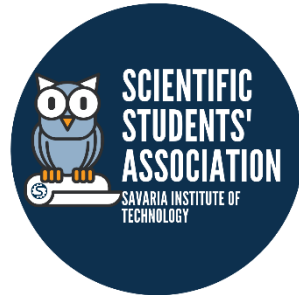




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SCIENTIFIC STUDENTS'S ASSOCIATION ESSAY

Camera-Based Tool Wear Monitoring for Enhanced CNC Machining Processes

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Chapter 1

Introduction

Numerical Control technology as known today, emerged in the mid-20th century. It can be traced to the year 1952, the U.S. Air Force, Massachusetts Institute of Technology in Cambridge, MA, USA, and the name of John T. Parsons (1913-2007), who is closely associated with the invention of numerical control (fig. 1.1)[1].



Figure 1.1: John Parsons, the inventor of the Numerical Controlled machine

This technology was not applied in production manufacturing until the early 1960's. The real boom came in the form of CNC, around the year of 1972, and a decade later with the introduction of affordable microcomputers[1]. In the manufacturing field, particularly in the area of metalworking, Numerical Control technology has caused something of a revolution. Even in the days before computers became standard fixtures in every company and many homes, machine tools equipped with Numerical Control system found their special place in many machine shops[1]. The relatively recent evolution of microelectronics and the never-ceasing computer development, including its impact on Numerical Control, has brought enormously significant changes to the manufacturing sector in general and the metalworking industry in particular. These early numerical control developments were principally for the aerospace industry, where it was necessary to cut complex geometric shapes such as airframe components and turbine blades[2].

Numerical Control can be defined as an operation of machine tools employing specifically coded instructions to the machine control system[1].

The early to mid-1970s was a time of revolutionary advancement in the area of machine tool controller development, when the term CNC became a reality[2]. The multiple benefits of cheaper electronics with greater reliability have resulted in the CNC fitted to the machine tools of today, with their power and sophistication progressing considerably in the last few years, allowing an almost artificial intelligence (AI) to the latest systems.

In the highly competitive manufacturing sector, maintaining an ideal CNC environment, including optimal tool and workpiece conditions, is essential for enhancing productivity, minimizing costs, and guaranteeing product quality.

In manufacturing industries, conventional machining operations, such as turning, milling, drilling, and grinding, are classified as the most common activities in production environments. With the rapid development of computer applications and technology, conventional machining has been gradually transformed into modern machining operations with efficient support for large-scale manufacturing. Although many of these advancements in machining have been implemented based on the programming language known as G-code (ISO 6936), it is a low-level programming language with a limited amount of information and is unable to provide data feedback[3].

As a result, CNC machines have limited capabilities in terms of their movement. They follow the programmed input even if unsuitable machining parameters are assigned. Furthermore, in the absence of a monitoring system, these scenarios may result in machine tool downtime. Machine downtime is defined as a certain duration of time during which no machining operation can be done on the workpiece[4], and can be divided into two—unavoidable and avoidable[3]. The former occurs due to machine maintenance or any replacement of the machine components, while the latter is due to disturbances during machining processes, which include overloading of spindle torque, excessive cutting force, chatter, tool wear, and other constraints[5]. Machine downtime due to tool breakage has been estimated to average 6.8%[6], but can be up to 20%[7].

Traditional methods of tool monitoring have faced challenges in terms of accuracy, adaptability, and real-time applicability, as well as the expenses related to necessary equipment. As a result, the development of innovative and efficient monitoring techniques has consistently been a topic of interest and continues to be an active area of research today.

This thesis presents the development and implementation of an innovative camera-based monitoring system for CNC machines, aimed at addressing the challenges associated with traditional monitoring methods while expanding its capabilities to include workpiece and workpiece holder monitoring. The thesis's objective is to offer a comprehensive understanding of the proposed system, including its design, implementation, and performance evaluation.

Chapter 2

Literature Review

2.1 Introduction to Industry 4.0 (I4.0)

The aim of IR 4.0 is to produce product models that are very flexible in terms of production and services.[8]

Industry 4.0, often termed I4.0, symbolizes the fourth revolutionary wave in manufacturing, underpinned by rapid strides in digital technology, automation, and data analytics. It is distinctly characterized by the integration of modern technologies and concepts, including the Internet of Things (IoT), cloud computing, mobile internet, and predominantly, artificial intelligence (AI)[9]. The convergence of these technologies has given rise to 'smart manufacturing'—a data-driven approach that leverages AI to enhance production processes[9].

This transformative shift has led to an exponential surge in data, particularly from manufacturing shop floors, bringing 'Big Data' to the forefront of manufacturing challenges[10]. To harness this data effectively, advanced computational techniques such as Machine Learning (ML) and Deep Learning (DL) have been employed. These methods have reshaped traditional manufacturing paradigms, from automating feature selection to facilitating optimal data fusion for varied analytic applications[9].

The modules of data-driven smart manufacturing, as outlined by Tao et al.[11], further elucidate the structure and functionality of this approach. These modules include:

- Manufacturing Module: Transforms raw material into the finished product.
- Data Driver Module: Implements the smart manufacturing approach throughout the data lifecycle, supporting real-time monitoring and problem processing.
- Real-Time Monitor Module: Provides a critical step that enforces quality improvement through real-time insights, allowing for condition monitoring and preventive maintenance.
- Problem Processing Module: Uses intelligent monitoring to enhance decision-making in a system.

One of the salient applications of the data-driven approach in smart manufacturing is intelligent machining[9]. Machining, also known as subtractive manufacturing, spans a broad range of traditional processes such as milling, turning, planning, drilling, and more[9]. Within this realm of intelligent machining, a pivotal component that has gained immense significance in the I4.0 context is Tool Condition Monitoring (TCM).

TCM is a method used in various metal removal processes including but not limited to turning, milling, and drilling[4]. Historically, TCM was characterized by the utilization of classical Artificial Intelligence (AI) methods to monitor and analyze the state of machining tools. However, during the early stages of TCM research that utilized classical AI methods, there were

significant constraints regarding the quality and volume of data[10]. Classical techniques such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and fuzzy clustering were previously adequate for the limited data from these processes. However, they lacked the accuracy and adaptability required to cater to changing conditions and operational parameters during machining[10].

Classical AI techniques soon became inadequate for the task of processing this volume of data. Deep learning algorithms, having shown immense success in various fields like autonomous driving and medical imaging, began to emerge as potent solutions for TCM in this new environment of big data[10].

However, in the academic world, the challenges related to data for deep learning applications are evident. With high experimental costs and intensive labeling requirements, strategies such as regression to finely labeled data have been proposed to produce synthetic data to meet deep learning's large dataset necessities[12]. The challenges persist, notably in selecting the right deep learning method for a specific machining process. The success of these methods often depends on the quality of the processed signal which feeds the deep learning algorithm[10]. The choice of feature selection, extraction, and signal transformation methods plays a pivotal role in ensuring a high-performance system.

A noteworthy mention is the distinct behavior of metal cutting methods. Interrupted processes like milling offer more detailed insights into the tool's state or mode of wear, as these processes can imprint this information on the signal's nonstationary time-frequency profile[13]. Leveraging deep learning can effectively detect this intricate information, provided the appropriate signal transformation technique is applied[10]. However, this approach can sometimes lead to increased data sizes, presenting processing and storage challenges[10].

The vast data generated on the shop floor calls for more robust methodologies. While predominant deep learning methods like DMLP, CNN, and LSTM rely on accurately labeled data from varied operational conditions, a shift towards unsupervised and semi-supervised approaches may provide a more comprehensive solution to enhance the self-learning capabilities of deep learning[10].

An innovative approach discussed in the context of TCM is the application of transfer learning (TL) to deep learning. TL focuses on adapting knowledge from one task to another related task, which can improve the generalization capabilities of deep learning methods and reduce training costs. There are opportunities to create pre-trained networks specialized for specific processes, such as "Turn-Net" or "Mill-Net"[10].

Furthermore, the relevance of TCM systems in the context of I4.0 is undebatable. A robust TCM system ensures compatibility between software and hardware components, optimizing tool life and preventing machine tool failures, establishing it as a linchpin in the successful realization of Industry 4.0 ideals[14, 15, 16].

To encapsulate, the march towards Industry 4.0 is at the intersection of advancements in technology and the need for smart, efficient manufacturing. as the manufacturing sector evolves under the umbrella of Industry 4.0, tool condition monitoring stands out as a crucial aspect that can significantly impact manufacturing efficiency, quality, and safety. The integration of advanced deep learning algorithms offers promising avenues for enhancing TCM, potentially revolutionizing the way machining processes are monitored and optimized in the age of Industry 4.0[10].

2.2 Related Solutions In CNC Machines

CNC milling has emerged as an intricate machining process with profound significance across various industries, notably in the automotive and aerospace sectors. A critical challenge faced by manufacturers is to ensure both minimized maintenance costs and augmented reliability

of their manufacturing equipment[17]. Within this backdrop, a paramount need arises to extend the service life of cutting tools. This involves steering clear of premature replacements, thus sidestepping potential scrap incidents resulting from tool breakages[17]. Such demands underscore the growing necessity for a transition from traditional maintenance approaches to condition-based ones, emphasizing the value of robust, adaptive, and efficient tool condition monitoring (TCM) methods[17].

While a plethora of analytical and empirical models have been established to predict tool wear trends during CNC milling, their applicability in the labyrinth of real-world scenarios remains questionable[17]. These models, while efficacious in controlled settings, falter in representing the myriad of factors affecting tool wear rates in diverse operational circumstances. The inherent non-linearity in tool wear trends, combined with the influence of a vast array of milling operation variations, renders the development of universal models an elusive goal[17]. Addressing these concerns, there has been a marked shift towards data-driven TCM approaches, which typically offer a superior balance of cost and performance[17]. Machine learning methodologies, particularly sequence models, Support Vector Machines (SVM), Artificial Neural Networks (ANN), and more recently, deep learning, are leading the forefront of this transformation, promising potential solutions to prevailing TCM challenges[17]. Key areas of TCM research have surfaced:

- **Enhancements in Data Pre-processing and Feature Engineering:**

The pre-processing of signal data holds crucial importance in TCM, as it lays the foundation for subsequent modeling processes. Current models, though data-driven, may not be entirely compatible with existing signal processing techniques like Fourier Transform (FT) and Wavelet Transform (WT)[17]. Advancements here could either be realized through refining hand-engineered features or by pivoting towards autonomous feature extraction. In this realm, deep learning architectures, particularly, stand out for their prowess in adaptive feature extraction without reliance on separate feature processing stages[18].

- **Evolution of Deep Learning Models with Incremental Learning:**

Tool wear, with its inherent complexity, necessitates deep learning architectures like Convolutional Neural Networks (CNN) that can assimilate vast datasets[19, 20]. To cater to the expansive data requirements, ANN models equipped with incremental learning capabilities offer potential solutions, permitting models to integrate new training samples seamlessly[21, 22].

- **Focus on Sequential Relationships in Data:**

Recognizing the sequential nature of input data remains essential for TCM. While sequence models like Markov models and Kalman filters have proven effective for such data, they grapple with issues pertaining to long-term dependencies[17]. In contrast, Recurrent Neural Networks (RNNs) embrace sequential relationships, with variants like bidirectional RNNs and gated recurrent units showing promising outcomes[18, 23].

- **Emerging Trends and Areas for Future Exploration:**

As the TCM landscape evolves, the convergence of diverse machine learning methodologies into hybrid models or ensemble methods presents a promising direction[17]. Moreover, while ample research has focused on tool wear diagnosis, the domain of tool wear prognosis, especially Remaining Useful Life (RUL) prediction, remains relatively underexplored. Yet, RUL predictions are indispensable for industrial applications, potentially superseding diagnosis in TCM relevance[17].

2.3 Image Processing in CNC Machining

With the increasing demands for high-speed production, the complexity inherent in today's CNC processes has grown exponentially. Concurrently, there's an augmented risk associated with collisions due to the discrepancies between actual machining scenarios and virtual scenes depicted in CAD/CAM processes[24]. A burgeoning solution to this challenge is the integration of image processing techniques into CNC operations, aiming to make the process smarter and more adaptive.

The essence of this approach is grounded in the real-time acquisition and processing of images from either real machining scenarios or virtual machine scenes. These images facilitate object identification, especially if these objects are pre-existing in the CAD database[24]. By harnessing image processing, it becomes plausible to determine safe and efficient trajectories, which can be a modification of previously established paths from the CAM systems. Such trajectories are then implemented in real-time machining environments, significantly enhancing the safety and efficiency of CNC operations.

Central to this innovative approach is the Safe and Efficient Trajectory (SET) algorithm designed for point trajectory management. An extended version, termed the Rectangular Enveloped object Safe and Efficient Trajectory (RESET) algorithm, is tailored for object trajectories[24]. These algorithms ingeniously produce secure, un-functional trajectories for multi-axis machine tool envelopes. Concurrently, the objects in the scene are identified and pinpointed via image processing tools, allowing trajectories and setups to be optimized and adjusted to prevent potential collisions[24]. This level of optimization proves pivotal for setup corrections, both prior to and post-production, and also for real-time or "online" production scenarios.

Interestingly, the advancements documented herein bridge the communication gap that has historically existed between virtual and actual CNC scenarios. By implementing image processing techniques, both tools and obstacles within a scene can be accurately identified and localized. Such enhancements have profound implications for trajectory generation, as it facilitates intelligent, optimized paths for multi-axis machine tools, especially for real-time setup corrections[24]. While the results documented in the study were predominantly anchored on virtual machine images (owing to their cleaner nature and simplicity), the scope for applying these techniques to real images is evident. Such virtual images simplify the integration process with CAD systems and image processing units. Moreover, leveraging these virtual images can bolster the link between actual and virtual scenarios, making real-time adjustments and communications more seamless[24].

In perspective, the incorporation of image processing in CNC machining offers avenues for enhancing the communication and operational bridge between reality and virtuality. As the study suggests, such techniques might eventually be integrated into STEP-NC technology, which represents the broader context of this work[25]. Future avenues might also entail the consideration of various parameters, like the mobility, knowledgeability, controllability of obstacles, and machine tools[24].

2.4 Tool Setting and Workpiece Determination

The technological landscape of manufacturing has been significantly altered by the introduction of Industry 4.0 (I4.0), characterized by increased connectivity, automation, and data-driven decision-making. As such, traditional methods for tool setting and workpiece determination are being critically evaluated for their fit in this advanced setting. This review explores these conventional techniques, their limitations, and the challenges they present in the dynamic and demanding environment of I4.0.

Traditional methods for tool setting primarily revolve around manual adjustments, often

guided by operator experience and sometimes assisted by basic instruments or gauges. Workpiece determination, on the other hand, involves setting the workpiece’s position and orientation, typically based on visual inspection, edge finders, or touch probes. The given excerpt from the handbook highlights a specific method known as position compensation, which utilizes G-codes to make adjustments to the machine’s position based on pre-defined offsets stored in memory (either using the H or D address). This form of compensation provides a correction for the distance between the machine’s zero and program zero.

2.4.1 Limitations and Challenges

While these traditional methods have served the manufacturing industry well for decades, they present several limitations in the context of I4.0:

Manual Dependencies: Traditional tool setting often relies heavily on operator expertise, leading to variability in outcomes and potential for human error. As I4.0 pushes for consistent and optimal production results, this reliance on manual intervention becomes a bottleneck.

Time Consumption: Given I4.0’s emphasis on speed, the time-intensive nature of manual tool setting and workpiece determination is a significant limitation. Techniques like position compensation, while automated to a certain extent, still require manual input for defining offsets.

Precision Limitations: With I4.0’s high standards for precision and repeatability, the potential inaccuracies stemming from visual inspections or basic instruments in traditional methods become glaringly evident.

Lack of Real-time Adaptability: Traditional methods, like the position compensation mentioned in the excerpt, rely on pre-set values and lack the capability to adapt in real-time to changing conditions or to optimize based on real-time feedback, a cornerstone feature of I4.0.

The evolution from traditional manufacturing to I4.0’s advanced paradigm underscores the urgent need for updated tool setting and workpiece determination methods. As I4.0 integrates cyber-physical systems, Internet of Things (IoT), and advanced analytics into manufacturing, the methods to set tools and determine workpieces must also evolve to be more automated, precise, and adaptable.

Industry 4.0, with its emphasis on speed, precision, and automation, necessitates a re-evaluation of traditional methods used in manufacturing, particularly in tool setting and workpiece determination. While traditional methods have their merits, their limitations, especially in the face of I4.0’s stringent requirements, underscore the need for innovative approaches that can seamlessly integrate with the smart manufacturing paradigm of the future. As the manufacturing realm continues its march towards more connected and automated systems, the tools and techniques must concurrently evolve to meet the new challenges head-on.

2.5 Tool Monitoring with Other Sensors

The precision and timeliness of tool monitoring in CNC machining are vital to minimize machine downtime, prevent tool breakage, and optimize the manufacturing process. A failure in detecting tool breakage can result in compromised surface quality, increased production costs, and potential harm to both the workpiece and the machine. While traditional methods like monitoring cutting forces, vibrations, acoustic emissions, and spindle power consumption have been employed[26, 27, 28], they often fall short in providing real-time and accurate monitoring solutions.

Acoustic emission (AE) techniques have proven effective for tool wear monitoring in high-speed machining processes due to their sensitivity, quick response time, and consistency[26]. AE-based monitoring of milling processes for fiber-reinforced plastics has also demonstrated

versatility and robustness, with the ability to detect workpiece damage and tool wear state[29]. Despite these advantages, AE techniques still face challenges in accurately determining tool wear and breakage in real-time. For instance, AE methods are susceptible to interference from ambient noise sources, which can lead to false alarms or missed detection of tool wear and breakage events. Furthermore, the interpretation of AE signals can be complex, as they can be influenced by various factors such as cutting conditions, material properties, and machine tool dynamics. This can make it difficult to accurately identify tool wear or breakage using AE techniques alone.

Force analysis has been another widely used method for monitoring tool wear and breakage in CNC machining processes. By measuring cutting forces during the machining process, this technique can provide valuable insights into the condition of the cutting tool. Cutting forces tend to increase as the tool wears, and any sudden change in the cutting force can indicate tool breakage or other issues[30]. Force-based monitoring systems have been widely adopted due to their simplicity. However, these systems are relatively expensive and have certain disadvantages that limit their effectiveness in detecting tool wear and breakage. First, the accuracy of force-based monitoring systems can be affected by factors such as varying cutting conditions, material properties, and machine tool dynamics[31]. These factors can introduce noise into the force measurements, making it challenging to accurately identify tool wear or breakage. Furthermore, force analysis typically requires specialized sensors and equipment to measure cutting forces, which can be cumbersome to install and maintain. In addition, the calibration and setup of these sensors can be time-consuming and complex, potentially leading to inaccuracies and inconsistencies in the monitoring process.

In light of these limitations, researchers have turned their attention to alternative monitoring techniques, such as automatic control systems and machine vision. The growing interest in recent years stems from the potential that machine vision and image processing techniques offer in monitoring tool wear and breakage more effectively. For instance, a study by Peng et al.[32] proposed an automatic tool wear monitoring system based on machine vision, using the wear area of the flank face as a new evaluation index. One such study by Kratochvil et al.[27] explored the possibilities of tool breakage detection using the OpenCV system implemented in Python.

Artificial neural networks (ANNs), particularly wavelet neural networks (WNN), have been applied to tool wear monitoring in CNC milling processes. The WNN has shown superior performance in predicting tool wear when compared to other types of ANNs and statistical models[28]. Tool wear monitoring using ANNs has been found to be at least 10% more accurate than response surface methodology (RSM)[28].

By harnessing the capabilities of computer vision, researchers aim to develop a tool wear monitoring system that can provide real-time feedback and enable proactive decision-making to maintain optimal cutting conditions and extend tool life. In this context, our goal is to propose a new method that leverages the potential of computer vision techniques to develop a more effective system for tool wear monitoring. By exploring innovative approaches and building upon the strengths of existing methods, we aim to address the challenges associated with traditional monitoring techniques and ultimately contribute to the development of a superior monitoring system.

Chapter 3

Methodology

3.1 Objective

Given the heightened competitiveness of the manufacturing sector and the limitations of traditional tool wear monitoring methods, innovative solutions are paramount for ensuring both efficiency and quality. The primary objective of this study is to design, develop, and validate a camera-based diagnostic system tailored for *real-time* tool breakage detection in CNC milling machines. By applying sophisticated image processing techniques to high-resolution video recordings, this system aims to provide a quantifiable analysis of tool profile variations, facilitating a robust determination of tool integrity and addressing the historical challenges associated with tool wear monitoring.

3.2 Camera Setup and Video Acquisition

The cornerstone of this study hinges upon the precise capture of the CNC milling tool's operations in high detail. This precision was achieved through the deployment of a high-resolution mobile phone camera, chosen for its ease of integration, and high-quality video capabilities. The mobile phone used was iPhone 12 Pro and its camera specifications are as follows:

- Sensor: 12 MP (1.4 micron photo sites)
- Lens: 26 mm-equivalent f/1.6-aperture lens
- Features: PDAF, OIS
- 4K Dolby Vision HDR video at 24/30/60 fps

A pivotal factor for accurate tool profile capture is camera positioning. To this end, a tripod was strategically positioned inside the CNC machine cabin, ensuring an unobstructed and stable viewpoint of the tool at its original set position. (see Fig. 3.1). Additionally, it is crucial to place the camera as close as possible to ensure high-quality images free from noise and disturbances.

For this project, only videos were recorded, and pictures were not used. The recorded videos have a resolution of 1920 pixels in width and 1080 pixels in height, providing a sharp representation of the tool's surface. Additional video specifics include a data rate of 23,165 kbps, a total bitrate of 23,346 kbps, and a frame rate of 59.97 frames per second. These specifications ensure smooth video playback and enable the extraction of detailed frames for subsequent image processing.



Figure 3.1: Camera and tripod inside the CNC cabin.

To synchronize the camera's frame rate with the CNC machine's operation, it was essential to establish a clear correspondence between frames and tool rotation. The CNC machine was programmed such that the tool rotates at 60 degrees per second. This setting, combined with the camera's capture rate of approximately 60 frames per second, ensures that each frame of the video corresponds to exactly 1 degree of the tool's rotation. As a result, the tool completes a full 360-degree turn in 6 seconds, aligning perfectly with 360 frames. This one-to-one relationship between frames and degrees facilitates accurate and comprehensive visual coverage of the tool's entire rotation within the video's duration.

3.3 Image Processing

The image processing methodology involves a systematic sequence of operations designed to extract relevant features from the captured video frames. This allows for the accurate identification and assessment of the tool's condition. The process is as follows:

3.3.1 Frame Extraction and ROI Cropping

From the recorded videos, individual frames were extracted to facilitate a frame-by-frame analysis. Given the unique design of the CNC machine, wherein the tool only moves in the Z-direction while the workpiece maneuvers in the X and Y directions, the tool maintains a consistent position in the frame when elevated to its highest position. Due to this consistent positioning and the fixed camera setup, it's feasible to define a region of interest (ROI) that encapsulates the dominant position of the tool in the frame.

Subsequent to frame extraction, each frame was cropped to this predefined ROI. This cropping isolates the tool, eliminating unnecessary background and ensuring that the subsequent image processing techniques are exclusively applied to the area where the tool is prominently

visible. By focusing on this ROI, the analysis becomes both computationally efficient and more precise, as it concentrates solely on the tool's appearance and condition.



Figure 3.2: A cropped frame highlighting the region of interest (ROI) where the tool is prominently visible.

3.3.2 Background Subtraction

Background subtraction is a crucial image processing step that aims to isolate the tool from its surrounding context, allowing for clearer and more precise analysis. In this study, multiple background subtraction methods were evaluated. Each method was subjected to rigorous testing to determine its efficiency and accuracy in isolating the tool from the background. After an extensive assessment, the median-based background subtraction method emerged as the most effective. This approach was adept at minimizing noise and offered optimal distinction between the tool and the surrounding machinery. (Fig. 3.3)



Figure 3.3: Resultant frame using Median Frame Differencing

While median frame differencing demonstrated proficiency in eliminating background elements, particularly yielding clean edges around the tool, the method was not without its limitations. The spindle head, subject to slight positional shifts possibly due to variations in the tool's operation, occasionally remained partially visible in the processed frames. These positional shifts, although minor, could introduce inaccuracies when determining the tool's height. Therefore, while the median frame differencing method excels in certain aspects, its application alone does not suffice for the precise measurement of the tool's height. To address this, additional methods were explored and implemented to ensure the accurate extraction of the tool's height, thus maintaining the reliability of the diagnostic system.

3.3.3 Thresholding

After the application of median frame differencing, the processed frames exhibited a high level of detail around the tool edges. However, the subtraction process introduced minor imperfections in the form of holes within the tool's structure. To address this issue and enhance the image for further processing, a thresholding technique was employed.

The thresholding step served as a preparatory measure for the subsequent morphological operations. By converting the grayscale output of the median differencing into a binary format, the contrast between the tool and the background was accentuated, which is essential for the effectiveness of morphological closing.

This binarization process was crucial in facilitating the identification and filling of the gaps within the tool's structure. The resulting binary images thus provided a more solid representation of the tool, setting the stage for the morphological closing operation to effectively seal the discontinuities and refine the tool's silhouette in preparation for precise height extraction.

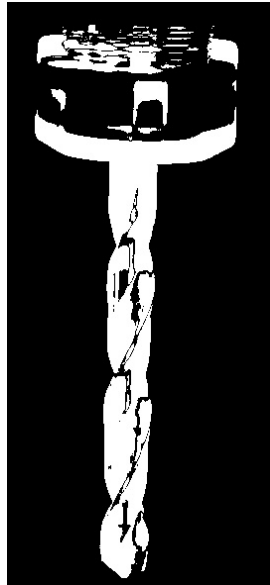
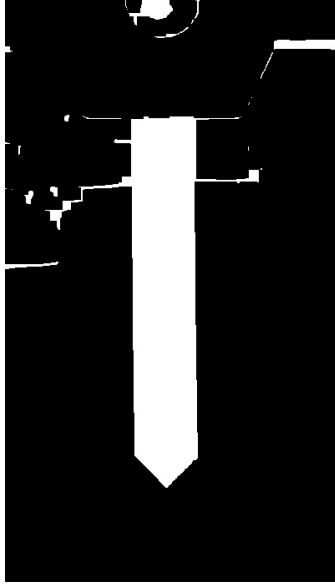


Figure 3.4: Binary image of the tool following thresholding. The process enhances contrast between the tool and the background, preparing for morphological closing to address discontinuities within the tool's structure.

3.3.4 Morphological Closing

Morphological closing is a dilation operation followed by erosion, applied to binary images. This technique is particularly effective at sealing small holes and gaps within the foreground objects and removing small objects in the background, which in this context is the tool's representation.

The selection of kernel size was pivotal to the effectiveness of this procedure. A kernel size of 5 was chosen based on multiple trials. Smaller kernel sizes failed to address the holes on the edges adequately, leading to an incomplete representation of the tool. On the other hand, an increase in the kernel size might compromise the detail on the tool's edges. The size of 5 represented a balanced approach, aiming to maintain tool detail while filling unintended gaps as shown in Fig. 3.5.



(a) Cutter after morphological closing



(b) Drill after morphological closing

Figure 3.5: Comparative representation of a cutter (a) and a drill (b) post morphological closing operation, demonstrating the technique's effectiveness in filling gaps while preserving structural detail across different tool types.

The result of the morphological closing was a more cohesive and accurate binary representation of the tool, which facilitates the subsequent steps in the tool's profile analysis. This refinement step is pivotal in preparing the image for further analysis of tool wear, ensuring that subsequent measurements reflect the true condition of the tool without artifacts from prior processing steps.

3.3.5 Identification of the Tool's Extent

The binary segmentation and morphological closing stages significantly clarified the tool's image, yet some remnants of the tool holder persisted, potentially confounding subsequent analyses. To precisely delineate the tool's boundaries, a computational method was devised to identify the start and end of the tool within the image.

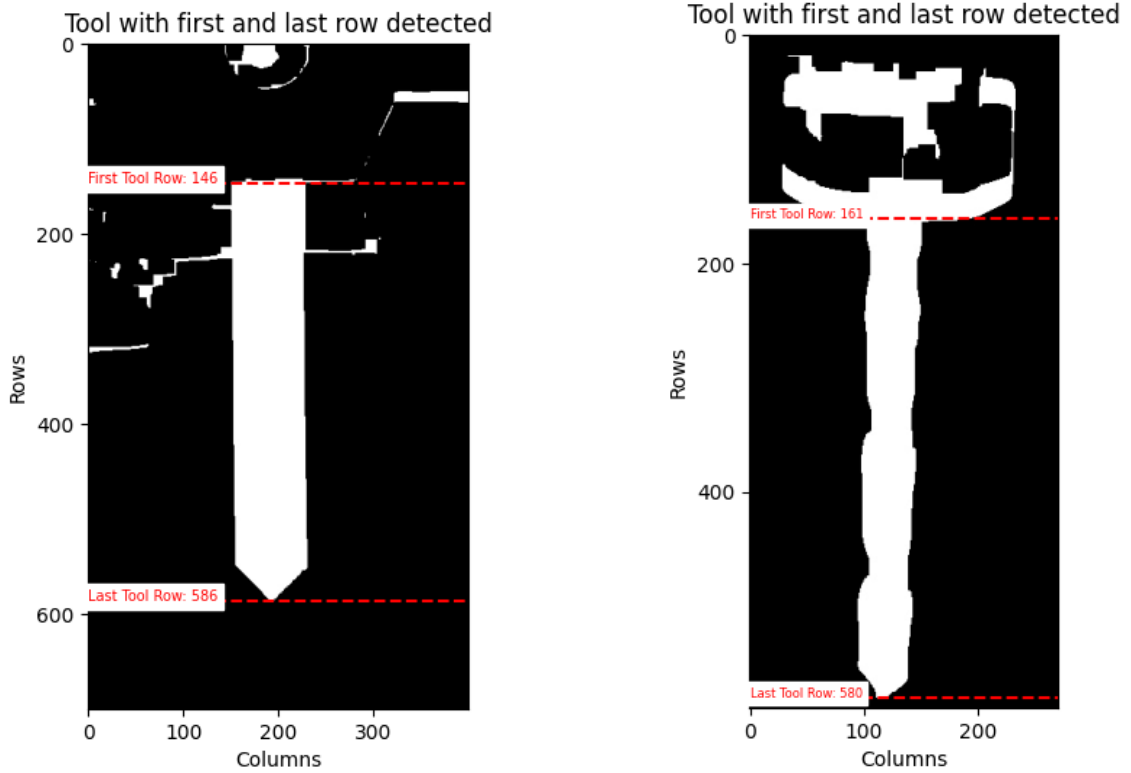
The approach for identifying the upper boundary of the tool involved analyzing the distribution of white pixels across each row of the binary image. The tool was differentiated from the tool holder by a concentration of white pixels within a central region, observed consistently across consecutive rows. This pattern was distinct from the tool holder, where white pixels were more dispersed. Even when these pixels appeared in a central position and next to each other, they did so only for a few rows, distinguishing them from the pattern observed in the tool. To quantify this pattern, the criterion was based on the average number of white pixels per row, considering only those rows with white pixels, plus or minus one standard deviation of these counts.

An algorithm was then utilized to scan through the rows, applying this pixel count range as a criterion. To confirm the initial presence of the tool, the algorithm required that the

defined pixel count be maintained consistently over 76 consecutive rows, equivalent to 10mm or 1cm, given the scale of the imaging. If this consistency was observed, the first row in this sequence was designated as the upper boundary of the tool. This approach ensured a more robust identification of the tool's start, minimizing potential errors from transient or isolated pixel count anomalies.

Locating the lower boundary of the tool was a more straightforward process, owing to the clear distinction between the tool's end and the surrounding space in the processed image. The last row containing white pixels that matched the tool's characteristics was identified as the lower boundary. This was typically clear and unambiguous, as the morphological processing had effectively removed any extraneous pixels below the tool.

A representation of the detected first and last rows for both a cutter tool and a drill tool is illustrated in Figures 3.6a, 3.6b.



(a) First and last row detection in a cutting tool. (b) First and last row detection in a drilling tool.

Figure 3.6: Comparative representation of the first and last row detection in cutting and drilling tools.

3.3.6 Summation of White Pixel Counts in Terminal Tool Region

A critical aspect of the image analysis involved calculating the sum of white pixel counts in the last 50 rows of the tool's binary silhouette for each frame. This metric was chosen to capture the density of the tool's cutting edge, which is the most susceptible to wear during the machining process. This quantitative measure provides insight into the tool's condition at each degree of rotation, as each video frame corresponds to one degree of the tool's rotation.

The methodology for this analysis entails systematically summing the white pixels in the specified terminal region across the sequential frames. This process generates a data set that

reflects the wear pattern along the tool's cutting edge over its entire rotation.

The subsequent graphical representation of these summed pixel counts will be detailed in the results section. This graph will plot the white pixel counts against the corresponding tool rotation degrees, offering a comprehensive view of the wear pattern. This visualization is not just a result of the analysis but also a critical tool for interpreting the tool's condition, revealing wear patterns that might not be apparent from the raw data alone.

Chapter 4

Results

4.1 Introduction to Results

This chapter presents the findings of the study, focusing on two critical aspects of tool condition monitoring in CNC milling machines: the detection of tool breakage and the assessment of tool edge wear. These findings are the culmination of the comprehensive methodology detailed in the previous chapter, where tool height measurements and white pixel count analyses were conducted on high-resolution video frames of the milling tool.

The results explained in this chapter are twofold: first, the detection of tool breakage using precise measurements of tool height, which is vital for maintaining operational efficiency and safety. Second, the innovative analysis of white pixel counts for the detection of tool edge wear, a subtler but equally significant indicator of tool condition. These findings represent a significant advancement from conventional monitoring methods, offering real-time insights into the tool's condition.

Together, these results not only validate the proposed diagnostic system but also offer valuable insights into the tool's operational integrity, demonstrating the system's potential in enhancing the predictive maintenance capabilities of CNC machining. This chapter will detail these results, providing a comprehensive analysis of the tool's condition and discussing the implications of these findings in the context of advanced manufacturing processes.

4.2 Detection of Tool Breakage

This section presents the results derived from the tool height measurements, a critical parameter for identifying tool breakage. The analysis focuses on the variations in tool height captured through the high-resolution video frames, which were meticulously processed as outlined in the methodology chapter.

4.2.1 Tool Height Variations and Breakage Detection

The process of accurately measuring the tool's height commenced with the establishment of its upper and lower boundaries, as detailed in the previous sections. The distance, in terms of the number of rows between these two points, provided a direct pixel count that corresponded to the tool's height. To translate this pixel measurement into real-world dimensions, a calibration factor was applied. Based on the camera specifications, each pixel was found to represent an area of $0.132 \times 0.132 \text{ mm}^2$. This calibration derived from the observation that a tool with a diameter of 5mm spanned 38 pixels in the image.

The effectiveness of the precise height measurements was underscored by their application in detecting tool breakage. To demonstrate this, representations of a drill tool in both intact

and broken forms are provided in Fig. 4.1. Following the mounting of these tools onto the tool holder, their heights were accurately measured using precision measurement devices to establish a reliable baseline. The intact tool height after mounting was measured to be 57.2mm and the broken tool was measured to be 51.8mm. The tool holder was then mounted, and the tool heights were recalculated using the camera-based system, translating pixel counts into real-world dimensions as shown in Fig. 4.2a and Fig. 4.2.

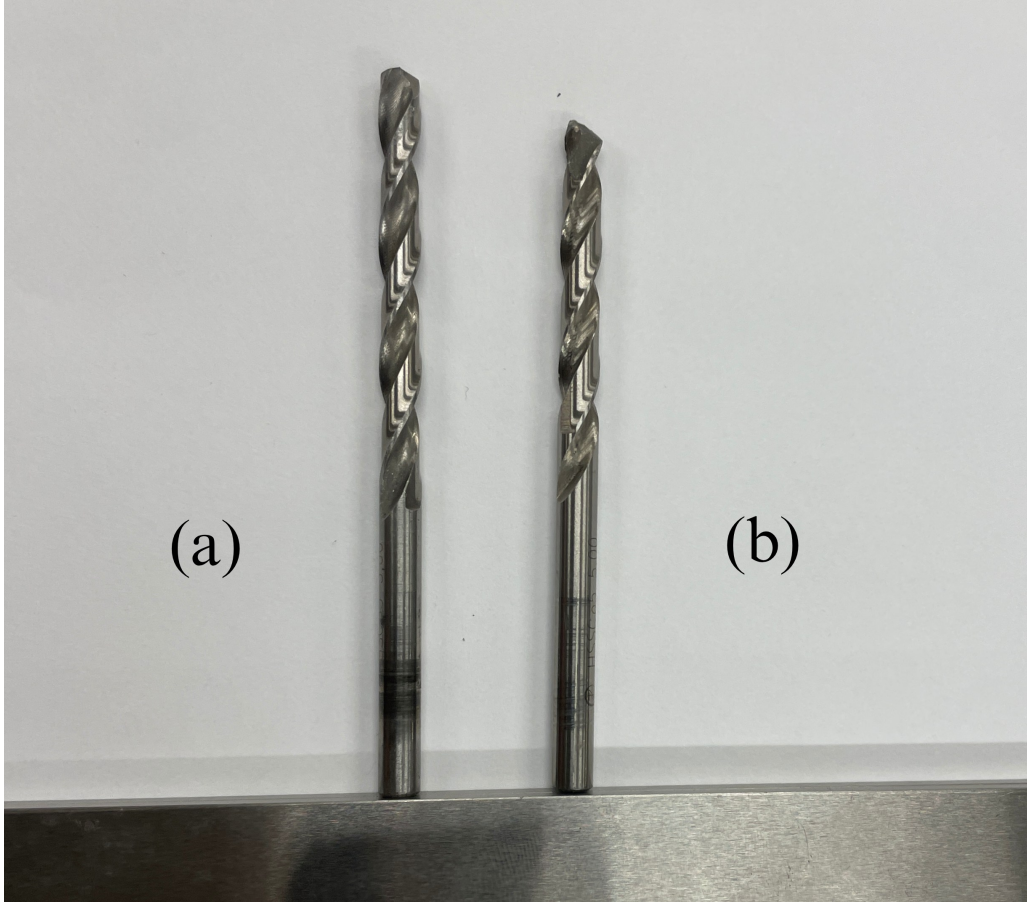


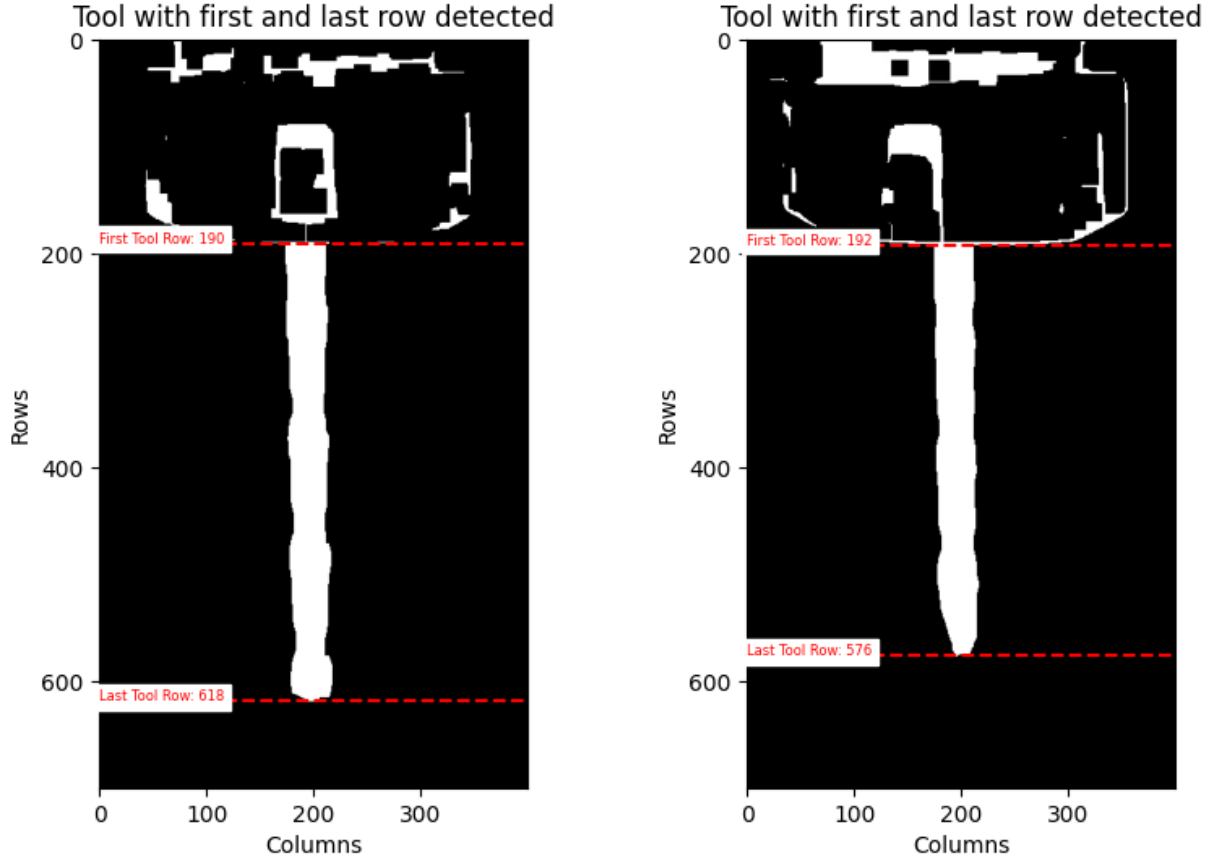
Figure 4.1: Drilling tool with 5mm diameter. a) Intact tool b) Broken tool

The results were promising, showing a mere 2% error between the heights measured by the camera system and those obtained with standard measuring devices. Specifically, the intact tool, which measured 57.2mm using precision devices, was calculated to be 56.5mm by the camera-based system. Similarly, the broken tool, originally measured to be 51.8mm, was calculated as 50.7mm by the camera system.

This marginal error margin of 2% is noteworthy, especially considering the complexities involved in translating pixel counts into real-world dimensions. The accuracy achieved by the camera-based system is commendable and falls well within acceptable limits for industrial applications. It demonstrates that the camera-based diagnostic system is not only a viable alternative to traditional measurement methods but also offers the added advantages of real-time monitoring and analysis.

Another instance, involving cutter tools, was similarly subjected to the diagnostic process. The methodology applied for the cutter tool followed the same principles as detailed for the drill tool. The camera-based system captured high-resolution video frames of the cutter tool, from which the tool's height was meticulously measured.

These findings underscore the potential of integrating advanced image processing techniques and machine vision in the field of CNC machining. The ability to accurately measure tool



(a) Intact tool height: 428 rows equal to 56.5mm. (b) Intact tool height: 384 rows equal to 50.7mm.

Figure 4.2: Height of the tools calculated using the camera based system (Calculated based on the established conversion factor where each row represents a height of 0.132mm).

dimensions, with minimal error, is a significant step forward in enhancing the efficiency, safety, and productivity of manufacturing processes.

4.2.2 Implications for Tool Monitoring

As demonstrated by the results, the camera-based diagnostic system accurately measures tool heights in CNC machines, with a minimal error margin. This precision is vital for detecting tool breakage, a common and costly issue in CNC machining. The system's ability to detect even slight changes in tool height ensures timely identification of tool breakage, potentially preventing costly downtime and damage to the machine or workpiece.

The implications of this development are significant for the manufacturing industry. By integrating this camera-based system, manufacturers can enhance the reliability and safety of their CNC operations. Early detection of tool breakage not only saves time and resources but also contributes to maintaining consistent quality in manufacturing processes.

Having demonstrated the efficacy of the system in the realm of tool breakage detection, attention is now directed towards another crucial aspect of tool condition monitoring: edge wear detection. Edge wear, often manifesting more subtly compared to tool breakage, can markedly impact the precision and quality of the machining operations. The ensuing section delves into how the camera-based system is adept at extending its functionalities to encompass the monitoring and analysis of tool edge wear, thus presenting a holistic solution for tool

condition monitoring.

4.3 Detection of Tool Edge Wear

The edge wear monitoring segment of this study utilizes an innovative approach to assess tool condition in CNC machining. The essence of this method lies in analyzing the terminal region of the tool, specifically focusing on the last 50 pixels, approximately equivalent to 6.6mm of the tool's edge. This region is critical as it bears the brunt of wear during machining operations.

For each frame of the high-resolution video captured during the machining process, which corresponds to every degree of the tool's rotation, a systematic analysis is conducted. The process involves summing the number of white pixels within the terminal 50-pixel region of the tool's silhouette. This quantifiable approach provides a pixel-based measure of the tool's edge integrity.

The data thus obtained is plotted on a graph, where the x-axis represents the tool rotation in degrees, and the y-axis denotes the sum of white pixels in the specified terminal region. This graphical representation offers a comprehensive view of the tool's edge wear pattern over a complete rotation.

To demonstrate the effectiveness of this method, a specific cutting tool at varying stages of wear was analyzed. Fig. 4.3 presents four instances of the same cutter tool, each depicting a distinct stage of wear, thereby providing a comprehensive overview of the tool's condition over time:

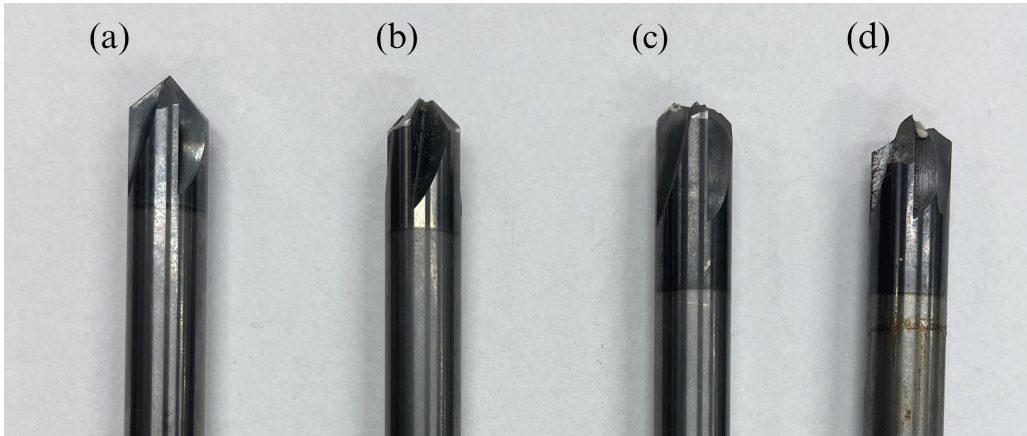
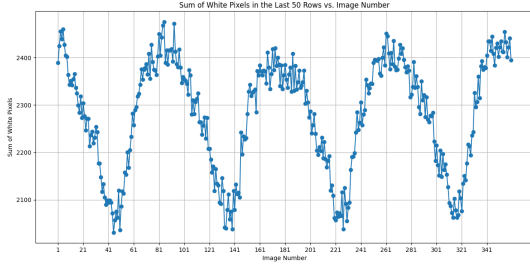


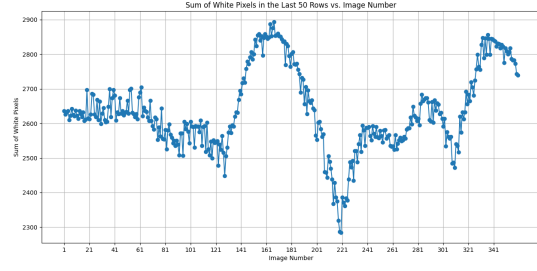
Figure 4.3: Progression of wear in a specific cutter tool, exhibited through four distinct stages: (a) New and unused condition, (b) Slight wear, noticeable primarily at the tip, (c) Advanced wear, characterized by the absence of the tip and evident wear on the sides, (d) Severe and extensive wear, with significant deterioration at both the tip and sides of the tool.

Fig. 4.4 below is the representative graphs depicting the white pixel count corresponding to each degree of rotation within the terminal region (last 50 pixels) of the cutting tool. These graphs effectively illustrate the variations in pixel count across four distinct wear states of the tool, providing a clear visual analysis of the tool's condition through its operational cycle.

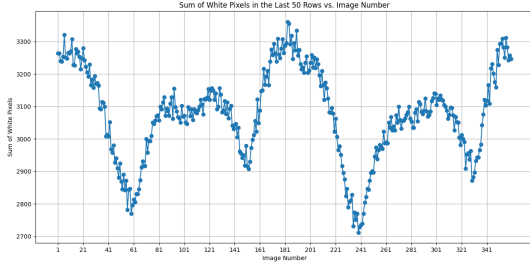
As observed in the graphs, the symmetrical patterns reflected in the pixel count distributions align with the anticipated outcomes, informed by the inherent geometry of the cutter tool. In its original condition, the tool, possessing four edges, exhibits a distinct and repetitive form in the graph (Fig. 4.4a). This characteristic pattern serves as a baseline for comparison. In contrast, the graphs representing worn tools (Fig. 4.4b, 4.4c and 4.4d) reveal a disruption in this pattern. The irregularities and inconsistencies in the pixel count graphs are indicative of edge wear, diverging markedly from the uniformity observed in the new tool.



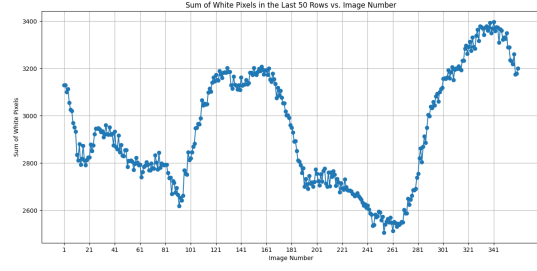
(a) New cutter tool



(b) Slightly worn cutter tool



(c) Slightly advanced worn cutter tool



(d) Severely worn cutter tool

Figure 4.4: Comparative white pixel count analysis of the cutter tool at different stages of wear.

For the drill tools, the results exhibited a similar trend to those observed with the cutter tools. A comparison is presented between a sample drill tool with two edges in its original state and a similar one exhibiting signs of wear, as illustrated in Fig. 4.5.

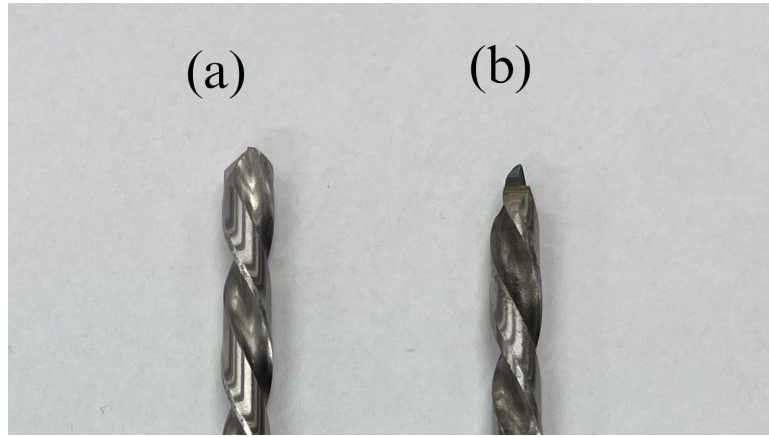
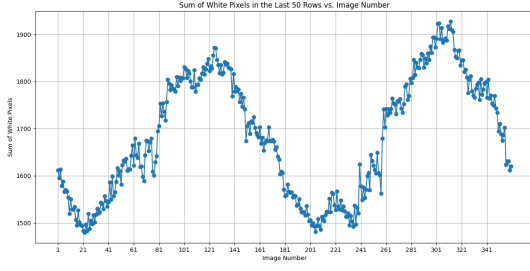


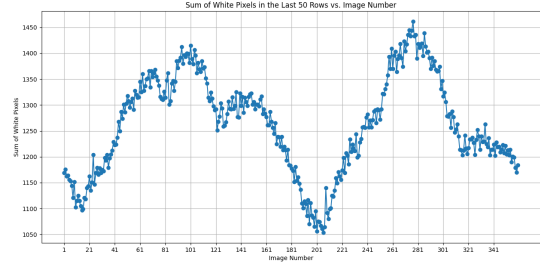
Figure 4.5: Progression of wear in a specific drill tool, exhibited through 2 distinct stages: (a) New and unused condition, (b) Advanced wear, characterized by the absence of the tip and evident wear on the sides

The ensuing graphical analysis further elucidates the wear patterns. Fig. 4.6 below is the representative graph that detail the variations in the white pixel count corresponding to each degree of rotation within the terminal region of the drill tool. These graphs serve to quantitatively illustrate the differences in tool wear between the new and worn conditions, offering a comprehensive view of the tool's edge integrity throughout its operational cycle.

Examination of the figures reveals a noteworthy distinction in the pixel count patterns between the new and worn drill tools. In the graph corresponding to the new tool, a repetitive and consistent pattern is evident, reflecting the intact geometry and uniform edges of the



(a) New milling tool



(b) Worn milling tool

Figure 4.6: Comparative white pixel count analysis of the milling tool at two different stages of wear.

tool. Conversely, this regular pattern is conspicuously absent in the graph for the worn tool. The disruption of this pattern in the worn tool graph is indicative of the irregularities and degradation in the tool's structure, affirming the tool's diminished integrity and effectiveness.

This comparison not only underscores the consistency of the camera-based monitoring system across different tool types but also demonstrates its effectiveness in detecting wear in tools with varying geometries and functionalities.

This analysis not only highlights the deviations in the tool's condition but also underscores the precision and dependability of the camera-based monitoring system. By capturing these nuanced changes in the tool's profile, the system demonstrates its capacity to detect and quantify edge wear effectively.

In conclusion, the camera-based system offers a sophisticated and accurate means of monitoring tool wear. The ability to discern and visually represent the degradation of cutting tools through pixel count analysis is a testament to the system's potential in enhancing predictive maintenance strategies in CNC machining. The system not only identifies tool wear in its early stages but also provides a quantifiable measure of the severity of the wear, thereby enabling timely and informed decision-making in manufacturing operations.

Chapter 5

Discussion

5.1 Overview of Key Findings

This research embarked on a journey to develop a novel camera-based diagnostic system for monitoring tool condition in CNC milling machines, emphasizing not just the detection of tool breakage but also the assessment of tool edge wear. The system operates by examining the tool at its original set position, either after each machining operation, periodically, or in response to changes in machining forces or signals. The key findings of this study are presented in two primary areas:

5.1.1 Detection of Tool Breakage

One of the cornerstone achievements of this research is the precise detection of tool breakage. Through meticulous analysis of tool height variations captured via high-resolution video frames, this system demonstrated remarkable accuracy in identifying tool breakage. The calibration and translation of pixel measurements into real-world dimensions yielded a marginal error margin of only 2%, showcasing the system's reliability in an industrial setting. This precision is crucial for preventing operational inefficiencies and ensuring safety in CNC machining operations.

The precision in detecting tool breakage, as evidenced by the 2% error margin in tool height measurements, signifies a breakthrough in predictive maintenance for CNC machining. The ability to detect even minor deviations in tool height is crucial for preemptively addressing tool failures, thereby mitigating the risk of machine damage and workpiece spoilage. This aspect of the system not only contributes to operational safety but also aids in reducing downtime and maintenance costs, which are critical factors in the highly competitive manufacturing industry.

Moreover, the system's reliance on high-resolution video frames for tool assessment translates to a non-intrusive, easily implementable monitoring mechanism. Unlike some traditional methods that may require physical contact or complex sensor setups, this approach offers simplicity and adaptability to various CNC machining contexts.

5.1.2 Assessment of Tool Edge Wear

The study also made significant strides in assessing tool edge wear. The system quantifies wear by analyzing the sum of white pixels in the terminal region of the tool when it returns to its original set position. This method allows for a detailed and quantifiable analysis of the tool's edge condition over time. It offers the capability to detect edge wear at various stages, from early to advanced, thereby providing valuable insights for predictive maintenance and enhancing the tool's operational life.

Collectively, these findings underscore the potential of the camera-based diagnostic system in revolutionizing tool condition monitoring in CNC machining. The system’s ability to provide accurate, real-time assessments of tool breakage and wear at crucial intervals positions it as an invaluable tool for improving efficiency, quality, and safety in manufacturing operations.

Furthermore, the correlation between the tool’s physical wear and the variations in white pixel counts provides a strong foundation for developing more sophisticated, data-driven maintenance strategies. By accurately quantifying tool wear, the system opens avenues for optimizing tool usage and lifecycle management, thereby contributing to cost-effective and sustainable manufacturing practices.

In summary, the interpretation of the results underscores the transformative potential of the camera-based diagnostic system in CNC tool condition monitoring. This system not only challenges the traditional paradigms of tool monitoring but also introduces a more dynamic, accurate, and efficient approach to maintaining tool health and operational integrity in CNC machining environments.

5.2 Integration with Industry 4.0

The development of the camera-based diagnostic system for CNC machining aligns seamlessly with the principles of Industry 4.0. This integration represents a significant stride in the realm of smart manufacturing, where the emphasis is increasingly on digital interconnectivity and intelligent data utilization. The implementation of this system exemplifies the shift towards automation and data-driven decision-making, which are hallmarks of Industry 4.0. Utilizing high-resolution video data and advanced computational techniques, the system underscores the potential for enhanced efficiency and precision in manufacturing processes, resonating with the objectives of Industry 4.0 to harness data for smarter production.

The proposed diagnostic system marks a substantial advancement over traditional tool setting and workpiece determination methods. Traditional approaches, often reliant on manual intervention and basic instruments, are fraught with limitations such as variability in outcomes, potential for human error, and time-intensive processes. In contrast, the camera-based system offers a novel solution by providing precise and efficient tool condition monitoring. This system reduces the reliance on operator expertise, thereby mitigating the risk of variability and human error, and aligns with the Industry 4.0 ethos of consistent and optimal production results. Furthermore, the automation of tool condition monitoring processes with this system significantly reduces the time required for tool setting and workpiece determination, addressing a crucial gap in traditional methodologies.

The camera-based diagnostic system presents several advantages over traditional sensor-based tool monitoring techniques. Traditional methods, such as monitoring cutting forces, vibrations, and acoustic emissions, have been integral to CNC machining but often fall short in delivering real-time and accurate monitoring solutions. The proposed system, through its utilization of machine vision and image processing, offers a more accurate and cost-effective solution compared to these conventional approaches. Notably, the system provides enhanced capabilities in real-time monitoring, a critical requirement in modern manufacturing settings, which is often a challenge for traditional sensor-based methods. This comparative advantage underlines the system’s potential as a more effective tool for tool condition monitoring in CNC machining.

The camera-based diagnostic system adeptly addresses several challenges posed by Industry 4.0. One of the primary challenges in modern manufacturing is the need for real-time monitoring to ensure operational efficiency and precision. The system’s capability to provide real-time feedback on tool condition is instrumental in meeting this challenge. Moreover, the precision offered by the system aligns with the high standards of accuracy and repeatability demanded

in Industry 4.0-driven manufacturing processes. By providing real-time data and precise monitoring, the system not only enhances operational efficiency but also contributes to improved safety and quality in manufacturing.

Chapter 6

Conclusion

This research aimed to develop and validate an innovative camera-based diagnostic system for tool condition monitoring in CNC milling machines. The system was designed to address two primary challenges in CNC machining: the detection of tool breakage and the assessment of tool edge wear. Through the application of sophisticated image processing techniques on high-resolution video data, the system demonstrated remarkable accuracy and efficiency, thereby making significant strides in the realm of smart manufacturing.

The primary achievements of this research include:

- The development of a camera-based system capable of detecting tool breakage with a marginal error margin of only 2%, illustrating its reliability and precision in an industrial setting.
- A novel approach to assess tool edge wear by quantifying wear using the sum of white pixels in the terminal region of the tool, providing a detailed and quantifiable analysis of the tool's edge condition over time.
- The integration of the system within the framework of Industry 4.0, demonstrating its potential to enhance efficiency, quality, and safety in CNC machining operations.

The introduction of this camera-based diagnostic system marks a significant advancement in CNC machining processes. By enabling accurate, real-time assessments of tool breakage and wear, the system contributes to operational safety and reduces downtime and maintenance costs, which are crucial factors in the highly competitive manufacturing industry. The ability to detect tool conditions preemptively ensures enhanced manufacturing efficiency and contributes to maintaining consistent quality in production.

This research contributes to the field of CNC machining and tool condition monitoring by introducing a more dynamic, accurate, and efficient approach to maintaining tool health and operational integrity. By challenging traditional paradigms of tool monitoring and introducing a novel, data-driven approach, this system sets a new standard in the realm of intelligent machining. It also opens avenues for further research and development in the integration of image processing and machine learning technologies in smart manufacturing.

In conclusion, this research successfully demonstrates the transformative potential of the camera-based diagnostic system in the field of CNC tool condition monitoring. As the manufacturing sector continues to evolve under the umbrella of Industry 4.0, systems like the one developed in this research will be pivotal in advancing the capabilities of smart manufacturing and ensuring the longevity and efficiency of machining operations.

Chapter 7

Future Research

The research presented in this thesis provides a foundational framework for tool condition monitoring in CNC machining using a camera-based diagnostic system. Building upon this foundation, several avenues for future research emerge, offering opportunities to further enhance and expand the capabilities of the system. One of the most promising directions involves the integration of machine learning models, particularly supervised learning, to augment the system's diagnostic capabilities.

7.1 Integration of Supervised Machine Learning

The utilization of supervised machine learning models presents a substantial opportunity for advancing the camera-based diagnostic system. Future research could focus on developing a model that analyzes the white pixel counts obtained from the high-resolution video frames and classifies tools as functional or non-functional. This approach has the potential to automate the decision-making process in tool condition monitoring, reducing the reliance on manual interpretation and increasing the system's overall efficiency and accuracy.

7.1.1 Model Development and Training

The development of a supervised learning model would involve:

- Collecting a large dataset of high-resolution video frames with corresponding labels indicating the tool's condition (functional or non-functional).
- Extracting features, such as white pixel counts, from these frames to serve as inputs for the model.
- Training the model on this dataset to learn patterns associated with tool wear and breakage.

7.1.2 Potential Machine Learning Algorithms

Several machine learning algorithms could be explored for this purpose, including:

- Support Vector Machines (SVM)
- Decision Trees
- Neural Networks

Each of these algorithms offers unique strengths and could be evaluated for their effectiveness in classifying tool conditions.

7.2 Labeling and Annotation Challenges

An important aspect of this future research will be addressing the challenges associated with data labeling and annotation. Accurate labeling is crucial for the success of supervised learning models. Strategies to ensure the precision of labels and annotations should be developed, potentially involving expert input or cross-validation methods.

7.3 Enhancing Predictive Maintenance

Integrating machine learning into the camera-based system aligns well with the principles of predictive maintenance in Industry 4.0. The ability to accurately predict tool failure before it

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