DETECTION OF CHIPPING IN CERAMIC CUTTING INSERTS FROM WORKPIECE PROFILE SIGNATURE DURING TURNING PROCESS USING MACHINE VISION

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DETECTION OF CHIPPING IN CERAMIC CUTTING INSERTS FROM
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USING MACHINE VISION

by

LEE WOON KIOW

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<tr>
<td>2-D</td>
<td>Two dimensional</td>
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<tr>
<td>3-D</td>
<td>Three dimensional</td>
</tr>
<tr>
<td>ACF</td>
<td>Autocorrelation function</td>
</tr>
<tr>
<td>AE</td>
<td>Acoustic emission</td>
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<tr>
<td>AFM</td>
<td>Atomic force microscopes</td>
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<tr>
<td>AISI</td>
<td>American Iron and Steel Institute</td>
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<tr>
<td>ASME</td>
<td>American Society of Mechanical Engineers</td>
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<tr>
<td>CCD</td>
<td>Charge coupled device</td>
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<tr>
<td>CPU</td>
<td>Central processing unit</td>
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<tr>
<td>CWT</td>
<td>Continuous wavelet transform</td>
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<td>DFT</td>
<td>Discrete Fourier transform</td>
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<tr>
<td>DSLR</td>
<td>Digital single-lens-reflex</td>
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<tr>
<td>DWT</td>
<td>Discrete wavelet transform</td>
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<tr>
<td>FFT</td>
<td>Fast Fourier transform</td>
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<tr>
<td>GLCM</td>
<td>Gray level co-occurrence matrix</td>
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<tr>
<td>ISO</td>
<td>International Organization for Standardization</td>
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<tr>
<td>MVIM</td>
<td>Multi-valued influence matrix</td>
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<tr>
<td>PCBN</td>
<td>Polycrystalline cubic boron nitride</td>
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<tr>
<td>PSD</td>
<td>Power spectral density</td>
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<td>RGB</td>
<td>Red Green Blue</td>
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<td>RMS</td>
<td>Root mean square</td>
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<td>ROI</td>
<td>Region of interest</td>
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<td>SEM</td>
<td>Scanning electron microscope</td>
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<td>Acronym</td>
<td>Definition</td>
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<tr>
<td>SSA</td>
<td>Singular spectrum analysis</td>
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<td>SSD</td>
<td>Sum square of deviation</td>
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<td>STFT</td>
<td>Short time Fourier transform</td>
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<td>SVM</td>
<td>Support vector machine</td>
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<td>TSK</td>
<td>Takagi-Sugeno-Kang</td>
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LIST OF SYMBOLS

* Complex conjugation
\( \phi \) Random dislocation of the workpiece profile caused by chipping
\( \lambda \) Wavelength of the surface waviness
\( \pi \) Pi
\( \tau \) Lag distance
\( \Delta \tau \) Lag interval
\( \beta \) Workpiece rotation angle between successive images
\( \alpha \) Sample variance
\( \gamma \) Average of amplitude spectrum in a specific spatial frequency band
\( \psi(t) \) Mother wavelet
\( \psi_{a, b}(t) \) Wavelet basis/ wavelet function
\( a \) Dilation/ scale
\( a_n \) Coefficients of the cosine term
\( A(\tau) \) Autocorrelation function coefficient
\( A(m\Delta\tau) \) Autocorrelation function coefficient for discrete data
\( b \) Translation
\( b_n \) Coefficients of the sine term
\( C_n \) Amplitude of dislocation in the workpiece profile
\( CWT(a, b) \) Wavelet coefficient
\( d_1, d_2, d_3 \) Number of pixels between the wavelength
\( \exp \) Exponential
\( f \) Feed /feed rate
\( F_1, F_2 \) Frequency range
$G(x)$  Actual surface profile/ unshifted surface profile

$G(x + \tau)$  Shifted surface profile

$G(i)$  Surface profile at position $m\Delta\tau$

$G(i - m)$  Surface profile at position $(i - m)\Delta\tau$

$G(t)$  Surface profile in time domain

$h_1, h_2$  Brightness

$I_p$  Intersection points between the nose profile and workpiece

$i$  Column in image of workpiece profile

$j$  Complex number

$K$  Sub-pixel edge location of the workpiece

$L$  Total length of workpiece profile

$m$  Integer number

$m_i$  Moments of the input data sequence in the gray-scale image

$n$  Number of input data

$n_r$  Number of rotations

$N$  Total number of pixel/ points in the workpiece profile

$O$  Centre of the nose profile

$p_1, p_2$  densities of the gray level brightness

$r_c$  Nose radius

$R_a$  Arithmetic average height of surface profile

$R_t$  Peak-to-valley height of the surface profile

$R_p$  Maximum height of peaks

$R_d$  Root mean square roughness

$R_q^2$  Square of root mean square roughness

$RMSW_a$  RMS of CWT coefficient at particular scale of $a$
\( s \) Skewness

\( S \) capturing time between the successive images

\( t \) Time

\( u(x) \) Dislocation profile results from the vibration

\( U_s(x) \) Ideal surface profile

\( V \) Spindle rotational speed

\( V_f \) Fundamental feed frequency

\( V_n \) Spatial frequencies

\( \text{VB} \) Width of wear land

\( \text{VB}_B \) Average flank wear

\( \text{VB}_{\text{max}} \) Maximum flank wear

\( w \) Length of window

\( \omega \) Fundamental angular frequency

\( x \) \( x \) vector for \( x \)-coordinate of surface profile

\( x_n \) Length of workpiece profile at particular position

\( x_c \) Intensity of the pixel in gray-scale images

\( (x_i, y_i) \) Coordinate of surface profile

\( y \) \( y \) vector for \( y \)-coordinate of surface profile

\( Y(\omega) \) Amplitude of spatial frequencies for continuous Fourier transform

\( Y(V_n) \) Amplitude of spatial frequencies for discrete Fourier transform

\( z \) Row in image
PENGESANAN SERPIHAN PADA MATA ALAT SERAMIK DARIPADA TANDA PENGENALAN PROFIL BAHAN KERJA SEMASA PROSES PELARIKAN MENGGUNAKAN PENGLIHATAN MESIN

ABSTRAK

turun naik dengan nyata selepas mata alat gagal menjadi serpihan. Proses pemotongan yang stokastik selepas mata alat menjadi serpihan menyebabkan amplitud frekuensi ruangan yang lebih rendah daripada frekuensi suapan asas meningkat dengan meruncing. Kaedah CWT didapati lebih efektif untuk mengesan permulaan serpihan mata alat dengan tepat pada masa 16.5 s berbanding 17.13 s yang diperolehi daripada sub-tetingkap FFT. Punca min kuasa dua pekali CWT bagi profil bahan kerja pada skala yang lebih tinggi didapati lebih peka bagi mengesan serpihan mata alat seramik dan seterusnya boleh digunakan sebagai petunjuk untuk mengesan kejadian kegagalan serpihan mata alat seramik.
DETECTION OF CHIPPING IN CERAMIC CUTTING INSERTS FROM WORKPIECE PROFILE SIGNATURE DURING TURNING PROCESS USING MACHINE VISION

ABSTRACT

Ceramic tools are prone to chipping due to their low impact toughness. Tool chipping significantly decreases the surface finish quality and dimensional accuracy of the workpiece. Thus, in-process detection of chipping in ceramic tools is important especially in unattended machining. Existing in-process tool failure detection methods using sensor signals have limitations in detecting tool chipping. The monitoring of tool wear from the workpiece profile using machine vision has great potential to be applied in-process, however no attempt has been made to detect tool chipping. In this work, a vision-based approach has been developed to detect tool chipping in ceramic insert from 2-D workpiece profile signature. The profile of the workpiece surface was captured using a DSLR camera. The surface profile was extracted to sub-pixel accuracy using invariant moment method. The effect of chipping in the ceramic cutting tools on the workpiece profile was investigated using autocorrelation function (ACF) and fast Fourier transform (FFT). Detection of onset tool chipping was conducted by using the sub-window FFT and continuous wavelet transform (CWT). Chipping in the ceramic tool was found to cause the peaks of ACF of the workpiece profile to decrease rapidly as the lag distance increased and deviated significantly from one another at different workpiece rotation angles. From FFT analysis the amplitude of the fundamental feed frequency increases steadily with cutting duration during gradual wear, however, fluctuates significantly after tool has chipped. The stochastic behaviour of the cutting process after tool chipping leads to a sharp increase in the amplitude of spatial frequencies below the fundamental feed frequency. CWT method was found more effective to detect the onset of tool chipping at 16.5 s instead of 17.13 s by sub-window FFT. Root mean square of CWT coefficients for the workpiece profile at higher scale band was found to be more
sensitive to chipping and thus can be used as an indicator to detect the occurrence of
the tool chipping in ceramic inserts.
CHAPTER ONE

INTRODUCTION

1.1 Background of the study

Tool condition monitoring plays a significant role in machining process because the worn out cutting tool can be identified and replaced in time to avoid the deterioration in the surface quality and dimension accuracy of the machined part. Flank wear is often selected as the tool life criterion in the tool wear monitoring and is accomplished by direct and indirect methods. Direct tool condition monitoring method is usually performed by means of optical devices such as toolmaker’s microscope, scanning electron microscope (SEM) and CCD (charge coupled device) camera. Toolmaker's microscope and the SEM are the most popular devices used to measure the flank wear in the past. However, these devices have severe limitation as they can only be used in offline measurement which requires the cutting tool to be removed from the machine for inspection and measurement. Numerous previous works have been conducted to measure the flank wear using CCD camera without the need of dismantling the worn tool from machine. However, this method can only be applied between the cutting operations (Lanzetta, 2001; Wang et al., 2006; Zhang et al., 2012; Chethan et al., 2015).

One major prerequisite of an automated manufacturing system is uninterrupted machining to achieve maximum productivity which require continuous monitoring of the cutting process and cutting tool condition. Most of the in-process tool condition monitoring is conducted by indirect methods. Indirect methods of
monitoring the tool condition depend upon the measurement of sensor signals, which are indirectly related to the condition of the cutting tool edge. With recent advancement in signal processing technology, a large number of indirect methods have been attempted to achieve the in-process tool wear monitoring based on sensor signal features associated with the tool condition such as cutting force, vibration, acoustic emission (AE) and tool temperature (Rehorn et al., 2005; Teti et al., 2010). Many researchers have even combined several sensors to monitor the multitude of information available during machining to assess the tool condition such as the combination of AE and cutting force (Jemielniak et al., 2011a), cutting force and vibration (Kalvoda & Hwang, 2010), AE and vibration (Bhuiyan et al., 2014), cutting forces, vibration and AE (Jemielniak et al., 2011b), AE and cutting sound (Zhang et al., 2015).

The acquired sensor signal obtained from the machining process has been correlated with flank wear by extracting the signal features from any time domain signal using statistical parameters such as the mean value, the root mean square (RMS), kurtosis and skewness. Sensor signals are also transformed into frequency domain and time-frequency domain. The signal features such as the amplitude of the dominant spectral peaks and wavelet coefficient extracted from these transform are used to correlate to the flank wear (Yesilyurt, 2006; Kious et al., 2010; Fang et al., 2011). Other methods such as statistical regression method, neural network, artificial intelligence and pattern recognition have also been widely explored to establish the correlation between the sensor signal and flank wear (Siddhpura & Paurobally, 2013).

The detection of the tool failure by chipping has become more important recently since hard tools such as ceramic cutting tools are commonly used in the
cutting of difficult-to-cut materials such as stainless steel (Lin, 2008; Sobiyi et al., 2015), superalloy (Bushlya et al., 2013), tool steel and hardened tool steel (Özel et al., 2005; Özel et al., 2007; Meddour et al., 2015). Although advances in ceramic processing technology has resulted in high performance tools by improving the toughness, fracture strength and shock resistance, tool chipping and fracture are still serious issues when machining difficult-to-cut material using ceramic cutting tool (Yin et al., 2015). Failure by chipping has more severe effect on the surface finish compared to progressive wear because the cutting forces fluctuates and increases (Liao & Stephenson, 2010). Thus, in-process tool chipping detection as early as possible in ceramic cutting is considered important, in order to stop the machine tool before a catastrophic failure occurs.

Tool chipping occurs when a small piece tool material breaks away from the cutting edge of the tool. The chipped pieces from the cutting edge may vary from microchipping to macrochipping. Breakage of a cutting tool can lead to the total loss of contact between the cutting tool and the workpiece. Chipping and breakage are different from wear which is a gradual process. Chipping and breakage usually occur abruptly resulting in a sudden loss of tool material due to mechanical shocks. The onset of chipping or fracture in a cutting tool results in a change in the contact characteristics between the tool and the workpiece. This in turn results in a significant change in the sensor signals.

Cutting force signal monitoring is one of the most promising methods to detect the precise moment of tool failure. Cutting forces was found to be more effective to detect tool failure than other sensor signals (Li & Mathew, 1990). The measurement of cutting force is usually performed by using a dynamometer. When
the tool breaks the cutting force increases slightly above the pre-set threshold and then drops sharply because of the loss of contact between the tool and the workpiece (Cakir & Isik, 2005). However, chipping can also cause failure of a cutting edge without decreasing the cutting force significantly when turning of carbon steel using ceramic insert (Jemielniak, 1992). In addition, tool chipping has been reported to be more difficult to detect using cutting force as the variation of cutting force due to tool chipping may not exceed the threshold limits (Shi & Gindy, 2007).

Previous researchers have reported that AE could be used effectively in detecting tool tip chipping. The AE intensity increases as the tool wear increase and a burst AE signal is produced when the cutting tool has chipped (Jemielniak & Othman, 1998; Wang et al., 2003; Belgassim & Jemielniak, 2011). Strong burst in AE was found after tool fracture because of the sudden increase in the contact area between the workpiece and the chipped cutting tool (Lan & Dornfeld, 1984; Wang et al., 2003). However, these results were contradicted by the recent work of Neslušan et al. (2015) who considered that conventional processing of AE signals does not enable the different phases of the tool wear be clearly recognised during turning of bearing steel using ceramic insert. Besides, most AE sensors have been designed for non-destructive testing and are not suitable for tool wear monitoring as they cannot withstand extreme conditions at the cutting point such as high cutting temperatures and impacts from the chip.

The use of sensors fusion allows more reliable tool failure by chipping detection. Sensor signals from different sources are integrated to provide extended information for tool chipping detection such as the combination of AE and motor power (Wang et al., 2003) and AE and cutting force (Balsamo et al., 2016). However,
previous study have reported that multiple sensor signals used together produced results a little worse than using a single sensor signal during turning of Inconel 625 using ceramic cutting tool (Jemielniak et al., 2011a).

Direct monitoring methods such as vision and optical approaches have been utilized for tool chipping observation on ceramic cutting tool (Patil & Tilekar, 2014). However, this method is only feasible for in-cycle or intermittent observation which requires the machine to be stopped because the continuous contact between the cutting tool and the workpiece does not allow the capture of images of the cutting tool tip during turning. In order to overcome the limitations of the in-process direct observation on cutting tool, identifying the cutting tool condition by analyzing surface texture of machined surface using digital image processing methods from the images of machined surface has been attempted in the past.

The surface texture of machined surface image contains information about the interaction between the tool and the workpiece such as machining conditions (e.g. feed rate, machining speed), waviness, roughness, vibration and chatter. The machined surface image also carries the information about the cutting tool condition by tool imprint on the workpiece. The surface texture of turned workpiece changes remarkably due to the changes in the cutting tool by wear and chipping. For example, previous study has reported that the groves are even and straight with clear ridge lines when the cutting tool is sharp but the groves appear uneven and ridge lines become disjoint when the cutting tool is dull (Kassim et al., 2007). However, the images of workpiece surface were captured between cutting operation using a CCD camera.
Several attempts have been made to evaluate the tool condition by extracting the surface finish descriptors from the images of the freshly machined surface texture to be correlated with the flank wear (Datta et al., 2013; Dutta et al., 2015). The textural analysis methods showed some potential to interpret the tool condition, but they are subject to the changes in illumination condition and the contamination of the dirt and cutting fluid. In addition, their work was conducted offline and no attempt was made to investigate the correlation between the extracted textures features with tool chipping.

According to machining theory, the surface profile of a turned workpiece is formed by the repetition of the nose radius of the cutting insert at a regular interval of feed rate. Thus, nose radius has direct effect on the surface profile of the workpiece and all predominant tool wear such as the flank wear and notch wear can have significant influence on the surface roughness of the workpiece (Penalva et al., 2002; Grzesik, 2008b). An attempt has been made to determine the nose wear and the flank wear from the silhouette of the workpiece profile captured using CCD camera with the aids of backlighting (Shahabi & Ratnam, 2009a; Shahabi & Ratnam, 2009b). However, the work was carried out in-cycle, i.e. in between cutting process.

The development of an effective in-process tool condition monitoring method to detect the onset of tool chipping has not been attempted by previous researches. The case of tool chipping detection in ceramic cutting tool has not been given great attention by the researchers in the past and this is the motivation of the present study.
1.2 Problem statement

Although the vision method has the advantages of capturing the actual geometric changes arising from the wear and chipping of the cutting tool, the direct assessment of the cutting tool using machine vision is not possible during turning. This is because the cutting area is inaccessible due to the continuous contact between the tool and the workpiece as well as presence of coolant and obstruction by chips during turning operation.

In-process tool chipping monitoring is usually performed by using indirect method based on various sensor signals. However, a number of previous studies have shown that tool chipping is hardly detected using sensor signals due to the significant contradictory findings (Jemielniak, 1992; Wang et al., 2003; Cakir & Isik, 2005; Belgassim & Jemielniak, 2011; Neslušan et al., 2015). Thus, there still exists a need to develop a more reliable in-process tool chipping monitoring method.

Previous studies show that with the advancement in image processing technology, the features extracted from the images of the machined surface texture could be used to correlate well with the cutting tool condition. However, this method requires the machine to be stopped before the images of the machined surface can be captured (Datta et al., 2013; Dutta et al., 2015).

Since the cutting tool tip is directly in contact with the workpiece during the turning operation, an imprint of the cutting tool profile is replicated on the machined surface (Kassim et al., 2007). Therefore, the workpiece profile of turned part is directly dependent on the geometry of the cutting tool tip. As the tool chips, the
contact geometry changes, thus affecting the surface being machined. Two dimensional (2-D) image of the surface profile of the turned workpiece has been successfully used for in-cycle nose wear and flank wear measurement in the past (Shahabi & Ratnam, 2009b).

It should be noted from the abovementioned investigations that existing in-process tool condition monitoring method using sensor signals have limitations in detecting tool chipping. The monitoring of tool wear from the turned profile using machine vision shows great potential to be applied in-process. However, to date, no attempt has been made to explore the potential of the 2-D images of the workpiece profile for in-process tool chipping detection in ceramic cutting tool and this has motivated the present study.

1.3 Objectives

The objectives of this research are as follows:

i. To develop a novel approach of in-process tool chipping detection in ceramic cutting insert based on the workpiece profile signature using machine vision.

ii. To investigate the effect of the tool chipping in ceramic cutting inserts on the workpiece profile using autocorrelation function (ACF) and fast Fourier transform (FFT).

iii. To detect the onset of tool chipping by extracting the features from the workpiece profile using sub-window FFT and continuous wavelet transform (CWT).
1.4 Research approach

The approaches of this study are as follows:

i. A 2-D machine vision system consisting of a digital single lens reflex (DSLR) camera and backlighting was developed to capture the images of the edge of the turned workpiece.

ii. Experiments were carried out using aluminium oxide based ceramic cutting insert and the workpiece materials were AISI 01 Arne oil hardening tool steel and SUS 304 stainless steel with diameter of 50 mm.

iii. The condition of the cutting insert was evaluated using the SEM.

iv. Invariant moment method was used to extract the workpiece profile.

v. ACF, FFT and CWT were utilised to extract the features from the 2-D workpiece profile that correlate to tool chipping.

1.5 Scope of study

The scopes of this research are as follows:

i. Proposed tool chipping detection method only considers in turning process.

ii. This study focuses on the tool chipping detection in the aluminium oxide based ceramic cutting insert.

iii. This study distinguishes the sign of tool chipping from gradual wear using 2-D images of turned workpiece.

1.6 Organization of thesis

This thesis is organized into five chapters. The overview of the research is presented in the Chapter One. The background of the research and the existing
problems in similar studies are addressed. The objectives, research approach and the scopes of the research are listed. Chapter Two is about the literature review focusing on the in-process tool condition monitoring methods. The advantages and limitations of the existing in-process tool condition monitoring methods are discussed in detailed. Literature reviews reveal that an effective in-process tool chipping detection methods in ceramic cutting insert has not been thoroughly investigated.

The methodology for in-process detection of tool failure by chipping from the 2-D workpiece profile signature using machine vision method is outlined in Chapter Three. The proposed vision system using high resolution digital camera at high shutter speed has been used in this study for capturing the images of the workpiece profile during turning operation is presented. Detailed workpiece profile extraction method from 2-D images of the workpiece up to sub-pixel accuracy is described in this chapter. Finally, analysis of the 2-D workpiece profile to detect the tool chipping is discussed. The specific procedures in detection of tool chipping in ceramic cutting insert based on the 2-D surface profile extracted from the images of the edge of turned workpiece using ACF, FFT and CWT are discussed.

The results of the simulations and experiments are described in Chapter Four. The effects of the tool chipping on the workpiece surface are discussed. The results on detection of tool chipping in ceramic cutting insert from workpiece profile signature using vision method is presented. Finally, Chapter Five provides conclusion of the thesis and recommendations for future work. The contributions of the proposed method in the field of tool chipping detection are also presented.
CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

A review of previous research works that are closely related to the studies on the tool failure monitoring in a turning process is presented in this chapter. Firstly, types of tool failure are presented. Previous research works related to the monitoring of tool failure by gradual wear and premature failure by chipping are reviewed in the next section. Emphasis is placed on the in-process detection of the tool chipping for ceramic cutting tool. A summary of the literature review is presented at the end of the chapter.

2.2 Types of tool failure

The turning process is widely used in industry for finish machining of a wide range of components. Tool failure monitoring in turning is essential to achieve not only optimum productivity by reducing machine downtime and unnecessary tool changes, but also to obtain high surface quality and dimensional accuracy as well as minimize the damage to the workpiece or machine tool.

Tool failure can be classified into two groups namely wear and fracture. Wear is generally the removal of material from a cutting tool and is a result of the relative motion between the tool and workpiece. Flank wear at the front edge of the tool flank face and crater wear at the tool rake face are the most typical modes of tool wear in turning (Figure 2.1). Flank wear is mainly caused by the abrasion between the
workpiece and the cutting tool. Crater wear is the formation of a groove on the tool rake face where the chips rubs the tool surface.

![Tool-workpiece interaction and location of crater wear and flank wear](image)

Figure 2.1: (a) Tool-workpiece interaction, and (b) location of crater wear and flank wear (Özel & Davim, 2009)

Directly measured dimensional features of a typical wear pattern have been applied in the past to assess cutting tool's performance which are standardized in International Organization for Standardization (ISO, 1993). Compared to crater wear, flank wear is often used as a criterion to define the end of effective tool life as the wear progresses gradually as shown in Figure 2.2 and thus can be easily monitored.

![Flank wear versus time curve](image)

Figure 2.2: Typical flank wear versus time curve (Wang & Gao, 2006)
Flank wear appears in the wear land and is defined by the width of the wear land $VB$ as shown in the Figure 2.3. According to the ISO (1993), the cutting tool is considered to have failed if the average flank wear ($VB_B$) and the maximum flank wear ($VB_{\text{max}}$) exceeds some critical value such as $VB_B > 0.3 \text{ mm}$ and $VB_{\text{max}} > 0.6 \text{ mm}$.

![Figure 2.3: Typical wear pattern according to ISO (1993)](image)

Tool fracture is the damage on the cutting edge that range from microchipping to gross chipping. Premature tool failure by chipping refers to the breaking away of small piece from the edge of a cutting tool in micro-scale to massive chipping of cutting edge as shown in Figure 2.4(a) and Figure 2.4(b) respectively. Tool breakage, on the other hand, is the breaking of the entire insert that leads to a total loss of contact between the cutting edge and workpiece as shown in Figure 2.4(c). Chipping of a tool is different from wear, which is a gradual process, premature tool failure by chipping and breakage mostly occur as a sudden and unpredictable breaking away of tool material from the cutting edge. The main reasons for chipping and breakage include brittle nature of the cutting tool materials, the rapid growth of the crater wear, pre-existing potential cracks on the cutting edge, inclusions in the workpiece profile leading to mechanical shocks and impact loading.
resulting from the sudden engagement of the cutting tool into the workpiece (Grzesik, 2008a).

![Diagram of tool failure by chipping and breakage](image)

Figure 2.4: Tool failure by chipping and breakage (Grzesik, 2008a)

### 2.3 Monitoring of gradual wear

Monitoring of gradual wear generally can be divided into two types: direct and indirect method which is explained in Section 2.3.1 and Section 2.3.2, respectively.

#### 2.3.1 Monitoring of gradual wear using direct method

Extensive efforts have been focused on tool wear monitoring using optical methods which is conducted by directly analysing the change in the geometry of the cutting tool. Toolmaker's microscope is the most popular device used to measure wear of cutting tools (Grzesik, 2008a; Čerče et al., 2015). SEM with magnification in the range of several hundred to several thousand is most often used for micro examination. More advanced measuring techniques such as white light interferometry and confocal microscope can be of interest when the analysis in the
nano-scale range is necessary and is useful for crater wear measurement (Devillez et al., 2004; Dawson & Kurfess, 2005). However, the abovementioned direct methods have one main limitation, which is they can only be used for offline measurement. For the offline measurement, the cutting tool has to be dismantled from the machine tool for inspection and this causes interruption to the cutting process as well as is time consuming. Atomic force microscopes (AFM) are powerful tools for 3-D profile measurement with a very high resolution. However, it is very difficult and time consuming to accurately align the AFM cantilever probe with respect to the cutting edge (Cazaux, 2004; Mazzeo et al., 2009).

The past decades has seen the rapid development of tool condition monitoring using machine vision coupled with image processing techniques as direct method in flank wear measurement. In this method, a CCD camera with appropriate lighting reflected in the plane of wear surface is used to acquire the image of the cutting tool. Kurada and Bradley (1997) carried out pioneering work in direct tool condition monitoring by capturing images of flank wear using two fibre optic guided lights and CCD camera. Lanzetta (2001) recognized the types of defects of cutting tool and simultaneously measured the flank wear using a CCD camera equipped with an auto-focus zoom lens for different sizes of cutting tool. However, their study was performed offline.

Pfeifer and Weigers (2000) captured images of tool inserts using CCD camera with a ring light in different angles of incidence for controlled illumination. But there still remain the problem of accuracy because the measurement of flank wear using digital image processing method is highly dependent on the quality of captured images as it is vary considerably although there is a small variation in
illumination. This leads to error in dimensional measurements. Sortino (2003) developed an automated flank wear measurement software by using statistical filtering method from a colour image. However, this measurement method is limited for small flank wear width.

Jurkovic et al. (2005) proposed a vision system which comprised of a CCD camera, laser diod with linear projection as a light, frame grabber for capturing and a personal computer as direct means in flank wear and crater wear measurement. Castejón et al. (2007) and Barreiro et al. (2008) applied machine vision to determine flank wear by means of the discriminant analysis based on geometrical descriptors. The main advantages of their methods is the information about the condition of cutting tool can be obtained without having to remove the cutting inserts from the tool holders. However, the proposed wear measurement techniques using machine vision method were performed between the cutting operation such as in-cycle or intermittent, which requires the machine tool to be stopped. Fadare and Oni (2009) used Canny edge operator to detect significant edges of the worn area of a cutting tool in order to determine the flank wear and notch wear. Although this method is very useful for flank wear determination, but the method is very much sensitive to the fluctuation of ambient light.

Nose wear measurement has also gained attention in the recent years since the machined surface is mainly formed by the tool nose in finish turning. The nose wear can be measured by subtracting the 2-D image of a worn tool from the image of an unworn tool. Kwon and Fischer (2003) determined the nose wear by subtracting the worn tool image from a template after spatial registration of these images. A similar method was also carried out by Shahabi and Ratnam (2009a). The nose wear
was determined by subtracting the 2-D image of a worn tool from the image of unworn tool. The subtraction method can effectively and accurately determine the nose wear, but it requires two images that are aligned precisely before the subtraction. To overcome the limitation, a new approach was proposed by Mook et al. (2009) for measuring nose wear using a single worn cutting tool image. However, this method is not feasible to implement in-process.

In a recent work, Čerče et al. (2015) developed an intermittent 3-D cutting tool wear measurement system using a 2-D profile laser displacement sensor. With movement of the laser displacement sensor across the cutting insert, the sensor measured the distance from the measurement head to the points projected onto the cutting insert and the profile data of cutting insert were grabbed in a matrix form for further evaluation. The depth of flank wear is clearly visible from the comparison of the new and worn cutting inserts cross-sections profiles. Nose wear and crater wear can also be determined by calculating tool wear volume. However, the disadvantage of this method is that it is sensitive to contaminants such as coolant, chips and dust that may remain on the cutting inserts to be measured, which can cause error in the measurement. Chethan et al. (2015) used digital camera with a halogen light to capture the images of cutting insert. The wear region of the cutting insert was estimated using Blob analysis in order to extract the features such as wear area, perimeter and compactness to correlate with the flank wear. However, this method was carried out offline.
2.3.2 Monitoring of gradual wear using indirect method

In-process tool wear monitoring is gaining considerable importance in the manufacturing industry. This can be attributed to the transformation of manufacturing systems from manually operated production machines to highly automated machining centres. In-process tool condition monitoring implies identifying the cutting tool conditions without interrupting the machining process. The direct tool wear evaluation on cutting tool using machine vision system is very simple and accurate, but this method only can be implemented in between cutting operations when the cutting tool is not in contact with the workpiece.

In-process monitoring of tool wear is usually performed by indirect methods that depend upon the measurement of sensor signals which are indirectly correlated to the condition of the cutting tool during the machining operation. Commonly used sensor signal in previous studies including cutting force, AE, vibration, temperature, motor current and power consumption.

Cutting force has been proven to be the one of the significant indicator of tool wear as gradual increase in tool wear during machining causes the cutting force to increase (Gao et al., 2015). The cutting forces generally increases with flank wear because an increase in contact area of the wear land with the workpiece. The use of dynamometer is the most popular method for measurement of cutting forces. It was reported that cutting force currently is the most reliable method employed in in-process tool wear monitoring because cutting force is more sensitive to tool wear than AE and vibration. Thus, many studies have been conducted in the past using
cutting forces to establish the relationship with the flank wear (Sikdar & Chen, 2002; Sick, 2002; Oraby et al., 2005).

Dimla and Lister (2000) used three perpendicular cutting forces to correlate with the flank wear through time series and FFT. They reported that the tangential cutting force is the most sensitive to flank wear while Li (2005) reported that the feed and radial forces are more sensitive to flank wear than tangential cutting force. Fang et al. (2011) concluded that feed force was more sensitive to flank wear. Salgado and Alonso (2007) also found that feed force was more suitable to be applied in tool wear monitoring system because the radial force and tangential force showed greater error in flank wear estimation which reduce the success rate and can cause false alarm. Zhou et al. (2003) indicated that the radial force showed a significant increase when the flank wear increase to 0.2 mm. Penedo et al. (2012) also suggested the radial cutting force to monitor the flank wear by using a hybrid incremental model. In a recent work, Liao et al. (2016) developed a novel approach for flank wear monitoring which is based on the multi-scale hybrid hidden Markov model analysis of cutting force signal. In their study, the instantaneous resultant forces was taken into account because the authors indicated that resultant force signal provides multi-scale information of different directions.

Cutting forces are often used to monitor the flank wear because cutting forces are easy to measure and they have a clear phenomenological relationship with flank wear. However, there is no agreement to which cutting force component has more closer relationship with tool wear. In addition, Liao et al. (2016) reported that the high temperature in tool tip and fast tool material losing rate always result in rapid
tool wear and large fluctuation of cutting force during machining of difficult-to-cut materials.

Ren et al. (2011) applied cutting forces in a Takagi-Sugeno-Kang (TSK) fuzzy approach for tool wear monitoring. Liu et al. (2013a) used several statistical parameters such as average value, RMS, kurtosis and skewness extracted from the cutting forces as input of back-propagation neural network and adaptive neuro-fuzzy inference system for in-process flank wear monitoring. In a recent work, Gao et al. (2015) proposed a data driven modeling framework for flank wear monitoring in turning which is based on statistical processing of cutting force wavelet transform by a hidden Markov tree model. The drawback of these methods is greater computational burden in training phase as a large number of observation samples were used as training data with different machining conditions to build the model to estimate the flank wear.

Ghani et al. (2009) presented a tool wear monitoring method from the cutting forces and cutting parameters using the regression model to predict the flank wear. Camargo et al. (2014) developed a mathematical model based on multiple regression analysis to estimate tool wear during turning of AISI D6 hardened steel using PCBN cutting insert. Although the developed regression model accurately determined the flank wear, the regression based method cannot be extrapolated to different range of cutting condition and to other workpiece and cutting tool materials.

Monitoring cutting tool wear via AE signal analysis has long been practiced. AE can be defined as the transient elastic wave generated by the sudden release of energy in a material. There are several sources of AE signal during machining such
as (i) friction contact between the flank face of cutting tool and workpiece resulting in flank wear, (ii) plastic deformation of cutting tool, (iii) chipping and tool fracture (Li, 2002). The main benefit in the use of AE signal in tool wear monitoring is that the frequency range of the AE signal is much higher than that of the machine vibrations and environmental noises.

Bhaskaran et al. (2012) used skewness and kurtosis of the RMS value of AE signal to monitor flank wear. The kurtosis of RMS value of AE signal increased as the flank wear increased. High skewness of the RMS value of AE signal was found when the flank wear land reached the critical value. Compared to the conventional data processing method, Chen and Li (2007) reported that the wavelet resolution coefficient norm of AE signal is more reliable and useful to estimate tool wear. However, low magnitude of AE signal was generated when the cutting tool undergoes gradual wear compared to the higher magnitude of AE signals which accompanies tool failure by plastic deformation or tool chipping. Thus, AE is not suitable for use as tool wear indicator in gradual wear monitoring applications, but could be used to detect the end of tool life when the tool has deformed due to the excessive wear.

Maia et al. (2015) reported that monitoring the tool wear through the AE signal processed using the average power spectral density (PSD) is sensitive to the wear rate, responding with the high magnitude AE signal value at the beginning of tool life and followed by a decrease at the middle of tool life and increase at the end of the tool life when the wear rate becomes higher. However, monitoring of tool wear using AE signal was difficult because each of the mild wear and severe wear excited a different frequency band (Hase et al., 2012).
During machining, the workpiece and chips rub against the worn tool and produce vibrations which can be used in various ways for tool wear monitoring. Accelerometers are often used to acquire the vibration response. Dimla (2002) reported that vibration increased with flank wear and the vibration signal in the feed and tangential direction were the most sensitive to flank wear. The results showed that time domain analysis of vibration signal to be more sensitive to cutting condition than tool wear, whereas sum total power of vibration signal correlated well with the flank wear. However, the author found that vibration signal can only give better estimation of flank wear in low feed rate because the vibration signal is noisier in higher feed rate.

Chen et al. (2011) monitored flank wear in turning based on logistic regression model by using vibration signals. The wavelet package transform was used to decompose the original vibration signal to find out the frequency bands which well correlated to flank wear and applied the extracted most related features of vibration signals into the logistic regression model to monitor the cutting tool wear. Alonso and Salgado (2008) proposed tool wear monitoring based on longitudinal and transverse vibration signal using singular spectrum analysis (SSA) to decompose the acquired vibration signal. The RMS and variance of the decomposed vibration signals were extracted and the corresponding cutting condition parameters were fed into a back-propagation neural network to determine the flank wear. However, not all the decomposed vibration signals correlated well with the flank wear. The information in the decomposed vibration signals about flank wear is contained mostly in the high frequency components. Alonso and Salgado (2008) indicated that the range of frequencies most correlated with the tool wear changes with the cutting
tool condition and tool wear. For this reason, implementation of the tool condition monitoring based on vibration signal becomes difficult because the frequency range that correlated with the tool wear was difficult to be identified.

Temperature has also been used as a parameter for monitoring tool wear because heat generation is unavoidable in all machining process and it will damage the cutting tool tip due to the effect of diffusion and plastic deformation. Several attempts have been made to monitor the wear of cutting tool based on temperature monitoring. To measure the temperature in the tool tips, thermocouples are the commonly used sensors (O'Sullivan & Cotterell, 2001; Choudhury & Bartarya, 2003; Korkut et al., 2011). However, due to the narrow shear band, chips obstruction and the contact phenomenon between tool and workpiece the measurement of the cutting temperatures closed to tool tip becomes much difficult. In addition, since the temperature varies during machining and cannot be uniquely described by discrete values at a point this can cause error in the tool wear estimation (Sivasakthivel & Sudhakaran, 2013). Infrared thermal cameras have been applied to overcome the limitation of the thermocouple (O'Sullivan & Cotterell, 2001; Davoodi & Hosseinzadeh, 2012). However, the major drawback of the infrared sensor is due the coolant and the chip that may come between the sensor and the surface to be measured thereby causing errors in measurement.

Application of microphone to measure the sound signal for tool condition monitoring has also been attempted in the past. Tekiner and Yesilyurt (2004) used sound signal to assess the flank wear, built up edge, radii of chip curl and surface roughness. Salgado and Alonso (2007) estimated flank wear progression by the emitted sound using singular spectrum analysis in turning of AISI 1040 steel. Samraj
et al. (2011) used singular value decomposition to extract the information regarding flank wear from the emitted sound during turning. Monitoring of flank wear using sound signal has been proven possible, however this method is difficult to implement in the real industry because the noise from adjacent machines and motors can influence the signals.

The use of current and power signal has also been proposed in tool wear monitoring, either from spindle motor or from feed motor. This is because a worn cutting tool require more cutting forces than an unworn cutting tool, thus resulting in more power and current. The major advantage of using current and power signals is its simple hardware implementation that does not interfere with the cutting process. However, current and power signals are not as sensitive to flank wear when compared to cutting forces, AE and vibration signal (Kaye et al., 1995; Silva et al., 1998; Fu & Hope, 2006; Lee et al., 2007).

The need for a more reliable and accurate tool condition monitoring system over a wide range of industrial application is driving the research works towards a multiple sensor approach (known as sensor fusion). This is because signals from a single type of sensor are typically insufficient to provide enough information for tool wear monitoring. The use of several sensors at different locations simultaneously has been proposed for data acquisition in the past. Signals from different sensors are integrated to give the maximum information needed about the tool wear such as the combination of cutting force and vibration (Chelladurai et al., 2008; Chen et al., 2010; Fang et al., 2011), AE and cutting force (Youn et al., 1994; Jemielniak et al., 2011a), AE and vibration (Bhuiyan et al., 2014), cutting forces, vibration and AE (Jemielniak et al., 2011b; Gajate et al., 2012), AE and cutting sound (Zhang et al., 2015).
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