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Real-time monitoring and control of the edge quality in metal laser cutting

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Abstract

A real-time monitoring of the edge quality during laser cutting enables a permanently good and robust cut. Since direct measurements of edge quality, particularly burr and roughness, are hardly possible, monitoring of the process has been realized via a cutting head camera on a flatbed high-power laser cutting machine. The acquired in-process images are used together with an independent quality measurement to train an artificial neural network. The latter is trained to classify the cutting quality based on the process camera images into high and low burr and roughness, respectively. This feedback from the cutting process allows the implementation of a closed-loop controller to adapt cutting parameters and will enable to realize a self-learning machine. Several monitoring setups, including various illumination concepts were investigated. It was found that the cut quality estimation with a selectable acceptance threshold is reliably feasible with an F1-score of about 0.85, on average. Further, with a simple calibration or fast adaptation step, the model transferability to different machines, thicknesses, and alloys are well possible.

Keywords: laser metal cutting; real-time; in-process quality monitoring; deep neural network; closed loop control; camera

1. Introduction

Machine development in general strives to significantly increase machine autonomy to drive production

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with less manpower. Flatbed laser cutting machines are following this trend and become more and more autonomous. The main aspect in the increased autonomy in laser cutting is primarily the continuous monitoring of the cutting quality, where suitable sensor technology, such as camera-based process monitoring (Kratzsch et al., 2000; Sichani et al., 2010), and corresponding machine intelligence (Günther et al., 2014; Santolini et al., 2019; Pacher et al., 2021) have become important in recent years. Material, process, and machine imperfections can lead to unsatisfactory cut qualities and hence to a significant throughput reduction, material waste, and higher production costs. Thus, a real-time quality estimator of the cutting quality, followed by a feedback controller, can highly increase reliability, efficiency, and autonomy of the cutting process, making it possible to operate with considerably less manpower and higher efficiency. Sensors and intelligence were developed and implemented to detect loss of cut and estimate roughness of cutting edges, burr adhesion, and slag formation.

2. Setup and Method

2.1. Sensors and Monitoring Strategies

Already today, most cutting machines have at least a rudimental process monitoring system. Typically, a photodiode is mounted in the cutting head and observes the cutting process radiation. However, with only monitoring the radiation intensity trough a diode, basically only large process instabilities and loss of cut can be detected. To detect cut qualities like burr formation and edge roughness, more sophisticated sensors are needed, namely those that can measure quantities that intrinsically contain information about the cutting quality. Therefore, as shown in figure 1a, a coaxially arranged cutting head camera, looking down onto the process and observing the process radiation, was used beside the usual photodiode. Further, to observe the kerf formation and the workpiece structure, an additional process illumination can be switched on, leading to well illuminated images. In case the illumination is switched off as in figure 1b, mainly the process radiation is seen and in case the illumination is switched on as in figure 1c, primarily the kerf geometry and surface structure can be studied.

Different process monitoring strategies were investigated as only illuminated, only non-illuminated and alternating illuminated/non-illuminated images were taken. Further, the focal position of the camera was varied between top and bottom plane of the metal sheet and the recorded process camera images were combined with the signal from the photodiode.

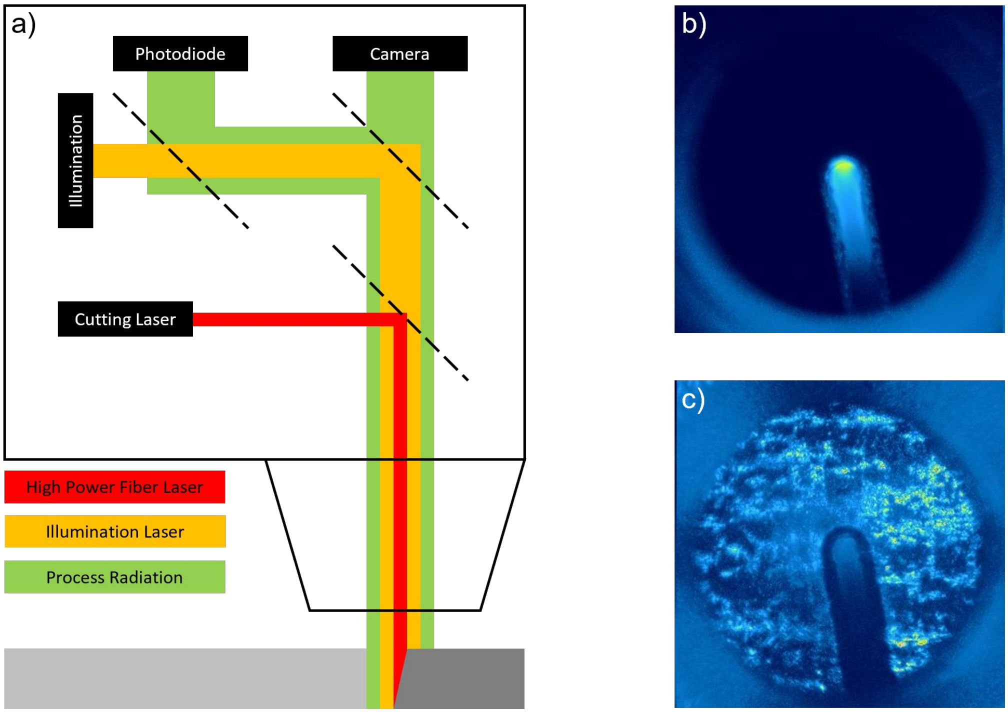

Fig. 1. Illustration of the cutting head featuring a photodiode, a coaxial process camera and an illumination laser (a) with examples of camera images of the cutting process without illumination (b) and with illumination (c).

2.2. Data Acquisition

The in-process data of the different sensors was acquired in the cutting head: the coaxial camera produced alternating illuminated and non-illuminated images with several hundred Hz and the coaxial photodiode recorded the radiation intensity with several kHz. Big data sets of approximately 250 parts each were generated to investigate different monitoring strategies. The variation of cutting quality in each dataset was ensured with an individually fitted Design Of Experiment (DOE) covering a large process window and as many relevant influencing factors as possible, meaning the most important laser cutting parameters (laser power, cutting speed, focal position, and gas pressure) and other outer factors, as for example the heating of the material and the protection glass soiling. The geometry of a randomly rotated test part ensures the variability in cutting direction and thus enables a better generalization of the neural network. The edge quality of each part, subsequently determined (localized on the cutting edge) by an automated optical surface measurement system, served as the ground truth for the training of neural networks.

All datasets were generated with fusion cutting in mild steel with thicknesses between 4 and 15mm. However, to investigate transfer learning feasibility and analyze the robustness of the network prediction, different alloys in various thicknesses were cut on different cutting systems.

2.3. Training of Neural Networks

The task of estimating the edge quality based on the cutting head sensor data can be separated in a feature extraction and a subsequent mapping. The burr attachment level for example can be estimated with a conventional image processing approach to extract multiple features followed by a mapping with a fully connected neural network (Pacher et al., 2021). The present work however followed a black box approach, extracting the features with a Convolutional Neural Network (CNN) and mapping them using fully connected layers. The architecture ResNet50 (He et al., 2015), implementing these two phases with good performance in various computer vision application, was applied in the present work.

Each dataset was split into a training, validation, and test set. These sets were formed by stratified sampling with respect to the target classes, ensuring that each test part belonged to only one split set. This approach prevented overfitting to data belonging to the same test part. In combination with appropriate regularization as well as augmentation techniques, e.g. mixup (Zhang et al., 2017), this guaranteed that the model learned generalizable image characteristics which correlate best with the cutting quality labels.

For each monitoring strategy a separate binary classification network was trained to predict the probability of loss of cut, large burr height and high roughness. The threshold to define the target labels was chosen individually per dataset to ensure well balanced classes. To include the temporal information of the images from the cutting head camera in the training, the network predictions are optionally averaged over multiple consecutive images. The performance of each network was computed on the test sets and the statistics of the final evaluation metrics (F1-score, ROC curve & AUC) are based on a 3-fold cross validation.

3. Results

3.1. Basic Learning

For a comparison of the different monitoring strategies, the prediction performance of the individually trained networks was evaluated. In all three classification tasks (loss of cut detection, burr height, and roughness) well performing networks were found for all investigated thicknesses. Exemplarily, for mild steel 6mm, the confusion matrix in figure 2 shows that in 98% of the data points a loss of cut was correctly detected based on the coaxial diode signal. A very similar performance was achieved with illuminated and non-illuminated camera images. Also, the burr height (see center plot in Fig. 2) and roughness (see right plot in Fig. 2) were well predictable using a suitable monitoring strategy with an AUC of 0.89 and 0.86, respectively.

The selection of the monitoring strategy had a high impact on the prediction performance as can be seen in figure 3, where the statistics of the main performance values, AUC (left) and F1-score (right), are shown for the networks using only the photo diode (blue dot), single images from the process camera (yellow dots), and sensor fusion and/or including temporal information (green dots).

For example, the burr prediction for 6mm mild steel based only on the photodiode, reached an average AUC of around 0.67 and an average F1-score of around 0.65, both with an elevated standard deviation (see blue dot in figure 3). For reference, a random binary classifier would achieve an AUC and F1-score of approximately 0.5 with a balanced dataset. The addition of the coaxial camera sensor significantly improved the prediction performance up to approximately an AUC of 0.92 and an F1-score of 0.83.

Both types of camera images (illuminated and non-illuminated) contained notable information on the cut quality. The best prediction performance was achieved by fusing the data from the illuminated and non-illuminated images and integrating the temporal information (green dots). However, to simplify the monitoring equipment, a good estimation of the cutting quality was also possible with only non-illuminated images, combined with the temporal information.

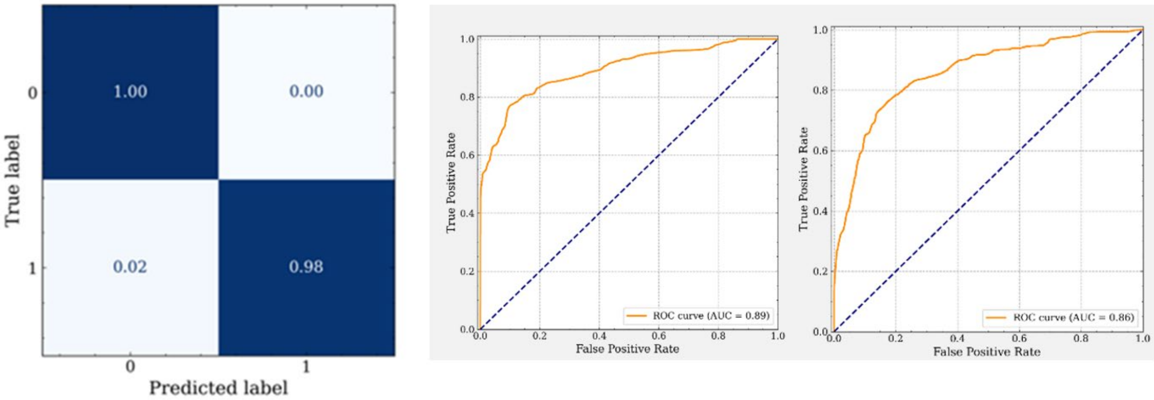

Fig 2. The confusion matrix for loss-of-cut detection (left), ROC for burr classification (middle), and ROC for roughness classification (right) on a 6mm thick steel material dataset.

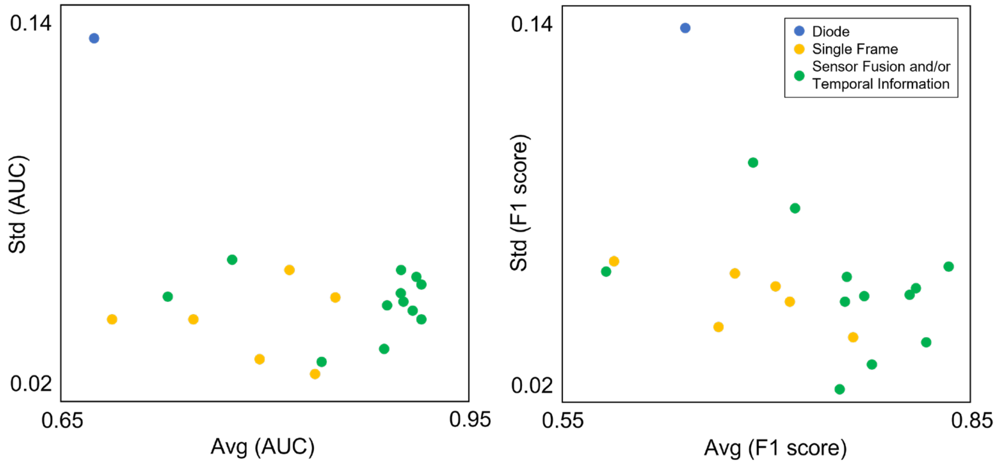

Fig. 3. The statistics of the performance metrics AUC (left) and F1-score (right) for the burr height estimation in a 6mm thick mild steel using different monitoring strategies were calculated over a 3-fold cross validation. The evaluated monitoring strategies include using only the diode signal (blue dots), single camera images (yellow dots), and sensor fusion and/or temporal information (green dots).

3.2. Assessment of Robustness

The prediction performance of the models, originally trained on standard material mild steel (DD11), was tested on different material alloys, both from standard (S355) and extended range (Hardox). Additionally, test sets were cut on other machines. Figure 4 shows the ROC curves obtained by inference on a dataset included in the training (gray) together with the ROC curves obtained with new data (orange) from a new material (left) and from a new machine (right). The prediction performance on the new, for the network unknown data was only slightly worse than the prediction performance on the data the network was trained on. Therefore, the obtained results confirmed the generalization capabilities and robustness of the neural networks against the tested material- and machine variability

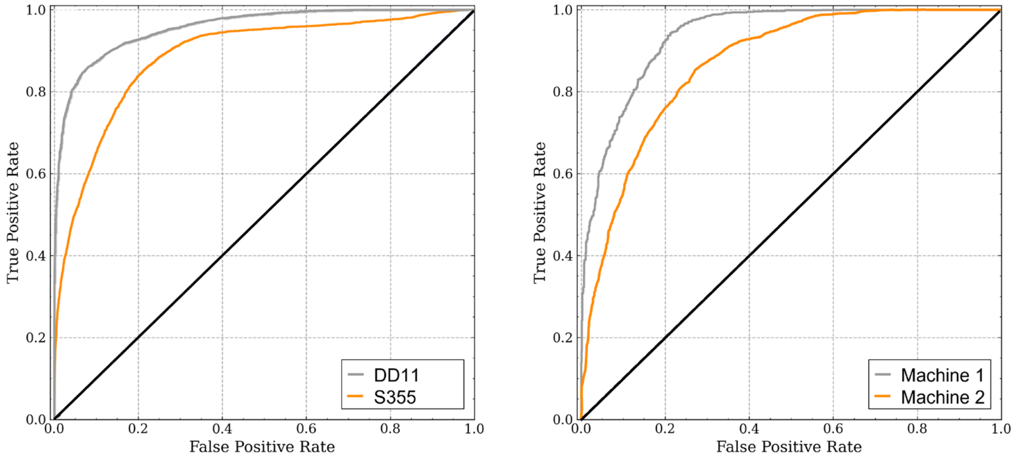

Fig. 4. ROC curves of the burr classification model trained on 15mm DD11 obtained by inference on 15mm DD11 (gray) and 15mm S355 (orange) to test robustness against material variability (left) and ROC curves of the burr classification model trained on data from 6mm mild steel cut on machine 1 obtained by inference on 6mm mild steel data from machine 1 (gray) and on 6mm mild steel data from machine 2 (orange) to test robustness against machine variability.

3.3. Transfer Learning

The ability of the trained models to quickly adapt to new material characteristic was tested with simple transfer learning algorithms. In the present work, the focus was on model adaptation for new metal sheet thicknesses. In particular, the models were trained using multiple thickness datasets (e.g. 5, 6 and 15mm) and adapted to 4mm and 8mm thickness. The AUC of the models increased with the number of parts used for transfer learning. For example, the extrapolation to 4mm reached a similar performance as a single thickness model with 20 parts used for transfer learning, as shown in the left plot in figure 5. This result suggests that the neural network can be quickly adapted to new material thicknesses with a suitable transfer learning algorithm using only few extra parts.

3.4. Demonstrator

The real time feasibility was shown with an additional computational unit beside the cutting machine equipped with a standard Graphics Processing Unit (GPU). For a specific alloy and thickness a closed loop controller was implemented and tested. To estimate the cutting quality while cutting, the camera pictures are sent from the machine to the GPU workstation where a python-based software received and pre-processed the images in real time, passed them through the pretrained networks to predict the burr and roughness, if necessary, sent a pre-defined control actions back to the machine, and finally represented the result graphically for the machine operator. The different tasks executed in parallel by multiple threads resulting in a delay from image reception to control action command and visualization of 100-150ms. This delay will be further reduced in future development.

For the tested use case, the operator was able to choose a probability threshold defining what output of the network (probability of high burr or roughness) was considered as too high. Since this prediction probability was linked to the actual burr height or roughness, this threshold setting allowed the user to indirectly set the threshold on the desired cutting quality. In case the cutting quality was deviating from the desired one, the controller adapted the most suspicious cutting parameters in an appropriate direction until the cutting quality was estimated as acceptable. When starting with cutting parameters producing a high burr, the real time estimation of the network correctly recognized it and made the controller adapt the cutting parameters until the burr height estimation dropped below the desired threshold as can be seen in figure 6. The cut part, represented in the lower part of figure 6, showed a high burr in the beginning, followed by a decreasing burr height, finally resulting in good quality on the second half of the piece. This burr height evolution was well represented by the model estimation (see figure 6).

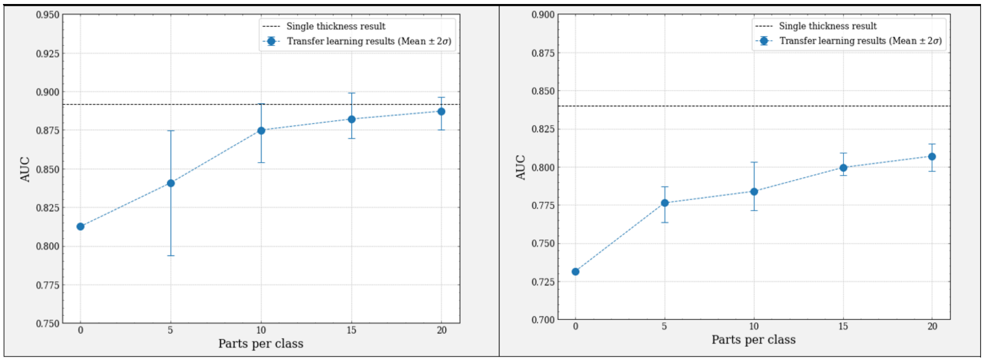

Fig. 5: AUC scores vs number of parts used for transfer learning from a model trained on 5, 6, and 8mm, to 4mm thickness (left) and to 8mm thickness (right). The horizontal line shows the AUC achieved by a model trained only on 4mm and 8mm thickness, respectively.

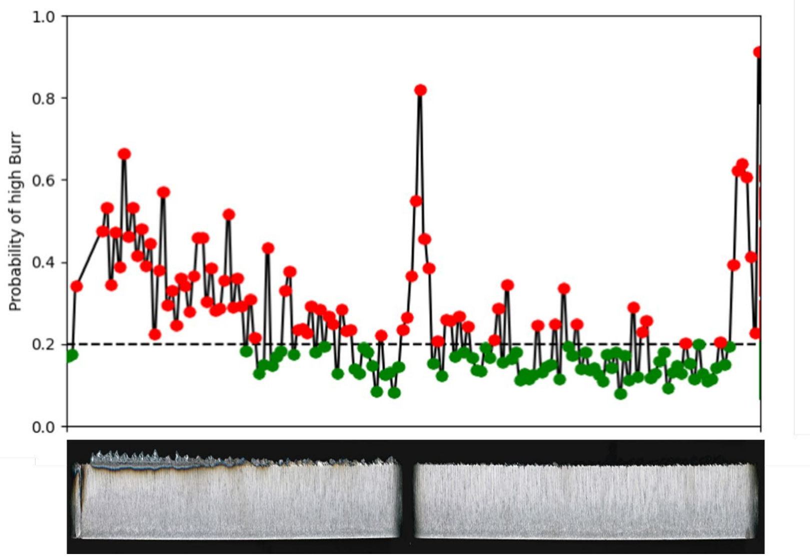

Fig. 6. The real time prediction of the probability of high burr is shown above of the cut piece (15mm mild steel). The user specific acceptance threshold (dotted line) defines which images are classified as low burr (green dots) and high burr (red dots). The curve of the predicted probability of high burr shows a very similar evolution as the burr height on the cut piece.

4. Conclusion

The main outcome of this project was that burr and roughness can be estimated by means of process monitoring, namely with non-illuminated images from a coaxial in-process camera and temporal information analyzed with deep neural networks, the way it is suggested in this work. To always have a reliable quantitative estimate, even if important influencing factors (e.g., the alloy, the workpiece surface, the cutting machine, etc.) are significantly different from what was in the training phase, a fast adaption or calibration step can be necessary.

As with the suggested technique and intelligence the burr and roughness can be estimated, also an optimization of the cutting parameter is possible. In case the cutting quality is deviating from the desired one, the few suspicious parameters can be changed in one or the other direction until an improvement is observable. Thus, with our findings a first self-optimization of a flat-bed laser cutting machine can become feasible.

Acknowledgements

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