Prabha Materials Science Letters
Vol. 2, No. 2, 62-74, 2023
https://doi.org/10.33889/PMSL.2023.2.2.006

Application of Image Processing in Different Machining Processes: A Short and Technical Review

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(Received on April 17, 2023; Accepted on May 3, 2023)

Abstract
This article discusses the use of digital image processing in a variety of machining processes and the benefits that it brings to the industry. In this article, we will also cover the benefits and drawbacks of using digital image processing techniques instead of the various different sensors that are utilized in machining in order to increase product quality. This article provides a concise introduction to several image processing methods that are utilized in the machining process. This paper contains a discussion of a comprehensive analysis of the applications of image processing that have been used in machining during the past ten years. In addition, an illustration of one approach to image texture analysis that may be applied for cutting tool condition identification through the examination of photographs of machined surfaces is shown. A general conclusion that can be drawn from this and leads to the necessary further research in this area has also been discussed.

Keywords- Machining, Image processing, Machined surface, Tool wear.

1. Introduction

Various methods have been developed to be used in the measurement of surface roughness until today (Matuszewski et al., 2017; Bustillo et al., 2018; Korkmaz and Günay, 2018; Gandla et al., 2020). In the oldest and still-used method of touching, the probe is rubbed on the surface perpendicular to the machining direction (Krolczyk et al., 2017; Wang et al., 2021). In addition, hydraulic, pneumatic, mechanical, capacitance, surface dynamometer, X-ray, optical microscope, sectioning, optical reflection, replica, electro fiber, light band, interference microscope, levin, spring-type profilometer, and air gauge methods are also used to measure surface roughness (Rothberg et al., 2012). Tracker-tip instruments are based on the principle of recording or reading from the gauge by magnifying the vibrations that occur when moving on the measured surface, transverse to the surface irregularities, and along the evaluation length, using a very sharp tracking tip (Schmitt et al., 2016). In devices manufactured with mechanical, pneumatic, electronic or optical support, the pressure of the tracer tip on the surface can be very low, and the roughness magnification can be up to 100,000 times (Bhushan, 2000). The transducers used in electrical equipment are preferred because they can easily convert the mechanical displacements of the follower tip into electrical signals (Bhushan, 2000; Zhou et al., 2015).

Today, the basic principle in existing systems for roughness measurement has been the classification and grading of two-dimensional roughness profiles by comparison (Cao et al., 2021; Ross et al., 2023a). In addition to these, many commercial and scientific studies are carried out in the determination of surface roughness (Zhang et al., 2019; Sakakibara et al., 2021; Korkmaz et al., 2022a). However, these studies were mostly carried out at laboratory scale for materials such as metal and plastic (Yaşar et al., 2017; Çamlı et al., 2022). In addition, there are various measuring devices commercially available on the market to determine material surface roughness (Günay and Korkmaz, 2017). Commercially available surface roughness profilometers can measure low measuring areas at a short distance (Boy et al., 2016). The general texture images of the machine surfaces and laser speckle pattern are shown in Figure 1.

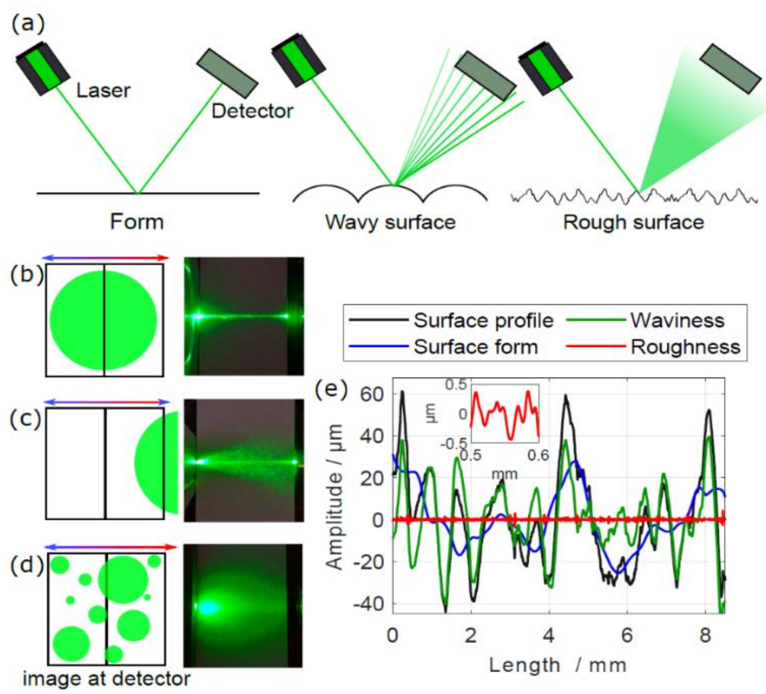

Figure 1. General texture images for machined surfaces and laser speckle pattern (Li et al., 2023).

Surface effects on the probe laser beam are depicted in Figure 1(a). When the surface is smooth, the form is essentially flat with respect to the detection, and the laser returns to the detector; when the surface is wavy, the local gradient means the returning light is reflected at a different angle when the sample moves, and this can cause the light to return outside of the acceptance angle of the collection optics and be lost.

Roughness on a microscopic scale causes a large dispersion of incident light. The instrument's knife-edge detector has trouble with the variations in the returned probe light, as shown in Figure 1(b). In this scenario, the laser reflects off the smooth surface and back to the detector, where both photodiodes are equally illuminated thanks to the reflection. The biggest difficulty here is keeping the optical system's focus where it needs to be on the specimen's surface. Figure 1(c) depicts the effect of a surface with waviness, in which the surface normal is rapidly shifting, displacing the reflected spot from its centered location and, in the worst case, reflecting light outside the acceptance angle of the optical system, leading to signal dropouts. As seen in Figure 1(d), the return light travels in all directions, but the introduction of speckles across both photodiodes causes both the light and dark regions to shift across the knife edge as a result of the presence of sound, resulting in a loss of signal.

With the setup established in literature studies (Dutta et al., 2016; Pour, 2018), the machined surfaces are shifted in a horizontal plane with stepping motors to the right-left, and up and down, and the right-left (x) horizontal and vertical down-up (y) coordinate information and the (x, y) displacement at this point (Samtaş, 2014). The 3-dimensional information (x, y, z) consisting of the roughness value (z) obtained with the meter was transferred to the computer and recorded, and the roughness map of the surface was obtained by scanning the entire surface (Figure 2). In Figure 2, a stylus profilometer is a type of contact-based profilometer that determines the topography of a surface by bringing the tip of its stylus into direct contact with the surface being measured and tracing a route that the user specifies on the surface.

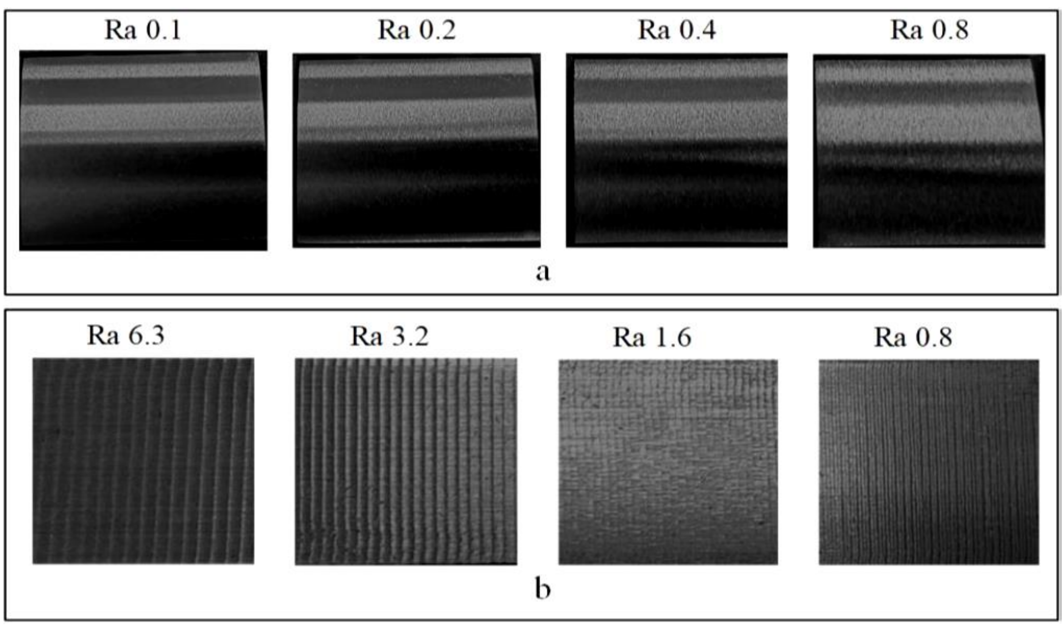

Figure 2. Converting to binary image and experimental measurement direction for stylus method (Zhang et al., 2022).

However, this system requires a significant amount of time and storage space, depending on hardware and scanning resolution, due to matrix development. Technological advances in digital computers have made image processing techniques popular in various applications in the field of machining as well as in many other fields (Liu et al., 2022).

2. Image Processing in Manufacturing Sector

Image processing technology is one of the most difficult but important systems of the future. It is accepted as a technology that has taken its place in many sectors and carried efficiency to higher levels in terms of application (Khashaba et al., 2021).

Image processing is the processing of an image to obtain useful information and transfer it to digital media. It is the improvement of a digital image transferred to the system by converting it into compressed data by means of different numerical algorithms and converting it into a work output to be used in the final stage (Guimard et al., 2009; Darafon et al., 2013; Pour, 2018).

2.1 The Advantages of Image Processing

Increase in productivity: Performing operations such as counting and measuring performed by the personnel through cameras accelerates processes, prevents errors and increases productivity.

Easy Integration: It supports end-to-end transparent and integrated management by easily integrating into your systems such as Enterprise resource planning (ERP), automation, etc.

Minimum hardware cost: It can be used with image processing technology in the existing camera system without making any extra investment.

With the widespread use of image processing, serious developments are observed in the activities in the field of manufacturing (Pour, 2018). The efficiency of the personnel in manufacturing is improved with industrial camera applications that facilitate their work (Dutta et al., 2013). For example, in button production, it plays an important role in identifying faulty products by controlling hundreds of similar products by defining button types in the system once. Thanks to this technology, faulty products are detected by the comparison method and production quality is increased. The cameras placed on the clothes of the personnel and the human and robot power work in sync, increasing efficiency. Today, high-sensitivity cameras are designed to weigh less than 40g. In this way, when the decision-making abilities of people in the industry and the working power of robot automation combine, faster and more accurate product-oriented productions emerge. These systems record activities and studies, interpret results accurately, and make this data available for human use. Defect detection in manufacturing is seen as an important control mechanism in areas such as the number of daily employees and material counting. It is actively used in many fields such as agriculture, health, biomedical, robotics and the defence industry (Franke et al., 2020; Korkmaz et al., 2022c). As a result, super-standard image processing systems created with the rapid development of today's technology have become much more active, efficient and useful (Dutta et al., 2016). This technology, which will continue to develop without slowing down in the future, will enable us to have a say in many new areas with the training and support provided (Zhao et al., 2017; Liu and Ou, 2020).

3. Machining Processes Related to Image Processing

3.1 Turning

The use of digital image processing methods in the evaluation of tool wear and surface roughness (Demirsöz and Boy, 2022) can be focused on the evaluation of the surface quality of machined surfaces after the turning process (Shahabi and Ratnam, 2009; Dutta et al., 2013; Korkmaz et al., 2022b). A comparison can be performed with the results obtained with the electronic device called the tracer tip used in the market. High similarity between the physical measurements and the image measurements shows the effect on image processing in machined surface and tool wear images (Gupta et al., 2023) after machining, as shown in Figure 3. At the same time, it is aimed at measuring in a non-contact, non-destructive and precise manner (Liu et al., 2022).

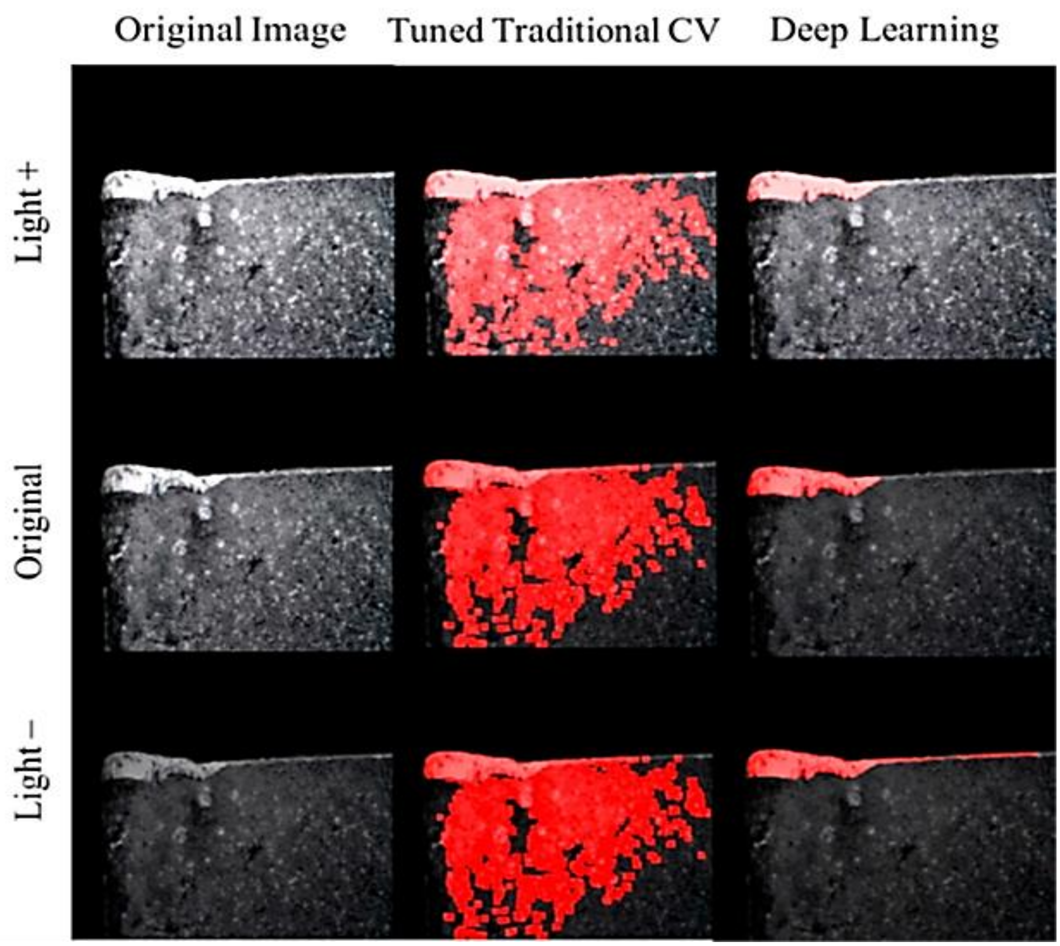

Figure 3. Transformation of a tool image into binary image after a turning process (Bergs et al., 2020).

3.2 Milling

Miniaturized end mill cutters are highly susceptible to minor vibrations and extreme forces that can be detrimental to tool life and control of surface quality. As a result of these effects, it is difficult to detect damage to the cutting edge of micro end mills and even poor surface quality (Ross et al., 2022). Several scientists managed several sensors and image processing systems mounted on the Computer numerical control (CNC) to monitor surface quality (Bradley and Wong, 2001; Dutta et al., 2018). The feed rate of the tool per tooth in micro end milling is quite high compared to conventional end milling. Thus, it is very important to determine the cutting factors. The tool is worn and creates poor surfaces (Kassim et al., 2007), which causes a waste of money and time if the cutting factors are not suitable. Consequently, the analysis of forces during micro end milling plays an important role in defining the machining characteristics, namely tool wear and surface roughness (Lam et al., 1992; Ross et al., 2023c). Accurate measurement of micro-cutting forces via image processing techniques and improving tool quality have become important (Ross et al., 2023), because excessive load is employed on small tools, and even small vibrations can have an important influence on machining. (Akkoyun et al., 2021). Figure 4 shows the surface quality of machined workpieces after milling with chatter and a stable situation.

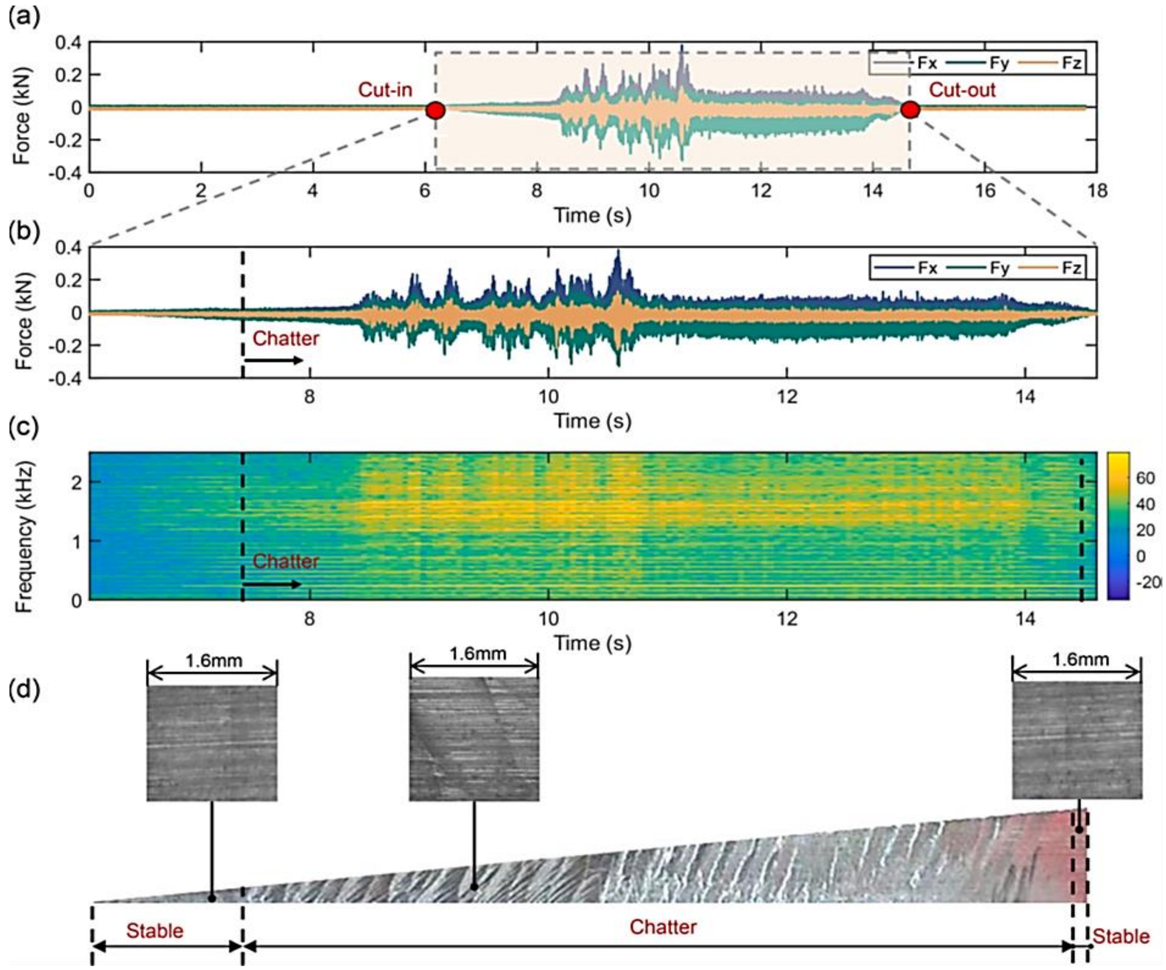

Figure 4. Milling experiment results for (a) cutting force collection; (b) cutting force excluding air cut; (c) STFT diagram excluding air cut; and (d) surface quality of machined workpieces (Zhang et al., 2023).

3.3 Drilling

A monitoring system must track the drilling process as a control (Binali et al., 2022; Uslu et al., 2022). In addition, metrology aspects are also taken into account to avoid possible damage caused by machine or tool collisions and reduced production quality (Davim et al., 2007). Sensors read a variety of information during the drilling process, form part of the information system at the scientific position, and pass and process the flow of information (Yaşar et al., 2021; Demirsöz et al., 2022). In other words, it acts as a link between the scientific process of the drilling itself and the control scheme of the machine (Berzosa et al., 2020). The image subtraction of a sample hole for the delamination factor is shown in Figure 5. However, the traditional method of hole surface measurement standards after drilling does not allow for real-time inspection without contact with the measured surface and cannot provide an objective inspection (Persson et al., 1997). Therefore, it is only very difficult image processing to use conventional profilometers (portable only) with the ability to directly check the surface of holes in automated production, online or offline. The main drawback of optical methods for evaluating surface micro geometry is their dependence on optical features and workpiece dimensions. With the development of optoelectronics, surface roughness can now be measured quickly and non-contactly (Kurek et al., 2017).

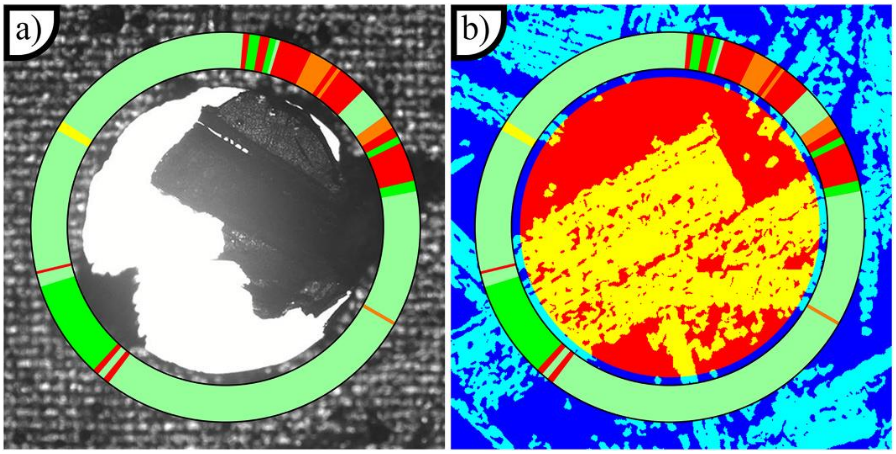

Figure 5. Image subtraction for the straight drilling experiments of Carbon fiber reinforced polymer (CFRP) composite (Geier et al., 2022).

3.4 Grinding

Grinded samples do not have clear color characteristics, and direct photography of the sample does not provide important color difference information (Kishore et al., 2022). Therefore, image processing is a new way to take advantage of the quality of the virtual image of the polished surface in the reference color image to detect the roughness of the polished surface. Color images are considered reference objects in these color images based on changes in the virtual image sharpness of the ground surface, and the surface roughness of the sample may be evaluated. In addition, the objective clarity index and the subjective judgement of the HVS (Human Vision System) are combined to detect surface roughness quickly and accurately (Pandiyan et al., 2020). The schematic diagram of digital image analysis of a sample grinding process is shown in Figure 6.

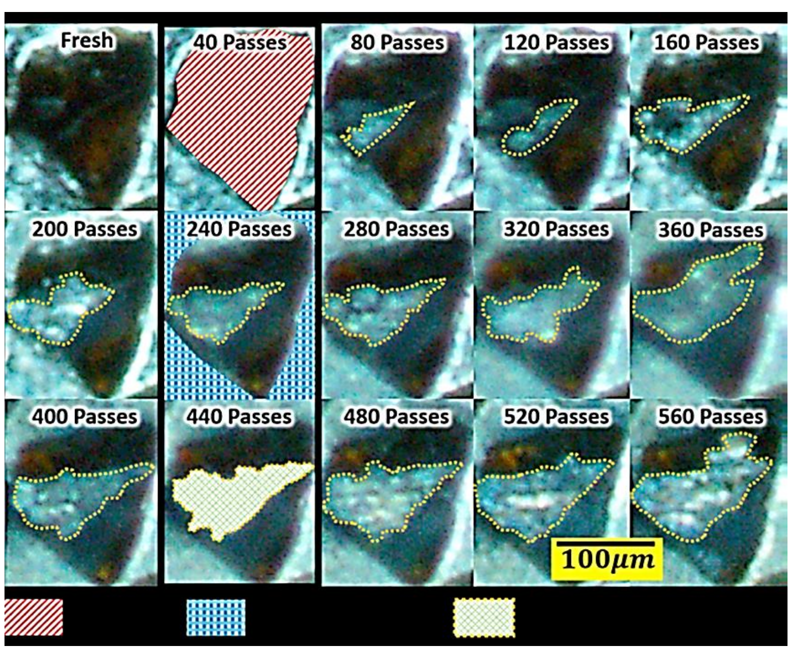

Figure 6. Schematic diagram of digital signal processing during a sample grinding (Lee et al., 2021).

3.5 Other Machining Methods

Creating an image processing algorithm that classifies finished cut surfaces treated by WEDM (Wire Electric Discharge Machine) based on surface microdefects The algorithm also detects the location of defects and suggests setting alternative parameters to improve surface integrity. The proposed automated analysis is more accurate, efficient, and repeatable than a manual scan. This method can also be used for automatic data generation, which suggests changing the parameters of a closed-loop system. The average, standard deviation, and defect area percentages of the improved binary image during the learning phase can be extracted and stored. If the processed surface image is not classified as a soft image, it can be suggested to set alternative input parameters to minimize model microdefects. This is based on the Euclidean distance between the "soft" class of data points closest to the current image data point (Dutta et al., 2013; Liu and Ou, 2020; Abhilash and Chakradhar, 2021). Table 1 shows the applications of image processing in different types of machining processes.

Table 1. Application of image processing in machining.

Machining Process	Year	Main application	Reference
Grinding & Milling	2008	Surface image of machined workpiece	Dhanasekar et al. (2008)
Turning	2016	Surface image of machined workpiece	Dutta et al. (2016)
Turning	2016	Surface image of machined workpiece	Li and An (2016)
Turning	2016	Surface image of machined workpiece	Bhat et al. (2016)
Drilling	2017	Drilling hole image	Kurek et al. (2017)
Milling	2017	Surface image of machined workpiece	Sun et al. (2017)
Face milling	2017	Surface image of machined workpiece	Pimenov et al. (2018)
Grinding	2017	Surface image of machined workpiece	Zhao et al. (2017)
Turning & Milling	2018	Surface image of machined workpiece	Rifai et al. (2019)

4. Conclusion and Future Trends

There are several advantages and disadvantages of the digital image processing techniques compared to other methods used in the processing, mainly for monitoring conditions. Some of the advantages are that the machine-view system is relatively low-cost system. Flexible is another important advantage of the machine composition system, in that the system can be moved, assembled, and disassembled on request. Surface defects can be easily discovered by machine vision, in addition to surface roughness. The ability to damage machining surfaces is limited by the surface-type slideshow of the exposure type, while the surface-limiting measurement is limited by the vision of the correction machine. However, there are some limitations to the use of the image processing techniques. A suitable lighting system and powerful image processing algorithm protected against machining noise (chip, cladding, etc.) are essential for the successful implementation of visual engineering techniques. Monitor drilling parts with very difficult digital image processing due to their inaccessibility.

The benefits of image processing vary according to the techniques used. Each of these techniques used in image processing approaches the image from a different angle. At the core of the studies on image processing lies image analysis and therefore digitization, and nowadays image processes includes design, manufacturing, electronics, machinery, etc. It is a general field of study used in many different fields, and considering the diversity of the areas used, the number of studies in this area is increasing day by day. For this reason, this study aims to make a general evaluation of the machining studies in the field of image processing.

Conflict of Interest

No conflict of interest between authors.

Acknowledgements
No acknowledgement.

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