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# A Novel Approach Integrating Deep Learning and Machine Vision for Tool Wear Detection

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## Extended Abstract

Smart manufacturing has gained a lot of attention as the emergence of big data and artificial intelligence, particularly in the area of tool condition monitoring (TCM). TCM is very crucial for achieving efficient and precise manufacturing, as it involves real-time monitoring of tool conditions such that processing quality can be improved [1]. Both direct and indirect methods are applied to tool wear detection. Direct monitoring methods are primarily based on image processing techniques and involve capturing and processing the images of tools to assess the wear level. Indirect methods are based on the signals generated during the cutting process, such as vibration, sound, and cutting force. These signals can be utilized to estimate the wear and life of the tools. Kurada [2] determines the tool's status by analysing the image texture of tool blades.

In recent years, integration of AI technology to TCM could highly improve the accuracy of tool wears. AI models can learn and recognize patterns of tool wear from large amounts of data to predict the state of the tool. Wang et al. [3] analysed the signals during the cutting process to determine the tool conditions. Wang et al. [4] applied the U-Net deep learning model on tool wear images such that the tool wear could be accurately estimated.

In this paper, a novel tool wear detection system that integrates deep learning algorithm and machine vision techniques is proposed. First, 300 images are captured during the tool rotates and the image stitching technology is applied to obtain the tool panorama of the profile. Then the deep learning SegFormer model [5] is applied to locate the positions of each tool blade. The technique is crucial for eliminating interference from cutting fluid and chips, which can often obscure the tool's visibility. After obtaining the tool blade locations, the edge detection methods in machine vision is to compute the wear levels of each blade. The tool wear profile for each blade could be obtained correspondingly. It is shown that the approach is more versatile that could be applied to different types of tools. Furthermore, the measurement noises such that cutting fluids and chips could be removed after application of deep learning technology which improves the robustness of the algorithm. Experimental results show that the novel approach could provide a more accurate and automated tool wear methodology as compared to the traditional machine vision method.

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