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Tool wear monitoring using an online, automatic and low cost system based on local texture

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ABSTRACT

In this work we propose a new online, low cost and fast approach based on computer vision and machine learning to determine whether cutting tools used in edge profile milling processes are serviceable or disposable based on their wear level. We created a new dataset of 254 images of edge profile cutting heads which is, to the best of our knowledge, the first publicly available dataset with enough quality for this purpose. All the inserts were segmented and their cutting edges were cropped, obtaining 577 images of cutting edges: 301 functional and 276 disposable. The proposed method is based on (1) dividing the cutting edge image in different regions, called Wear Patches (WP), (2) characterising each one as worn or serviceable using texture descriptors based on different variants of Local Binary Patterns (LBP) and (3) determine, based on the state of these WP, if the cutting edge (and, therefore, the tool) is serviceable or disposable. We proposed and assessed five different patch division configurations. The individual WP were classified by a Support Vector Machine (SVM) with an intersection kernel. The best patch division configuration and texture descriptor for the WP achieves an accuracy of 90.26% in the detection of the disposable cutting edges. These results show a very promising opportunity for automatic wear monitoring in edge profile milling processes.

1. Introduction

The quality of the machined parts in milling, turning or drilling operations largely depends on the state of the cutting inserts. There are factors like abrasion, corrosion or fatigue that influence tool wear [1,2]. Thus, tool wear monitoring becomes crucial in machining processes in order to find the optimal tool replacement time. This plays an important role not only because of the cost of the cutting tools themselves, but also for the indirect costs due to the unproductive time needed to carry out the tool replacement. Therefore, optimizing tool replacement operations significantly improves efficiency and competitiveness of the manufacturing systems.

The most widely studied techniques to assess the status of the cutting tools are based on monitoring signals that have some correlation with the level of wear. Such techniques are known as indirect methods. Thus, some works propose the use of force signals to measure wear in real time [3–5]. Another example is the work developed by Drazen et al. [6] in which they examine the influence of three cutting parameters on surface roughness, tool wear and cutting force components in face

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milling as part of an off-line process control. Other works are based on vibrations such as the one developed by Painuli et al. [7] in which descriptive statistical features from vibration signals are used in an online cutting tool condition monitoring system, or the work by Wafaa et al. [8] in which the vibratory signatures produced during a turning process were measured by using a three-axis accelerometer to monitor the wear on the tool. Acoustic emissions have been also shown to be sensitive to changes in cutting process conditions [9]. However, indirect methods present an important drawback: all these signals can be seriously affected by the inherent noise in industrial environments, which reduces their performance.

Recent advances in digital image processing have led to proposals for tool condition monitoring using machine vision, which are gaining importance day by day. In this case, tool wear is measured directly, achieving higher levels of precision and reliability than that of indirect methods. These computer vision approaches are mainly based on the wear shape contour, the wear shape properties, the texture of the wear region or combinations of some of them [10–18].

Antić et al. [14] apply a texture filter bank over the image formed by the Short Term Discrete Fourier Transform (STDFT) spectra of vibration sensors to get descriptors for tool wear monitoring. In [15,17], Mikołajczyk et al. used unsupervised classification by means of Artificial Neural Networks for segmenting the tool wear region and thereafter, use it to predict the tool wear life. D'Adonna et al. use Artificial Neural Networks and DNA-based computing for predicting, based on information extracted from preprocessed images of tool wear images, the degree of wear [18]. Some works attempt to describe the wear taking into account the wear shape contour [10,19]. Both methods are based on the ZMEG (Zernike Moment Edge Gradient) shape descriptor [20] obtaining promising results in the tool wear monitoring field. However, the use of just shape information may be quite limited to describe the wear since there are many other factors that characterize its level. In [12], the wear region is described using nine geometrical descriptors. This study shows that eccentricity, extent and solidity are the top three most informative features regarding wear level categorization. However, most methods based on geometric features have their limitations when applied to real environments, because the correct extraction of these features depends on a precise segmentation which becomes a complex stage due to the machining operation and other factors such as illumination conditions. In [11], some image processing techniques are developed to quantify two wear mechanisms (abrasion and micro-pitting) in polymers. They are based on local and global thresholding segmentation with different possible corrections and addresses the labelling processes as the mean opinion scores given by several experts, what is an interesting approach for this challenging task. This study paves the way towards an automated system to identify different wear mechanisms in this field.

Nowadays, the analysis of the wear region texture is the most widely studied approach. Thus, Datta et al. [21] rely on texture analysis and the extracted features were correlated with measured tool flank wear of turned surfaces. In [22], image analysis of surface textures produced during machining operations are used as indicators for predicting the condition (e.g., the wear) of the cutting tool. A computer vision that uses the grey level co-occurrence matrix (GLCM) for characterising surface roughness under different feed rates in face turning operations is proposed in [23]. Dutta et al. implemented an online acquisition system of machined surface images [24] which were subsequently analysed using an improvised GLCM technique with appropriate pixel pair spacing or offset parameter in turning processes. Later, the same authors proposed to use the discrete wavelet transform on turned surface images [13] and also texture analysis and support vector regression [25]. None of these works, however, deal with edge profile milling processes. In [26] a reliable machine vision system to automatically detect inserts and determine if they are broken is presented. Unlike the machining operations studied in the literature, they are dealing with edge milling head tools for aggressive machining of thick plates (up to 12 cm) in a single pass.

In this paper, we propose a new method based on image texture analysis for tool wear monitoring in an edge profile milling machine that can be embedded in a portable system. We consider it an *online* method because this evaluation is carried out with no external intervention to extract the inserts from the tool head. Our approach is based on obtaining local texture features individually from several regions extracted from the zone of the tool where the wear tends to appear according to the experts' knowledge and corroborated by the hundreds of inserts images captured. We will refer to these regions as Wear Patches (WP). This approach presents two main advantages: firstly, establishing WP with different sizes and orientations allows to detect small – but important- worn areas that otherwise (i.e. using methods that extract a single feature vector from the whole image) would have been overlooked. Secondly, it avoids the segmentation stage, which saves time and computational resources, making feasible a low cost portable implementation. Additionally, since each WP classification is addressed individually using supervised learning techniques based on kernels (i.e., SVM), the monitoring system is able to provide an estimation of the tool wear percentage by aggregating the individual results. This method can be successfully implemented in a small single-board computer, e.g. a Raspberry Pi. We consider that it is a *low-cost* system because, taking into account the components of the implemented system (i.e. the single-board computer, digital camera and LED bars that compose the illumination system), the cost may be in the range of €1500–€2100.

The rest of this paper is organized as follows: Section 2 introduces the full process used for tool wear monitoring. Section 3 provides a description about the materials and methods that have been used in our experiments. Specifically, an explanation of the image acquisition process is detailed in Section 3.1, a study about the way to extract the patches of the images is presented in Section 3.2 and a description of the texture methods employed (i.e. LBP (Local Binary Pattern), ALBP (Adaptive Local Binary Pattern), CLBP (Completed Local Binary Pattern) and LBPV (LBP Variance)) is provided in Section 3.3. A new image dataset with cutting edges of an edge profile milling head is presented in Section 4 along with the experimental results and finally, the conclusions are listed in Section 5.