A Model Approach for In-Process Tool Condition Monitoring in CNC Turning Using Machine Vision

Worapong Sawangsri (fengwps@ku.ac.th)
Kasetsart University Bangkok
Pakanun Wattanasinbumrung
Kasetsart University Bangkok

Research Article

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Abstract

Tool wear monitoring and real-time predicting tool life during the machining process is becoming a crucial element in modern manufacturing to properly determine the ideal point to replace tool, remains a challenge currently. In this paper, the model approach for in-process monitoring and predicting progressive tool wear by using machine vision is proposed. The developed method adopts machine vision to acquire tool wear images from a CCD camera. The emerged wear analysis is conducted based on the in-progress of signal processing on captured tool wear images, received throughout the cutting process. This automated analysis is carried out with programming to assess and compare a number of pixels of cutting edge images between cutting tools before machining and during the machining process.

The developed system is evaluated through experiments of actual cutting conducted on the CNC turning machine with the proposed system installed to evaluate progressive wear during the machining process. Experimental results are capable of indicating the emerged wear at the current state by comparing the number of pixels between the new and used tools. Average flank wear (VB) is also evaluated linked to tool rejection criteria.

The developed system is validated by the 3D microscope measuring actual wear on the used tool after cutting experiments. Comparative wear analysis is then performed by finding the correlation equation of pixels examined by a developed system and SMr2 value measured by the microscope. The results showed that the relationship between the number of pixels and SMr2 is a strong correlation.

1. Introduction

Tool wear monitoring with the direct measurement method has always been of interest to researchers because its results are more accurate and reliable than indirect ones. In particular, measurement is conducted during machining the workpiece, so-called online measurement or real-time measurement, which is often measured without direct contact to the cutting tool (Non-contact measurement) due to the limitations of the method. Therefore, the direct method is preferable to non-contact measurement, especially the machine vision method because it has many advantages such as high flexibility, high spatial resolution, and high measurement accuracy, etc. [1-4].

Machine vision has become popular and applied to various types of automatic inspection tasks in the modern industry. For example, crop monitoring, precision agriculture, in-line inspection such as in the automotive industry, semiconductor, electronic device, food and pharmaceutical industry and non-destructive inspection, as well as quality control and classification in production lines. [5-7]. Especially, machine vision and image processing technology have been used to analyze and verify the wear and tear of cutting tools in the past decade. It can be used to directly monitor the wear conditions of the cutting edge or the workpiece while being machined. This leads to the development of various types of vision sensors consequently [8-10]. However, machine vision and image processing technology have also been less applied for monitoring on cutting tool conditions. This is because of machine vision and image sensors have not been developed to be efficient and resolution enough, especially for real-time measurement. Another important issue is the limitations of the machine vision installation on the machine and the obstruction of chips, coolant, equipment, etc., during machining. [11, 12] Thus, it is consequently reason that the machine vision is not often used to develop a system for monitoring the condition of cutting tools during machining operations.

There are some examples of research using machine vision systems for tool condition monitoring (TCM) system. For example, Shahabi and Ratnam [13] indicated that although machine vision is generally used to monitoring for cutting tool wear, it is an offline measurement or measurement after finished machining. But they conducted the initiative to use the machine vision system while machining workpiece. They did not measure the cutting tool directly, the surface roughness of the machined part was instead analyzed in relation to the cutting tool wear. Chen and Jilin [9] developed a wear condition monitoring system of ball-end milling cutter in milling operations using an offline machine vision. However, although they measured the cutting edge wear directly, it is not assessed during machining, just measured before and after machining of each experiment.

Regarding, analysis and inspection of cutting tool conditions with machine vision, most research works prefer to use the technique of converting image information into binary images or black and white images. This is an image that occupies only 1 bit per pixel, with only two color values; 0 or black and 1 or white, respectively. The condition of the used cutting tool is then analyzed [14, 15]. Analysis techniques are varied from various researches. For instance, Dutta and the team [14] analyzed the flank wear of turning tool from turned surface images by extracted features analysis technique. Yu and his team [16] used a curve fitting technique to plot the collected data from the captured image of the cutting edge in each machining state, then calculate the wear area that occurs at the tool tip., etc.

In this paper, the model approach of an in-process monitoring and predicting progressive tool wear has been purposed. The system is adopted a machine vision system with a charged couple device (CCD) camera for processing and obtaining image information of cutting edge. The progressive tool wear analysis is accomplished based on the automated analysis to assess and compare a number of pixels of cutting edge images between before machining and during the cutting process. The average flank wear (VB) is also evaluated by the developed system. The experimental study is conducted on the OKUMA GENOS L250E CNC lathe with the developed system installed to observe the emerged wear during the machining process. Furthermore, the developed system has been validated by measuring and comparing the occurred wear of cutting tools before and after cutting experiments by using the 3D Measuring Laser Microscope.

2. Schematic Approach For In-process Monitoring Of Tool Wear

2.1 Tool wear mechanism

The abrasion, adhesion, and diffusion during metal cutting process are known as the mechanisms of tool wear. Thus, tool wear always occurs with the deterioration of machining efficiency due to the changes in tool shape and geometry. The different classifications of tool wear are flank, crater, nose, notch wear, etc. [15, 17]. The flank wear is one of the most important and common wear that affecting on drastically decreasing in cutting tool performance [18, 19]. It is the wear of the cutting edge due to ploughing process between workpiece surface and tool flank face. Based on the ISO3685 standard [20] and [17], two parameters related to flank wear were defined namely included the average width of the flank wear land (VB) and the maximum width of the flank wear land (VB_{max}), as shown in Figure 1. These indicate the minimum wear area that the consideration of replacing the new tool should be decided. Thus, the measurement of VB is assigned as automatic detection during the cutting process by the developed system to present progressing wear related to the tool rejection criteria [20, 21].

2.2 Cutting tool wear image capturing and analyzing techniques

Flank wear detection on the cutting edge is a crucial issue that needs to be precisely and accurately detected. Otherwise, the tool wear cannot reliable observed and evaluated by the developed system. Pixel matching is claimed that it is one of the best image processing techniques for accurately detecting tool wear area within machine vision system [15]. The pixel matching [9, 15, 16, 23-25] is a method that converted images captured by CCD camera to binary images and counting the number of pixels within the selected area on the tool surface to determine emerged wear (Figure 2). Algorithm of the developed system has been set up as an automatic comparison of the number of objective pixels between the unused (so-called the referent tool) and worn tools. The progressive tool wear is thus analyzed by comparing the numbering of pixels between the referent tool and the used tool during machining process. The system is also conducted to evaluate the average wear land (VB) on the tool flank face. The VB is thus used as the tool rejection criteria that whenever the users should be deciding to replace a new tool, will be notified by the system.

2.3. Algorithm and system setup

The development of the purposed system is performed based on the image checker which is embedded software and system of the Panasonic ANPVT30 (CCD) camera. The system architecture has been developed by the MS Visual Basic programming. Thus, algorithm approach and features are designed with the following steps (Figure 4). Firstly, images of the tool are captured by CCD camera and converted into binary images. Secondly, the number of pixels on the binary image of an in-process tool during machining process is counted and compared to pixels of the referent tool by the pixel matching technique. Finally, the wear area is evaluated from the missing pixels that occurred on the used tool images. Further diagnosis also has been made to analyze the VB in deciding for tool replacement.

All image information and analysis are either automatically or manually manipulated by the control algorithm. Also, the basic control of the system such as start/stop inspection and capture image can be handled, as well as its consequently results are displayed on the control panel of the display screen of GUI (graphical user interface) as shown in Figure 5. Furthermore, the system can be connected to the output signal of the machine (i.e., the I/O port) to provide an interface between the proposed system and the machine tool. This allows the system to realize the current position of cutting tool in each machining cycle. This enables the system to automatically analyze and assess the image data for tool wear conditions in any cutting cycle.

2.4. Experimental design and set up

The experimental study is established and installed as a wiring diagram as shown in Figure 6. The system comes along with a CCD camera and a bar light, which are attached to the wall opposite to the cutting tool holder within the machine. This position is above the main spindle and passed through the test for acquiring clearly captured images of cutting edge during the machining process without obstacles. Thus, a certain distance from the camera's lens to the cutting edge is fixed and pointed to the same selected area on the tool in any cutting cycles. The camera and the bar light are contained in a square-jig box and well-sealed to be protected from hot chips, coolant, and absorb vibration. Installation and setup of the developed system are presented in Figure 7. 3 sets of the unworn turning insert of T and V types are used for rough and finish cutting, respectively. The cutting experiments are conducted on the material SCM440 to perform 3 different products with varies in cutting and related parameters in dry cutting condition. The determined parameters and details presented in Figure 8 and Table 1, respectively. Cutting trails are set in a cutting cycle, 1 cycle (included facing, roughing, and finishing) means that a workpiece is completely produced, keep continuing in a cycle until the tools are beginning to wear, then stop and change a new tool set.

The number of pixels and VB of the cutting edge during the cutting process are targeted evaluations on progressive wear. Both concepts are based on counting pixels on the selected area and line inspections, respectively, as shown in Figure 9. A number of pixels are automatically analyzed for emerged wear within the selected area. The lesser pixels mean the more occurring wear. While VB is assessed by counting and averaging pixels on lines laid down on the cutting edge across the flank face, presented in Figure 10. Counting and averaging pixels for VB is performed only pixels that present the unworn area on the tool face, i.e., the white pixels (the black is a wear area). Thus, VB is automatically computed by counting and averaging pixels on lines above the boundary of the cutting edge then compares to pixels on the last line at the boundary. The more VB means the more flank wear land which related to the tool rejection criteria. If VB is reaching the tool rejection criteria, the system will automatically notify for deciding to replace a tool.

Table 1: The different cutting parameters assigned for each tool set

Tool sets	Operation	Tool type	Diameters (mm.)	Feed (mm.)	RPM	Depth of cut (mm)
1	Face	T	17	0.15	1000	-
	Rough	T	17	0.25	1000	0.5
	Finish	V	17	0.06	1800	0.1
2	Face	T	10	0.15	1400	-
	Rough	T	10	0.4	1400	1.2
	Finish	V	10	0.05	2900	0.1
3	Face	T	5	0.15	1100	-
	Rough	T	5	0.4	1100	2
	Finish	V	5	0.05	2400	0.15

2.5 Analysis and prediction of tool wear

The system has been developed with user-friendly to control various functions of the system via GUI. The system automatically detects pixels on the captured images in 2 categories namely includes a number of pixels in the specified area and on the 5 lines parallel dragging to the cutting edge across the tool face. The number of pixels is checked to analyze occurred wear within the specified area. The different pixels are re-calculated in any measuring cycle by comparing to pixels of a referent tool and expressed on a feature of GUI named Tool Condition (Figure 5, 9). Therefore, the less Tool Condition value indicates the more occurring wear. Meanwhile, inspection on the lines that automatically dragging is performed for VB average analysis, the system counts the number of pixels (on top 4 lines) of the non-wear on the flank face which the pixels have seen as white. Calculation of average is then conducted on the numbering of white pixels on mentioned 4 lines to compare with pixels on the fifth line (bottom line) that is drawn across the base or the bottom of the cutting edge. Thus, the evaluable mean VB by the system can compare to the VBmax or the tool rejection criteria to ensure the tool performance during machining. In other words, if the VB has not exceeded the tool life criterion, it is able to keep using the cutting tool, but if it is similar or higher than the tool rejection criteria it is better to decide for replacing the cutting tool.

2.6 Inspection of tool wear with a microscope

The experimental measurement has been made after cutting trials to validate the emerged wear of the used tool by the 3D Measuring Laser Microscope (Olympus LEXT OLS5000). The Material Ratio Curve [26-28] is adopted to examine and analyze actual wear on the cutting edge. In this research, SMr2 (valley material portion) was measured and the wear results were analyzed from different SMr2 values between the unused and the used tools. Due to the used cutting edge, the Valley Void Volume (Sv) at the cutting edge surface is higher because the worn surface is deeper (valley) where the wear is more occurred. In other words, the area in the Valley Void Volume increases which resulted in the decrease in the Percent Contact Area of SMr2 (Figure 11). Therefore, the more occurred wear, the less measuring SMr2. Incidentally, the selected area on the cutting edge measured and inspected by microscope is determined as an identical area as assessed by the developed system. This performed based on the mark point by microscope.

3. Experiment Results

The initial test after installed the developed system clearly seen the images of the cutting tool (Figure 12). The experiments are conducted to produce 3 different parts as shown in Figure 13 and recorded all data results in order for assessing both numbers of pixels and VB. The cutting experiments start with the first set of new tools and keep machining as a cutting cycle until the tool starting to wear, then change the tool until finishing 3 sets of tools. The captured images of V and T types are accordingly performed in each cutting cycle. Thus, the collected data are shown as graphical results represented decreasing trends of pixels on both V and T types throughout experiments (Figure 14). Furthermore, the results show the different levels of emerged wear on each cutting tool due to the different cutting parameters is assigned to each tool set. It is observed that the second tool is the most wear occurring while the first tool is the least one because the highest cutting parameters especially the RPM (Table 1) are assigned to the second tool set, in accordance with the different values of pixels and also SMr2 in Tables 2 and 3, respectively. However, the shortest time of cutting is the last (third) tool for both T and V types due to the most depth of cut is applied. The results presented that the longest time is approximately 170 minutes for the first tool while the shortest time is approximately 35 minutes for the last tool, respectively.

The collected data also presented in 2 separate kinds of evaluated results namely a number of pixels and a VB. The assessments of the number of objective pixels of V and T types presented in Figures 15 and 17, respectively. Meanwhile, the VB of both types showed in Figure 16 and 18, respectively. Curve fitting of correlation equations is also conducted and placed on each graphical result. Each graph is presented that the starting time of the cutting experiment, and ending with the time of replacing a tool. It can be seen that the slowly decreasing trends in the number of pixels happened to all tools, it is assumed that emerged wear gradually occurs until deciding to change a new tool. Moreover, it can also be observed that the tool type T has lost pixels rather than type V, it may be assumed that type T is more wear occurring due to it is used for rough machining.

Table 2: The average of numbers of pixels and the differences

	Pixels of V type			Pixels of T type		
	1st tool	2nd tool	3rd tool	1st tool	2nd tool	3rd tool
Average of the first 5 data	15,635.8	15,839.4	15,607	11,615.8	11,143.4	11,964.8
Average of the last 5 data	15,389.2	15,518.8	15,306.2	10,581.2	9,836.2	10,802
Different values	246.6	320.6	300.8	1,034.6	1,307.2	1,162.8

With regard to VB evaluation, it can be found that the slowly increasing trends in the VB values for all tools. It is assumed that the flank wear land gets slowly increasing on the flank face according to the VB values until reaching tool rejection criteria. Besides, the emerged wear on T type getting bigger and quicker than V type, this confirmed that T type has worn rather than V type in term of wear area and time.

4. Experimental Measurement Of Cutting Tool Wear For Validation

The experimental measurements of emerged wear are performed to validate the developed system. Before and after cutting experiments and collected data, all unused and used tools are taken to measure the occurred wear by using the 3D Measuring Laser Microscope. The Material Ratio Curve has been used to evaluate the occurred wear on the cutting edge by measuring and analyzing the SMr2 [29-31]. The comparison between SMr2 values before and after cutting experiments is explored that how much wear is exactly occurred. It can be seen that all SMr2 values after cut is lower than before cut, presented in Table 3. However, the different values of SMr2 compared before and after cuts are increasing when increased in levels of cutting parameters, this can be observed through all tool types. It indicated that V and T types get worn after cutting experiments that level of wear is well related to the cutting parameters.

Table 3: SMr2 values before and after machining of each tool set

Type	Tool set	SMr2 before machining (referent tool)	SMr2 after machining	Different values
V	1	90.909	89.176	1.733
	2	92.008	89.144	2.864
	3	91.808	89.044	2.764
T	1	91.309	88.944	2.365
	2	91.009	84.382	6.627
	3	90.11	85.547	4.563

Figures 20-21 are a correlation between the numbers of pixels examined by a developed system and the SMr2 values measured by the microscope for both tool types. They were found to be highly correlated and tend to be in the same direction, expressing with the following correlation equations (1) and (2) for tool V and T types, respectively.

$$y = -0.0951x^2 + 0.079x + 91.515 \quad (1)$$

$$y = -0.1308x^2 - 0.5088x + 92.315 \quad (2)$$

5. Discussion And Conclusion

The model approach to the system of in-process monitoring and predicting progressive tool wear is developed in this paper. The developed system adopted machine vision with a CCD camera for obtaining captured images of the cutting tool. The pixel matching technique is applied to evaluate and compare the number of pixels between the referent and the used tools. The key finding is the missing pixels of the used tool indicate an occurred wear. The emerged wear and average flank wear (VB) are thus automatically analyzed based on algorithm design and implementation. The experimental testing is conducted to validate the developed system by installing the system on the CNC lathe machine and machining the actual products. Progressive tool wear is thus evaluated considering the number of pixels and VB assessments through the cutting experiments.

Results presented that numbers of pixels tend to decrease steadily for all cutting tools due to the ever-increasing wear of the cutting edge while machining the workpiece. This reduction trend can be described by the correlation equations between the number of pixels and the machining time for every tool. It is also found that there is a greater reduction in the number of pixels when setting higher cutting parameters. Also, the reducing rate of pixels of T type is greater than that of V type because the higher the cutting parameters, the faster and more likely the cutting tool wear. Meanwhile, it is also observed that the verifiable mean VB tended to increase as the wear gets increasingly more and more during machining. The correlation equations can also be used to describe the increasing trend of the mean VB.

Installation and testing of the developed system on the machine and comparing results to the actual wear measurement with the microscope. It is found that the number of pixels verifiable by the system and the SMr2 values measured by microscope is similarly decreasing trend as well as in the same direction. It is able to find correlation equations between the number of pixels and the SMr2 value of 2 tool types. This strong relationship benefits the tool wear monitoring applications that if the system is validated with this correlation, the actual wear level on the cutting edge is able to be assessed with the developed system. Moreover, the system is able to evaluate and analyze the mean VB at real-time machining which determines the acceptable limit for tool rejection criteria. Thus, the system is able to predict and automatically notify users the optimal time to replace a new tool before damaging the workpiece. This potentially benefits a mass or continuous production in the manufacturing industry.

Declarations

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Conflicts of interest/Competing interests (include appropriate disclosures)

There is no conflict of interest

Availability of data and material (data transparency)

Data and materials were obtained on the basis of research

Code availability (software application or custom code)

Custom coding developed with MS Visual Basic based on the CCD camera software application named the image checker

Ethics approval (include appropriate approvals or waivers)

Disclosure of potential conflicts of interest - Not applicable

Research involving Human Participants and/or Animals - Not applicable

Informed consent - Not applicable

Consent to participate (include appropriate statements)

The authors agree to participate in the article

Consent for publication (include appropriate statements)

The authors agree with the publication

Authors' contributions (optional: please review the submission guidelines from the journal whether statements are mandatory)

Not applicable

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Figures

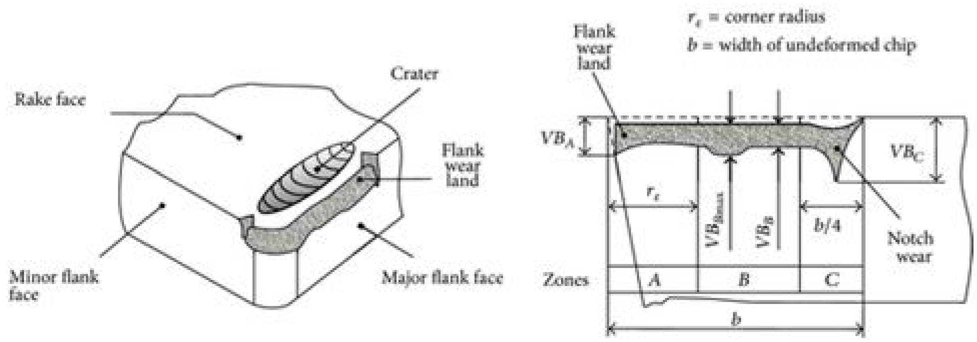


Figure 1

Classifications of wear on the cutting edge [22]

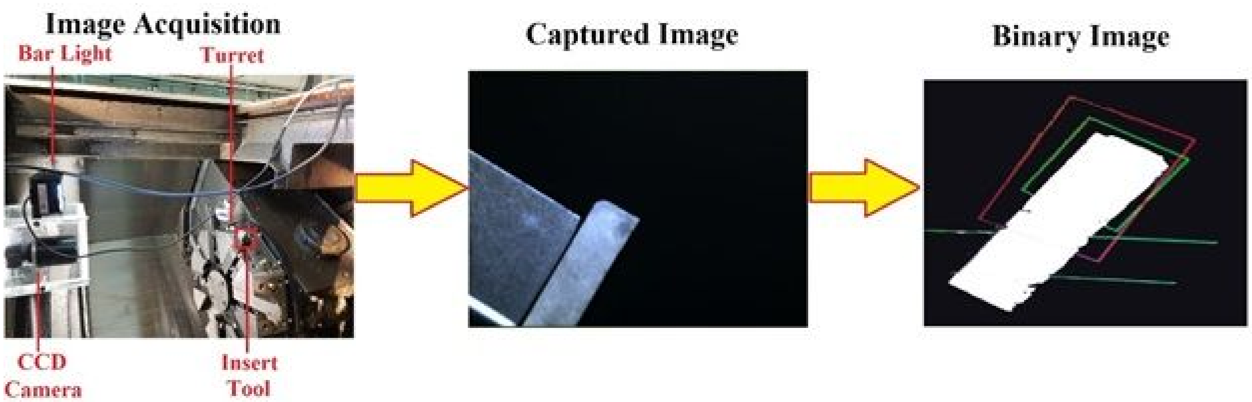


Figure 2

Binary image (right) converted from captured image (middle) by CCD camera attached opposing to the tool turret

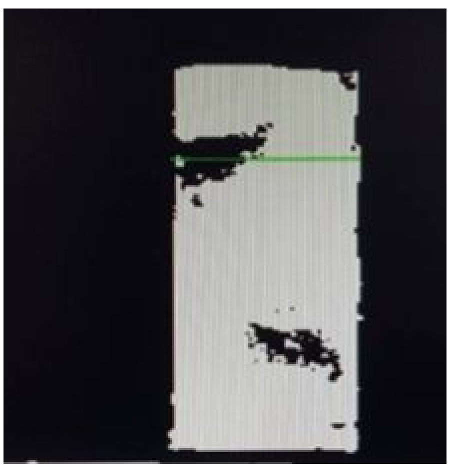


Figure 3

Cutting edge wear patterns found in binary image.

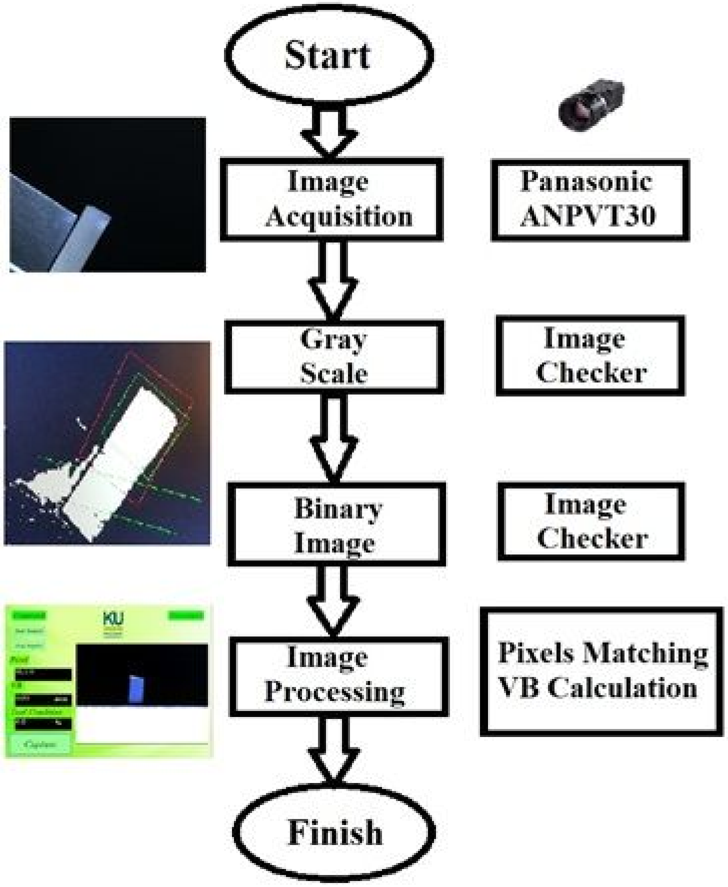


Figure 4

Flowchart showing the operation of the system

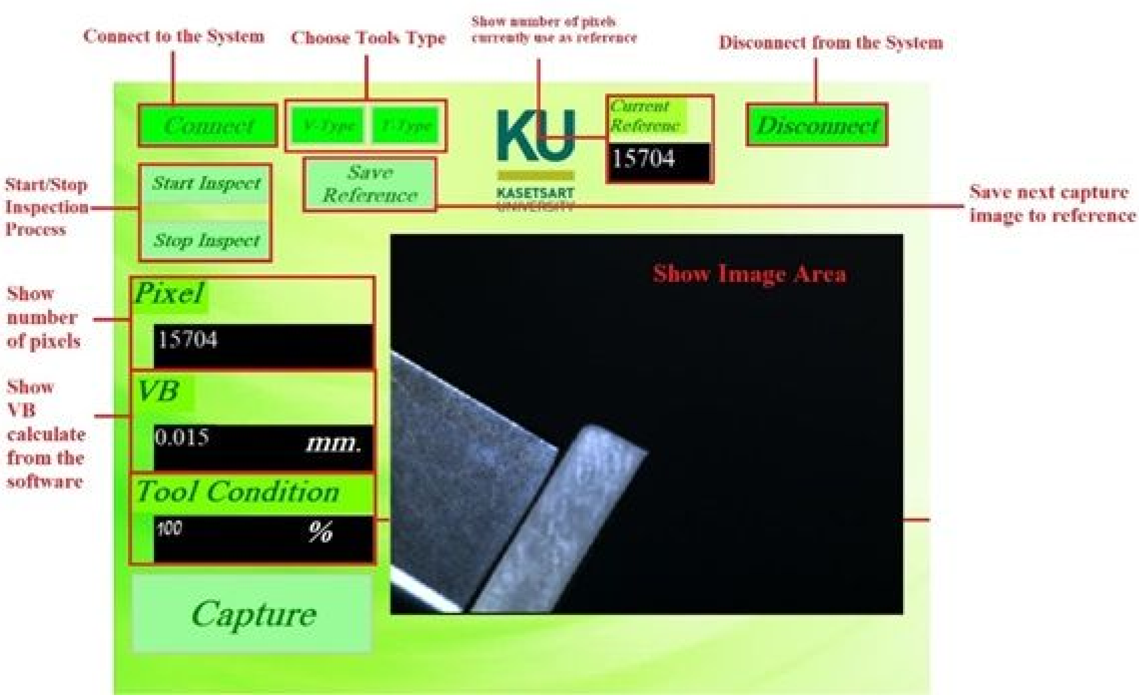


Figure 5

Display screen and features of GUI

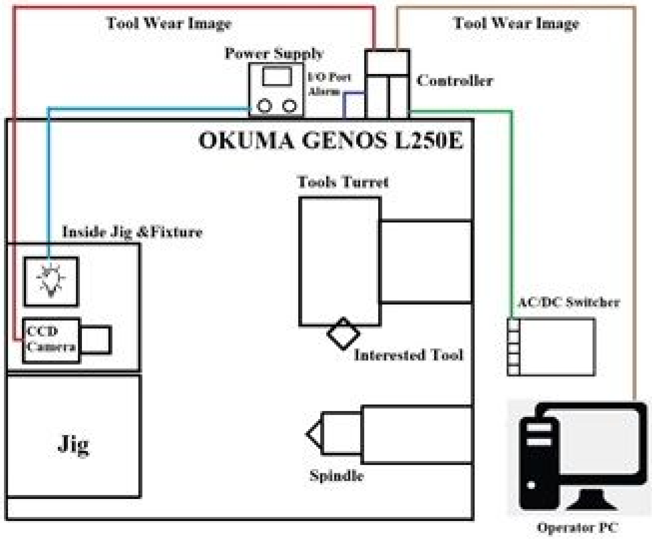


Figure 6

Experimental components and setup

Figure 7

The developed system installed in the CNC lathe machine

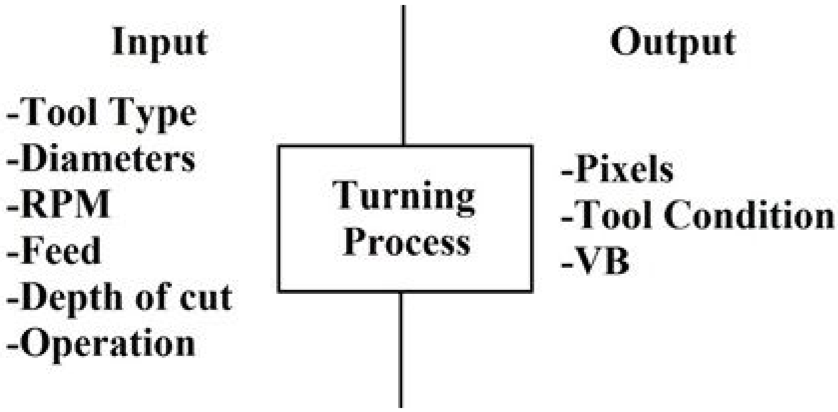


Figure 8

Cutting and related parameters applied in cutting experiments

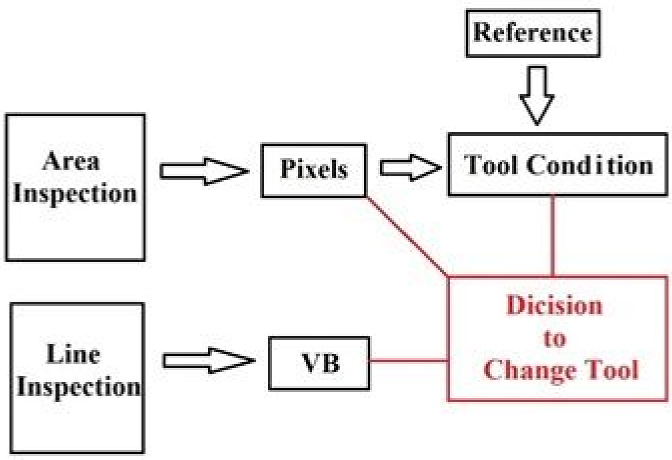


Figure 9

Algorithm design of tool wear analysis and prediction

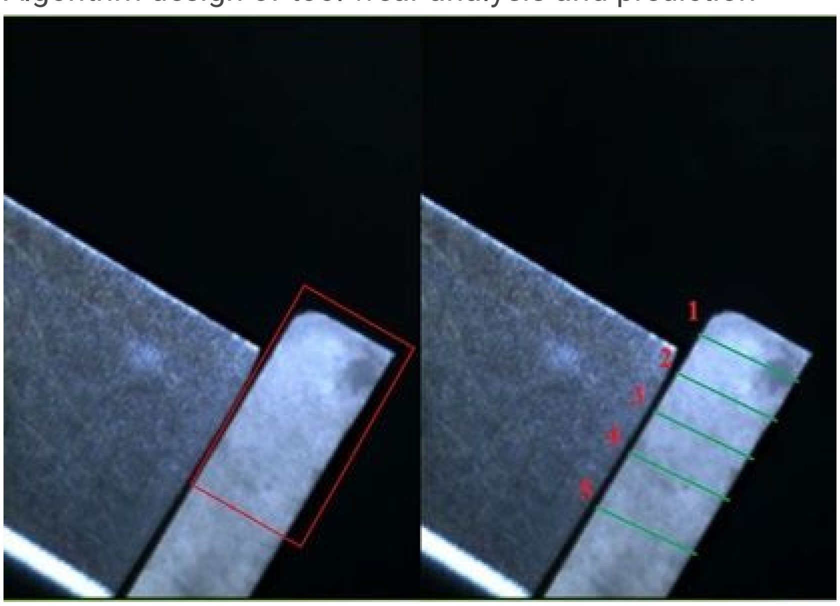


Figure 10

Pixels counting in a selected area (left) and pixels counting and averaging on the lines (right)

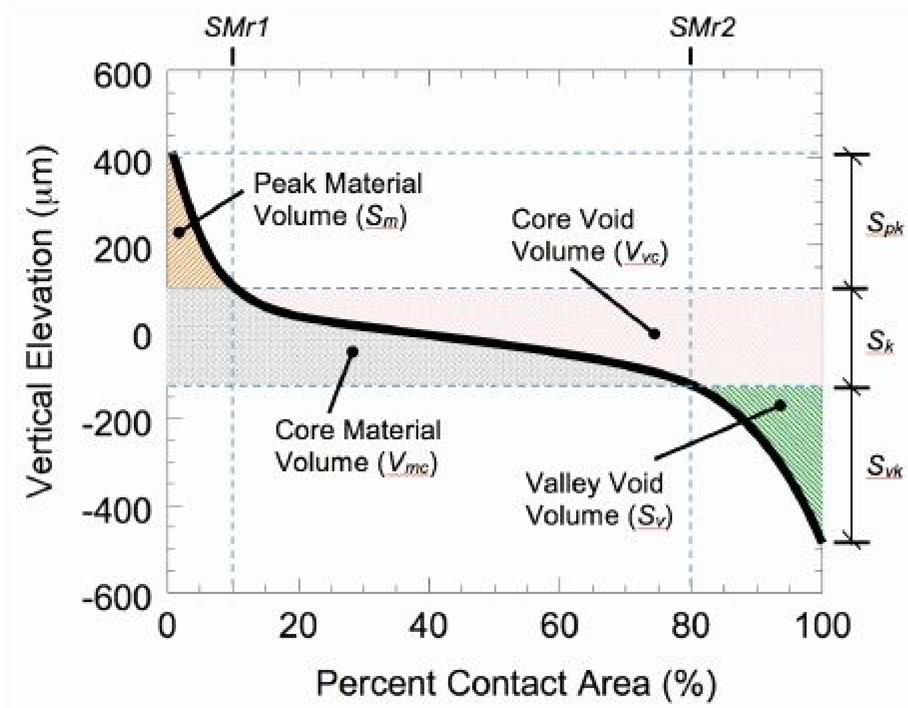


Figure 11

Areal material ratio curve [27]

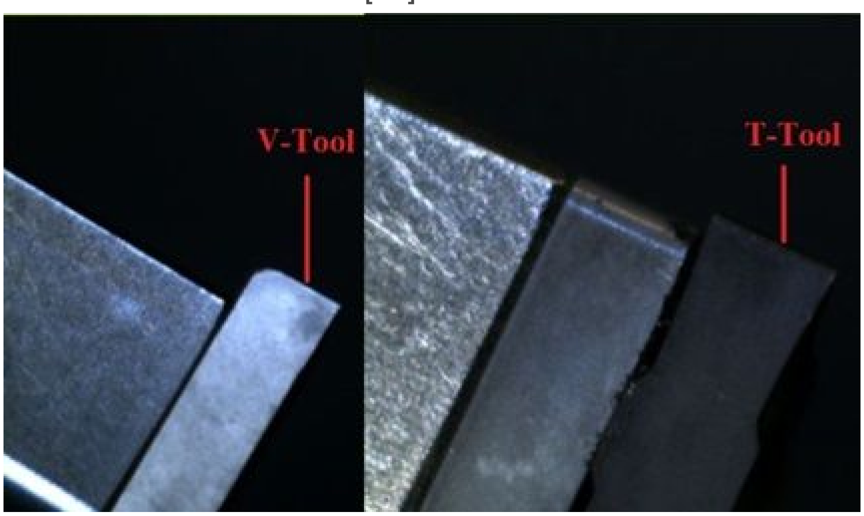


Figure 12

The captured images of V and T types before experimental trials

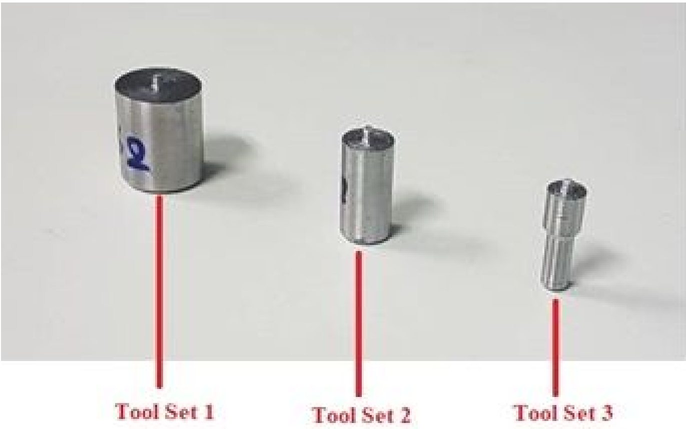


Figure 13

Finished products conducted through the experiments

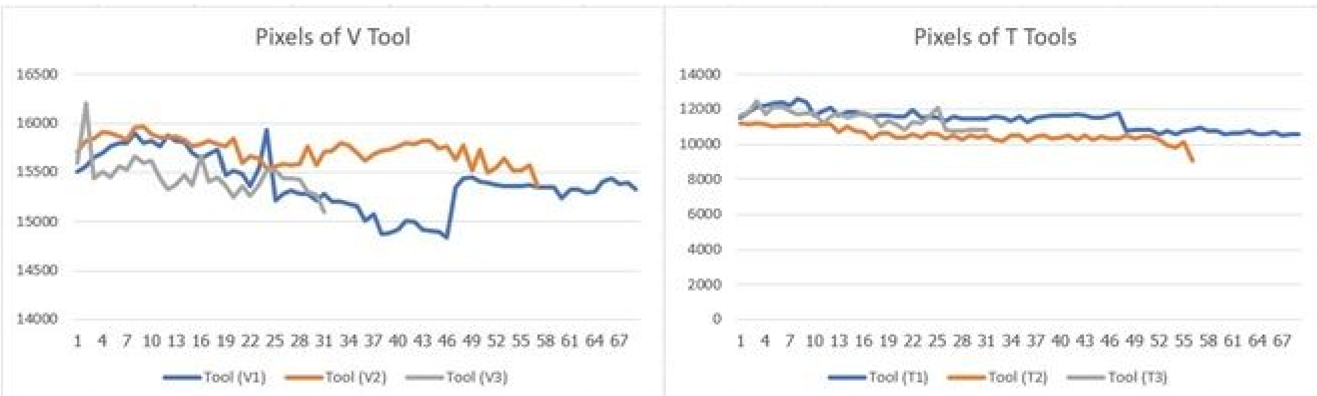


Figure 14

Trends of pixels on V and T types throughout experiments

V type (Pixels)

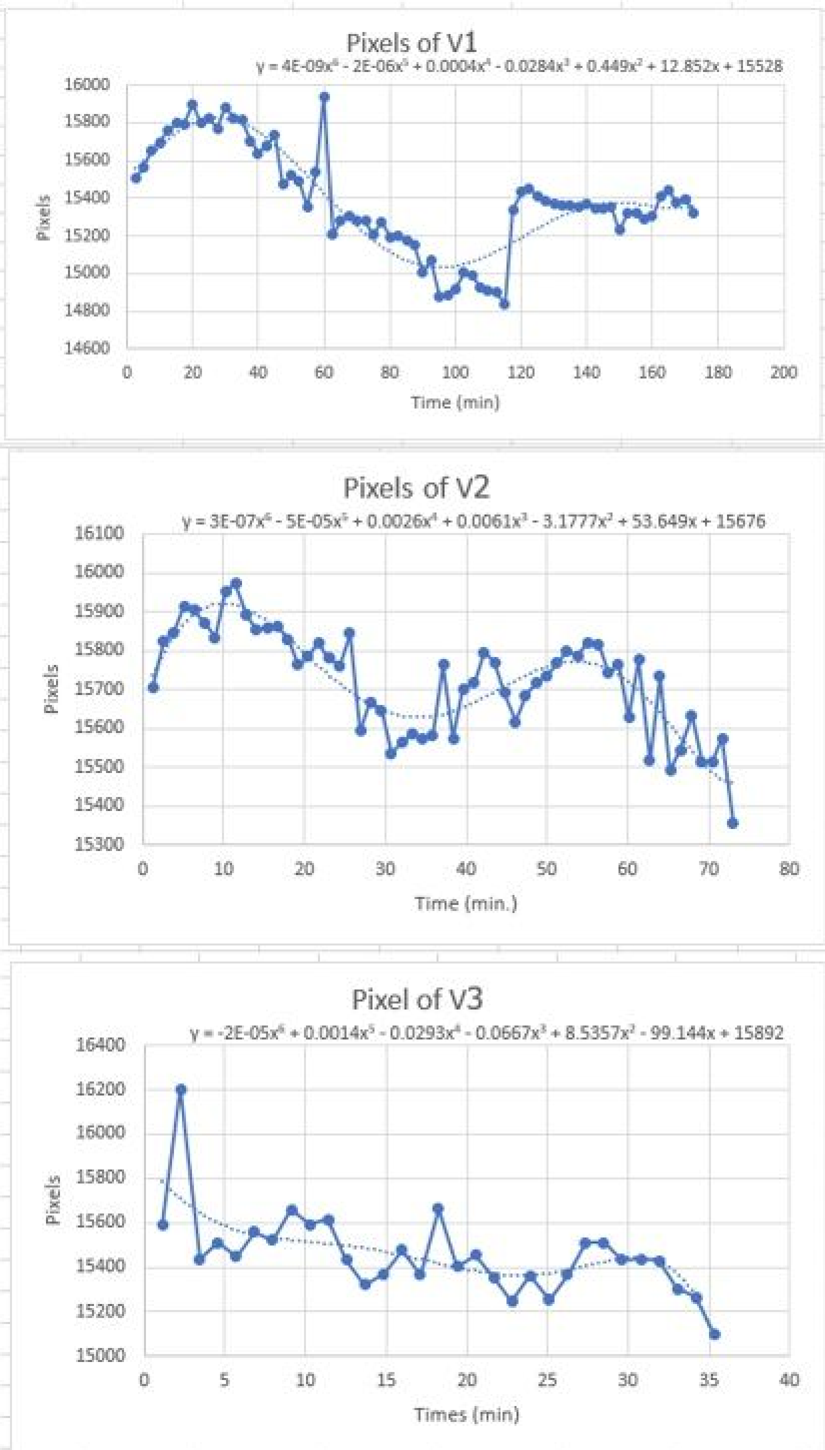


Figure 15

Pixels of V type: 1st tool (above), 2nd tool (middle), and 3rd tool (below)

V type (VB)

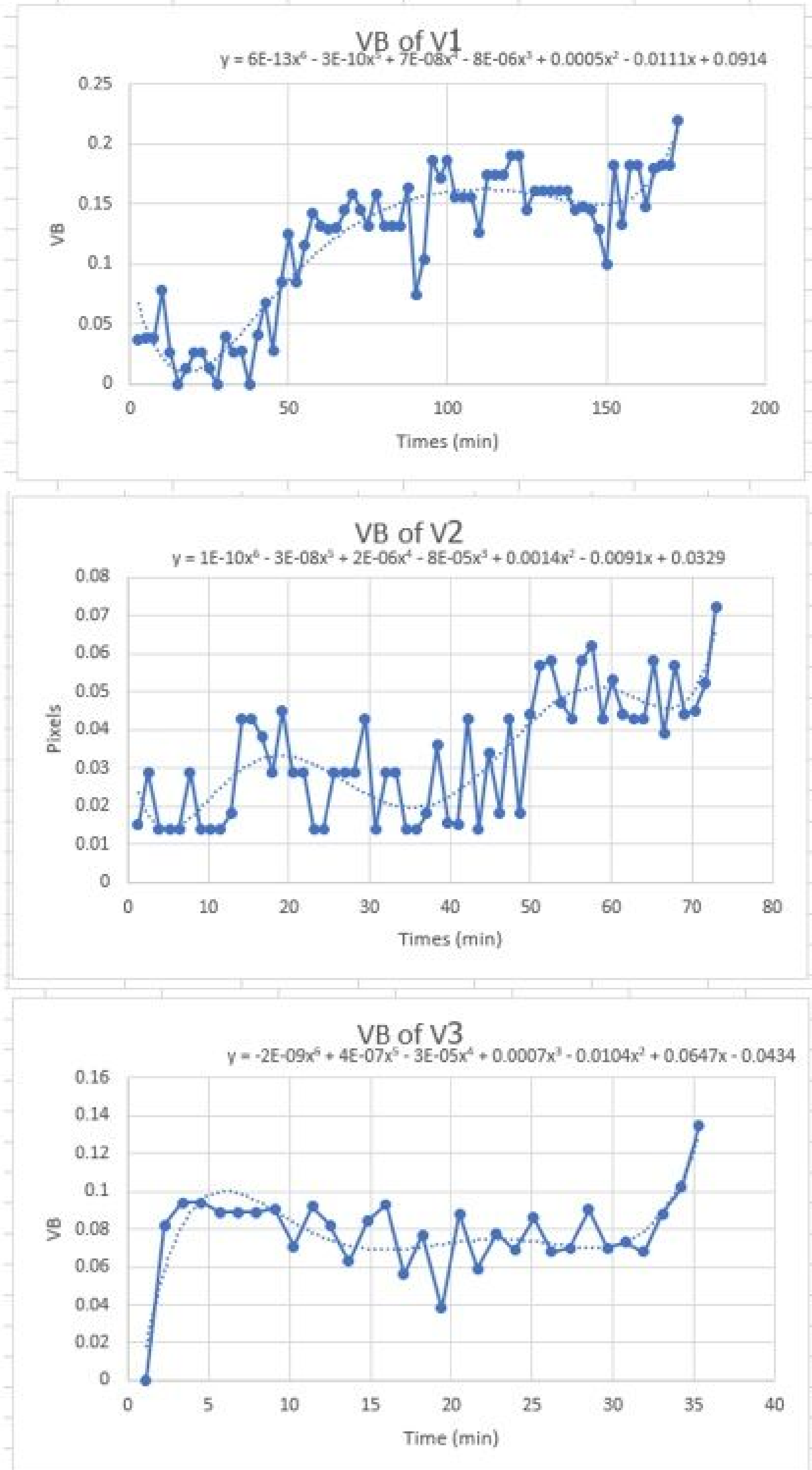


Figure 16

Average VB of V type: 1st tool (above), 2nd tool (middle), and 3rd tool (below)

T type (Pixels)

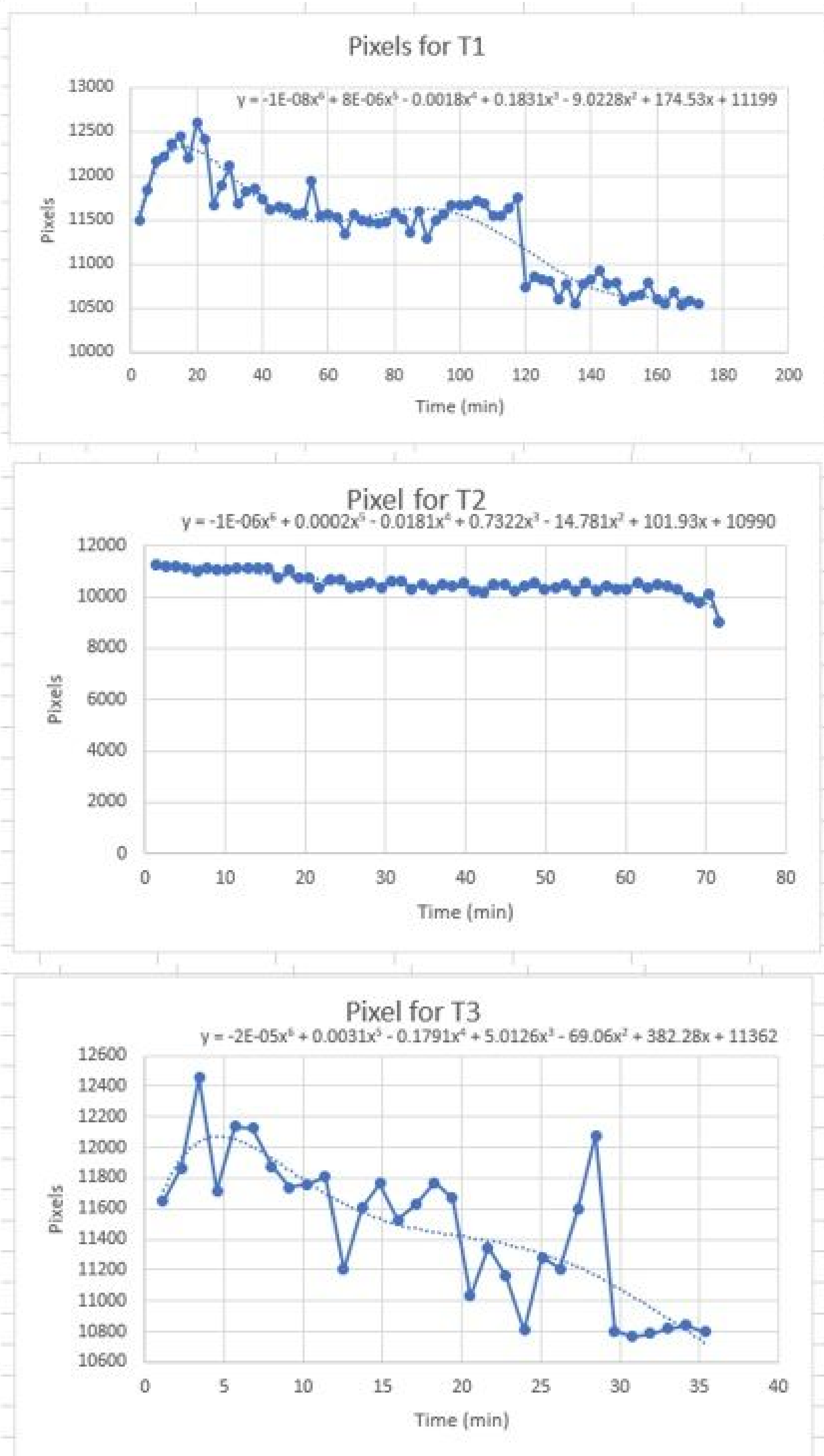


Figure 17

Pixels of T type: 1st tool (above), 2nd tool (middle), and 3rd tool (below)

T type (VB)

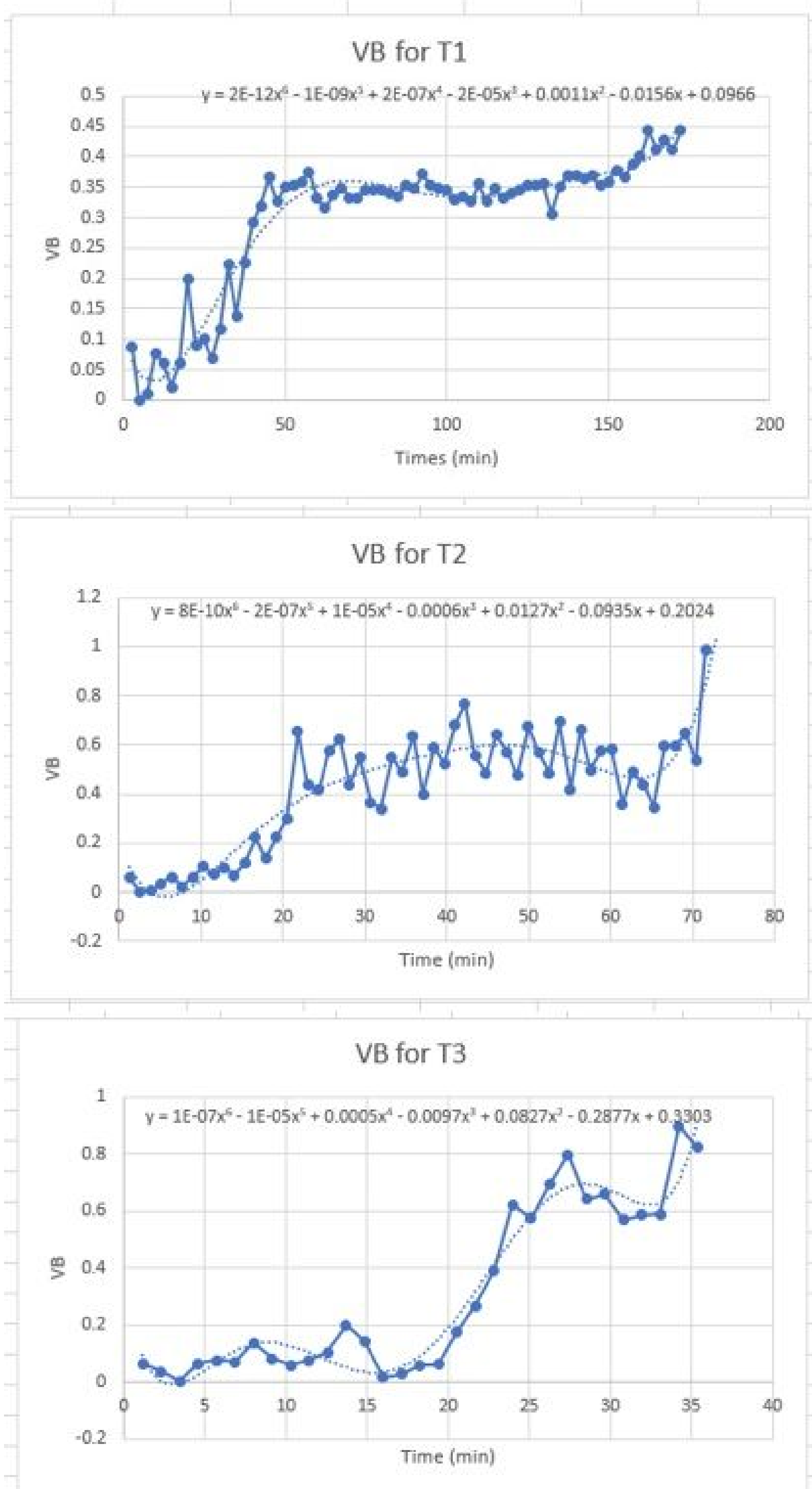
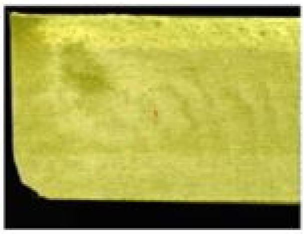
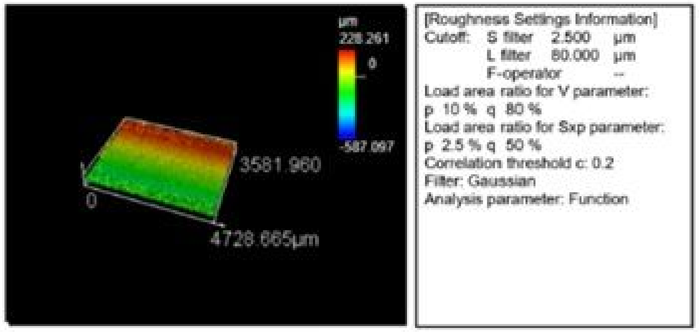


Figure 18

Average VB of T type: 1st tool (above), 2nd tool (middle), and 3rd tool (below)





No.	Result	Smr(c)[%]	Smc(mr)[µm]	Sk[µm]	Spk[µm]	Svk[µm]	SMr1[%]	SMr2[%]	FOperator	S-filter[µm]	L-filter[µm]
1		80.000	-1.697	5.788	38.745	64.314	16.284	89.510	--	2.500	80.000

Figure 19

Measurement results and analysis of SMr2 according to the Material Ratio Curve principle

Material Ratio Curve for V type

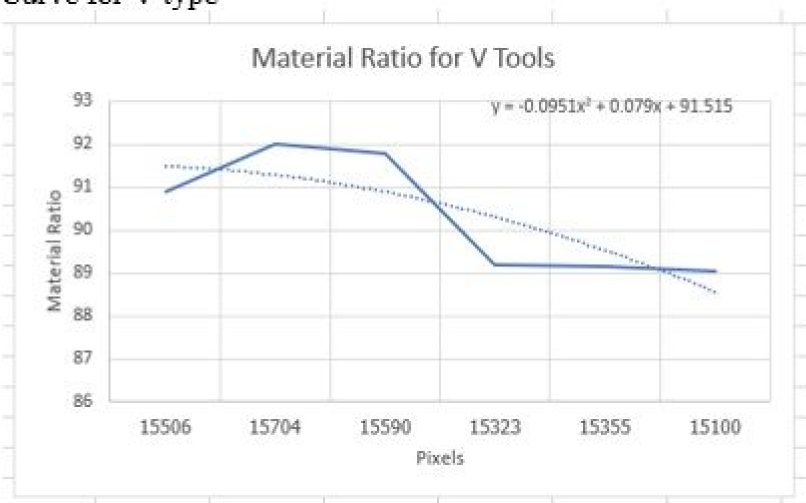


Figure 20

Graphical relationship between the number of pixels and the SMr2 value of V type

Material Ratio Curve for T type

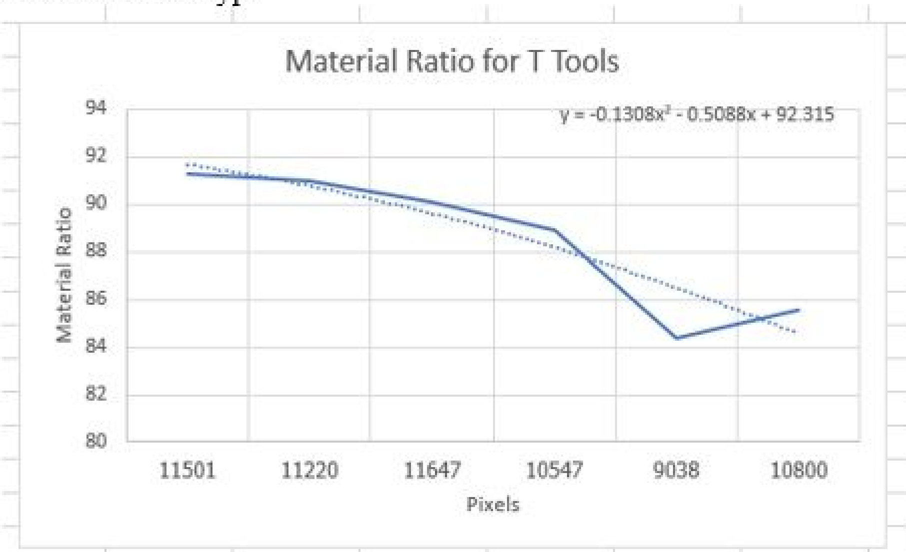


Figure 21

Graphical relationship between the number of pixels and the SMr2 value of T type