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Burr detection and classification using RUSTICO and image processing

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ABSTRACT

Machined workpieces must satisfy quality standards such as avoid the presence of burrs in edge finishing to reduce production costs and time. In this work we consider three types of burr that are determined by the distribution of the edge shape on a microscopic scale: knife-type (without imperfections), saw-type (presence of small splinters that could be accepted) and burr-breakage (substantial deformation that produces unusable workpieces). The proposed method includes RUSTICO to classify automatically the edge of each piece according to its burr type. Experimental results validate its effectiveness, yielding a 91.2% F1-Score and identifying completely the burr-breakage type.

1. Introduction

The presence of collaborative robots in the manufacturing industry is becoming commonplace. By supporting the operators on the decision-making process linked to the production of high quality items, the quality requirements are met with a reliability that subjective human visual inspection cannot compete against. In manufacturing, the aim is to achieve high levels of quality while offering a competitive price by improving part completion so as to maintain the highest possible standards [1].

This paper focuses on the detection and study of end milling work-pieces, which is typically carried out visually by human operators according to their experience. The automation of this procedure eliminates subjectivity or acceptance criteria. Computer vision and image processing techniques extract information and quality measurements from the acquired images of the machined work-piece. In the method proposed in [2], the threshold for establishing the three types of burr was manually set according to visual inspection of a set of slope functions. On the contrary, the system that we propose uses a classifier to remove subjectivity and confers generalization ability. Also, new techniques of computer vision are introduced in this work to improve the burr detection and classification.

The paper is organized as follows. Section 2 reports the related works. Section 3 explains the proposed method and the feature extraction stage and Section 4 specifies the parameter configuration. Experimental results are discussed in Section 5. Finally, Section 6 draws the conclusions and future works.

2. Related works

The study of the edge finishing of milling work-pieces to determine the presence of burrs is an active field of research as it influences the manufacture cost. In [3], a protocol was proposed for the measurement of wear on microtools using different materials such as brass or titanium. Although the slots machined provided information about tool wear, it cannot be measured directly. Also in [4], multiple steps to assess micro-milling machine performance are defined. Digital images combined with 3D reconstruction was used for verification of micro manufacturing installations [5].

Recent works have found evidence that cutting forces, vibrations, burr formation, and surface quality affect micro milling processes [6]. Moreover, the use of instant adhesive as supporting material causes burrs on the supporting material instead of on the work-piece material [7]. Specifically, for stainless steel 316L the milling process significantly affects the burr height [8]. In [9], a review of micro-milling was provided, highlighting the importance of burr removal and detection of burr-causing mechanisms.

Sometimes the quality of the end-milling burr measurements is performed with manual methods that only consider a few readings

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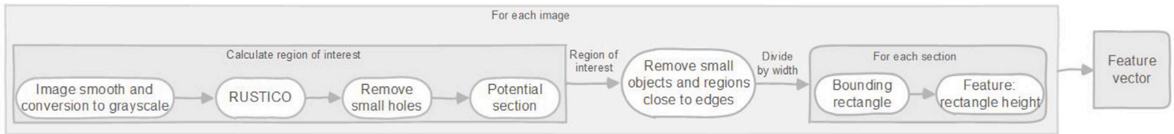


Fig. 1. Scheme of the pipeline to convert each image in a feature vector.

at random locations on the edge of the milling parts. However, a comparison of manual and image processing methods has revealed that the latter are more accurate since they cover a greater length of the part [10]. In that work, manual methods yielded greater percentage errors for approximating the burr height of work-pieces when the burr profile is irregular.

Image processing techniques are widely used to automate industrial processes. In [11], images were passed through a threshold determined by a maximum histogram valley method, then they were smoothed with morphological operations and finally a burr contour tracking method and a coordinate transformation were used to detect burrs. In order to analyze the burr formation, in [12] the image was converted to grayscale; after that, the area to analyze was specified and finally, it was filtered and judged by an expert. It was revealed that a spindle speed of 45 krpm and a feed per tooth of 1.5 generated a large amount of burrs (177.13%).

More complex techniques have also been investigated. A deep convolutional neural network was used to detect different types of geometric contour of edge features [13] by developing a differential algorithm which compares with a standard workpiece to detect the inconsistencies of the edge. Also a Single Shot MultiBox Detector (SSD) based on MobileNet-SSD was used to detect surface defects like breaches, dents, burrs and abrasions on the sealing surface of a container in the filling line in [14], achieving a positive rate of 95%. A method to calculate automatically The roughness of milled surfaced is calculated in [15] by using a Convolutional Neural Network (CNN) what reduces the measurement time compared with traditional methods.

However, previous works mainly dealt with the status of the micro-milling tool, which has been more widely studied than the machined parts. In [16], authors use morphological component analysis (MCA) to detect wear regions in tools. This method reduces the effects caused by the background of the image and the noise. Similar to this, in [17] the micro tool life was studied by monitoring the tool condition with an automated machine vision system. In [2], burrs in digital images are detected by studying the function generated with the percentage of white pixels over the image height, obtaining a precision and recall of 76.32%. Also a deeper study of the related work can be found in [2].

In this paper, we extend the work in [2] by using state-of-the-art techniques to detect contours, doubling the sample number. Computer vision techniques eliminates operator subjectivity and streamlines industrial validation processes.

3. The proposed vision-based method

The developed system detects and classifies burrs in workpieces whose images are taken by a microscope camera connected to an industrial rigid boroscope so as to analyze their edge shape on a microscopic scale. More details are given in [2,18]. The acquired images are processed by applying a method for delineation of structures of interest called RUSTICO (RobUST Inhibition-augmented Curvilinear Operator) [19], followed by morphological operations and a topological structural analysis to retrieve the contour of the workpieces [20]. A scheme of the whole procedure that is explained in the next subsections is shown in Fig. 1.

3.1. Acquisition system

The pieces present cylindrical holes and, therefore, a specific capture system is needed in order to acquire images of the edge finishing. A microscope camera captures the RGB images provided by the boroscope with a resolution of 2592×1994 pixels. Images are labeled by experts according to the criteria proposed in [21,22]. Fig. 2 shows the three considered categories: if there is no imperfections (knife-type burr, K) that would be the ideal situation, if it presents small splinters (saw-type burr, S), which could be accepted depending on the use of the machined piece or if it has suffered a large deformation (burr-breakage, B) that produces an unusable piece [2].

3.2. Region of interest identification

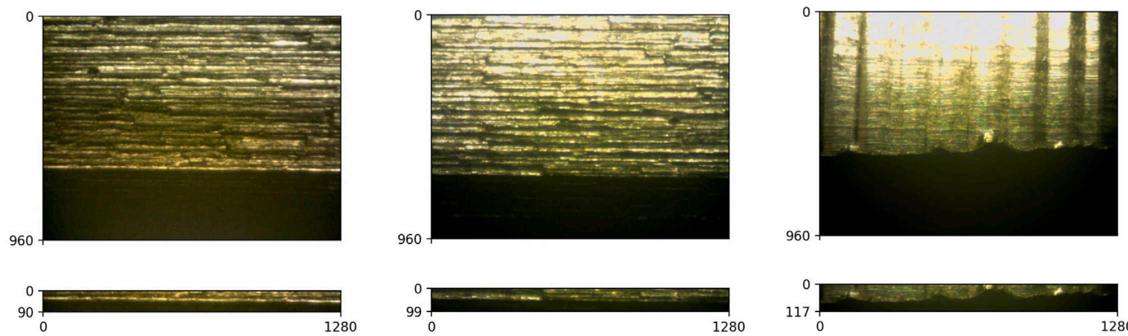
As the burrs are located at the end of the piece, the region of interest is the area next to that end (Fig. 3 a). To automatically identify such region, we first apply RUSTICO to the image [19] in order to detect curvilinear structures (Fig. 3 b). RUSTICO is a trainable operator based on the B-COSFIRE filters [23]. It combines the response of several Difference-of-Gaussians (DoG) filters, and achieves robust detection of curvilinear patterns also in presence of noise and spurious texture, as it is embedded with a noise suppression mechanism inspired by the push–pull phenomenon that occurs in some neurons of the visual system of the brain. Smoothing the image before with a filter of 5×5 pixels and 1/15 value shows clearer results. RUSTICO can be optimized by choosing different parameters: σ_0 and α regulate the tolerance to deformation of the patterns of interest; λ and ξ regulate the robustness to the noise in the image; ρ and σ are the polar coordinates of the considered DoG responses with respect to the reference point. In this paper, these parameters are $\sigma_0 = 3$, $\alpha = 0.1$, $\lambda = 0.5$ and $\xi = 1.5$, $\rho = 16$ and $\sigma = 2.5$, which are extracted from [19], where all the equations are deeply explained. Finally a threshold of 0.2, which was manually selected, is applied in order to binarize the image.

Next we apply a morphological closing operation with a disk of 67 pixels of radius to remove small holes presented in the image produced by *RUSTICO* (Fig. 3 c). Then, the image is divided in 100 sections horizontally and the region of interest is calculated as in [2]; that is, those points whose difference with its previous point is higher than 5 are selected and those ones whose position over the x axis is higher than 10 are discarded, which removes noise sections (Fig. 3 d).

3.3. Feature vector computation

Considering the image provided by RUSTICO (Fig. 4 b), the feature vector is calculated as follows. The first step consists of dilating the image with a kernel of 31×79 pixels, which causes the lines to widen and merge with nearby ones to differentiate between what is background and what is piece (Fig. 4 c). Then, a border of 10 pixels is added around the image and, with morphological closing operations, small objects are removed as well as those regions close to the edges. Image contours are retrieved and filled with a topological structural analysis [20] (Fig. 4 d). Finally, the region of interest is divided in vertical sections and for each section the biggest closed area determines a bounding rectangle that starts at the workpiece edge and ends at the end of the region of interest. The height of that rectangle for each section builds the final feature vector.

As some of the images are overexposed, information is lost. For that reason, the method discards the images where the region of interest is not properly identified or contours are not detected in all the vertical divisions.

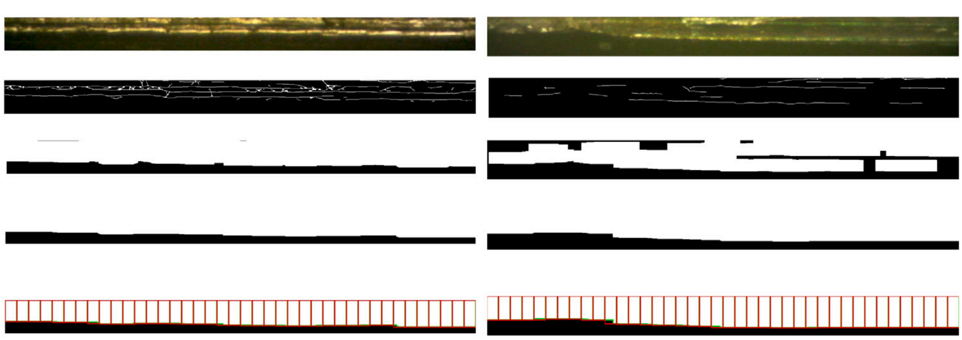


(a) Knife-type burr (K) (b) Saw-type burr (S) (c) Burr-breakage (B)

Fig. 2. Labeled samples of original images (first row) and regions of interest (second row).

(a) Original (b) RUSTICO (c) Closing (d) Percentage of white pixels per image row

Fig. 3. Image sequence of the complete process: from the original image (a), the contour is detected (b), it is processed (c), a criterion to determine the end of the piece is applied (d).



(a) Original
(b) RUSTICO
(c) Dilation
(d) Morphological operations
(e) Vertical divisions

Fig. 4. Samples of the process to obtain the feature vector from the region of interest of the image.

3.4. Classification

As experts labeled each image according to their criteria, we used a supervised machine learning method in order to classify the images. In particular, we deployed a C-support Vector Classification (C-SVC) implementation based on libsvm [24], which is a library for Support Vector Machines (SVM).

4. Experimental setup

Parameters are determined by using a grid search of different kernel size (47, 53, 67) and shape (79 × 79 –square–, 31 × 79 –horizontal–, 79 × 31 –vertical–). For the considered dataset, available in [25], best results are achieved with a 67-pixel disk kernel of size 31 × 79 (see Table 1). About the dataset, it shows an overlapping of mean and standard deviation of their features (see Fig. 5), specially between the knife-type (K) and the saw-type (S).

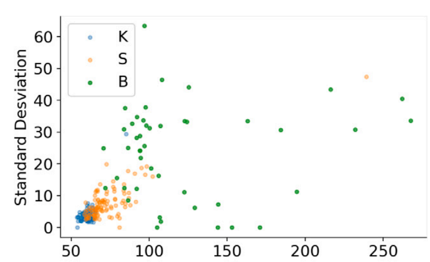


Fig. 5. Statistics of the features of the dataset.

To choose the best configuration parameters, a grid search with 12-fold cross validation was carried out. We thus determined a C value of 9, which is the regularization parameter and prevents overtraining. That C value also balances the influence of the samples from different

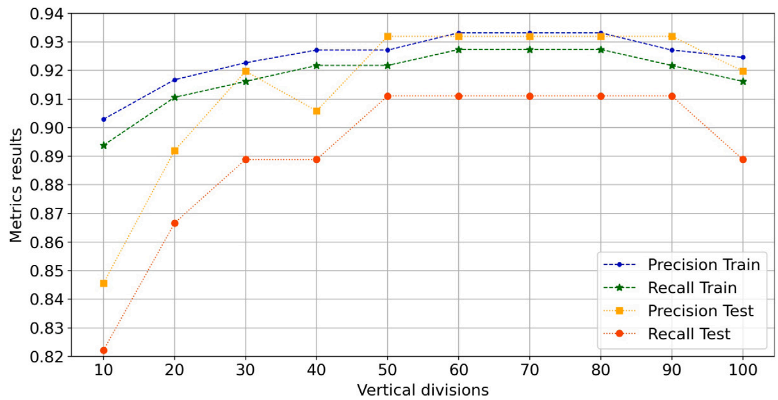


Fig. 6. Evolution of training and test results according to the number of vertical divisions. Mind that the y axis is labeled from 0.82.

Table 1
Grid search of parameters of morphological operations.

		Kernel size		
		79 × 79	31 × 79	79 × 31
Disk size	47	0.64	0.55	0.7
	53	0.75	0.83	0.8
	67	0.83	0.92	0.8

Table 2
Confusion matrix of test set.

	K	S	B
K	13	0	0
S	4	16	0
B	0	0	12

classes on the training error by weighing them inversely-proportional to the class frequencies.

We carried out experiments on a collection of 224 images of multiple machined parts subject to different illumination conditions. Images were processed as detailed in Section 3, first to detect the section of the ending of the piece and then to compute the feature vector. This process was repeated with different vertical divisions. All code is available in [26].

We compute the feature vectors and use them as input to the C-SVC, using 80% of the data for training and the remaining 20% for test. The parameters of the C-SVC are adjusted using the grid search procedure explained previously.

5. Experimental results

Fig. 6 shows the results obtained in the training and test by considering different number of divisions over the image width (vertical divisions). Training results show higher performance for 60, 70 and 80 divisions, obtaining 93.32% of precision, 92.74% of recall and 92.75% of F1-Score. And on the test data, 93.20% of precision, 91.11% of recall and 91.21% of F1-Score was equally yielded for 50 to 90 divisions. All metrics are calculated for each burr type, and find their weighted average (the number of true instances for each type).

Because the best results for training were obtained from 60 to 80 vertical divisions, we made a deeper study of the results with 60 vertical divisions, being the smallest number of them, which implies less computational cost. Table 2 shows the confusion matrix achieved on the test set. It indicates that the burr breakage (B) and knife-type (K) cases, which are the two main types of edge finishing, are well detected by the proposed method. However, saw-type (S) burrs sometimes are erroneously determined as knife-type when the imperfections are really subtle.

The results reported by existing methods are generally lower than those obtained by the proposed method. So, in [2] the dataset is smaller and the results were 76.32% of precision, recall and F1-Score. Whereas [14] is focused on defect detection and classification with an accuracy of 80.83% with Support Vector Machine. The achieved results demonstrate that the proposed method has substantially improved with respect to existing methods.

6. Conclusions and future work

We proposed a new and efficient method to detect and classify burrs in industrial machine work tools. The method is based on the use of RUSTICO for robust delineation of structures of interest in images, followed by morphological operations and retrieving contours to obtain a feature vector. Best results were obtained by considering from 60 to 80 vertical divisions, that achieve a precision of 93.20%, a recall of 91.11% and a F1-Score of 91.21% for test images. For 60 vertical sections, we observed a perfect detection of burr breakage (B) that has large deformations due to fractures in manufacturing process, as well as the knife-type (K or ideal) ending. However, the saw-type (S) burr is sometimes mistaken as a knife-type because of their similarity. The results that we achieved demonstrate that the proposed method outperforms previous research and complies with manufacturer requirements. The use of computer vision techniques, such as those presented in this article, allows to eliminate operator subjectivity and speed up industrial validation processes. Possible improvements include the use of deep learning techniques for image processing and classification, which requires a larger labeled dataset.

CRediT authorship contribution statement

Virginia Riego: Software, Investigation, Resources, Data curation, Validation, Writing – original draft, Writing – review & editing, Visualization. **Lidia Sánchez-González:** Conceptualization, Software, Investigation, Data curation, Methodology, Writing – original draft, Writing – review & editing, Supervision, Visualization. **Laura Fernández-Robles:** Software, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing, Visualization. **Alexis Gutiérrez-Fernández:** Investigation, Writing – original draft, Writing – review & editing. **Nicola Strisciuglio:** Software, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing, Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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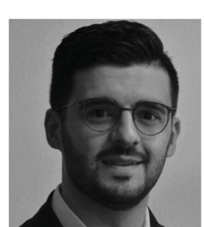

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