Evaluation of Deep Learning for Semantic Image Segmentation in Tool Condition Monitoring

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In tool condition monitoring, vision sensors enable enhanced insight into the state of the cutting tool.

**Approaches for tool condition monitoring**

- **Indirect observation:**
  - Vibration [1, 2]
  - Acoustics [3, 4]
  - Power [4]
  - Current [1, 5]
  - Torque [6]
- **Direct observation**
  - Laser scanner [7]
  - Vision [8-13]

**Relevant types of tool wear**

- a) Flank wear
- b) Groove
- c) Build-up-edge [10]

**Image of cutting tool insert**

- Microscope

- Flank wear
- Groove
- Build-up-edge
Deep Learning appears to be a promising method for solving the defined goals.

Goals

• Assistance system for machine operator
  • Automated detection of different wear regions
  • Calculation of relevant metrics such as flank wear width or area of groove
• Robustness against different illumination situations
• Adaptability for different types of cutting tool inserts

Examples from other fields:
• Robot-assisted surgery [14]
• Tumor detection in ultrasound data [15]
• Analysis of RMI scans [16]
• Detection of human cells [17]
In the presented solution, a sliding window approach using CNNs is used to provide wear information to the worker.
For every raw image a mask is created indicating whether a pixel depicts background, the tool or a type of wear defect.
Some of the classes seem to be easy separable whereas others look similar to the human eye.
After hyperparameter optimization, the model reaches a prediction accuracy of 91.5%.

**Pre-Processing**
- Slicing into windows of size 48x48 pixels
- For training: Balancing of data due to uneven distribution

**Class** | **Share**
---|---
Background | 39.2 %
Undamaged insert body | 54.0 %
Flank wear | 5.5 %
Groove | 0.8 %
Build-up-edge | 0.5 %

**Architecture:**
- 5 CNN layers
- 16, 32, 64, 128, 256 kernels respectively
- 32 neurons in fully connected hidden layer
- ReLu activation functions

**Training:**
- Adam optimizer [18]
- 200 epochs & 0.001 learning rate

**Post-Processing**
- Rearrangement of predicted classes to shape of raw data
- Noise removal using morphological operations

**Prediction accuracy:** 91.5 %
The proposed solution enables additional process insight, automated wear metric calculation and improved accuracy.

Resulting worker information system:

### Wear analysis:

- **Flank wear:** Detected; width: 360 µm
- **Groove:** Not detected
- **Build-up-Edge:** Detected; size: 0.25 mm²

### Segmentation result:

#### Flank wear width calculation:
Comparison of proposed solution to manual assessment:
- Average error manual procedure: 30.6 µm
- Average error proposed procedure: 17.1 µm
- For most samples, the proposed solution outperforms the manual assessment
The study showed, that deep learning is a promising tool for image segmentation in tool condition monitoring.

Summary

- Deep Learning through CNN can be used for automated semantic segmentation of images for cutting tools
- It is possible to detect and differentiate defects such as flank wear, grooves and build-up-edges
- The developed algorithm outperforms the manual approach in comfort and accuracy

Future research

- Increase of dataset for accuracy improvement
- Investigation of transfer learning strategies for incorporating new type of cutting tool inserts
Literature


Thank you!

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