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Real-time roughness estimation in laser oxidation cutting via coaxial process vision

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Abstract

Laser cutting is an established technology for the processing of metal sheets and tubes given its elevated productivity and high part quality. However, external influences or variations in the process conditions may affect the quality of the final product. In oxidation cutting, cuts are typically evaluated by means of profile roughness whilst critical defect formation consists in loss of cut. Real-time estimation of the cut quality via process monitoring is of great interest since it enables inline evaluation of the manufactured components and identification of defected parts. Such capabilities were investigated during the cutting of high thickness mild steel, acquiring process emission images with a coaxial monitoring system and correlating them to the profile roughness via Machine Learning algorithms. Results indicate roughness predictions with good fitting (R2>80%) and with a Mean Absolute Error below 10 µm (R_z parameter).

Keywords: Laser cutting; Oxidation cutting; Monitoring; Roughness; Machine Learning

1. Introduction

Laser oxidation cutting in the current industrial scenario is one of the reference technologies for the cutting of mild steel sheets. The strive for intelligent sensorized machines which can exploit advanced sensing options to extract relevant process information is a rising topic within both the industrial and scientific communities. The in-situ monitoring of the laser material interaction is a fundamental aspect to derive the actual state of

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the cutting process. Various works in literature have reported a strong correlation between process emission and defect formation (Levichev et al., 2021).

Fallahi Sichani *et al.* exploited a coaxial monitoring set up for an adaptive control of the oxidation cutting process however they did not disclose a direct correlation to a quality parameter(Sichani et al., 2010). Pacher *et al.* developed an approach to estimate dross formation in real-time as an indicator of dross formation during the fusion laser cutting process. (Pacher et al., 2020, 2021). Alternatively, to camera-based monitoring approaches, integrated sensors may also be employed to diagnose the processing conditions.(De Keuster et al., 2007; Decker et al., 1997; Levichev et al., 2020; Schleier et al., 2018). Thermal cameras are also often employed to detect the temperature fields in the proximity of the laser-material interaction area to predict cutting conditions. (Bison et al., 2019; Levichev et al., 2022)

Although several studies have been published on the monitoring of the oxidation laser cutting, a clear correlation between typical process defects, such as the profile roughness, and the observable process emission has not yet been established. Previous investigations have typically built the correlation between the signal from integrated sensors and the defects through qualitative or simple statistical relations. However, the use of Machine Learning (ML) approaches can allow to disclose complex relationships and provide predictions with a higher degree of accuracy and robustness.

The current investigation reports a novel methodological approach for the real-time estimation of the profile roughness during the laser oxidation cutting process. The experimental methods and materials are initially reported, providing details with regards to the laser cutting system and monitoring chain. The Machine Learning approach for the training and testing of the real-time estimation method is then presented alongside with the experimental design. Finally, the results reporting the performance of the approach developed are shown. Quantitative measurements of the cut profile are correlated to the features extracted from the process emission acquired via the monitoring chain and enable a sensing architecture for the real-time estimate of the profile roughness.

2. Materials and method

2.1. Experimental set up

An industrial laser cutting system (LC5, BLM Group, Levico Terme, Italy) was employed to perform the cuts. The system is equipped with a laser cutting head with a collimating lens with focal length of 100 mm and a focusing lens with focal length 200 mm (HPSSL, Precitec, Gaggenau, Germany). A 6 kW laser source emitting at λ=1070 nm from a transport fiber diameter of 100 µm was employed as the light source in the optical set up (YLS-6000-CUT, IPG Photonics, Cerro Maggiore, Italy). The process light is therefore focused to a minimum beam waist diameter of 200 µm and its position can be regulated by a translational movement of the focusing lens. The overall configuration of the process is reported in Table 1.

The process chain is equipped with a coaxial monitoring system which allows to observe the process emission via a dichroic mirror positioned between the collimator and the focusing lens. The monitoring system has been presented in past publications and features an imaging camera (XiQ MQ013MG-ON, Ximea, Munster, Germany) filtered in the near infrared wavelength in order to acquire the process dynamics(Pacher et al., 2020; Vasileska et al., 2022). The imaging chain observes the laser-material interaction with a spatial resolution of 9.6 µm/pixel over a 200 pixel x 200 pixel field of view. The system is thus configured with an optical magnification of 2 and was set to acquire the process emission a 750 Hz. Table 1 reports also the synthetic data of the monitoring chain.

Table 1. Specifications of the laser cutting system and monitoring chain

Laser cutting system	
Parameter	**Value**
Maximum emission power, P_{max} (kW)	6
Emission wavelength, λ (nm)	1070
Beam Parameter Product, *BPP* (mm*mrad)	3.722
Fiber diameter, d_{f0} (µm)	100
Focal length of collimating lens, f_{col} (mm)	100
Focal length of focusing lens, f_{foc} (mm)	200
Beam waist diameter, d_0 (µm)	200

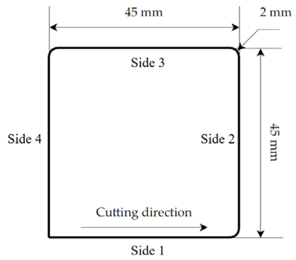
Monitoring Chain	
Parameter	**Value**
Acquisition frequency, f_{acq} (Hz)	750
Pixel size of camera, d_{pix} (µm)	4.8
Spatial resolution, *SR* (µm/pixel)	9.6
Optical magnification, *m* (-)	2
Field of View, *FOV* (pixel*pixel)	208x208

2.2. Experimental design

The aim of the experimental design was to induce quality variations on the cut profile in terms of surface roughness and correlate them to process emission images obtained with the coaxial monitoring equipment. The cut geometry of the test samples corresponded to a square with 45 mm characteristic length and rounded edges with a radius of 2 mm as shown in Table 2. The different sides of the cut were numbered progressively in order to identify any dependence on the cutting direction. The experiments were run on the same batch of material which corresponded to RAEX 400 mild steel with a thickness of 8 mm. The laser power was maintained constant at P=4 kW with a continuous wave emission mode corresponding to a duty cycle δ=100%. The cutting speed was varied between 1100 mm/min to 2600 mm/min with a step of 300 mm/min whilst the other process parameters were selected from standard literature values (Levichev et al., 2020). The upper boundary of the cut was set in correspondence to the loss of cut condition. The overall experimental design with the fixed and variable parameters is reported in Table 2.

Table 2. Fixed and variable parameters of the experimental design

Fixed factors	**Value**	**Cut geometry**
Material	RAEX 400	
Sheet thickness, *t* (mm)	8	
Laser emission power, *P* (kW)	4	
Assist gas	O_2	



Variable factors	**Value**
Cutting speed, *v* (mm/min)	1100 – 1400 – 1700 – 2000 – 2300 – 2600

Every experimental condition was replicated three times to provide three separate datasets for the training of Machine Learning algorithms. The quality of the cut profile was characterized by means of roughness measurements in order to disclose the dependence with respect to the process parameters. From the process emission images acquired, it was possible to extract synthetic features which provided information regarding the cutting conditions. These features were therefore utilized to establish a correlation with the measured surface roughness of the profile via different ML algorithms, aiming to identify the highest performing relationship.

2.3. Material characterization

The cut profile was characterized in accordance with standard ISO 9013:2002 by measuring the peak height of the profile R_z with Mahr PGK profilometer (Mahr, Wuppertal, Germany). The profile roughness was measured at 1/3 of the sheet thickness from the top surface of the sheet. For each cut side, three profile roughness measurements were performed and were coordinated with the process emission images acquired via the coaxial monitoring set up.

2.4. Machine Learning approach

Features are fundamental for the successful implementation of a Machine Learning algorithm. They are measurable properties or attributes of the phenomenon being studied. The performance of the ML model developed to correlate the features to the measured roughness strongly relies on the quality of the extracted features. In this study, a series of geometrical features was extracted directly from the analysis of the frames captured from the video of the process emission. The video was acquired with the coaxial NIR camera during the cutting process. The single frames were stored in a temporary buffer (lookback window) which was exploited to engineer the features for the development of the Machine Learning algorithms.

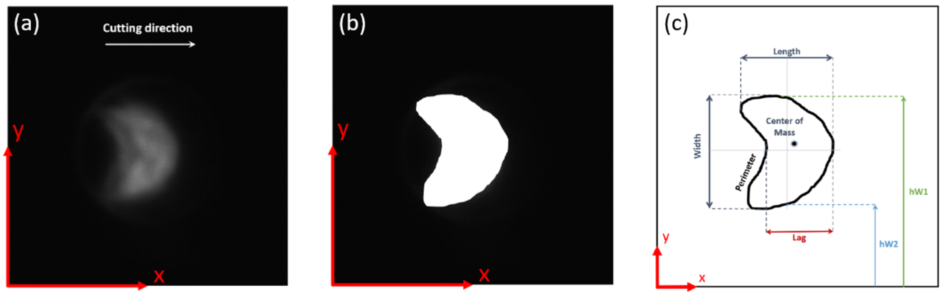


Fig. 1. (a) Process emission image (b) binarized image with a hard-threshold of 15 and (c) graphical representation of the geometrical features extracted from the binarized image

Given the presence of a lookback window it was possible to increase the dimensionality of the feature space by calculating for each feature the mean (μ) and the standard deviation (σ). Geometrical features could be extracted from binary images after hard thresholding of the grayscale images at predetermined values. Examples of such features are the area, length, width as depicted graphically in Fig. 1 (c).

As mentioned previously, feature selection plays a fundamental role in developing effective Machine Learning models. Hence, all of the proposed features were correlated with the measured profile roughness by means of Pearson's coefficient. Then, redundancy between the selected features was verified to further reduce their number.

In order to identify the most performing algorithm for the real-time estimation of the roughness, different Machine Learning models were tested using standard quality and error indicators, i.e. the R^2 value, the Root Mean Square Error and the Mean Absolute Error defined as follows:

$$R^2 = \frac{\sum(y-\hat{y})^2}{\sum\left(\mathrm{y}-\mathrm{mean(y)}\right)^2} \tag{1}$$

$$RMSE = \sqrt{\mathrm{mean}((y - \hat{y})^2)} \tag{2}$$

$$MAE = \mathrm{mean}|y - \hat{y}| \tag{3}$$

The models under evaluation corresponded to standard machine learning algorithms: first order Linear Regression (LR), Decision Tree (DT), Random Forest (RF), eXtreme Gradient Boosting (EGB) and Multi-Layer Perceptron (MLP). Different configurations of the acquired datasets were exploited for the training and testing phase of the model predictions with respect to the measured variable. A final evaluation of the performance of the models was done exploiting the Leave-One-Out Cross-Validation (LOOCV). With the LOOCV, for each specimen belonging to the entire dataset a model is trained on all the other specimens and tested on the excluded one. The procedure is then iterated for all the remaining ones, keeping track each time of the model performance.

3. Results

3.1. Cut profile roughness

The cut quality at the different cutting speeds was evaluated by means of the profile roughness in order to determine the trend as a function of the varied parameter. Fig. 2 shows the profile roughness for the different sides as a function of the cutting speed. From the results, it clearly appears that higher cutting speeds allow to achieve cut profiles with lower roughness. However, when cuts were performed at 2600 mm/min the loss of cut defect began to present itself. Only in the case of the first dataset it was possible to perform the cut with a cutting velocity of 2600 mm/min whereas in the other replicates of such condition resulted in a loss of cut. The roughness trend illustrated in Fig. 2 demonstrates the need to find a balance between achieving the desired profile roughness and the occurrence of the loss of cut condition. Overall, the roughness profile did not vary in a statistically significant manner between the different sides of the specimen indicating, as expected, an independence from this factor.

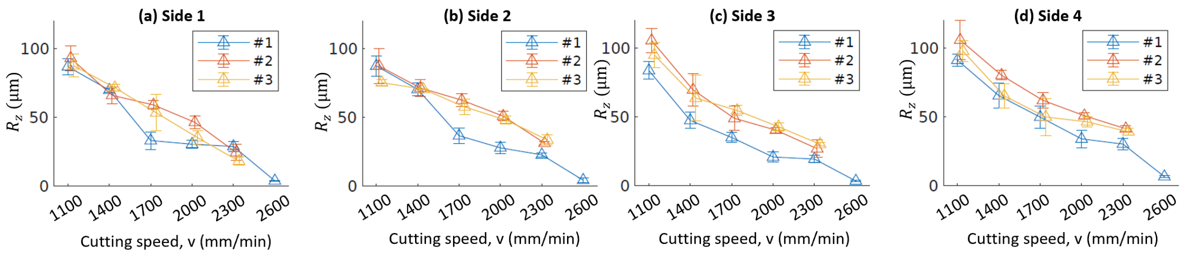


Fig. 2. Profile roughness of the cut profiles for the different sides of the sample specimen (a) side 1, (b) side 2, (c) side 3 and (d) side 4. Error bars indicate the standard deviation of the measurement.

The variation of surface roughness was deemed to be representative of realistic process variations during industrial use of laser cutting system and is in agreement with previous observations by Levichev *et al.*(Levichev et al., 2021). Thus, in the following section the process emission images were analysed in order to correlate them with the quality of the cut profile.

3.2. Feature selection

Fig. 3 shows representative frames of the process emission images acquired via the coaxial monitoring set up during the cutting of the 8 mm thick RAEX mild steel. It clearly appears that the geometrical and intensity features vary in the different processing conditions. From a semi-lunar shape visible at v=1100 mm/min the acquired process emission moves towards a spherical shaped blob. This variation is consistent with the expected process physics, where higher cutting velocities correlate to an increased inclination of the cutting front.

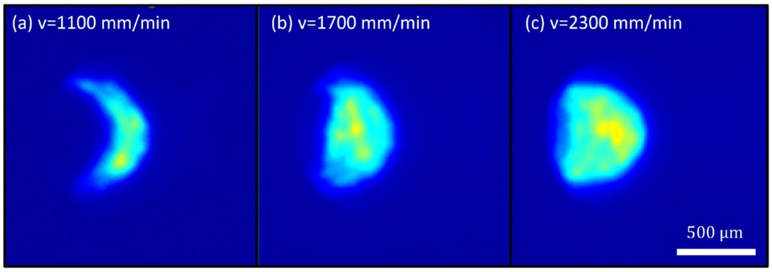


Fig. 3. Single frame acquisitions at different cutting velocities corresponding to (a) v=1100 mm/min, high roughness (b) v=1700 mm/min mid roughness and (c) v=2300 mm/min low roughness. Dark blue indicates 0 intensity value whilst yellow corresponds to saturated pixel at 255.

As mentioned, the different geometrical features were elaborated and correlated to the corresponding roughness measurement via the Pearson's coefficient; then the number of features has been reduced to five by evaluating the redundancy of the most correlated features.

3.3. Machine Learning model selection

Following the feature selection, the different ML models indicated in section 2.4. were trained exchanging the training and testing datasets in order to verify the redundancy and performance of the same. The results in terms of R^2, Root Mean Square Error and Mean Average Error are shown in Fig. 5.

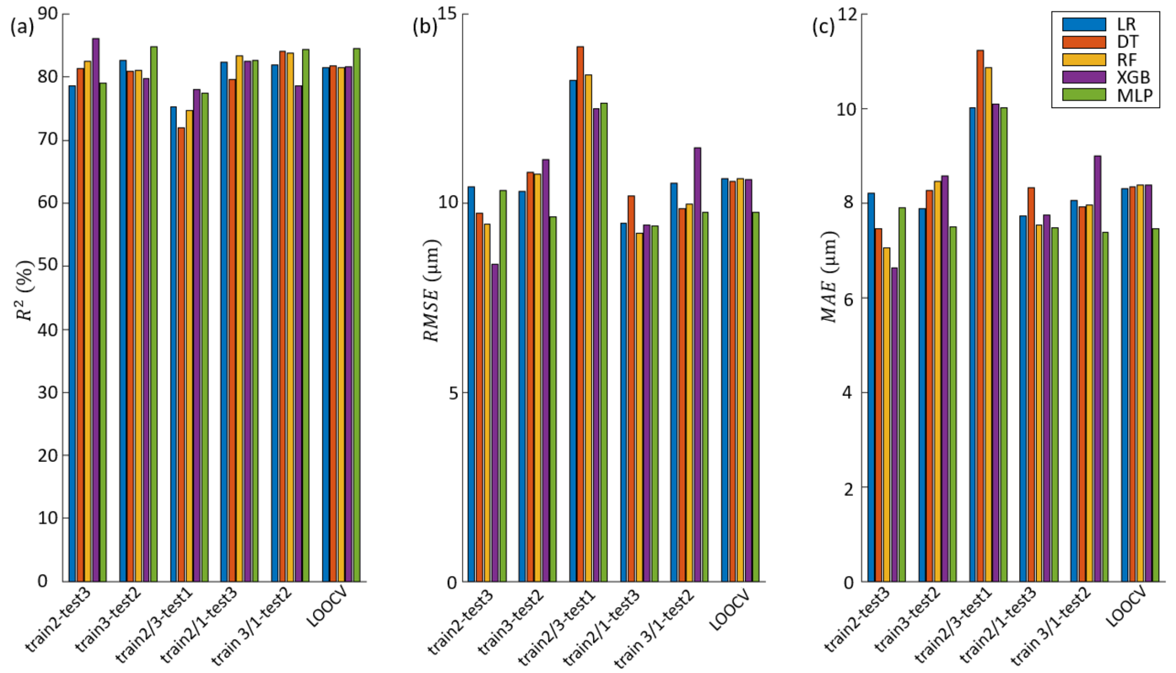


Fig. 4. Performance of the different ML models with the different combinations of training and testing datasets in terms of (a) R^2, (b) Root Mean Square Error (RMSE) and (c) Mean Average Error (MAE). Linear Regression in blue, Decision Tree in orange, Random Forest in yellow, eXtreme Gradient Boosting in purple and Multi-Layer perceptron in green.

Overall, observing the results, it is possible to view that none of the trained ML algorithms significantly outperformed the others. The R^2 value in all cases exceed 70% with values typically in the range of 80% whilst the RMSE and MAE were in the range of 10 µm which was deemed to be acceptable for the real-time estimation of the profile roughness of the cut components (R_z parameter). The Linear Regression model certainly guarantees an easier implementation into the machine architecture for the future industrial implementation of the Machine Learning approach developed. However, in terms of model performance the Multilayer Perceptron algorithm can be indicated as the most performing.

In Fig. 6, the predictions of the Linear Regression model are shown graphically against the actual values of roughness measured. It is possible to observe clearly that although the MAE and RMSE error are within the order of 10 µm, the model can effectively predict the quality of the cuts performed and indicate the overall trend of the process. This aspect is fundamental in order to provide the industrial users with a clear indication of the process performance.

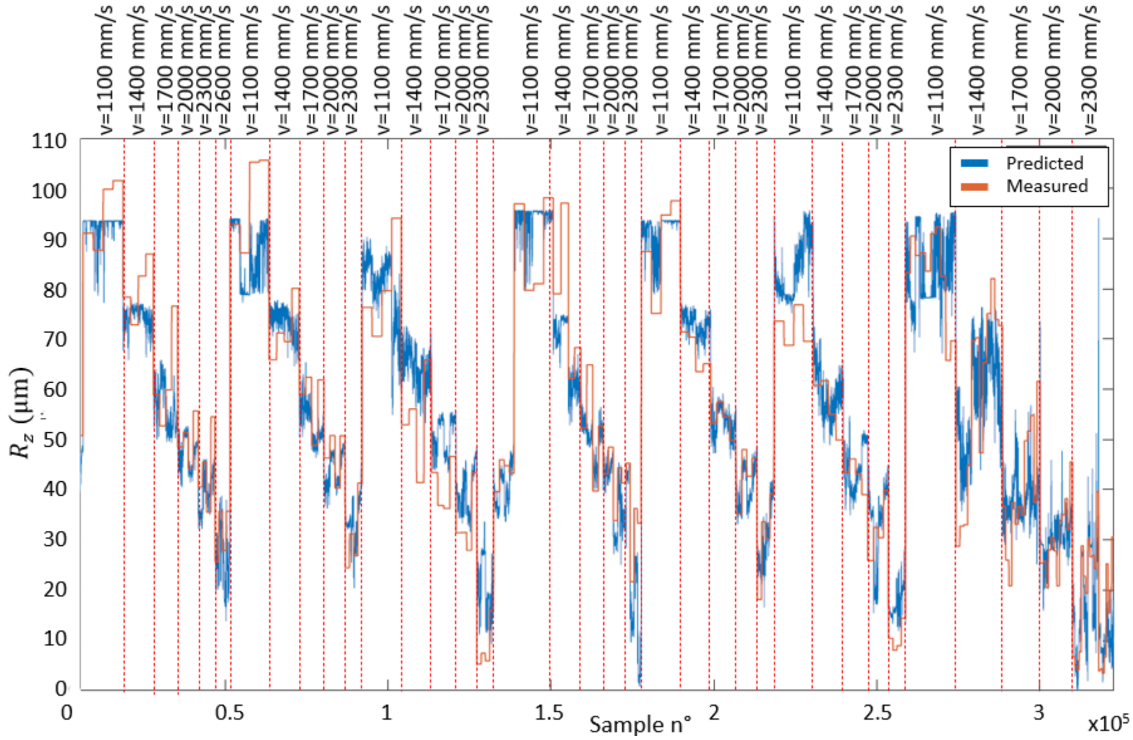


Fig. 5. Predicted roughness (blue) against measured roughness (orange) as a function of sample number calculated with the LOOCV procedure in the case of the Linear Regression model. Dashed lines delimit data from different samples with the relative cutting velocity labels at the top of the graph.

The results obtained indicate that Machine Learning approaches can effectively predict the profile roughness during the laser cutting process. The present investigation shows the approach applied for a single sheet thickness however the methodological approach developed may be easily applied to feedstock material with higher or lower thickness. A fundamental consideration regards the predictability of surfaces with more complex surface features. Profile roughness is certainly a valid indicator for the surface quality in oxidation cutting however when processing higher thickness materials further indicators may be required when processing higher thickness materials in order to take into account the effects of the complex process dynamics.

In the present investigation, roughness variations were induced by varying the cutting speed of the system. However, other factors may influence the performance of the laser cutting process and hinder the cutting quality. For instance, dirty protective windows may induce focus shifting or variations on the beam energy distribution. A relevant research question which remains open is thus the robustness of such approach when exposed to non-predictable external influences.

4. Conclusions

The current work defines the methodological approach for developing a real-time roughness estimation technique during laser oxidation cutting. The monitoring chain effectively captures the process dynamics and geometrical features of the melt front. Such information can then be exploited to train Machine Learning algorithms for the real-time prediction of the roughness profile. Statistically significant and independent features were selected for the training and testing of the various Machine Learning algorithms. The results obtained indicate that different ML algorithms may be employed and present similar performances. Overall, the prediction capability for the roughness parameter R_z of the developed architecture achieves an R^2 fitting value above 80% with a Mean Average Error below 10 µm. The monitoring chain and the real-time estimation approach lay the foundation for active control of the process that will be explored in future works.

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