Machine-vision-based identification of broken inserts in edge profile milling heads

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Abstract

This paper presents a reliable machine vision system to automatically detect inserts and determine if they are broken. Unlike the machining operations studied in the literature, we are dealing with edge milling head tools for aggressive machining of thick plates (up to 12 centimetres) in a single pass. The studied cutting head tool is characterised by its relatively high number of inserts (up to 30) which makes the localisation of inserts a key aspect. The identification of broken inserts is critical for a proper tool monitoring system. In the method that we propose, we first localise the screws of the inserts and then we determine the expected position and orientation of the cutting edge by applying some geometrical operations. We compute the deviations from the expected cutting edge to the real edge of the inserts to determine if an insert is broken. We evaluated the proposed method on a new dataset that we acquired and made public. The obtained result (a harmonic mean of precision and recall 91.43%) shows that the machine vision system that we present is effective and suitable for the identification of broken inserts in machining head tools and ready to be installed in an on-line system.

1. Introduction

Tool wear monitoring (TWM) systems have been widely developed over the last decades for the evaluation of the wear level of inserts, also known as cutting tools. In this paper, we present a method to identify broken inserts in a milling machine. This is an important application in the field of face milling as broken inserts pose a threat to the stability of milling heads. An unnoticed broken insert may go on working without being detected, and can cause a decay of the quality of the final manufactured product or a breakage of the milling machine itself [1].

Fig. 1 shows the machine used in this study, which manufactures metal poles of wind towers. Milling is performed in a single pass across very thick and long plates (up to 12 cm and 42 m, respectively) which is not common in standard milling machines.

The current state of the art in TWM comprises two approaches known as direct and indirect methods. Indirect techniques can be applied while the machine is in operation. These methods evaluate the state of the inserts through measurable quantities (e.g. cutting forces and vibrations) that are typically affected by noisy signals [2345]. On the contrary, direct techniques monitor the state of the inserts directly at the cutting edge when the head tool is in a resting position [6]. As to direct methods, image processing and computer vision techniques are the most popular ways for measuring flank and crater wear [5]. Ongoing progress in the fields of machine vision and computing hardware has permitted the implementation of reliable on-line TWM systems [78]. The method that we present falls into the direct approach category. Many machine-vision-based systems have dealt with the detection of parts or imperfections in production environments [91011].

The problem that we deal with here presents two challenges: (i) the localisation of inserts and their cutting edge and (ii) the identification of broken inserts. Fig. 2 shows a milling head tool that contains indexable inserts. In this case, each insert has four edges, with the cutting edge being the (nearly) vertical one on the left hand side.

1.1. Related work

There is a large body of work in the literature that evaluates the state of given inserts without having to localise them in images [2121314]. Other methods capture images directly on the head tool but they are focused on ball-end milling cutters [5] or microdrills [61516], in which only two flutes and therefore two inserts are present. The others deal with face milling heads where it is easy to set the acquisition system to only capture one insert per acquired image.
In our application, the head tool contains 30 rhombohedral inserts leading to 8–10 visible inserts per image, which makes the localisation of the inserts a new and challenging task. In our previous work [20], we introduced a method to localise inserts in images of such head inserts and here we improve it and propose a new method that evaluates the status of the inserts.

As to the identification of broken inserts, approaches based on texture analysis have been widely used in the literature for wear monitoring when dealing with machining operations [7]. Tool wear or degree of tool wear have been determined by using GLCM based texture analysis in turning and milling [21–23]. Barreiro et al. [28] estimated three wear levels (low, medium, and high) of the tool insert by means of the Hu and Legendre invariant moments. Datta et al. [29] used two texture features based on Voronoi tessellation to describe the amount of flank wear from machined surface images. The machines that we are dealing with in this study, however, use an aggressive edge milling in a single pass for the machining of thick plates. This may cause the breakage of inserts, such as the examples marked with a blue rectangle in Fig. 2. Part of a cutting edge may be torn without harming the texture of the remaining part of the insert. For this reason we believe that texture features are not suitable for the concerned application.

Other approaches use the contours of the inserts to determine the state of the inserts. For instance, Atlı et al. [30] classified drilling tools as sharp or dull using a new measure namely DEFROL (deviation from linearity) to the Canny-detected edges. Makki et al. [31] captured images of a drilling tool at 100 rpm rotation speed and used edge detection and segmentation methods to describe the tool wear as the deviation of the lip portion. Also, Chetan et al. [32] compared image areas of the tool obtained through a texture-based segmentation method before and after cutting in order to determine the state of a drilling tool. For turning operations, Shahabi and Ratnam [33] applied thresholding and subtraction of worn and unworn tool images to measure the nose worn regions.

Some papers also deal with micro-milling or end milling in this line of work. Otieno et al. [34] compared images captured before and after the usage of two fluted micro and end mills thresholded by an XOR operator. Neither edge detection, nor tool wear quantification and nor wear classification was performed. Zhang and Zhang [5] also compared images of ball-end milling cutters before and after machining process in order to monitor the state of the tool. Liang et al. [35] presented a method based on image registration and mutual information to recognise the change of nose radius of TiN-coated, TiCN-coated and TiAlN-coated carbide milling inserts for progressive milling operation. They perform logic subtraction of two images before and after milling. The mentioned works share one common requirement; they all must have an image of the intact tool to evaluate any discrepancies of a new image of the same tool.

In this paper we propose a novel algorithm that evaluates the state of cutting edges without requiring image references of intact inserts. This avoids calibrating the system each time an insert is replaced and allows to free memory after each monitoring. It automatically determines the ideal position and orientation of the cutting edges in a given image and computes the deviation from the real cutting edges. This means that from a single image we can determine the broken inserts.

The paper is organised as follows. First we explain the method in Section 2. In Section 3 we present the publicly available dataset that we created for an edge profile shouldering head and describe the experiments that we carried out. In Section 4 we discuss the results and certain aspects of the proposed method, and finally we draw conclusions in Section 5.

2. Method

In the method that we propose, we first localise cutting edges in a given image, and then we classify every cutting edge as broken or unbroken. From the image analysis point of view, an unbroken insert is one which has a straight cutting edge (Fig. 3b), while a broken insert has a curved or uneven cutting edge (Fig. 3c).

Fig. 4 presents a schema that shows the proposed method. First we localise the inserts and the cutting edges and then, we evaluate the inserts using a three-stage method: applying an edge preserving smoothing filter, computing the gradient of the image and finally using geometrical properties of the edge to assess its state. Below we elaborate on each of these steps.

2.1. Detection of inserts and localisation of ideal cutting edges

We use the algorithm that we introduced in [20] to detect inserts and localise the respective cutting edges. We apply the contrast-limited adaptive histogram equalisation (CLAHE) method [36] in order to improve the contrast quality of the images and facilitate the detection of edges. In Section 3.2.1 we provide the parameter values that we used.
In our experiments, the algorithm works by first applying a circular Hough transform (CHT) with a two-stage algorithm to detect the circular shapes of the screws. The CHT is a feature extraction technique for localising circles based on the standard Hough transform (SHT). The SHT [37] aims at detecting straight lines. The main idea of the Hough transform is to map a parametric curve (line, ellipse, and circle) into a new feature space. For instance, in the standard Hough transform (SHT), the Cartesian coordinates of edge points are mapped into a 2-dimensional feature space, referred to as the accumulator array. The accumulator array is characterised by the slope of a linear equation in the form of slope-intercept on one axis and the intercept on the other axis. For each edge point in the given image, the cells of the accumulator array are incremented by one. In order to avoid numerical errors in the slope of vertical lines, a generalised Hough transform uses a polar parameter space that satisfy the line parameters in the new feature space. For instance, in the standard Hough transform (SHT), the Cartesian coordinates of edge points are mapped into a 2-dimensional feature space, referred to as the accumulator array. The accumulator array is characterised by the slope of a linear equation in the form of slope-intercept on one axis and the intercept on the other axis. For each edge point in the given image, the cells of the accumulator array that satisfy the line parameters in the new feature space are incremented by one. In order to avoid numerical errors in the slope of vertical lines, a generalised Hough transform uses a polar coordinate system instead.

In the case of the CHT algorithm, the Hough parameter space is defined by three variables, namely the two polar coordinates of the centre of the circle and its radius. After applying the CHT, we crop a rectangular area of 205 × 205 pixels centred around a detected screw on the images of size 1280 × 960 pixels, Fig. 3b and c. The dimensions of the cropped area are determined from the largest insert in the training images. For a particular head tool, all parameters can be estimated from the images of a small training set (in our case we use 10 images) and no further need of adjustment is required as long as the parameters of the camera are not modified.

We use Canny’s method [38] to detect edges in the automatically cropped inserts. Then, we detect lines by applying a SHT to the resulting edge map. We use the known geometry of the inserts (widths, heights and angles) to determine which lines define the edges of the inserts. For a more detailed explanation, we refer the reader to [20]. We take the (nearly) vertical edge in the left of the screw to be the ideal cutting edge. Finally, for each localised insert, we consider a set $I$ of Cartesian coordinates that form the ideal cutting edge:

$$I = \{(x_i, y_i) | i = 1…u\}$$

where $u$ is the number of locations of the ideal cutting edge of a localised insert.

We determine a region of interest (ROI) from the ideal cutting edge and the horizontal edges that are detected by the algorithm that we published in [20]. In Fig. 5a we show examples of ROIs in broken and unbroken inserts. An ROI is determined by considering two parallel lines to the ideal cutting edge, one 3 pixels to the left and the other one to the right with a distance of 0.7 times the space between the ideal cutting edge and the centre of the screw. Moreover, we consider a parallel line to the top edge 3 pixels towards the bottom and a parallel line to the bottom edge 3 pixels towards the top. From the resulting quadrilateral, we remove a segment from a circle (with a radius of 45 pixels) around the centre of the screw that coincides with the quadrilateral. Such a ROI is sufficient to evaluate the state of a cutting edge while ignoring possibly worn edges coming from the top or bottom parts of the insert as well as ignoring any texture coming from the screw. In the end, we consider a rectangle around the ROI with a 3-pixel width boundary and use it to crop the corresponding part of the image that contains the ROI, Fig. 5b. We also consider a mask defining the ROI in such a rectangular area, Fig. 5c.

### 2.2. Detection of real cutting edges

The heterogeneous texture and the low contrast of the insert with respect to the head tool make the detection of the real cutting edge an arduous task. If an edge detector is applied directly to the cropped images, many edges apart from the cutting edge would be recognised. In order to enhance the edge contrast, we apply the edge-preserving smoothing filter of Gastal and Oliveira [39] to the cropped region. We choose this approach due to its efficiency and its good performance. This filtering method smoothes the heterogeneous texture of the insert and of the background but preserves the edges of the insert. The images in Fig. 5d show examples of the output of this algorithm.

After that, we apply Canny’s method [38] to find edges by looking for local maxima of the gradient on the filtered region. Other edge detectors, such as the ones based on Sobel, Prewitt, Roberts and LoG, performed worse. Canny’s algorithm computes the gradient after

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1. Standard deviation of the spatial filter equals 60 and standard deviation of the range filter equals 0.4, as the default configuration.
applying a Gaussian filter that reduces noise. Non-maximal suppression is applied to thin the edges. This is followed by hysteresis thresholding which uses a low and a high threshold in order to keep the strong edges (above the high threshold) and only the weak edges (with a value between the low and high threshold) that are connected to any of the strong ones. We show examples of Canny’s gradient magnitude and binary edge maps in Fig. 5e and f. Finally, we only consider the edges within the ROI (Fig. 5g).

For each localised insert, we define a set $R$ of 3-tuples that represent the Cartesian coordinates $(x_q, y_q)$ and the corresponding gradient magnitude value $g_q$ of each location in the real cutting edge:

$$R = \{(x_q, y_q, g_q) | q = 1 \ldots v\}$$  \hspace{1cm} (2)

where $v$ is the number of locations of the real cutting edge of the localised insert.

2.3. Measurement of deviations between real and ideal cutting edges

For a pair of coordinates $(x_t, y_t)$ in the ideal set of edges $I$, we determine a set $P_t$ of coordinates $(\tilde{x}, \tilde{y})$ and the corresponding gradient magnitudes $\tilde{g}$ from the set of real edges $R$ such that $(\tilde{x}, \tilde{y})$ lie on a line that passes through $(x_t, y_t)$. The slope $m$ of this line is the gradient of the top edge:

$$R = \{(x_t, y_t, \tilde{g}) | \tilde{g} = m(x_t - x_t) + y_t, (\tilde{x}, \tilde{y}, \tilde{g}) \in R, (x_t, y_t) \in I\}$$  \hspace{1cm} (3)

Examples of such lines are marked in blue in Fig. 6a. Next, we denote by $E_t$ the set of Euclidean distances from $(x_t, y_t)$ to all coordinates in the set $P_t$:

$$E_t = \{(x_{t'}, y_{t'}) | (x_{t'}, y_{t'}) \in P_t, \forall (x_{t'}, y_{t'}) \in P_t\}$$  \hspace{1cm} (4)

$E_t$ could be an empty set. Let $D$ be the set of minimum distances of $E_t$ for each point $t$ in $I$. $D$ represents the minimum deviations between the ideal and real edges:

$$D = \{\min(E_t) | t = 1 \ldots |I|\}$$  \hspace{1cm} (5)

Let $G$ be the set of gradient magnitudes of the points in $P_t$ with the minimum distance in $E_t$ for each point in $I$:

$$G = \{g_i | g_i \in R, i = \arg\min(E_t), t = 1 \ldots |I|\}$$  \hspace{1cm} (6)

In Fig. 6 we plot the values of the sets $D$ and $G$. We remove abnormal deviations that are usually caused by texture on the surface of the insert rather than by the cutting edge. For example, Fig. 6e presents two such abnormal deviations (spikes) at the
beginning and end of the set $D$. We denote by $f_{A,N}(D, t)$ a function that evaluates a neighbourhood of width $A$ within the given set $D$ centred at point $t$:

$$f_{A,N}(D, t) = \begin{cases} D_t & \text{if } D_t \leq N \times \text{median}_{j=N}^{A}(D_{t+j}) \\ \emptyset & \text{otherwise} \end{cases}$$  

This function returns the element $D_t$ if $D_t$ is higher than a fraction $N$ of the median within a local window of width $A$, otherwise it returns $\emptyset$. We define a set $D'$ which is formed by applying the function $f$ two consecutive times in order to remove spikes with a length of at most 3 points:

$$D' = \{f_{A,N_2}(f_{A,N_1}(D, t), t) \mid \forall t \in D \}$$  

The first insert in Fig. 6 shows a typical problem in this application.

The lower part of its cutting edge has low contrast and as a result the corresponding edge points have very low gradient magnitudes. We are only interested in evaluating the parts along the cutting edge that have high contrast because they are more reliable. Formally, we define a new set $D''$ whose elements are copied from the set $D'$ when the corresponding edge points have gradient magnitudes higher than a threshold $B$, otherwise they are set to $\emptyset$:

$$D'' = \{g_t \geq B \rightarrow d_t \wedge g_t < B \rightarrow \emptyset \mid \forall t \in D' \}$$  

In order to ensure that an insert is broken, the deviation should be sufficiently high along a region of the cutting edge and not just in one isolated pixel. We apply a mean filter using a window of width $C$ and subsequently take the maximum deviation $\delta$ of the cutting edge.
\[ J = \max \left\{ \frac{1}{2C + 1} \sum_{j=1}^{C} (d_{i,j}) \mid \forall d_i \in D' \right\} \]  

(10)

Moreover, we also compute the mean gradient magnitude \( g \) along the cutting edge.

\[ g = \frac{1}{|G|} \sum_{j=1}^{G} g_j \quad \forall g_j \in G \]  

(11)

As a result every localised insert is represented by the two parameter values \( J \) and \( g \).

2.4. Classification of inserts

The evaluation of inserts is performed during the resting state of the milling head tool between the processing of two metallic plates. Plates are mechanised in a single pass. We set up a capturing system at this location as shown in Fig. 7a, with a fixed camera and the head tool makes 24 rotations of 15° each. For every rotation we take a picture of the head tool. The same insert is captured in several images (between 7 and 10) under different poses as the head tool rotates, Fig. 8. In this work, the correspondences of the same insert in multiple images is manually labelled. In Section 4 we provide a suggestion how the correspondence issue can be implemented automatically. For each insert we compute the maximum deviation \( J \) and the mean gradient \( g \) for every image where it is detected.

We classify an insert as broken if the image with the highest mean gradient magnitude \( g \) along the cutting edge has a maximum deviation \( J \) higher than a threshold \( T \), or if the maximum deviations of at least two images (irrespective of the mean gradient magnitude) are greater than \( T \). Otherwise we classify the insert as unbroken. Formally, we define the classification function \( z \) as:

\[ z(e) = \begin{cases} 1 & \text{if } (\arg\max_{i \in \mathbb{N}} (d_{i,k}) > T) \lor (\sum_{i=1}^{r} (d_{i,k} > T)) \geq 2 \\ 0 & \text{otherwise} \end{cases} \]  

(12)

where \( r \) is the number of images where the same insert \( e \) is detected.

3. Evaluation

3.1. Dataset

To the best of our knowledge, there are no publicly available image datasets of milling cutting heads in the literature. For this reason, we acquired a new dataset with ground truth and we published it on-line. It is made up of 144 images of an edge profile cutting head used in a computer numerical control (CNC) milling machine. We conducted experiments on a milling TECOI TRF machine, using a bevelling tool by Kennametal. The inserts used were rhomboid type fastened by screws, without chip breaking and a rake angle of 0. The head tool, with cylindrical shape, contains 30 inserts in total from which 7 to 10 inserts are seen in each image of the dataset. The inserts are arranged in 6 groups of 5 inserts diagonally positioned along the axial direction of the tool perimeter, as illustrated in Fig. 7b. The last insert of each group is vertically aligned with the first insert of the following group. It gives a total of 24 different positions along the radial perimeter of the milling head tool in which at least one insert is aligned with the camera in intervals of 15°.

We created the dataset following an iterative process. We mounted 30 inserts in the head tool and took 24 images of the head tool in different orientations that differ by 15°. We repeat this process for 6 times, where each time we use a different set of inserts, thus collecting (6x 24=) 144 images that contain (6x 30=) 180 unique inserts, of which 19 are broken and 161 are unbroken. All inserts that we used to acquire this dataset were taken after some milling operations by the same machine.
kind of substances that can cause a filthy tool.

Together with the dataset, we provide the corresponding ground truth masks of all ideal cutting edges along with the labels of the state of the inserts (broken or unbroken). Moreover, we labelled each distinct insert, by giving them unique identification numbers. In Fig. 8, we show three consecutive images that contain the same inserts (with the same identification number) in different locations and poses due to the rotation of the milling head tool in steps of 15°.

3.2. Experiments and results

We used Matlab on a personal computer with a 2 GHz processor and 8 GB RAM. The complete process to identify broken inserts in a head tool with 30 inserts takes less than 3 min. This is sufficient for the application at hand because according to the consulted experts the milling head tool stays in a resting position between 5 and 30 min, during which the milled plate is replaced by a new one.

3.2.1. Localisation of ideal cutting edges

In this work we improve the localisation of ideal cutting edges by better fine tuning the parameters described in [20]. In particular, in order to determine the cutting edge in the Hough transform map we consider the lines that deviate by at most 22° from the vertical orientation and choose the one which is at least 47 pixels to the left of the centre. Similarly, for the detection of the top and bottom edges, we consider the lines that deviate by at most 11° from the horizontal orientation and choose the ones that are at least 52 pixels away from the centre. With this new selection of parameter values we improve the localisation accuracy from 98.84% to 99.61%.

The fact that we have a controlled environment (fixed camera and fixed resting position of the head tool), this set of parameters is fixed only once for every given milling machine.

3.2.2. Classification of inserts

Our dataset is skewed with 19 broken inserts and 161 unbroken ones. We refer to the broken inserts as the positive class and the unbroken as the negative class. Therefore, a true positive (TP) is a broken insert classified as broken; a false positive (FP) is an unbroken insert classified as broken and a false negative (FN) is a broken insert classified as unbroken. We compute the precision $P = TP/(TP + FP)$, recall $R = TP/(TP + FN)$ and their harmonic mean $F = 2PR/(P + R)$ for a set of thresholds $T \in \{5, 5.01, \ldots ,8\}$ used in the classification function, and obtain a $P-R$ curve. We consider the best pair $(P, R)$, the one that contributes to the maximum harmonic mean.

We apply a repeated random sub-sampling validation where in each run we randomly (stratified sampling) split the dataset into training (70%) and validation (30%) sub sets. For each such split, we use the training data to determine the set of parameters $(A_1, N_1, A_2, N_2, B, C)$ that achieves the global maximum harmonic mean $F$. This is obtained by applying a grid search on $A_1 \in \{3, 5, 7\}$, $N_1 \in \{1, 1.5, 2\}$, $A_2 \in \{3, 5, 7\}$, $N_2 \in \{1, 1.25, 1.5\}$, $B \in \{0.18, 0.2, 0.22\}$ and $C \in \{3, 5, 7\}$ and computing the maximum harmonic mean for each combination. If several sets of parameters yield the same maximum mean, we take a random one. In Fig. 9, we show the $P-R$ curves obtained for two combinations of parameters of the grid search by varying the threshold $T$.

The determined set of parameters is then used to evaluate the validation set. We repeat this process 20 times and finally we average the results obtained from the validation sets. We obtain an average harmonic mean $F = 0.9143(\pm 0.079)$ with a precision $P = 0.9661(\pm 0.073)$ and a recall $R = 0.8821(\pm 0.134)$. The most repeated (6 out of 20 runs) set of parameters in the training is $(A_1 = 5, N_1 = 1.5, A_2 = 3, N_2 = 1, B = 5, C = 0.2)$. When we evaluate the entire dataset with these parameter values we achieve precision $P=1$ and recall $R=0.95$ for the maximum harmonic mean $F=0.9744$.

4. Discussion

The contribution of this work is threefold. First, we performed an effective classification of the inserts according to the state of their cutting edges as broken and unbroken. Second, we presented a dataset of 144 images of a rotating edge milling cutting head that contains 30 inserts, analysing 180 inserts in total. It contains the ground truth information about the locations of the cutting edges and broken inserts are labelled by experts. We made our dataset publicly available (see footnote 2). Third, we improved the selection of parameters for the localisation of multiple inserts and cutting edges presented in [20].

The high precision and recall rates that we achieved demonstrate the effectiveness of the proposed approach and suggest that it is ready to be applied in production. The performance can be further improved by using more appropriate illumination conditions and better quality of the lenses in order to obtain higher contrast between inserts and background.

Typically, an insert appears in 7–10 images in different positions and poses. In this work, the ground truth contains the identification numbers of the inserts in all images. This means, that an insert that appears multiple times is manually given the same identification number. Alternatively, the approximate position of inserts in the consecutive images can be inferred from the radius of the head tool cylinder, the distance of the fixed camera from the head tool and the degrees of rotation. In this way, after automatically detecting the positions of inserts we can automatically determine the correspondences (labelling) according to the expected positions.

Inserts on the sides of an image appear skewed due to the cylindrical shape of the milling head tool. This, however, has little effect on the classification of an insert because the decision is based on at least 2 (out of the 7–10) images where the insert is visible. In most of such images, the inserts appear roughly perpendicular with the camera, allowing us to take reliable decisions.

In this work we are concerned with detecting broken inserts as it is the most critical evaluation for the stability of the milling head tool. In future, we will also evaluate the wear of inserts in order to detect the weak ones as early as possible. Moreover, we would also like to compare the performance of different image acquisition methods.

In addition, the proposed method can be set up for different machining heads that contain polygonal inserts fastened by screws, a typical design in milling machines.
5. Conclusions

The approach that we propose for the identification of broken inserts (cutting tools) in milling machines achieves a harmonic mean of precision and recall equals 0.9143 (± 0.079) and can analyse all inserts in a milling head tool (24 images of size 1280× 960 pixels) in less than 3 minutes on a 2 GHz processor. It is based on computer vision methods and does not require the comparison with reference images of intact inserts. To our knowledge, this is the first automatic solution for the identification of broken inserts in edge profile milling heads. The presented system can be set up on-line and it can be applied while the milling head tool is in a resting position without delaying any machining operations. This system highly reduces the risk of head tool collapse, which is very expensive and time consuming to replace.

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