Optical tool condition monitoring techniques in milling process

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Abstract: *Recent most important improvements in metal cutting industry are utilization of cutting tool and tool condition monitoring systems. These systems help to prevent damage to both machine tools and workpieces. New technologies in optical measurements allow construction of tool condition monitoring systems which does not affect manufacturing processes and are relatively cheap to build because of low prices of optical sensors compared to standard sensors and measurement techniques, built on cutting machines. Our paper summaries various monitoring methods for tool condition monitoring in the milling processes that use optical sensors and optical methods combined with machine vision and image processing, that have been practiced and described in literature.*
Keywords*: MACHINING, MILLING, TOOL CONDITION MONITORING, MACHINE VISION, VISUAL SENSOR MONITORING*

1. Introduction

High quality of the final product is the main goal in any machining process. The best way to approach and achieve this high product quality is automatization of machining processes. Automatization is a process improvement that can be possible by monitoring and control of machining process. One of the most innovative monitoring applications is Tool condition monitoring (TCM), which is inevitable for reducing machine downtime. With the reduction of machine tool downtime improvements in production rate can be achieved. One of the main causes of downtime is excessive wear and breakage of cutting tools. Damaged tool can therefore decrease quality of machined surface, due to unevenly distributed forces during cutting process. With appropriate TCM techniques [1] cutting speeds can be increased by 10-50 %. The acquisition of machining process data in TCM system is affected by the geometry and machining process conditions of the cutting tool, including cutting force, sound energy, power, current, surface finish, vibration, and temperature. To measure these conditions several high-level intelligent sensors can be used, such as dynamometers, acoustic emission sensors, power and current sensors, surface profilers or vision-based systems, accelerometers and pyrometers [2]. Using signal processing techniques, sensory information is filtered and processed, and relevant features are extracted. Design of experiments (DoE) and artificial intelligence (AI) techniques can then be used to predict process data and optimize processes based on the extracted and selected features. To determine the precision of the technique, it is also necessary to compare actual and predicted values of selected features. Optimized data then goes to the machine controller and servo mechanism, which can control the machining process.

Product quality depends primarily on the machined surface. The surface quality depends primarily on the wear of the cutting tool, the wear of cutting tool depends on the conditions, the workpiece, tool material and the tool geometry. There are four types of cutting tool wear: adhesive wear due to deformation of the shear plane, abrasive wear due to cutting of hard particles, diffusive wear due to high temperatures, and fracture wear due to fatigue. There are four main types of wear that can occur in cutting tools: nose wear, flank wear, crated wear, and notch wear. Cutting tools are also subject to three phases of wear [3], namely initial wear (occurs in the first few minutes of machining), uniform wear (the quality of the cutting tool deteriorates slowly during machining) and severe wear (rapid deterioration when the tool reaches the end of its life).

Basically, TCM systems can be divided into two groups: direct techniques and indirect techniques. In the direct techniques conditions such as flank wear width, crater depth and crater area are measured directly in off-line method (machining process must be stopped during measurement) using 3D surface profiler, electron microscope or optical microscope. Previously mentioned conditions can also be measured using in-process methods (it does not require stoppage of the machining process) with CCD camera. In indirect TCM techniques the following signals of cutting process are measured: force, current, power, surface finish, acoustic emission, etc. Measurement of those signals allow conclusions to be drawn about the degree of tool wear using in-process methods. These TCM systems are typically based on comparing a reference signal from an optimized cutting process to the actual process signal acquired from previously mentioned sensors [4]. These techniques have been implemented mainly by using various technologies such as acoustic emissions, cutting force, spindle current and vibration sensors [5]. However, there are also some very serious limitations when using these methods. To overcome these limitations, much research is currently being conducted to determine the degree of tool wear by analyzing different images acquired using different optical sensors such as lasers, CCD and CMOS cameras, and thermal IR cameras. There are a wide range of applications that combine optical sensors with digital image processing and machine vision which are used for quality control, tool wear measurement, workpiece surface measurement, etc. in machining processes such as milling.

This paper is composed of the following components: The first component presents the advantages and disadvantages of using optical sensors for tool condition monitoring. The second component presents direct TCM techniques using optical sensors. The third component presents indirect TCM techniques using optical sensors. The final component presents conclusions and suggests future directions for TCM research through the usage of optical sensors combined with digital image processing and machine vision.

2. Advantages and disadvantages of using optical sensors in TCM

Monitoring any manufacturing process with digital image processing and machine vision techniques has some advantages over other methods. For example:

- It does not apply any force or load to the surface structure under investigation.
- It is a non-contact, in-process application [6].
- Monitoring systems based on digital image processing are more flexible and cost-effective compared to other systems.
- These systems can be operated and remotely controlled, which is very useful for unmanned production systems.
- These systems do not depend on the frequency of the chatter, such as acoustic emission (AE) sensors; moreover, AE sensors mainly detect tool breakage during machining [7]. Therefore, monitoring the progressive wear of cutting tools with AE sensors is very difficult.
- Vibration sensors such as accelerometers can monitor tool breakage, machine collisions and parts that are out of tolerances [8], however monitoring the progressive wear was not possible with vibration sensors.
- For proper monitor and control of machining process, the fusion of multiple sensors (such as AE sensor, dynamometer, vibration sensors, etc.) is required, which is not very cost-effective [8].
- The image of the machined surface contains information about the imprint of the toll as well as the change in tool geometry [9], therefore information about roughness, waviness and

shape can be obtained by analyzing an image of the machined surface [10].

- 2D information can be obtained from an image of the machined surface, which is not possible with a 1D surface measuring devices [11].
- The information of machining parameters can also be obtained from images of the machined surface [12].
- Machine vision is more and more accepted in industry due to the development of CCD cameras, because CCD cameras are less sensitive to the adverse industrial conditions.
- Optical imaging has provided the ability to add, subtract, multiply, store and even perform various image transformations on images using optical devices.

There are also some limitations in using machine vision systems for monitoring tool condition [13]:

- A suitable illumination system, a roboust image processing algorithm and protection from machining noises (such as chips, dirt, coolant fluid, etc.) are very important for the successful implementation of this technique [9].
- In some applications the placement of vision sensors must be studied very well due to inaccessibility.

3. Direct optical TCM techniques

Two most important types or tool wear mechanisms in machining processes are flank wear and crater wear. Flank wear is mostly caused by abrasion because of friction between the tool and the machined surface and can be seen on Figure 1(1a) [14]. Notch wear shown on Figure 1(1b) and (1c) is type of flank wear that is caused by severe abrasion at the depth of cut mark on machining tool. Crater wear usually occur on the rake face of the machining tool. Crater wear shown on Figure 1(2). Flank wear can be directly determined by capturing images of cutting tool. However, more complex techniques are required when determining the crater depth [15]. Both cutting tool wears have been measured using two and three-dimensional techniques.

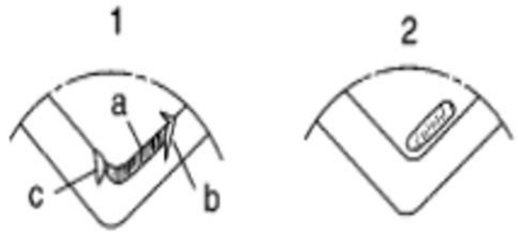

Figure 1: *Flank wear (1a) with notches (b) and (c), Crater wear (2) [14]*

Flank wear can be determined with two-dimensional techniques. The first pioneering work in direct TCM was done by Kurada and Bradley [16]. In their work they created a system that consisted of a fibre-optics light source to illuminate the tool and a CCD camera. The picture of illuminated tool flank region was processed using texture-based image segmentation technique which consisted of image enhancement for noise reduction, image segmentation for flank wear region extraction from background, feature extraction and calculation of flank wear. The whole system is based on offline mode using video zoom microscope.

In offline TCM techniques the machining process must be stopped and cutting tool or inserts must be removed from the machine. This procedure is time consuming and can also be dangerous for the alignment of the cutting tool. Weis [17] pioneered the detection of the tool wear area of milling tools without removing the tool from the machine. Infra-red band filter was used for background fading. Tool wear region was captured whit the combination of diode flashlight and CCD camera. Tauno and Lembit [18] created a system that provided automatic measurement of surface area, average wear length and perimeters of flank wear profile using non-linear median filter for noise removal and Roberts filter operation to detect edges. Sortino [19] in his work developed a system for flank measurement using new edge detection method from colour image. Using cross correlation between successive image pairs, Wang et al. [20] developed an automated system of capturing and processing successive images of moving inserts in milling to measure flank wear. Using technique that was based on moment invariance to select the exact bottom portion of flank wear they were able to determine flank wear with maximum 15 μm error and minimum 3 μm error compared to microscope measurements [21,22]. However, the computation time of their methods was 2 s, which was not practical for real time measurements. Fadare and Oni [23] in their work evaluated notch and flak wear of machining tool using the insert images. They used length, width, area, centroid, equivalent diameter, minor and major axis length, eccentricity, orientation and solidity as descriptors of wear. Their vision system had 3.13 % absolute difference of measurements compared to microscope measurements. Kerr et al. [24] analyzed textures of worn regions of turning and milling inserts using utilization of different texture analysis techniques: histogram processing, gray level co-occurrence, frequency domain-based technique and fractal method. In research [25] a system for accurate tool edge and tool wear detection was created, that was based on neural network technique. However, developed system was not implemented for any online monitoring using CMOS or CCD cameras. Using ring illuminators and CCD cameras, Schmidt et al. [26] developed an automated flank wear measurement system that combines side illuminated and full illuminated images of flank wear portions of cutting inserts. While their system is highly accurate, they did not emphasize the computation time in their work. Alegre et al. [27] used contour signature of the binary image of flank wear profile to determine the average and maximum flank wear width. They used multi layer perceptron neural network for classification of tool wear with 5.1 % minimum error. Using an environmental scanning electron microscopic (ESEM) image of the tool, Jackson et al. [25] developed a method for accurately detecting very small wear developed in very small diameter milling cutters using neural image processing method. Gonzalez-Arias et al. [28] captured images of worn surfaces of cast iron specimens that were subjected to abrasion wear tests using Scanning Electron Microscopy (SEM). Surface features of worn surfaces were used to obtain a learning model of wear severity using Histogram of Oriented Gradient (HOG). Bodini et al. [29] worked with micrographs of sample sections to determine damage progression in twin-disk tests. Above mentioned works used two dimensional techniques to determine tool wear.

There were also some studies where three-dimensional techniques for measuring crater depth were used. In researches [30,31] a microscope equipped with a CCD sensor was used to capture noisy images of rake face of worn out milling tool to measure the depth of crater during different levels of wear. Automatic focusing technique was also used in those works. According to Devillez et al. [32], crater wear depth was measured using white light interferometry and the optimal cutting conditions (cutting speed and feed rate) were determined to achieve the best surface finish during orthogonal dry turning of 42CrMo4 steel with an uncoated carbide insert.

Latest research of tool wear detection methods based on image processing and machine vision mainly include the following types of methods: edge-based methods, texture analysis combined with contour-based methods, and neural network-based methods. By finding the pixels with sharp changes in brightness, the edge-based tool wear detection method can segment tool wear regions. Zhang et. Al. [33] optimized the wear detection region using pictures of the tool top. They used sub-pixel precision detection method to improve accuracy. Zho et al. [34,35] created a system using an area growth algorithm based on morphological component analysis to determine tool wear edge. Their method overcome problems of tool wear detection in different orientations that existed in traditional edge detection methods. By using texture analysis and contour analysis, a wear detection method based on high levels of visual processing can be used to monitor tool wear. The study by García-Ordás et al. [36] used texture descriptors to characterize the wear of different regions and determined if the tool changed under the conditions of different regions of inspection. In the research [37] new system based on combinations of a shape descriptor and a contour descriptor has been created for classification of inserts in milling processes according to their wear level. Although texture analysis and contour-based methods are typically used to classify the condition of tool wear, they cannot accurately measure tool wear. With low sensitivity to noise and high damage resistance, the tool wear detection method based on neural networks is a promising technique for analyzing tool wear. Addona et al. [38] determined the degree of tool wear using two different heuristic learning methods: ANN and DBC, and compared their effectiveness. Wang et al. [39] created a system that utilized hybrid machine learning that integrated heterogenous data for tool condition prediction. In research [40] new system was created based on two-step method for prediction of tool life. Two-step method combined flank wear image recognition and Artificial Neural Networks. You et al. [41] proposed a new method of high-precision tool wear monitoring under wide field of view camera. The performed tool wear monitoring through location, segmentation and measurement pf tool wear area. Dai et al. [42] proposed a novel configuration for online TCM in micro milling based on machine vision, that improved the part quality and extended the micro tool life. Fernández-Robles et al. [43] proposed a novel method for detecting broken inserts in milling heads using machine vision. Their approach did not require comparison to reference images. Created system was highly efficient and worked without delaying any machining operations. Wei et al. [44] created a system based on image acquisition and image processing methods that was able to detect internal spiral of end milling cutter using three light sources and two cameras mounted on a moving frame. In recent years researchers are focusing more on creating online TCM systems based on machine vision [45,46,47], which can detect tool wear faster and without stopping the machining process.

In the direct technique, condition monitoring is preformed by analyzing changes in the geometry of the cutting tool. During tool observation signals such as chatter, vibration, cutting force change etc. are not considered. However, the surface finish can highlight those changes and it can also show changes in cutting tool geometry. Thus, new research will focus on measuring surface finish with indirect TCM techniques combined with image processing and machine vision.

4. Indirect optical TCM techniques

Image processing can be used, in indirect tool condition monitoring, to extract surface finish descriptors from machined surface textures. Obtained texture information of machined surface can be directly used to evaluate the quality the of machined surface while, at the same time, being indirectly used to detect abnormal condition of machine tools such as chatter vibration and tool wear [6].

Most important early works in indirect TCM using texture information of machined surfaces have been done by Gupta and Raman [48]. They measured surface roughness of pre-turned cylindrical bar utilizing with laser scatter pattern developed on the turned surface image. Liu et al. [49] reviewed different data acquisition setups for TCM of machine tool using information from machined surface texture. They also reviewed the development and statistics of descriptors for feature extraction. They found out, that infrared cameras can be used for temperature measurements to detect details such as pores and other irregularities caused by insufficient heat dissipation. On the other hand, CCD and CMOS cameras are more suitable for general detection tasks like discontinuities of powder supply processes. However, laser-based measurements are the most accurate in detecting roughness anomalies on machined surfaces [50].

Dutta et al. [6] reviewed different analysis techniques in indirect TCM by evaluating machined surface images. They discovered, that most often used analysis methods for surface finish evaluation were statistical and signal processing-based texture analysis. Dhanasekar et al. [51] used autocorrelation technique to inspect speckle pattern of milled surfaces. However, his system for speckle pattern creation is less useful for on-machine inspection and is costly. On-machine surface roughness evaluation was carried out in [9], where authors used statistical texture analysis of first order based on histogram. Nevertheless, Elango and Karunamoorthy [52] report that the change in illumination adversely affects the robustness of first-order statistical texture analysis. To overcome problems in previously mentioned work second order statistical texture analysis that is based on gray level co-occurrence matrix (GLCM) was used. Here co-occurrence of gray levels of pixel pairs is evaluated. Many researchers successfully implemented GLCM into TCM of milling operations. Gadelmawla et al. [53] in his work found that texture features from GLCM are in correlation with machining time. However, in their study they did consider tool wear prediction. Based on images of turned surfaces, Dutta et al. [12] found a correlation between GLCM features and tool flank wear. They have not, however, predicted tool flank wear. To detect progressive tool flank wear, Dutta et al. [54] used length statistical texture features extracted from GLCM, where high correlation of GLCM features with flank wear of machining tool was found. Research [55] used Voronoi tessellation (VT)-based texture analysis for inspection of the minute details of change in feed marks of machined surfaces. VT is a technique based on geometrical texture analysis. This technique reduces the effect of intensity variation this is caused by inhomogeneous illumination. With the help of features extracted from GLCM and discrete wavelet transform (DWT), Dutta et al. [56] developed a progressive tool flank wear prediction method for end milling. A study by Lei et al. [57] showed that chatter detection of high-speed milling could be achieved by extracting Fourier spectral analysis (FSA) features from machined surfaces. Over the decades, many types of methods for optical indirect TCM were studied. It is, however, challenging to find an excellent method that can be applied universally due to the differences in systems, data availability, and other application constraints. Therefore, some researchers examined strategies for integrating multiple methods [58]. Using spectral texture analysis and statistical model estimation to predict tool life in milling, Kumar et al. [59] developed a prognostic model in 2015.

In recent years, new techniques for on indirect TCM in milling have emerged. Zuperl et al. [60] proposed a cloud-based system for the optical monitoring of tool condition based on measuring chip surface size and identification of cutting force trends.

5. Conclusion

In this paper, different applications of tool condition monitoring systems based on optical sensors combined with image processing are discussed. Non-contact TCM techniques can be used for enhancing automation in machining centers. We collected and compared optical TCM systems based on indirect and direct methods.

In direct optical TCM systems, optical sensors are measuring tool condition directly from images of the tool or its parts. Usually CCD or CMOS cameras are used. Those techniques can be very useful for detecting various types of tool wear, such as crater wear, fractures and chips, that are difficult to detect using other techniques.

In indirect optical TCM systems, optical sensors combined with image processing and machine vision measure the quality of machined surfaces texture through images of machined surfaces. From those images tool wear can be determined. In those techniques analysis techniques such as texture analysis play an important role in monitoring tool condition. New techniques in recent year appeared, that measure tool wear indirectly through cutting chip size measurement, temperature measurement, etc.

In recent years, there has been a growing need for sensor systems that would allow rapid measurement of tool wear without interfering with the operation of the machine tool. With the great development of optical sensors and machine vision, optical TCM systems that are already capable of online operation have begun to appear in recent years. Developments in the coming years will focus on building robust systems based on optical sensors that will be able to determine the state of the tool in an industrial environment with sufficient accuracy and speed.

6. References

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