Monitoring of Micro Drill Bit Automatic Regrinding

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High-precision systems such as the automatic regrinding in-line equipment provide intelligent regrinding of micro drill bits; however, immediate monitoring of the grinder during the grinding process has become necessary because ignoring it directly affects the drill bit's life and the equipment's overall utility. Vibration signals from the frame and the high-speed grinding wheels reflect the different health stages of the grinding wheel and can be exploited for intelligent condition monitoring.

intelligent monitoring | spectral isolation | deep learning | grinding wheel wear | vibration signals

1. Introduction

Maintenance costs have been shown in recent studies [1][2][3] to contribute a significant portion of total operating costs. This has motivated industries towards integrating cost-efficient technologies (and practices) into their daily operations. In addition to this perspective, safety and reliability are often prioritized for ensuring maximum profit, maintaining ethical obligations, minimizing downtime, and achieving optimal utility of equipment [2][3][4]. As a consequence, intelligent equipment and tool monitoring, fault diagnosis, and prognostics are currently being integrated into maintenance management modules, and thanks to artificial intelligence (AI), intelligent monitoring has gradually attracted attention from industries since they require little or no domain knowledge, are user-friendly, and offer minimal false alarm rates [4][5].

In the modern manufacturing industry, high-density packaging technologies have become an unavoidable requirement. The design of printed circuit boards (PCB) demands high-precision cutting and drilling of small holes (as small as 0.1 mm or less), which requires the use of micro drill bits [6]. Due to prolonged usage, the micro scale, hole-location errors, reaming, and their brittle and delicate nature, drill fractures/breakage often occur during the drilling process. More often than not, these drill bit failures can be traced to the high-frequency vibrations generated during the drilling process; therefore, the demand regular tool monitoring and maintenance—regularly sharpening [7]. Most investigations on the vibration of micro drilling are focused on only drill self-structure. However, it is also important to monitor the maintenance efficiency of the drill bit regrinding machine to ensure that at all times, the drill bits produce the desired surface finish and geometrical accuracy of the finished workpiece—PCB.

Several direct, indirect, and/or hybrid tool monitoring techniques/technologies have been studied [8][9]. Direct methods such as optical devices and cameras, although more reliable for accurate monitoring, are faced with certain limitations. Their real-time usability may be affected since ARIS wheels rotate at high speeds and may produce unclear images in real-time, which often require interrupting the machine. Further, finding an optimal camera localization point is another major challenge. Against these limitations, indirect methods—cutting force, acoustic emission, spindle motor, temperature, vibration, machining sound, etc.—offer real-time efficiencies and the integration of multiple sensing opportunities for fully extracting deep and shallow machine behavior for optimal condition monitoring [7]. In addition, recent technological advancements have ushered in intelligent algorithms and the super computational resources for harnessing them—for intelligent tool monitoring [4]. These intelligent algorithms, such as convolutional neural networks (CNN) [5], recurrent neural networks (RNN), auto encoders (AE) [10], and MLPs [11], are quite robust for diverse predictive maintenance and equipment monitoring purposes and have been reported in many studies, including but not limited to hydraulic equipment monitoring [5], remaining useful life estimation, wear detection [7], and machinery fault diagnostics and prognostics [12][13]. Unlike the traditional Bayesian methods that require a significant level of hand-crafted discriminative and/or non-discriminative feature extraction as the case study demands, these intelligent algorithms—deep learning (DL) models—are designed to accept raw sensor inputs and follow a series of advanced mathematical processes for automatic feature extraction and predictive modeling in a comprehensive framework with less dependence on domain knowledge. Nonetheless, finding a balance between computational costs and accuracy remains a challenge, especially for real-time cases where both factors play major roles in the decision-making, selection, and deployment.

2. Monitoring of Micro Drill Bit Automatic Regrinding

Precision drilling, which requires an accurate drilling process, ensures a high-quality product; however, it is essential to understand the condition and dynamic performance of a drill bit in a drilling process, especially for high-speed micro drilling, to reduce the risk of hole-location errors, reaming fractures, and drill fractures [6]. Although only a few studies have examined the dynamics of drilling processes that result in undesirable effects, such as chatter and drill breaks, most studies have shown that breakage is the most common cause of drill failure, and this is most often traced to excessive drilling forces in the drilling process, as well as drill bit bluntness [14][15]. Cutting chip geometry and symmetry can significantly affect the cutting and dynamic properties of a drill bit. Even the tiniest variation in the complex geometry or symmetry of a cutting chip can significantly affect the cutting and dynamic properties of a drill bit.

As the recent industry 4.0 revolution becomes more apparent, which interestingly features micro (nano) technological advancement (amongst many other technologies), PCB production requirements are prioritizing higher cost efficiency, which invariably implies that PCBs are becoming smaller in size. This also implies a reduction in hole sizes on these PCBs to accommodate for the numerous micro chips and electronic units [16]. Unlike the past PCB holes that featured a minimum diameter of $\phi 0.2$ mm, recent PCBs feature more miniature holes that are ($\phi 0.15 - \phi 0.075$ mm) in diameter and are in higher demand. Unfortunately, these micro drill bits are difficult to regrind and are often scrapped after use. Therefore, it becomes imperative to devise reliable regrinding solutions that would minimize drill breakage, hole-location errors, reaming fractures, and drill fractures. Interestingly, the micro drill bit ARIS developed by Instern Co. Ltd., Seoul, Korea, offers a highly reliable (intelligent) solution for regrinding micro drill bits with high efficiency and durability [16]; however, amidst its efficiencies, due to the micro scale of these drill bits, the regrinding wheel surface of these high-precision regrinding systems should be monitored for wear. This is because there is a high positive correlation between the grinding wheel surface wear and poor cutting chip geometry and symmetry.

On the one hand, vibration monitoring has, by far, been proven across diverse applications to be effective for condition monitoring applications [5][12]. This is because most industrial equipment produces different ranges of mechanical vibrations during operation, which change as the equipment operating/health condition changes. On the other hand, the abundance of signal processing techniques provide conventional paradigms for understanding the spectral changes in the vibration signals using advanced computational methods, such as FFT, mel frequency cepstral coefficients, and wavelet transform [17]. Interestingly, the regrinding system's vulnerabilities to mechanical vibration offer an avenue for critically isolating unique (discriminative) frequency bands in the signals for accurate condition monitoring to ensure drill bit safety and retain acceptable drill bit efficiencies while achieving desired cost benefits. For instance, Lee et al. [7] explored the efficiencies of the FFT algorithm for isolating (denoising) auditory signals from the grinding wheel of a G50150 Automatic Surface Grinder machine to enhance the accuracies of a deep learning-based diagnostic model for wear monitoring. By isolating the discriminative frequency bands between 300 and 500 Hz, they were able to provide intelligent diagnostic support to assist operators in determining whether the grinding wheel was worn or not. Moreover, the authors of [18] proposed a comprehensive high-frequency vibration monitoring system for incipient fault detection and the isolation of gears, bearings and shafts/couplings in turbine engines and accessories, which feature a time synchronous averaging (TSA)-based denoising technique for noise reduction from events unrelated to the component of interest. These and many other studies reflect not just the efficiencies of spectral isolation as a denoising technique, but they also provide a verifiable rationale for developing computationally cost-effective and intelligent modeling, on the one hand, and improved discriminative modeling, on the other hand. In this domain, it may become an uphill task to determine which denoising technique is the most effective (considering all evaluation perspectives). However, the FFT offers a reliable solution for identifying critical frequency components in a signal [18][19].

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