同行专家业内评价意见书编号：20250855105

附件1

浙江工程师学院（浙江大学工程师学院）同行专家业内评价意见书

姓名：魏乃镇

学号：22260493

申报工程师职称专业类别（领域）：机械

浙江工程师学院（浙江大学工程师学院）制

2025年03月18日

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一、个人申报

（一）基本情况【围绕《浙江工程师学院（浙江大学工程师学院）工程类专业学位研究生工程师职称评审参考指标》，结合该专业类别(领域)工程师职称评审相关标准，举例说明】

1.对本专业基础理论知识和专业技术知识掌握情况(不少于200字)

在浙江大学台州研究院的实践期间，我系统掌握了机械工程领域的核心理论知识和前沿技术。在基础理论方面，深入学习了高精度数控机床的设计原理、机械动力学、热误差补偿技术以及精密加工工艺等知识。通过参与“基于中驱动电主轴的双面双刀塔高精度高速数控车床”项目，进一步理解了双面同步车削的中驱动技术、双向电主轴延展性设计以及几何与热误差协同控制等关键理论。

在专业技术层面，我重点掌握了多传感器数据融合、深度学习算法、迁移学习及数字孪生技术的应用。例如，针对刀具磨损预测问题，通过并行卷积神经网络（CNN）提取多传感器数据的深层次特征，并结合双向门控循环单元（BiGRU）处理时序信号，构建了RRP-Net模型，实现了单一工况下的高精度磨损监测。此外，通过迁移学习技术（如CORAL方法），解决了复杂工况下源域与目标域数据分布差异的问题，提升了模型的泛化能力。同时，基于数字孪生技术开发的刀具磨损监测系统，将物理实体与虚拟模型深度融合，实现了刀具状态的实时模拟与预测。这些技术的应用不仅需要扎实的数学基础和编程能力（如Python、TensorFlow框架），还需对机械系统特性有深刻理解，体现了理论与技术的综合运用能力。

通过实践，我对机械工程领域的前沿技术（如智能运维、工业物联网）有了更全面的认知，并能够结合具体工程需求灵活调整技术方案，验证了自身对专业知识的掌握深度与应用能力。

2.工程实践的经历(不少于200字)

在浙江大学台州研究院为期366天的专业实践中，我以研发工程师的身份全程参与了浙江省“尖兵”“领雁”研发攻关项目——“基于中驱动电主轴的双面双刀塔高精度高速数控车床研发及研究”。该项目旨在解决工程机械、汽车等行业对长轴类零件双面高精度同步加工的技术难题，研发具有自主知识产权的高端数控机床。

在项目中，我的核心任务是利用深度学习技术实现刀具磨损量及状态的智能预测与诊断。具体工作包括：

实验平台搭建与数据采集：选择Kistler三向力传感器、加速度传感器等设备，设计切削参数（切削速度、进给量、切削深度），采集刀具在不同工况下的振动、力信号和声发射信号。

数据预处理与特征提取：通过时域分析（均值、方差）、频域分析（FFT）及时频域分析（小波变换）提取信号特征，构建多维特征矩阵。

模型开发与优化：提出基于并行CNN与BiLSTM的RRP-Net模型，用于单一工况下的磨损监测；针对复杂工况，引入迁移学习技术，通过CORAL方法对齐源域与目标域数据分布，提升模型适应性。

系统集成与验证：开发基于数字孪生的刀具磨损监测系统，实现三维可视化与远程维护功能，并在合作企业（如三重工）进行实地测试，验证系统可靠性与实用性。

通过实践，我熟悉了从需求分析、方案设计到系统落地的完整工程流程，并在团队协作中提升了跨学科沟通与项目管理能力。

3.在实际工作中综合运用所学知识解决复杂工程问题的案例（不少于1000字)

在数控车床加工过程中，刀具磨损是影响加工精度与效率的核心问题。传统监测方法依赖人

工经验或单一传感器数据，存在实时性差、误报率高、无法适应多工况等缺陷。尤其在双面同步加工场景中，刀具磨损状态复杂多变，亟需一种高精度、自适应的智能监测方案。

一：问题分析与技术难点

1.数据异构性：多传感器（力、振动、声发射）数据维度高、特征耦合，难以直接融合。2.工况复杂性：不同切削参数（如转速、进给量）导致数据分布差异显著，单一模型泛化能力不足。3.实时性要求：需在毫秒级响应时间内完成磨损预测，对算法计算效率提出挑战。

二：解决方案

1.多传感器数据融合与特征工程

采用小波包分解对振动信号进行时频域分析，提取能量熵、峭度等特征；对力信号进行时域统计（峰值、均方根）。通过主成分分析（PCA）降维，消除冗余特征，构建融合特征矩阵。

2.深度学习模型设计（RRP-Net）

并行CNN模块：设计双分支CNN结构，分别提取时域与频域特征，通过跨通道融合增强特征表达能力。BiGRU时序建模：将融合特征输入双向门控循环单元，捕捉刀具磨损的时序演化规律。自适应损失函数：引入加权交叉熵损失，解决样本不平衡问题（正常状态样本远多于磨损样本）。

3.迁移学习实现多工况适配

采用CORAL（相关性对齐）方法，最小化源域与目标域特征分布的差异，实现知识迁移。在目标域数据稀缺时，使用预训练的RRP-Net模型进行微调，显著减少标注数据需求。

4.数字孪生系统集成

基于Unity 3D开发可视化界面，实时映射刀具物理状态；搭建云端运维平台，利用MQTT协议实现数据远程传输与故障预警。

三：实施效果与效益

精度提升：磨损状态识别准确率>97%（D31/D32达99.29%/99.65%），误判率降低70%。磨损值预测MAE低至1.1428，R^2>0.996，较单一传感器方案误差降低40%-70%。

效率优化：模型计算效率提升95%-98%，训练时间从182.66s缩减至110.33s，满足工业实时性需求。

数字孪生系统减少人工巡检频率70%，运维成本下降25%。

本案例通过多学科技术融合（机械、算法、软件），系统性解决了刀具磨损监测中的复杂工程问题。创新性提出轻量化模型结构与多传感器融合策略，兼顾精度与效率，并通过工业级验证证实了方案的实用性。研究成果不仅推动了数控加工智能化升级，也为智能制造领域的设备运维提供了可复用的技术范式。

（二）取得的业绩（代表作）【限填3项，须提交证明原件（包括发表的论文、出版的著作、专利证书、获奖证书、科技项目立项文件或合同、企业证明等）供核实，并提供复印件一份】					
1. 公开成果代表作【论文发表、专利成果、软件著作权、标准规范与行业工法制定、著作编写、科技成果获奖、学位论文等】					
成果名称	成果类别 [含论文、授权专利（含发明专利申请）、软件著作权、标准、工法、著作、获奖、学位论文等]	发表时间/授权或申请时间等	刊物名称/专利授权或申请号等	本人排名/总人数	备注
Research on Tool Wear Monitoring Based on Enhanced Convolutional Neural Networks	会议论文	2024年11月08日	Journal of Physics: Conference Series	1/5	EI会议收录
一种基于 Unity3D 的数控磨床状态远程监测系统	发明专利申请	2023年08月10日	申请号：202311002585.6	5/5	
一种基于Swin-Transformer的变工况下数控车刀磨损状态分类方法和装置	发明专利申请	2024年05月03日	申请号：202311669443.5	5/5	

2.其他代表作【主持或参与的课题研究项目、科技成果应用转化推广、企业技术难题解决方案、自主研发设计的产品或样机、技术报告、设计图纸、软课题研究报告、可行性研究报告、规划设计方案、施工或调试报告、工程实验、技术培训教材、推动行业发展中发挥的作用及取得的经济社会效益等】

<table>
<tr><td colspan="2">（三）在校期间课程、专业实践训练及学位论文相关情况</td></tr>
<tr><td>课程成绩情况</td><td>按课程学分核算的平均成绩： 85 分</td></tr>
<tr><td>专业实践训练时间及考核情况(具有三年及以上工作经历的不作要求)</td><td>累计时间： 1 年（要求1年及以上）
考核成绩： 74 分</td></tr>
<tr><td colspan="2">本人承诺</td></tr>
<tr><td colspan="2">个人声明：本人上述所填资料均为真实有效，如有虚假，愿承担一切责任，特此声明！

申报人签名：魏乃镇</td></tr>
</table>

22260493

二、日常表现考核评价及申报材料审核公示结果

日常表现考核评价	非定向生由德育导师考核评价、定向生由所在工作单位考核评价： ☑优秀　☐良好　☐合格　☐不合格 德育导师/定向生所在工作单位分管领导签字（公章）：　2025 年 3 月 19 日
申报材料审核公示	根据评审条件，工程师学院已对申报人员进行材料审核（学位课程成绩、专业实践训练时间及考核、学位论文、代表作等情况），并将符合要求的申报材料在学院网站公示不少于5个工作日，具体公示结果如下： ☐通过　☐不通过（具体原因：　　　　　　　　） 工程师学院教学管理办公室审核签字（公章）：　　　年　月　日

浙 江 大 学 研 究 生 院

攻读硕士学位研究生成绩表

学号：22260493	姓名：魏乃镇	性别：男	学院：工程师学院	专业：机械	学制：2.5年
毕业时最低应获：24.0学分		已获得：27.0学分		入学年月：2022-09	毕业年月：
学位证书号：			毕业证书号：		授予学位：

学习时间	课程名称	备注	学分	成绩	课程性质	学习时间	课程名称	备注	学分	成绩	课程性质
2022-2023学年秋季学期	工程技术创新前沿		1.5	88	专业学位课	2022-2023学年秋冬学期	工程伦理		2.0	85	专业学位课
2022-2023学年秋季学期	自然辩证法概论		1.0	60	公共学位课	2022-2023学年春季学期	研究生英语基础技能		1.0	77	公共学位课
2022-2023学年冬季学期	产业技术发展前沿		1.5	90	专业学位课	2022-2023学年春夏学期	智能装备与创新设计实践		4.0	87	专业学位课
2022-2023学年冬季学期	新时代中国特色社会主义理论与实践		2.0	91	专业学位课	2022-2023学年春夏学期	高阶工程认知实践		3.0	87	专业学位课
2022-2023学年冬季学期	工程中的有限元方法		2.0	98	专业选修课	2022-2023学年夏季学期	智能装备创新设计案例分析		2.0	92	专业学位课
2022-2023学年秋冬学期	研究生论文写作指导		1.0	90	专业选修课	2023-2024学年秋季学期	创新创业实践训练		2.0	通过	跨专业课
2022-2023学年秋冬学期	研究生英语		2.0	84	专业学位课		硕士生读书报告		2.0	通过	

说明：1.研究生课程按三种方法计分：百分制，两级制（通过、不通过），五级制（优、良、中、及格、不及格）。

2.备注中“*”表示重修课程。

学院成绩校核章：

成绩校核人：张梦依

打印日期：2025-03-20

Research on Tool Wear Monitoring Based on Enhanced Convolutional Neural Networks

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Abstract. Identifying the wear status of cutting tools during the machining process is essential because failure to promptly replace severely worn tools can significantly impact the quality of workpiece machining. Presently, machine learning methods are predominantly utilized for monitoring cutting tool wear status. However, these methods rely on manual feature extraction and exhibit low accuracy. This study introduces a novel RRP-Net model, built upon the RepVgg and ResNet frameworks, integrating a parameter-free self-attention mechanism called SimAM to expedite the model's solving speed without increasing parameters. Within the foundational module of the model, a structural reparameterization approach is employed to transform the multi-branch structure during training into a single-branch structure during validation. This method not only enhances model accuracy but also accelerates the model validation process. The publicly available cutting data from PHM2010 is employed for model training and validation. The findings demonstrate that RRP-Net surpasses classical convolutional neural network models in identifying cutting tool wear status within the PHM2010 dataset, achieving an average accuracy of 98.65% and enhancing recognition accuracy on relevant datasets by 2.41%. To verify the model's practical applicability, specificity and recall during the Break stage are computed at 99.73% and 98.18%, respectively, affirming the model's exceptional robustness and stability. The heightened accuracy and efficiency of RRP-Net further broaden its applicability within the industrial domain.

Keywords. Tool condition monitoring、Deep learning、Convolution neural network、Self-attention

1. Introduction

1.1. Background

The ongoing evolution of Industry 4.0 and intelligent manufacturing has led to a growing need for advanced manufacturing and processing technologies. In this context, CNC machine tools assume a pivotal role. Within the machining process of NC machine tools, the tool emerges as a critical determinant influencing machining quality[1]. The wear status of the tool directly impacts the precision and quality of workpiece processing, consequently influencing the efficiency of the machine tool and leading to amplified enterprise expenditures and resource depletion. Traditional tool condition monitoring typically necessitates halting the spindle, followed by extracting the tool for scrutiny and measurement under a microscope. This procedure elongates machine tool downtime, disrupts processing continuity, and diminishes efficiency. According to pertinent research, tool breakage-induced downtime constitutes 20% of the total downtime [2].

Tool wear undergoes a dynamic process that evolves over time. Initially, the rate of tool wear accelerates rapidly, followed by a deceleration phase where the wear process persists for a relatively extended period. Subsequently, during the severe wear stage, tool wear accelerates once more. Prompt replacement of tools in the severe wear stage during the cutting process is imperative since tools at this stage cannot ensure machining quality. Hence, analyzing tool wear status holds significant meaning and importance.

1.2. Related work

Before the advent of deep learning, tool wear monitoring predominantly relied on machine learning methodologies. Initially, researchers extracted features pertinent to tool wear from processing signals to serve as model inputs, subsequently employing conventional machine learning techniques to derive outputs. A survey conducted in 1997 indicated that over 60% of tool wear monitoring implementations employed machine learning approaches[3]. Notably, within the realm of tool monitoring systems, Support Vector Machines (SVM), Artificial Neural Networks (ANN), Bayesian networks, and Hidden Markov Models emerge as the most prevalent[4]. However, traditional machine learning exhibits inherent limitations: necessitating manual feature extraction, thereby risking feature loss and subjective biases; displaying feeble generalization capabilities, excelling in specific machine tool cutter scenarios yet faltering in broader contexts; further, necessitating preprocessing tasks like data dimensionality reduction or feature mapping, which may impede comprehensive representation of the entirety of tool wear information, consequently undermining model training efficacy and predictive efficiency.

In recent years, the development and widespread adoption of sensors have propelled the application of deep learning in the industrial sector[5]. In comparison to traditional machine learning methods, deep learning offers distinct advantages, notably the ability to incorporate multiple hidden layers. Consequently, deep learning can extract more intricate features, enabling continuous learning of characteristics pertinent to tool wear. This enhances the model's resilience to fluctuations in data and, by extension, augments the precision of tool wear monitoring. Presently, prominent deep learning techniques utilized for tool wear monitoring encompass Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Multi-Layer Perceptron (MLP). Zhou et al[6] employed Long Short-Term Memory Neural Networks (LSTM) to predict tool lifespan under varying conditions, thereby validating its effectiveness. Jin et al. [7]introduced a Parallel Long Short-Term Memory Neural Network (PLSTM) combined with Singular Spectrum Analysis (SSA) for predicting energy consumption, showing further improvements compared to other models. Wang et al.[8]developed a deep heterogeneous GRU model combined with local feature extraction for long-term equipment forecasting. However, due to the structural limitations of LSTM and GRU, they cannot be trained in parallel, leading to increased training time and computational resource consumption. Convolutional Neural Networks (CNNs), on the other hand, excel in parallel computation, speeding up calculations and reducing resource waste, making them commonly used in engineering.

Many researchers use CNNs for tool wear monitoring. Marei et al.[9]tool health status, suggesting direct application in current CNC machining. Cheng et al.[10]developed a Parallel Convolutional Neural Network (PCNN) structure combined with Bidirectional Long Short-Term Memory Neural Networks (BiLSTM) to predict tool wear values. However, CNNs also have drawbacks, notably their high computational resource requirements during convolution, leading to longer training times. Performing convolutions in industrial settings necessitates high-performance GPUs and other specialized hardware, posing significant challenges to deploying CNNs in industrial applications. Therefore, efficient and high-performance CNN models are essential in industrial settings.

1.3. Contribution of this study

（1） This study introduces the novel RRP-Net model, which is the first to integrate RepVGG with the ResNet framework, achieving high performance and rapid monitoring and identification of tool wear.

（2） The research employs an innovative data preprocessing technique that processes collected signals through sliding windows. These signals are analyzed in the time domain, frequency domain, and time-frequency domain to extract feature matrices corresponding to tool wear, which are then transformed into images for model input.

（3） The research employs an innovative data preprocessing technique that processes collected signals through sliding windows. These signals are analyzed in the time domain, frequency domain, and time-frequency domain to extract feature matrices corresponding to tool wear, which are then transformed into images for model input.

（4） The model has been trained and assessed using the PHM2010 public cutting dataset, where it demonstrated superior recognition accuracy, faster computation speeds, and fewer parameters compared to other tool wear recognition algorithms. In practical applications, the model has performed excellently. F1 score validation further confirms the RRP-Net model's robustness, generalization ability, and stability.

2. Proposed model framework

2.1. Data preprocessing

For the collected seven types of signals (force signals in xyz directions, vibration signals in xyz directions, and acoustic emission signal), sliding window processing is applied. The signals collected from a single tool pass are divided into 100 parts, and each part undergoes time-domain analysis, frequency-domain analysis, and time-frequency domain analysis. In the time-domain analysis, the absolute mean, peak, root mean square, root amplitude, skewness, kurtosis, waveform factor, impulse factor, skewness factor, peak factor, clearance factor, and kurtosis factor of the signals are calculated. In the frequency-domain analysis, the centroid frequency, mean square frequency, root mean square frequency, and frequency variance are determined. In the time-frequency domain analysis, a total of 24 characteristic values of wavelet packet energy are calculated. Subsequently, the values of each signal are aggregated into a matrix, where the rows represent the seven different types of signals, and the columns represent the 24 characteristic values. Finally, these feature matrices are transformed into three-channel images to serve as the output of data processing and the input to the main model.

2.2. Main Structure

In this paper, we improved the backbone network of RepVgg[11]by incorporating a parameter-free attention mechanism and integrating the design of ResNet[12], resulting in the RRP-Net model. The main structure of the network is shown in Figure 1. The model is composed of the following parts: input layer, RRP-Net block, SimAM, average pooling layer, fully connected layer, and output layer. After data preprocessing, the image is used as the input to the main model. The RRP-Net block mainly consists of three branches: a 3×3 convolution with a batch normalization layer, a 1×1 convolution with a batch normalization layer, and a pure batch normalization layer. Then, through convolution kernel re-parameterization, a new 3×3 convolution kernel is obtained, which integrates all the information from the above three branches. The output, after being dimensionally reduced by the average pooling layer, is fed into the fully connected layer, resulting in a five-classification model.

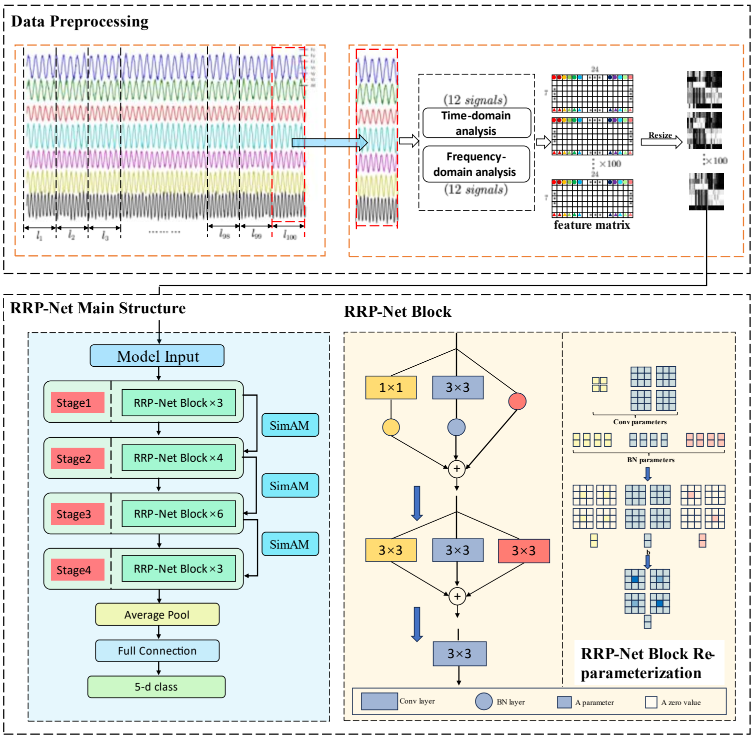

Fig.1. RRP-Net Structure

RRP-Net Block is the most critical module in this network model, which consists of the following parts: a 1×1 convolution kernel with BN layer, a 3×3 convolution kernel with BN layer, and a standalone BN layer. Adopting this multi-branch structure during training enables the model to capture different features of input data from different branches, thereby enhancing the model's ability to express and generalize data. In the validation process, we employed a method of structural re-parameterization, which merges the convolutional kernel parameters and BN parameters from three branches to ultimately obtain a fused 3×3 convolution kernel. The information extracted by this kernel after structural re-parameterization is consistent with the multi-branch situation during training. The specific process and formula of structural re-parameterization are shown in Eq.1. A parameter-free attention mechanism, SimAM, is introduced between different stages, which helps to improve the speed of the model[13]. It can take any intermediate feature tensor as input and transform it into an output with the same size as the input.

$$K^{(2)} = BN(K^{(1)}*W^{(3)},\mu^{(3)},\sigma^{(3)},\gamma^{(3)},\beta^{(3)}) + BN(K^{(1)}*W^{(1)},\mu^{(1)},\sigma^{(1)},\gamma^{(1)},\beta^{(1)}) + BN(K^{(1)},\mu^{(0)},\gamma^{(0)},\beta^{(0)})$$

$$BN(K,\mu,\sigma,\gamma,\beta)_{:,i,:,:} = (K_{:,i,:,:} - \mu_i)\frac{\gamma_i}{\sigma_i} + \beta_i$$

$$K'_{i,:,:,:} = \frac{\gamma_i}{\sigma_i}K_{i,:,:,:}\ ,\ b'_i = -\frac{\mu_i\gamma_i}{\sigma_i} + \beta_i \qquad (1)$$

$$BN(K*W,\mu,\sigma,\gamma,\beta)_{:,i,:,:} = (K*W')_{:,i,:,:} + b'_i$$

$W^{(3)} \in \mathbb{R}^{C_2 \times C_1 \times 3 \times 3}$ represents a 3×3 convolution kernel with C1 input channels and C2 output channels,, $W^{(1)} \in \mathbb{R}^{C_2 \times C_1 \times 1 \times 1}$ represents a 1×1 convolution kernel with C1 input channels and C2 output channels. We use $\mu^{(i)},\sigma^{(i)},\gamma^{(i)},\beta^{(i)}$ as the accumulated mean, standard deviation and learned scaling factor and bias of the BN layer following 1×1 conv。 $K^{(1)} \in \mathbb{R}^{N \times C_1 \times H_1 \times W_1}$ represents the input and $K^{(2)} \in \mathbb{R}^{N \times C_2 \times H_2 \times W_2}$ represents the output of the model, where $*$ represents the convolution operation.

3. Experiment Study

3.1. Datasets description

The dataset used in this experiment is the publicly available PHM2010 dataset[15], which includes the full lifecycle data of six cutting tools (C1-C6). After each cutting pass, the wear on the back face of the tool is measured using a microscope, and seven types of monitoring signals are collected: cutting forces in XYZ directions, vibration signals in XYZ directions, and acoustic emission signals. The specific wear values of the tools C1, C4, and C6 were published.

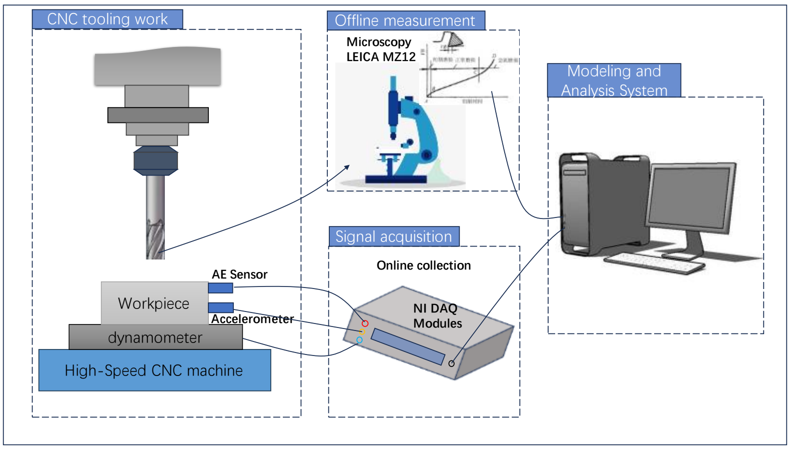

Fig. 2. Schematic diagram of the PHM2010 experiment

The experiment was repeated six times under the above cutting conditions for the entire lifecycle of each experiment. During the cutting process, three types of sensors were used: a triaxial force sensor to collect force signals in three directions, an accelerometer to collect vibration signals in three directions, and an acoustic emission sensor to collect acoustic emission signals. At the end of each cutting pass, the wear on the side faces of the three cutting teeth was measured offline using a LEICA MZ12 microscope. The average wear on the side faces of the three cutting teeth was then calculated as the tool wear value[16]. The specific process is shown in the Figure. 2. Based on the tool wear data, k-means clustering analysis can classify the tool states into five categories: state 1: 1-30 cutting passes, state 2: 31-130 cutting passes, state 3: 131-200 cutting passes, state 4: 201-260 cutting passes, and state 5: 261-315 cutting passes. Datasets T1, T2, T3 and the number of images corresponding to each state are shown in Table 1.

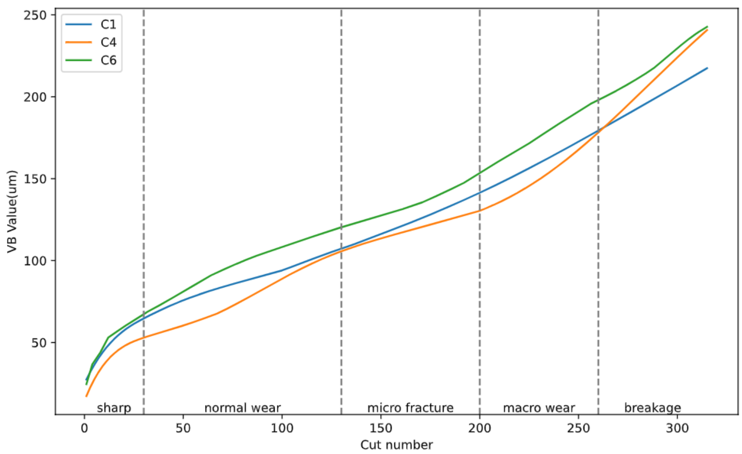

Fig. 3. Tool lifecycle wear curves of PHM2010 datasets

Table 1 Multiple datasets and model details

Datasets	Tool model	The number of images in each dataset				
		Sharp	Normal wear	Micro fracture	Macro wear	breakage
T1	C1					
T2	C4	3000	10000	7000	6000	5500
T3	C6					

3.2. *Model training and evaluation*

3.2.1. *Training configuration*

This experiment was conducted on a Windows 10 system, with the training environment set up on PyTorch 1.8.1, using an NVIDIA RTX3080 GPU and CUDA 11.1. The learning rate was set to 0.0001. Due to the large size of the model parameters, the batch size was set to 16. A smaller batch size allows for the use of more complex network structures and helps to prevent model overfitting, thereby enhancing the model's generalization ability. The model parameters were iterated using the Adam optimizer, which can adaptively adjust the learning rate, offering faster convergence speed and stronger robustness, suitable for large-scale and complex learning tasks.

3.2.2. *Accuracy comparison*

Currently, model performance evaluations primarily use accuracy metrics. In classification tasks, accuracy indicates the proportion of correctly classified samples out of the total sample count, with values closer to 1 denoting better model performance. This study compared common convolutional networks such as ResNet[12], VGG[17], and ConvNet[18], and found that RRP-Net outperforms other models in terms of accuracy and convergence speed. As shown in the fig.4., RRP-Net's accuracy steadily increases with more epochs. Compared to ResNet50, RRP-Net exhibits better stability, and compared to other models, it has faster convergence speed and higher accuracy. In the loss value chart, RRP-Net shows the quickest decline in loss values. This study also compiled the highest accuracy achieved during training and the average of the top five accuracies. RRP-Net's highest accuracy reached 99.11%, which is 2.41% higher than the ConvNet model. The average of the top five accuracies is 98.99%, indicating that RRP-Net achieves a very high level in monitoring the wear state of cutting tools.

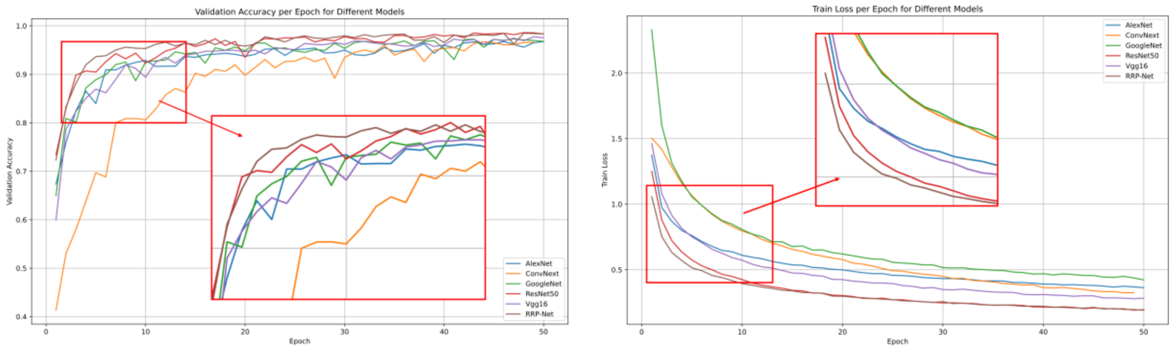

Fig. 4. Model accuracy and loss curve

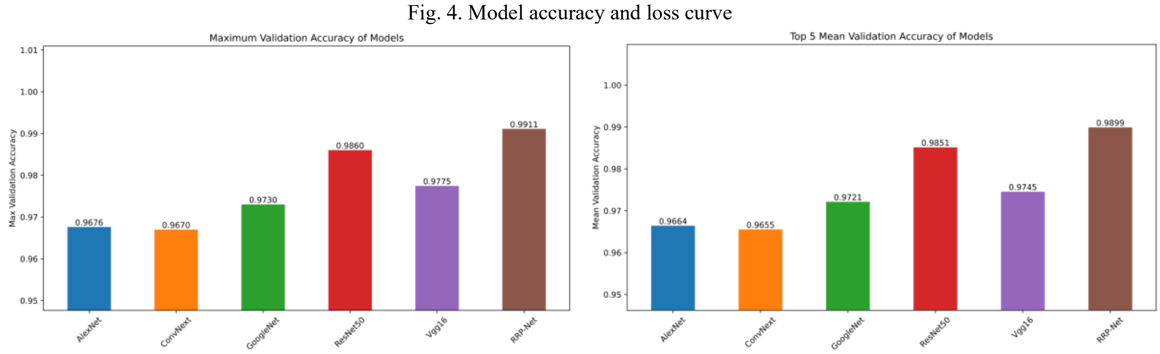

Fig.5. Highest model accuracy and average of the top five

3.2.3. *Performance evaluation*

The confusion matrix plays a very important role in assessing the actual performance of the model, demonstrating the model's predictive effectiveness across five different wear states[19]. By analyzing the confusion matrix, the model's accuracy, false positive rate, and false negative rate for different states of tool wear can be assessed. The figure below shows the confusion matrices for datasets T1, T2, and T3, with average accuracies for the five categories being 98.6%, 98.4%, and 97.4% respectively. In the T1 dataset, the model achieved a 100% prediction accuracy for category 1; in the T2 dataset, it also reached a 100% prediction accuracy for category 2. These high-accuracy results demonstrate that RRP-Net is very effective in recognizing tool wear under different datasets, proving the model's superior performance.

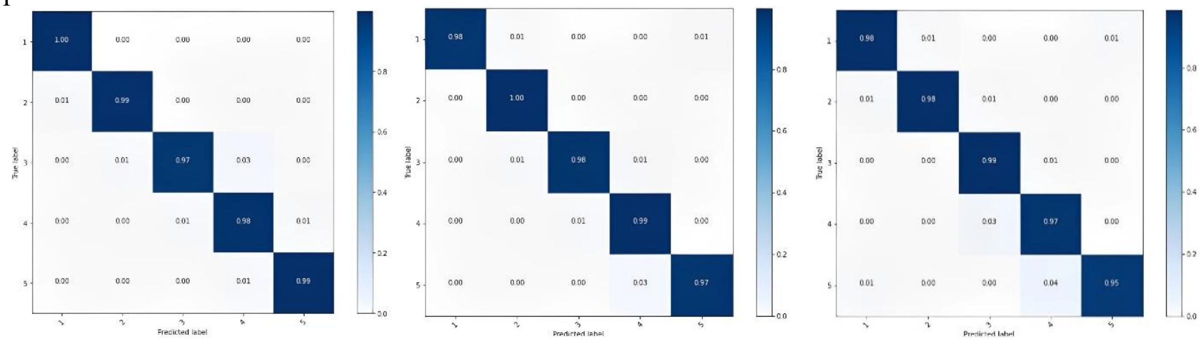

Fig.6. Confusion matrix of datasets T1, T4, and T6

3.2.4. *Actual application evaluation*

To further discuss the application of the RRP-Net model in practical scenarios, four secondary indicators of the confusion matrix were calculated: accuracy, recall, specificity, and F1 score, including both Macro F1 score and Micro F1 score. Accuracy measures the model's accuracy in recognizing categories, recall indicates the probability of the model successfully identifying true samples when the tool is at the break stage, and specificity measures the model's accuracy in predicting negative cases[20]. By analyzing the Macro F1 score and Micro F1 score, the model's performance in multi-class problems can be more comprehensively assessed, taking into account the balance and imbalance among categories. The metrics for the datasets are shown in the Table 2. During the Break stage, the average recall rate for the three datasets is 98.18%, with the T2 dataset achieving 99.27%. The average specificity for the three datasets is 99.73%, with the T2 dataset even higher at 99.77%. This indicates that the model has a high probability of successfully recognizing severely worn tools. The average Macro F1 score and Micro F1 score of the model are 98.14% and 98.20%, respectively, showing that RRP-Net performs well independently in each category and is also very effective overall.

Studies have shown that when the convolutional kernel size is 3x3, the number of floating-point operations per unit time is relatively the highest[11], as shown in the Table 3. This indicates that the computer can process more data in a short period of time and perform more complex computational tasks. The branch convolutional kernels in the RRP-Net Block have been structurally reparameterized into 3x3 kernels, improving the model's computational efficiency and application performance, which helps in accurately and timely monitoring the tool wear state, avoiding adverse consequences due to excessive tool wear. As the model's performance improves, its deployment scope in the industrial field is also further expanded.

Table 2 Evaluation indicators on the T dataset

Evaluation indicators		T1	T2	T3
Accuracy(%)		98.57	**99.37**	98.00
Recall(%)	P_{break}	98.18	99.27	97.09
Specificity(%)	P_{break}	99.73	**99.77**	99.69
F1_score(%)	P_{break}	98.45	99.09	97.80
Macro_F1_score(%)		98.46	98.93	97.03
Micro_F1_score(%)		98.53	98.92	97.14

Table 3 Theoretical TFLOPS with different kernel sizes

Kernel size	Theoretical FLOPs	Time Usage(ms)	Theoretical TFLOPS
1×1	420.9	84.5	9.96
3×3	3788.1	198.8	**38.10**
5×5	10522.6	2092.5	10.57
7×7	20624.4	4394.3	9.38

4. conclusion

This paper proposes a model for monitoring tool wear states based on the RepVgg combined with the ResNet framework (RRP-Net). This model can quickly and efficiently predict the wear state of tools, which has significant industrial application value. The specific content of this study is as follows:

(1) By processing multi-sensor signals with a sliding window, each signal is divided into 100 windows, and each window signal is analyzed in the time domain, frequency domain, and time-frequency domain. After the aforementioned feature processing, 24 features are extracted from each signal, resulting in a 7×24 feature matrix. Consequently, a single wear value of the tool corresponds to 100 of these 7×24 matrices. Subsequently, through image conversion, these 100 matrices are transformed into 100 images, serving as the input for RRP-Net. This method not only improves the accuracy of tool wear state recognition but also provides reliable input for the tool state recognition model.

(2) The model combines the advantages of RepVgg and ResNet, and includes the SimAM parameter-free attention mechanism module in the basic model block, which is a computational unit that enhances the feature expression capability of convolutional neural networks. During the training phase of the RRP-Net Block, multi-branch training is used, and during the validation phase, the convolution kernels are structurally reparameterized, turning multi-branches into a single branch, which further speeds up the model's operation while ensuring accuracy. This has promoted the deployment of the model in the industrial field.

(3) The RRP-Net model's predictive accuracy for different tool wear states in the publicly available PHM2010 dataset is higher than other convolutional neural network models, such as ResNet50, Convnext, and Vgg16, with an accuracy improvement of 2.41% compared to ConvNext. The highest prediction accuracies in the T1, T2, and T3 datasets were 98.57%, 99.37%, and 98.00%, respectively, with an average accuracy of 98.65%. This demonstrates the superiority of RRP-Net in monitoring tool wear states.

(4) The model was evaluated in practical applications, producing confusion matrices for different datasets in T1, T2, and T3, with average prediction accuracies of 98.6%, 98.4%, and 97.4%, respectively. Four secondary indicators were also calculated: precision, recall, specificity, and F1 score. During the Break stage, the average recall value for the three datasets was 98.18%, and the average specificity was 99.73%. This shows that the model can effectively recognize severely worn tools in practical applications, performs well independently in each category, and is also very effective overall, making it a very reliable and effective model for practical operations.

Prospect: This article focuses on tool wear monitoring under a single working condition and will consider conducting experiments under varying working conditions to verify the effectiveness of RRP-Net in monitoring wear under changing working conditions.

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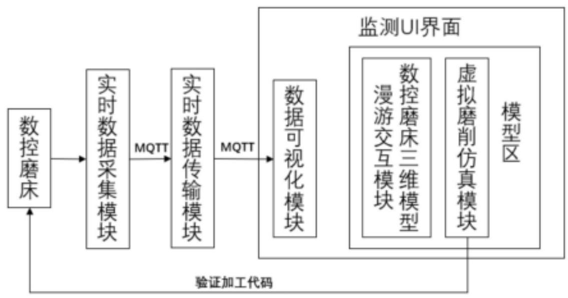
(54)发明名称

一种基于Unity3D的数控磨床状态远程监测系统

(57)摘要

本发明公开了一种基于Unity3D的数控磨床状态远程监测系统,包括:实时数据采集模块用于实时从数控磨床中获取运行状态数据;实时数据传输模块,用于接收来自实时数据采集模块的运行状态数据以及经由虚拟磨削仿真模块验证的加工代码,并基于消息队列遥测传输协议进行传输;数据可视化模块,用于接收并处理来自实时数据传输模块的运行状态数据,利用Unity3D进行可视化展示;虚拟磨削仿真模块,用于获取输入待检验的加工代码,通过加工代码进行数控磨床模型的仿真,若加工代码验证无误,则可通过实时数据传输模块将加工代码下发至数控磨床的数控系统中。上述系统实现了远程对数控磨床的有效监测。



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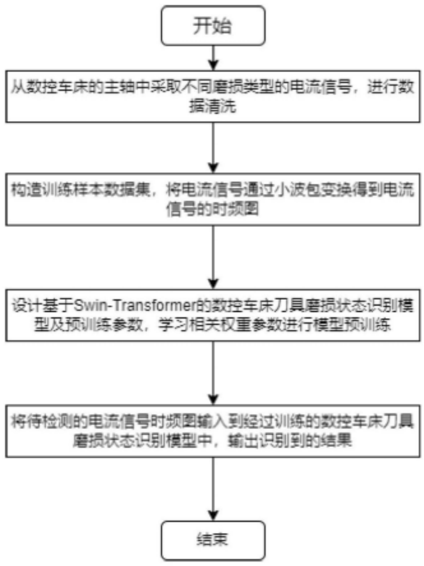
(54)发明名称

一种基于Swin-Transformer的变工况下数控车刀磨损状态分类方法和装置

(57)摘要

本发明公开了一种基于Swin-Transformer的变工况下数控车刀磨损状态分类方法和装置，方法包括：从数控车床的主轴中采集不同磨损类型的电流信号，进行数据预处理；将预处理后的电流信号划分为训练集、验证集和测试集，将电流信号通过小波包变换得到电流信号的时频图，对每张时频图标注磨损类别标签后进行图像预处理；设计基于Swin-Transformer的网络模型和预训练参数，输入预处理后的图像，对Swin-Transformer网络模型进行优化训练；将待检测的电流信号时频图输入到预训练的Swin-Transformer网络模型中，输出识别结果。本发明将Swin-Transformer模型应用于时频图数据，能够有效地捕获图像中的长距离依赖关系，从而适应不同工况下刀具磨损状态的变化模式，提高识别的准确性和稳定性。



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