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Investigation of Different Illumination Scenarios for the Evaluation of Thermally Cut Edges with Convolutional Neural Networks using a Mobile Device

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Abstract

In sheet metal production, the quality of a cut edge determines the quality of the cut itself. Quality criteria such as the roughness, the edge slope, and the burr height are of decisive importance for further application and quality determination. In order to be able to determine these criteria analytically, the depth information of the edge must be determined at great expense. The current methods for obtaining the depth information are very time-consuming, require laboratory environments and are therefore not suitable for a fast evaluation of the quality criteria.
Preliminary work has shown that it is possible to make robust and accurate statements about the roughness of a cut edge based on images when using an industrial camera with a standard lens and diffuse incident light, if the model used for this purpose has been trained on appropriate images.
In this work, the focus is on the illumination scenarios and their influence on the prediction quality of the models. Images of cut edges are taken under different defined illumination scenarios and it is investigated whether a comprehensive evaluation of the cut edges on the evaluation criteria defined in standards is possible under the given illumination conditions. The results of the obtained model predictions are compared with each other in order to make a statement about the importance of the illumination scenario. In order to investigate the possibility of a mobile low-cost evaluation of cut edges, cheap hardware components for illumination and a smartphone for image acquisition are used.

Introduction

In sheet metal production, the quality of thermally cut edges is of crucial importance. The quality determines whether costly and time-consuming post-processing of the sheet metal is necessary to obtain a suitable quality of the cut edge. Roughness, edge sloping and burr height are criteria defined in the standard [1] that are used to assess quality.
The quality criterion roughness is determined in the cutting direction. Depending on the vertical position of the measuring line, the roughness values change, since the cut pattern of the edge orthogonal to the cutting direction is not homogeneous. For the specification of the roughness in sheet metal production, only the maximum roughness value has to be specified. Several measuring lines are created orthogonal to the cutting direction. The roughness value is determined for each measuring line. The maximum roughness value is then used to specify the cut edge roughness.
The edge sloping is the average absolute height difference between a defined line placed at the top of the edge and a line placed at the bottom of the edge. The placement of the upper and lower measuring lines is defined in the standard [1].
The third quality criterion is the burr height. During thermal cutting of sheet metal, material can adhere to the underside of the sheet. The distance, in the direction of the sheet thickness, from the underside of the sheet to the maximum overhang of the material adhesions is called the burr height.

State of the Art and Related Work

One way to quantitatively determine the quality criteria is to measure the cut edge with expensive hardware. To measure the roughness and edge sloping, the depth information of the cut edge must be determined. By using this information, it is then possible to calculate the roughness and edge sloping analytically. For the determination of the burr height, the depth information from the underside of the sheet must be obtained in order to calculate the height difference between the underside of the sheet and the maximum material adhesion to the underside of the sheet. These procedures are very time-consuming, require a laboratory environment and expert knowledge. Therefore, they have proven to be unsuitable for practical implementation in a sheet metal production facility.
In practice, it has been shown that machine operators of thermal cutting machines rely on their subjective perception of quality when simply looking at the cut edge. This has the disadvantage that even experienced experts can only evaluate the criteria in a quantitatively imprecise and inconsistent manner. In addition, this leads to an individual and subjective quality assessment that cannot be used as an objective description of quality.
Known analytical image processing methods for determining roughness using 2D images assume, that the surfaces to be determined are homogeneous surfaces [2, 3, 4, 5]. Since this is not the case here, these methods are not suitable for determining the roughness of a cut edge.
Previous work has shown that, given sufficient data, a fast and robust evaluation of the roughness of a cut edge is possible [6] if a convolutional neural network [7] is trained to predict roughness based on image data. The image acquisition system used in [6] was a monochrome industrial camera with a high-quality standard lens and a ring light as incident light. These components, suitable for industrial image processing, resulted in high quality and high resolution images of the cut edge. Using machine learning techniques, convolutional neural networks were able to learn and identify the image features that correlate highly with the roughness values of the cut edge.
These results suggest the assumption that the burr height can also be evaluated using this approach, since the burr is visible in the images. In addition, it has to be investigated whether this procedure is also feasiblel for the prediction of the edge sloping. Since

in previous work the illumination was chosen based on the subjective impressions of the image processing engineer, the question arises whether this chosen illumination is the most appropriate illumination and, even more generally, how a cut edge must be illuminated in order to optimally visualize the features in the image that are indicative of the quality criteria.
It is obvious that the illumination used for the image acquisition of a cut edge has a direct influence on the visibility of features, which indicate to the quality criteria of the cut edge. The important influence of illumination conditions has also been demonstrated and studied in other areas of image processing, such as face recognition [8, 9, 10].

Aim of this Work

The aim of this work is to investigate whether and under which illumination conditions it is possible to quantitatively determine the quality criteria roughness, edge sloping and burr height on the basis of images of a cut edge. The influence of the illumination on the prediction quality of the respective quality criterion is to be investigated.
In contrast to the previous work, comparatively cheap hardware components are used here. A mobile device is used as image acquisition device and low-cost LED patches are used as illuminants. This approach is motivated by the fact that the scalability of a commercially viable cut edge evaluation can be greatly increased by the use of a mobile device. Therefore this possibility will also be investigated here.

Experimental Work

For this work, sheet metal samples were systematically generated, their cut edges were measured, and the associated quality criteria were determined analytically as described above.
A hardware and software setup was implemented that allows externally controlled image acquisition via a mobile device under defined illumination scenarios. The mobile device used in this work for image acquisition is the Samsung Galaxy S10+ smartphone.
Different model architectures of convolutional neural networks were used to evaluate the influence of the illumination scenarios. Using the k-fold cross-validation method, model prediction quality results are compared to identify the most suitable illumination scenarios for the given quality criteria. The prediction quality of the models is the evaluation criterion for the illumination.

Data Generation

For this work, images of 365 square stainless steel metal sheet samples with a thickness of 3 mm and a side length of 10 cm were used. Each sample was created with a unique set of cutting parameters. Due to the rolling direction of the metal sheets, the fluctuating material quality and the characteristics of thermal cutting, the edge quality of a sample varies. Each side of a sample shows a slightly different cutting pattern. As a result, we obtained a total of 1460 edges, which differ in quality.
To determine the depth information, a centered 5 cm section of all four edges of a sample was assessed using a 3D measuring device. Based on the determined depth information, the quality criteria described in standard [1] were analytically calculated.

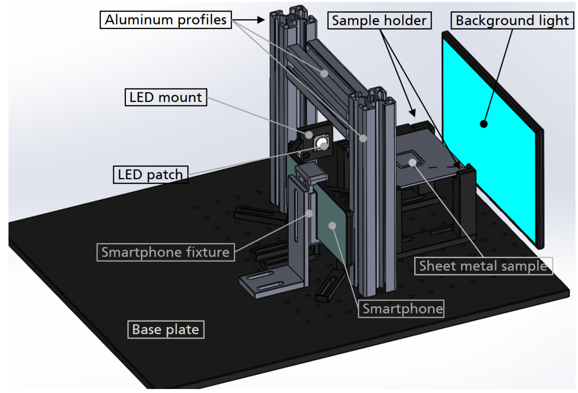


Figure 1: *CAD drawing of the hardware setup for image acquisition of cut edges using a smartphone under different illumination scenarios.*

Hardware-Setup

In order to implement an automated image acquisition under defined illumination conditions, a hardware setup was designed and built. A CAD drawing of the hardware setup can be seen in Figure 1. As can be seen in the figure, the sample is placed in a sample holder made for this purpose so that the cutting edge is aligned orthogonally to the optical axis of the image acquisition device. LED holders are used to place eight LEDs around the sample in a defined orientation. The smartphone is fixed in place using a smartphone fixture. To allow the placement of the LEDs on the left, right and from above the sample, the respective LED holders are mounted on aluminum profiles, which are shown in Figure 1. The mount for the illumination from below is mounted directly on the base plate, which is provided with threaded holes. At the level of the sample, the two LEDs oriented frontally to the sample are mounted orthogonally to the cutting edge surface with specially designed and fabricated fixtures. Two additional LEDs are aligned at a 45° angle to the left and right toward the center of the cut edge. Figure 2 shows the orientations of the LEDs relative to the sample. Behind the sample, an additional monitor is mounted as a homogeneous background illumination. This is intended to reduce unwanted light influences.
Using a DigIO card and eight switching relays, the LEDs can be switched individually using a software developed specifically for this purpose.

Software-Framework

The software architecture consists of two main applications. A WPF application that runs on the PC and an Android application that runs on the smartphone. The WPF application controls the LEDs via a DigIO card installed in the PC. Thereby each LED can be controlled separately. In addition to controlling the LEDs, the WPF application triggers the smartphone's image acquisition via the Android Debugging Bridge (ADB). This enables the WPF application to communicate with the Android application. Furthermore, the acquired images are transferred to the PC via the ADB, where the WPF application is responsible for systematically storing the images.
At the same time, the smartphone runs an Android application that controls the image acquisition. The camera focus is adjusted to a defined distance and the exposure time is dynamically adapted to the illumination scenario.

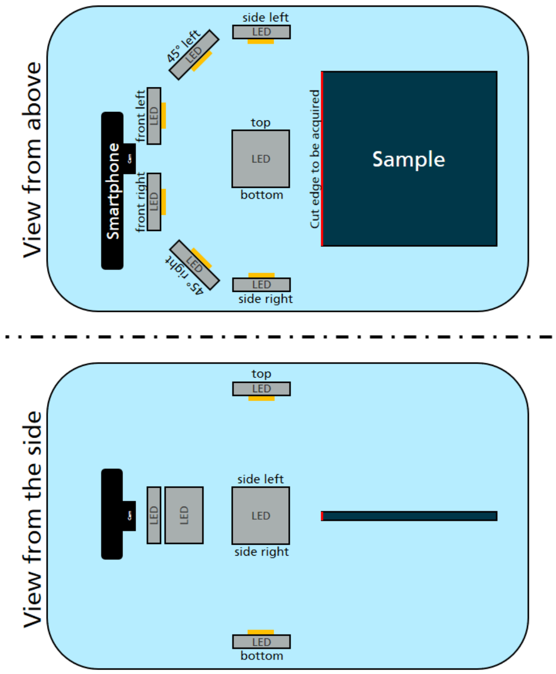


Figure 2: *Schematic arrangement of the LEDs around the sample. The upper illustration, shows the arrangement viewed from above, whereas the lower illustration shows the arrangement viewed from the side.*

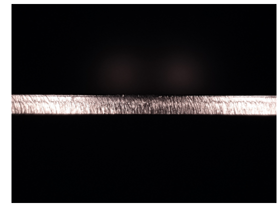
Image Acquisition

In order to realize a wide range of illumination scenarios with the eight LEDs, different illumination scenarios have been defined. For each scenario, a different combination of LEDs is turned on, with the monitor's backlight remaining on for all scenarios. The combination of LEDs turned on for each lighting scenario are enumerated as follows:

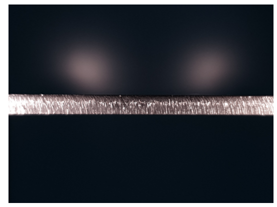
0. -
1. Front left, front right
2. 45° left, 45° right
3. Front left, front right, 45° left, 45 °right
4. Side left, side right, top, bottom
5. Side left
6. Side right
7. Top
8. Bottom
9. 45° right
10. 45° left
11. Side right, side left
12. Top, bottom
13. Front right, front left, top

The resulting images are shown in Figure 3a to Figure 3n. It can be clearly seen that the imaging of the edge surface and thus the expression of the features that indicate quality criteria differ per illumination scenario.

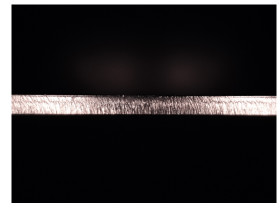
(a) *Illumination Scenario 0*



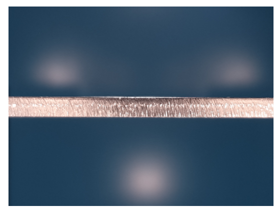
(b) *Illumination Scenario 1*



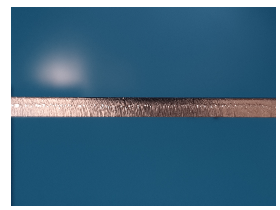
(c) *Illumination Scenario 2*



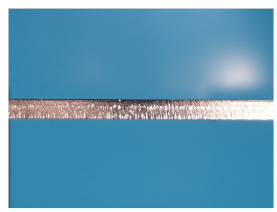
(d) *Illumination Scenario 3*



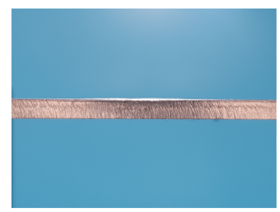
(e) *Illumination Scenario 4*



(f) *Illumination Scenario 5*

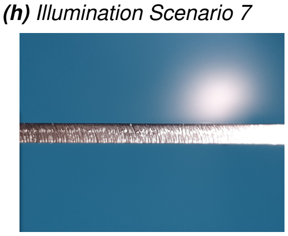


(g) *Illumination Scenario 6*



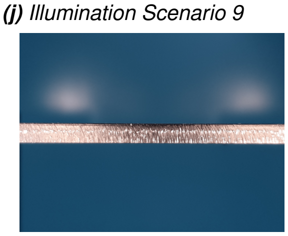
(h) *Illumination Scenario 7*

(i) *Illumination Scenario 8*

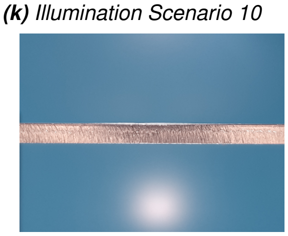


(j) *Illumination Scenario 9*

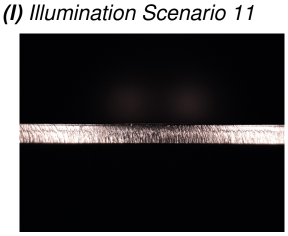
(k) *Illumination Scenario 10*



(l) *Illumination Scenario 11*



(m) *Illumination Scenario 12*



(n) *Illumination Scenario 13*

Figure 3: *Images of cut edges acquired with different illumination scenarios.*

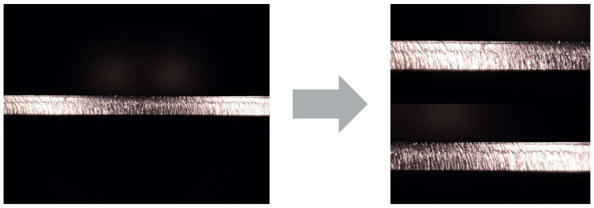


Figure 4: *Preprocessing of the cut edge image to incorporate more relevant image areas into one image.*

Data Preparation

For training the convolutional neural networks, the acquired images are pre-processed. As can be seen in the images in Figure 3a to Figure 3n, the cut edge itself fills only a small area of the overall image. To increase this proportion and therefore to obtain more relevant areas on an image, the images are preprocessed. In this process, the relevant image areas are extracted and stitched to form a square image, since common network architectures have been designed for square images. This image preprocessing is shown in Figure 4.

Networks used for Evaluation

Three different model architectures were used for training. Care was taken to ensure that these architectures represent a certain spectrum. The model architecture AlexNet [7] with a number of 25,854,425 trainable parameters, the lightweight model architecture MobileNet [11], with a number of 4,245,763 trainable parameters, and the more sophisticated model architecture Xception [12], with a number of 20,813,099 trainable parameters, were used. The model architectures were adapted to image input sizes suitable for them:

- AlexNet: 454 x 454 pixels
- MobileNet: 454 x 454 pixels
- Xception: 598 x 598 pixels

In addition, all the archtectures were adapted to the present multi-regression problem and the MSE function was selected as the loss function for the training processes. These three network architectures were chosen in order to cover a wide range of architectures and to verify that the results are not dependent on the network architecture.

Training and Evaluation

Due to the limited data set of 1460 cut edge images, the replicate sampling method k-fold cross-validation is used to evaluate the models. Therefore the dataset is randomly shuffled and divided into k groups. The model is trained k times with changing test and validation dataset in each iteration. Table 1 illustrates the splitting of the data set in each iteration. For each iteration, the model is fitted to the training dataset and evaluated based on the test dataset. The evaluation results of the test set are kept and the model is discarded. The predictive quality of the model is averaged over the test set results. This method is used to ensure that the results are not dependent on a specific partitioning of the data set. All models were trained with the optimizer Adam [13], a batch size of 8 and a learning rate of 0.0001. For each illumination scenario, five models were trained per architecture. The total number of trained models for this work therefore amounts to 210.

Table 1: *k-fold Cross-Validation with $k = 5$.*

	Part 1	Part 2	Part 3	Part 4	Part 5
Iteration 1	Train	Train	Train	Val	Test
Iteration 2	Test	Train	Train	Train	Val
Iteration 3	Val	Test	Train	Train	Train
Iteration 4	Train	Val	Test	Train	Train
Iteration 5	Train	Train	Val	Test	Train

To quantitatively and qualitatively assess the quality of the model predictions, the coefficient of determination was used [14]. The coefficient of determination is a measure for assessing the quality of fit of a regression to evaluate how well measured values fit a model. The coefficient of determination can be multiplied by 100 % to express it as a percentage value. The coefficient of determination R^2 is determined according to

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} , \tag{1}$$

where y_i is the analytically determined measured value of the quality criterion, $\hat{y}_i$ is the estimated value of the model, and $\bar{y}$ is the empirical mean $\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$.

Results

The results of the evaluation of the AlexNet architecture are shown in Table 2. For roughness evaluation, we obtain the best model predictions with illumination scenario 12 when the edge of the sample is illuminated from above and below. The second best model predictions for roughness are achieved with illumination scenario 8, where the edge is illuminated from below, followed by illumination of the edge from above with illumination scenario 7. Not surprisingly, the worst prediction is achieved with the images from scenario 0, where none of the LEDs are turned on and almost exclusively the outline of the cut edge is visible due to a background illumination.

Looking at the model predictions in terms of edge sloping, it can be seen that with 46.5 % the worst prediction is achieved with illumination scenario 10, directly followed by illumination scenario 0. The best predictions are achieved with the images from illumination scenario 7.

The model prediction quality for the burr height criterion, shows that the best model predictions are obtained with illumination scenario 0. The worst predictions were obtained with illumination scenario 1, where the cutting edge is illuminated with the frontal LEDs oriented orthogonally to the edge.

The averaged results of the model prediction for the different quality criteria are shown in the last column of the table. It can be seen that illumination scenarios 7, 8 and 12 are the most suitable for quantitatively determining edge quality using images. It is striking that in all three scenarios the cut edge is illuminated exclusively from above and/or below.

The evaluation of the model prediction with the MobileNet architecture can be seen in Table 3. When looking at the results, similarities to the results with the AlexNet architecture can be seen. Again, the best model prediction for edge roughness is obtained with illumination scenario 12. Followed by illumination scenario 8 and 7.

Table 2: *Results AlexNet*

Illumination Szenario	Rough-ness	Edge Sloping	Burr Height	Average
00	36.2 %	47.2 %	**91.4** %	58.3 %
01	56.1 %	56.8 %	74.9 %	62.6 %
02	54.4 %	50.4 %	81.4 %	62.1 %
03	55.8 %	57.1 %	78.2 %	63.7 %
04	56.9 %	57.7 %	86.7 %	67.1 %
05	53.4 %	59.2 %	86.1 %	66.2 %
06	61.4 %	57.1 %	83.2 %	67.2 %
07	67.6 %	**60.7** %	84.2 %	**70.8** %
08	70.0 %	58.8 %	83.0 %	70.6 %
09	60.0 %	55.7 %	79.1 %	64.9 %
10	54.1 %	46.5 %	79.1 %	59.9 %
11	58.9 %	59.4 %	85.4 %	67.9 %
12	**70.9** %	56.9 %	79.9 %	69.2 %
13	50.6 %	55.4 %	79.5 %	61.9 %

When evaluating the edge sloping, again the best model prediction is achieved with illumination from above at scenario 7.
For the evaluation of the burr height, the best predictions are obtained with illumination scenario 4, when the sample is illuminated from both sides and from above and below. It is noticeable that the illumination scenarios perform particularly poorly, in which the resulting images show inhomogeneous and partially associated overexposed illumination of the cut edge.
Averaged over all criteria, the best predictions are achieved with illumination scenario 12. Scenarios 8 and 7 come in second and third place.

Table 4 lists the results for training with the Xception architecture. It can be seen that for the prediction of the roughness the best results are achieved with the illumination scenario 8. Followed by illumination scenario 12 and 7. The worst results were obtained with lighting scenario 0, 13 and 2.
The best results for evaluating the edge slope are obtained here with scenarios 8 and 7. In addition to illumination scenario 0,

Table 3: *Results MobileNet*

Illumination Szenario	Rough-ness	Edge Sloping	Burr Height	Average
00	5.3 %	31.1 %	87.6 %	41.3 %
01	48.5 %	58.9 %	73.5 %	60.3 %
02	47.1 %	44.0 %	84.6 %	58.6 %
03	39.3 %	59.0 %	75.9 %	58.0 %
04	45.7 %	54.4 %	**89.2** %	63.1 %
05	43.4 %	56.0 %	84.1 %	61.2 %
06	40.8 %	45.2 %	82.2 %	56.1 %
07	59.1 %	**62.0** %	86.1 %	69.1 %
08	**67.6** %	58.3 %	87.2 %	71.0 %
09	39.9 %	43.6 %	75.3 %	52.9 %
10	34.2 %	42.9 %	65.5 %	47.6 %
11	40.9 %	53.4 %	85.7 %	60.0 %
12	68.8 %	59.2 %	85.6 %	**71.2** %
13	40.8 %	54.9 %	75.3 %	57.0 %

Table 4: *Results Xception*

Illumination Szenario	Rough-ness	Edge Sloping	Burr Height	Average
00	46.2 %	53.5 %	**87.6** %	62.4 %
01	53.5 %	60.8 %	65.5 %	59.9 %
02	52.0 %	54.3 %	77.4 %	61.2 %
03	55.5 %	60.9 %	66.8 %	61.0 %
04	57.4 %	58.4 %	85.4 %	67.1 %
05	56.0 %	58.6 %	85.2 %	66.6 %
06	57.0 %	58.7 %	82.4 %	66.0 %
07	65.4 %	61.7 %	86.6 %	71.2 %
08	**69.3** %	**64.2** %	84.2 %	**72.5** %
09	55.3 %	53.2 %	78.0 %	62.2 %
10	53.1 %	53.6 %	72.7 %	59.8 %
11	56.1 %	58.7 %	83.8 %	66.2 %
12	67.9 %	55.9 %	83.8 %	69.2 %
13	47.0 %	60.3 %	65.3 %	57.5 %

scenarios 9 and 10 perform the worst here. These are the scenarios in which the edge is illuminated from one side at an angle of 45°.
For the prediction of the burr height, illumination scenario 0 performs best with a value of 87.6 %. This is closely followed by lighting scenario 7 with a value of 86.6 %. The worst predictions are obtained with the images from illumination scenario 13, 1 and 3.
When looking at the results averaged over all three criteria, it is noticeable that the top 3 lighting scenarios, as in the evaluations with the AlexNet and MobileNet architecture, are again from scenarios 8, 7 and 12.

It is worth mentioning that the models were quite capable of making correct predictions based on the images taken by a smartphone. The prediction quality depends by a large extent on the type of illumination. The most suitable illumination scenarios were those that led to homogeneous illumination of the entire edge. It has been shown that the best predictions for roughness are achieved with illumination from above and below. If one wants to evaluate the edge slope of a cut edge, illumination from below or above has proven to be the most suitable. The best results for predicting burr height were obtained with images where the contour of the edge was best visible. For evaluating all three criteria with only one illumination scenario, illumination scenario 8, with illumination of the sample from below, is the most suitable.

Conclusion

In a conventional approach, the illumination depends on the inspection task and the subjective quality perception of the image processors. In this work, images of different illumination scenarios have been used to train convolutional neural networks, which evaluate the quality of the thermally cut edge for each illumination scenario. The results of this evaluation show which illumination scenario best illustrates the image features required for the task. Furthermore, this work shows that an objective evaluation of cut edges using images acquired with a smartphone and is possible even with comparatively cheap hardware. Combined with [15] even a complete mobile evaluation approach is thinkable.

The illumination type is cost-effective, highly variable. The illumination can be adjusted to the prediction of the desired quality criteria for an optimal result. This eliminates the need for costly illumination and image acquisition for objective evaluation of cut edges.

References

[1] Deutsches Institut für Normung, Thermisches Schneiden – Einteilung thermischer Schnitte – Geometrische Produktspezifikation und Qualität, DIN EN ISO 9013: 01.05.2017 (2017).

[2] Gadelmawla ES, Using the grey level histogram to distinguish between roughness of surfaces, Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture 215(4): 545–553. doi: 10.1243/0954405011518494 (2001)

[3] Lee K-C, Accurate estimation of surface roughness from texture features of the surface image using an adaptive neuro-fuzzy inference system, Precision Engineering 29(1): 95–100. doi: 10.1016/j.precisioneng.2004.05.002 (2005).

[4] Myshkin N, Surface roughness and texture analysis in microscale, Papers presented at the 3rd International Colloquim Micro-tribology 2001 254(10): 1001–1009. doi: 10.1016/S0043-1648(03)00306-5 (2003).

[5] Gadelmawla ES, A vision system for surface roughness characterization using the gray level co-occurrence matrix, NDT & E International 37(7): 577–588. doi: 10.1016/j.ndteint.2004.03.004 (2004).

[6] Janek Stahl, Quick roughness evaluation of cut edges using a convolutional neural network. Fourteenth International Conference on Quality Control by Artificial Vision. Vol. 11172. International Society for Optics and Photonics (2019).

[7] Alex Krizhevsky, Imagenet classification with deep convolutional neural networks, Communications of the ACM 60.6, pg. 84-90 (2017).

[8] David W. Jacobs, Comparing images under variable illumination, Proceedings. 1998 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (Cat. No. 98CB36231), (1998).

[9] Taiping Zhang, Face recognition under varying illumination using gradientfaces, IEEE Transactions on image processing 18.11 (2009): 2599-2606, (2009).

[10] Weilong Chen Illumination compensation and normalization for robust face recognition using discrete cosine transform in logarithm domain, IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics) 36.2 (2006): 458-466, (2006).

[11] Andrew G. Howard, MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications, CoRR, abs/1704.04861, (2017).

[12] François Chollet, Xception: Deep Learning with Depthwise Separable Convolutions, CoRR, abs/1610.02357, (2016).

[13] Diederik P. Kingma, Adam: A Method for Stochastic Optimization, arXiv preprint arXiv:1412.6980 (2014).

[14] Ludwig Fahrmeir, Statistik. Der Weg zur Datenanalyse. 8., überarb. und erg. Auflage, Springer Spektrum, Berlin/ Heidelberg, 2016, pg. 151.

[15] Omar De Mitri, Image acquisition, evaluation and segmentation of thermal cutting edges using a mobile device. Multimodal Sensing: Technologies and Applications. Vol. 11059. International Society for Optics and Photonics (2019).

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Macit Tuncel studied civil and mechanical engineering at the University of Stuttgart. From March 2020 to September 2020, he worked as a research assistant at Fraunhofer IPA. Since October 2020, he has been completing his industrial internship in the field of measurement automation for his master's degree in mechanical engineering. His areas of interest are machine learning, embedded software development and electrical machines.

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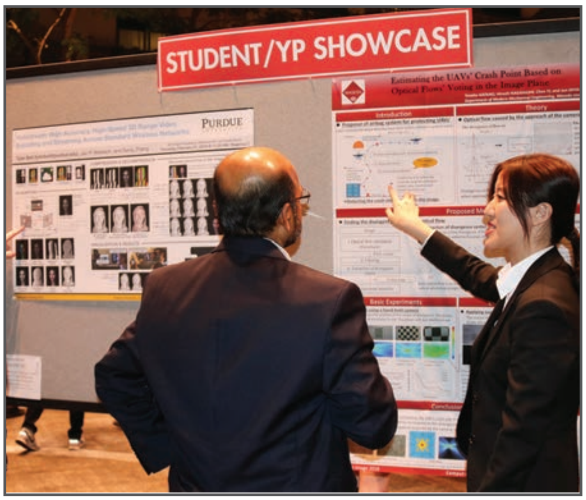

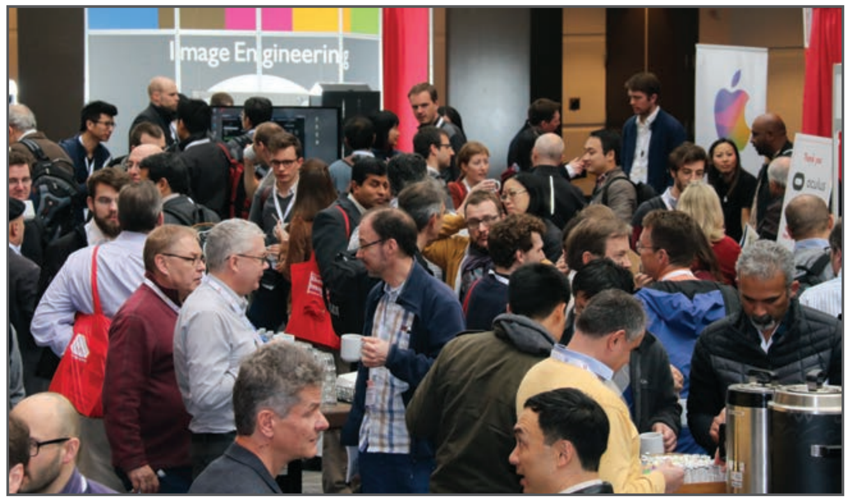

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