 m/min speed, 1 mm amplitude, 150 Hz wobble frequency

Speed, frequency and amplitude of the wobble path must be properly set to uniformly process the surface, otherwise local inhomogeneity due to extended or limited exposure to the laser beam may result. To this aim, single-track scanning with wobbling of the laser beam spot along the scanning length was simulated. Figure 2 shows the simulation with indication of the overall laser track width L , sum of wobble amplitude A and laser spot diameter D .

Based on the simulation results, all the combinations of the governing factors levels yielding improper wobbles, as the combination shown in Fig. 3, were excluded.

Then, a set of nine geometrically valid conditions (Table 2) was preliminarily tested in single-track LP: laser power P and wobble amplitude were varied, while processing speed s and wobble frequency were kept constant at 1 m/min and 200 Hz, respectively. These conditions were discussed in terms of mean roughness with respect to the delivered energy density E , which has been defined as a comprehensive parameter to take into account the main governing factors:

Table 2 LP process conditions employed for the preliminary tests of single-track scanning

Condition	Laser power (W)	A (mm)	Energy density (J/mm ²)
A	200	1	6
B	200	2	4
C	200	3	3
D	400	1	12
E	400	2	8
F	400	3	6
G	600	1	18
H	600	2	12
I	600	3	9

Fig. 4 Laser beam spot wobbling in multi-track scanning: 0.5 mm hatch spacing, 1 m/min speed, 1 mm amplitude, 200 Hz wobble frequency

$$E = \frac{P}{(A + D)s} \quad (3)$$

Among the tested single-track process conditions, two were selected to effectively reduce surface roughness, namely condition D (400 W laser power and 1 mm wobble amplitude) and H (600 W laser power and 2 mm wobble amplitude), and were used at the subsequent stage of the research. Indeed, to perform LP over a wider surface, multiple, adjacent and partially overlapping tracks are required. To this aim, simulation of LP was performed again by considering multi-track scanning in order to cover the whole part surface (Fig. 4), with the aim to find suitable values for the hatch spacing, H , between axes of adjacent tracks.

On this basis, an experimental plan of multi-track LP was set up and four values of hatch spacing were considered for each of the two conditions selected at the previous

Table 3 LP process conditions with multiple adjacent partially overlapping tracks

Condition	Laser power (W)	A (mm)	H (mm)	OR (%)
D1	400	1	0.5	75
D2	400	1	0.7	65
D3	400	1	1.0	50
D4	400	1	1.2	40
H1	600	2	0.5	83
H2	600	2	0.7	75
H3	600	2	1.0	65
H4	600	2	1.2	60

stage, as shown in Table 3. The percentage overlapping ratio $OR = 1 - H/L$, with L overall laser track width and H hatch spacing, was introduced as synthetic input parameter.

3 Surface characterization

3.1 Surface roughness

The surface roughness was measured by means of a Taylor Hobson device called Form Talysurf 50 with contact probe in compliance with the ISO 4287:1997 standard [19]; a Gaussian filter was applied. The average initial roughness R_a of the as-built parts was 16.2 μm . The surface roughness was measured in the direction of scanning in case of single-track (Table 4), while it was measured along 3 directions (parallel, transverse and at 45° to the LP direction) in case of overlapping tracks, as in Fig. 5. For each direction, 3 measurements were made over a sampling length of 12.5 mm and averaged (Table 5).

Table 4 Average surface roughness values for each single-track process condition

Condition	R_a average (μm)	R_z average (μm)
A	11.1	57.5
B	11.5	61.0
C	10.5	57.0
D	0.4	2.9
E	7.4	38.1
F	11.2	60.6
G	1.7	9.0
H	0.6	3.1
I	3.9	17.8

Fig. 5 Direction of sampling for surface roughness in case of multi-track and overlapping tracks

Table 5 Average surface roughness values for each multi-track process condition

Condition	Ra average (μm)	RSm average (μm)	Rz average (μm)
D1	4.6	724.4	23.2
D2	5.4	713.4	24.0
D3	3.5	650.1	17.5
D4	5.1	809.4	26.9
H1	4.5	467.9	24.1
H2	4.5	619.5	22.3
H3	6.2	933.6	26.3
H4	4.7	1180.2	21.9

3.2 Microstructural analysis

The depth of the fusion zone due to multi-track LP was observed on the cross-section of the AM parts: a sample

from each test was cut, mechanically ground and polished to mirror finish and finally chemically etched. The depth of the fusion zone was measured through conventional optical microscopy and imaging software (Fig. 6) and summarised in Table 6.

Vickers micro-hardness tests were performed along an indentation pattern in the direction of the plate thickness, starting from the polished surface, to assess the extension of the HAZ with 200 g indenting load, 10 s dwell period; 0.1 mm step between consecutive indentations, in compliance with EN ISO 6507-1 standard for hardness testing of metals [20].

3.3 Machine learning-based image processing for LP automation

Surface characterization was also performed through machine learning-based image processing using Convolutional Neural Networks (CNN) for automatic identification of LP process conditions yielding optimal polished surface quality and integrity.

CNN are a machine learning technique able to classify images using features which are learnt by the CNN itself during the training process [21]. CNN consist of a series of hierarchically-arranged convolutional layers gradually assembling low-level features (from small receptive fields) into high-level features (from large receptive fields) to better characterize the input image.

Each convolutional layer extracts information from patches (receptive fields) in the previous layer through

Fig. 6 Fusion zone depth measurement in the transverse cross-section for conditions #D4 and #H1

Table 6 Average depth of the fusion zone for each process condition

Condition	1	2	3	4	5	6	7	8
Depth (μm)	273	268	214	204	434	393	279	300

Fig. 7 Multi-track polished surface 333 px×150 px images for all testing conditions

Table 7 Convolutional neural network parameters

Layer	# feature maps	Stride	Activation	Pooling
Convul 1	8	2	ReLU	2×2 max pooling
Convul 2	16	2	ReLU	2×2 max pooling
Convul 3	32	2	ReLU	–
Fully conn	8, 4, 6 classes	–	Softmax	–

convolution operations using kernels, i.e. filters, traversing the image to extract features from the whole image.

In order to create the dataset for CNN-based machine learning, images of the multi-track polished part surfaces were acquired for each testing condition using a Leica S8-APO stereo microscope with apochromatic 8× magnification and 75 mm working distance. These images were pre-processed with the aim to build the dataset for CNN training. Specifically, each image was segmented into smaller images of size 333 px×150 px, each covering a polished surface area of ~3 mm×1.5 mm (Fig. 7), with the aim to obtain a suitable number of images for machine learning. In this way, 54 images were extracted for each testing condition, summing up to a total of $54 \times 8 = 432$ images for the CNN training dataset.

From the training dataset, 80% of the images for each class (344 in total) were employed for CNN training while the remaining 20% (88 in total) were employed for CNN validation.

The parameters of the CNN architecture are reported in Table 7.

A filter size of 10 px×10 px and a stride (the step size used by the filter to traverse the image) of 2 were adopted

in all the convolutional layers. A learning rate value of 0.01 was selected for CNN training, allowing to reach the classification convergence in a reasonable number of training epochs without incurring into unstable training or converging too quickly to a suboptimal solution. The maximum number of epochs was set to 20 based on the observation of the convergence behaviour of the validation accuracy of the CNN with the selected learning rate of 0.01. As a matter of fact, by increasing the maximum number of epochs (e.g. to 30), no improvement was observed in the CNN validation accuracy, while an increase of the training time (by about 50%) was verified. During training, network validation (the calculation of accuracy and loss on the validation data) was carried out with a frequency of 10 iterations to determine if the network is overfitting to the training data.

4 Results and discussion

Based on the outcome of single-track scanning LP (Fig. 8), the Ra and Rz values were discussed to select the proper wobble condition. Both Ra and Rz were found in convincing correlation with the energy density (Fig. 9): a simple linear regression proved to be effective over the investigation domain, with *R*-squared values of 86% for both Ra and Rz; the effectiveness of the regression even increased up to 94% when the observation was limited to the range $3 \div 12$ J/mm². Indeed, it is worth noting that increasing the energy density over a certain threshold yields a detrimental effect on the surface, because overmelting is produced. Conditions D (400 W laser power and 1 mm wobble amplitude) and H (600 W laser power and 2 mm wobble amplitude) were selected for the next stage of multiple-track scanning since they offered the best solution in terms of roughness reduction.

With the aim to assess the LP process consistency in multi-track scanning with reference to the hatch spacing value, the RSm surface roughness parameter (mean peak width) evaluated along the transverse direction (i.e., the direction of hatching) was considered. Indeed, this parameter is expected to directly reproduce the hatch spacing distance: this was effectively verified for all process conditions. In the case of process conditions 5–8, the relationship is virtually linear, in comparison with conditions 1–4, probably due to the presence of sharper track edges (Fig. 10).

At this stage, in order to select the most suitable processing condition, two responses were considered: the transverse surface roughness as a measure of surface improvement and the depth of the fusion zone as a measure of microstructural changes. The dependence on the processing conditions was investigated as a function of the percentage overlapping ratio to take into account both the wobble amplitude and the hatch spacing simultaneously.

	Laser power 200 W	Laser power 400 W	Laser power 600 W
Wobble amplitude 1 mm			
Wobble amplitude 2 mm			
Wobble amplitude 3 mm			

Fig. 8 Surface aspect in single-track LP

Fig. 9 Surface roughness as a function of the energy density

Fig. 10 Transverse surface roughness RSm vs. hatch spacing

To identify the optimal LP conditions, on the one hand conditions resulting in the lowest surface roughness should be preferred (Fig. 11). On the other hand, microstructural changes in terms of fusion zone depth should also be taken into account (Fig. 12).

Figure 11 shows that the trend of the transverse Ra with increasing OR is consistent when taking into consideration the two sets of conditions 1–4 and 5–8 of Table 3, where each set is characterized by the same power and wobble amplitude values. From Fig. 12, an increase of depth of the

Fig. 11 Transverse surface roughness Ra vs. overlapping ratio

Fig. 12 Depth of the fusion zone vs. overlapping ratio

fusion zone is observed with increasing OR due to the growing thermal impact on the polished material.

By jointly considering the results in terms of surface roughness and depth of fusion zone, an optimal LP condition was identified as condition #D3 characterized by an OR value of 50%.

To further investigate the impact of the LP process on the polished parts material in terms of microstructural changes, the HAZ extension was analysed based on the

Fig. 13 Vickers microhardness along the direction of LP part thickness

Table 8 CNN classification accuracy

Classification case	LP conditions	Hatch spacing	Overlapping ratio
Accuracy [%]	97.3	100.0	98.9

micro-hardness test results. In Fig. 13, the Vickers microhardness plot is reported for the selected LP condition #D3.

Material softening was observed in both the fusion and the heat-affected zone, as a consequence of annealing of the base material and loss of the original martensitic structure due to LP. Figure 13 shows that the thermal impact of LP becomes negligible starting from a depth around 1.0 mm, after which the reference material hardness 260 HV was verified. In the case of condition #D3, the HAZ extension is given by 1.0 mm minus the fusion zone depth 0.214 mm, equal to 0.786 mm, which is among the lowest values in the range 0.750–0.980 mm of HAZ extension values obtained for the considered conditions.

Machine learning based CNN image processing was applied to the polished part surface images for automatic identification of LP process conditions, providing a classification accuracy of 97.3%.

Based on the promising results in the classification of LP process conditions, the CNN approach was also applied for the automatic identification of hatch spacing which was earlier found well related to the surface roughness in terms of transverse RSm (Fig. 10). In this case, the classification accuracy of the CNN reached 100.0%.

The CNN approach was finally employed to identify the OR value since the polished part surface quality and integrity in terms of both fusion zone depth and surface roughness (transverse Ra) proved well related to the OR (Figs. 11, 12). In this case, a classification accuracy of 98.9% was achieved (Table 8).

The extremely good CNN performance for all the three classification objectives (Table 8) is the issue of the outstanding capability of the CNN to learn the characteristic features of the polished surface images for each output class.

To exemplify this capability, Fig. 14 reports illustrative feature maps outputted from the fully connected layer at different training steps (after 2, 4 and 20 epochs) for the OR classification case. The images highlight the features learnt by the CNN: the output maps of the fully connected layer, corresponding to the image classes, are high-level combinations of the features learnt by earlier layers.

From Fig. 14, it can be seen that, as training proceeds with increasing number of epochs, the CNN response displayed in the feature maps progressively converges to the main characteristics of the polished surface images used for training. As a matter of fact, going from Fig. 14a–c, the track edges, which are strongly related to the OR value, are ever more visible.

5 Conclusions

An innovative laser polishing process based on wobbling of the laser beam, able to notably improve surface finish while inducing low microstructural changes compared to traditional laser linear scanning, was applied to AM parts for the automotive industry.

To model the single-track LP process, the energy density can be referred as a proper synthetic index involving the laser power, the spot diameter, the wobble amplitude and the scanning speed. The LP wobbling process in multi-track scanning mode provided a significant surface roughness improvement between 62 and 78% according to process conditions compared with the as-built AM part surface.

Microstructural changes due to LP thermal impact were in all cases rather limited: the fusion zone depth is in the

Fig. 14 Output feature maps from the CNN fully connected layer for the OR classification case at different training steps after 2, 4 and 20 epochs

range 0.204–0.434 mm and the HAZ extension is in the range 0.750–0.980 mm.

The trends of the transverse Ra and fusion zone depth were found to be consistent with a proposed synthetic input parameter: percentage overlapping ratio OR. An optimal LP condition characterized by an OR of 50% was identified by jointly analysing the surface roughness and fusion zone depth trends.

Machine learning-based CNN processing of polished surface images allowed to automatically identify the LP process conditions, hatch spacing, and overlapping ratio with classification accuracy as high as 97%–100%, based on the classification task.

The remarkable ability of the CNN to correctly classify the OR from the surface images can be proficiently employed for LP process automation through on-line real time automatic recognition of the optimal LP condition, which within this research work was associated to an OR of 50%.

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