Real-time method of detection wood defects using YOLOv8 model

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Abstract

Today, there are a significant number of materials for the manufacture of various technological and design solutions. The most common were decorative elements made of wood of various species: welt elements, decorative consoles, wooden furniture facades, frames for paintings and mirrors, icons, curly legs, details of artistic cutting, souvenirs. Handicrafts are valued more than the machine, but are very expensive to manufacture. The easiest way to do this is to use numerical control (CNC) machines. Currently, decorative milling is carried out on pre-prepared workpieces with a given fiber orientation, and milling modes are selected experimentally or from previous experience. The paper proposes a method of wood milling with optical recognition of workpiece defects and subsequent adjustment of cutting modes. The proposed method takes into account the recommended cutting modes for machining wood, namely feed speed and cutter speed, taking into account the anisotropy of the workpiece structure and mechanical properties. The proposed method differs in that it allows you to adjust the parameters of machining depending on the quality of the workpiece and is based on the basic principles of the theory of automatic control, modeling of milling and turning processes, including simulation modeling, methods of processing the results of experiments using machine learning.

Keywords

Milling, decorative milling, machine learning, computer vision

1. Introduction

Modern production of products with decorative elements is characterized by high requirements for the quality of products and the technical level of production, made of solid wood. When decorative wood milling on CNC machines, the cutter moves in space along a complex trajectory with a simultaneous change from two to five coordinates. When processing wood, chips, scuffs or other defects are formed due to various technological parameters and local structures of the workpiece, which lead to defects or require additional efforts to correct defects. The most pronounced are defects made of wood, which has low mechanical properties and significant structural heterogeneity.

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Recently, there has been a significant demand for products with knots that are aesthetically valuable. Knotted areas of wood are particularly sensitive to machining. The proposed adaptive milling technology makes it possible to increase the productivity of the technological process, reduce surface roughness, increase machining accuracy, reduce the time for harvesting operation and reduce the percentage of defects.

Milling of decorative elements is an extremely complex technological process that has a number of requirements for the geometric parameters of the tool, rotational speed, feed, positioning accuracy and discreteness of tool movements. To facilitate the machining process, preliminary preparation of workpieces is carried out with the orientation of the fibers strictly in one direction, which reduces decorative processing to linear milling with profile cutters. Technological parameters are selected experimentally, or they use the experience already gained, which leads to constant adjustment of parameters. However, due to the anisotropy of the structure, the quality of the surface treatment is different along and across the fibers (Figure 1).

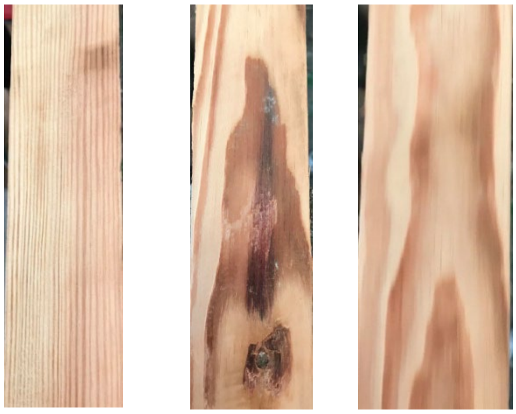

Figure 1: Example of the wood with knots.

Due to the pronounced symmetry along the axis of the tree trunk, the presence of annual layers is observed, which entails a significant difference in the properties of wood in the longitudinal, radial and tangential directions. Another indicator worth paying attention to is the moisture content of the raw materials. It should be borne in mind that products made of the same type of wood, made from blanks of different humidity, will have different quality of the finished product.

Wood differs in: color, pattern and texture, density and ability to split. Also, the processing of wood on CNC machines is influenced by factors such as the age of the tree and the place of its growth.

The main properties of wood of different species are given in Table 1.

Analysis of the data given in Table 1 shows that the strength of wood along the fibers is approximately several times greater than the strength across the fibers. In the transverse direction, the strength is greater than in the radial direction. Conifers have significantly lower tensile strength compared to deciduous ones. For most types of wood, there is no difference between the hardness of the radial and tangential planes, but for species with well-developed core rays (oak, beech), the hardness in the radial plane is 5–10% higher than the hardness in the tangential plane. The resistance of wood to splitting also depends on the orientation of the surface. For species such as (white acacia, beech, oak, birch, linden), the resistance to splitting varies significantly depending on the radial or tangential planes - by 20-40%.

Table 1
Characteristics of wood

Main physical and technical characteristics of wood							
Breed	Strength kgf/cm^2				Density kg/m^2		
	Compression along the fiber	On the bend	On the chip		At humidity 12%	Completely dry	Conditional
			Radial plane	Tangential plane			
Birch	44,7	99,7	8,5	11,5	630	600	500
Beech	55,5	108,5	11,6	11	670	640	530
Oak	52,0	93,5	8,5	10,4	690	650	560
Pine	43,9	79,3	6,9	8,0	500	470	400
Linden	39	68	7,3	8,7	495	640	400
Ash	51	115	13,8	13,3	680	640	550
Maple	54	109,7	8,7	12,4	690	650	5520
Alder	36,8	69,2	-	-	520	490	420

Therefore, application of computer vision for the optimization of milling process is an urgent and relevant task in order to automate the process of selecting the milling mode.

2. Literature Review

In the case of study, we conducted an analysis of the recent publication in the field of mechanical engineering and information technologies.

Paper [1] introduces an enhanced approach for detecting defects in ceramic products within an industrial setting by employing a computer vision system powered by deep learning models.

Study [2] offers an innovative method that utilizes Convolutional Neural Networks (CNNs) combined with image processing techniques to transform the way damage in wooden structures is evaluated through digital imagery.

The objective of [3] was to create an automated inspection system based on machine vision, featuring a robust algorithm capable of identifying minor defects in hardwood flooring during the manufacturing process. In [4], the YOLOv5 convolutional neural network is employed for wood defect detection, with adaptations made to both YOLOv5n and YOLOv5m variants.

Research [5] aims to tackle a key quality control issue in robotic-based manufacturing processes within the field of industrialized construction.

In [6], the authors introduce a novel method for detecting wood planks on a fast-moving conveyor and using a convolutional neural network (CNN) to segment surface defects in real-time.

The paper [7] provides an overview of the main wood defects affecting wood quality, introduces techniques for detecting and identifying wood defects using different technologies, highlights commonly used image recognition techniques for identifying surface defects in wood and introduces three advanced pieces of equipment for detecting and classifying such defects.

Work [8] presents a computer vision-based solution for object detection and tracking in forested environments.

In [9], an intelligent automated production system for solid wood is introduced, aiming to advance the adoption of automated industrial production methods for sawn timber in the wood structure construction sector. It also fosters deeper integration of artificial intelligence, internet technologies, and the broader wood processing industry, driving the transition of wood-based building materials toward intelligent manufacturing.

Paper [10] proposes an enhanced modeling approach based on ResNet-50 to improve the accuracy and efficiency of wood surface defect detection.

In works [11-12] we propose application of YOLOv8 CNN model for the purposes of different objects recognition. The same model will be applied in this research for the method of wood defects detection.

Also it was analyzed some neural networks approaches for other applications [13, 14, 15, 16, 17].

3. Research Methodology

3.1. Dataset

Large scale image dataset of wood surface defects [18] from Kaggle was used as a basis for model training. Original dataset contains 4000 images of wood surface defects. The domain analysis [19, 20] made it possible to determine the most common wood defects. The dataset was analyzed by the number of images with the following defects: Quartzity, Live Knot, Marrow, Resin, Dead Knot, Knot with Crack, Knot missing and Crack.

Figure 2 shows class distribution of the original training dataset. Thus, this dataset is imbalanced. However, firstly it was analyzed the whole images of dataset. Then the dataset was balanced.

Each image corresponds to a file with a description, indicating the coordinates of the corresponding defect, or the absence of any defects. An example of images from the training dataset is shown in Figure 3.

Figure 2: Class distribution of the original dataset.

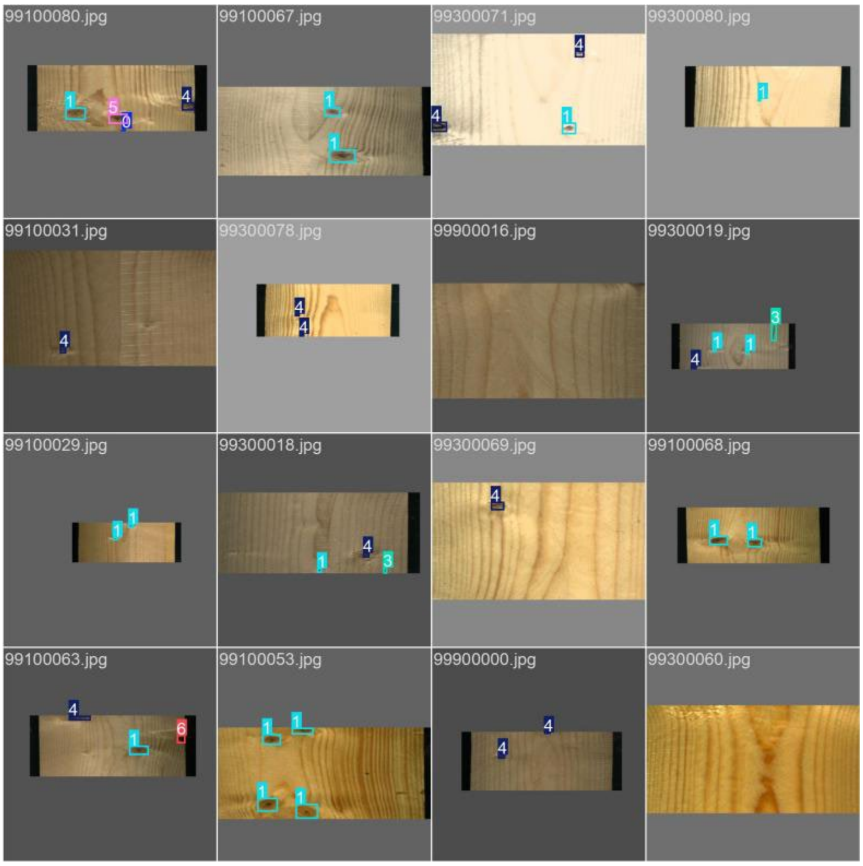

Figure 3: Images from the training dataset with marked defects and their type.

3.2. Metrics

The YOLOv8 model was used in the study. To evaluate the model it was used the following metrics [21]:

– Precision;
– Recall;
– mAP50;
– mAP50-95.

Precision measures the proportion between true positives and all detected objects:

$$P = \frac{TP}{TP + FP}, \tag{1}$$

Where:
P – precision;
TP (true positives) – correctly detected objects;
FP (false positives) – incorrectly detected objects.

$$R = \frac{TP}{TP + FN}, \tag{2}$$

Where:

FN (false negatives) – missed objects.

Average precision (AP) is calculated as the area under the precision-recall curve. For task of wood defects detection it can be calculated as:

$$\mathrm{mAP50} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{AP_i}, \tag{3}$$

Where:

N – number of classes.

Intersection over Union (IoU) is calculated as Area of Overlap divided by Area of Union.

Mean Average Precision across IoU thresholds (mAP50–95) is calculated as:

$$\mathrm{mAP50-95} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}} (\frac{1}{\mathrm{n}}\sum_{\mathrm{k}=1}^{\mathrm{n}} \mathrm{AP_{i,k}}), \tag{4}$$

Where:

n – number of IoU thresholds.

$\mathrm{AP_{i,k}}$ – the average precision for class i at IoU threshold k.

4. Results and Discussion

During the development of the model, experiments were conducted to determine the most optimal parameters for training.

The original dataset was splited into training and validation sets. Since the values of the metrics were not satisfactory, the balancing of the dataset was carried out and the removal of classes for which there was insufficient data. This made it possible to speed up the operation of the model from 104.1 to 0.78 ms per image. This result allows to use the model for real-time image analysis.

According to the per-class analysis, it can be concluded that Live Knot and Dead Knot have precision over 0.8. The best value was observed for Live Knot – 0.868. Compared to the initial values, it was possible to increase recall, although its value is still insufficient, especially for Resin.

Thus, Resin and Live Knot still have slightly lower performance in terms of recall and mAP50-95 compared to Dead Knot. The model demonstrates the best recognition results for Dead Knot, which is due to the large number of images with this defect in the dataset. Figure 4 shows work of the model on the validation set.

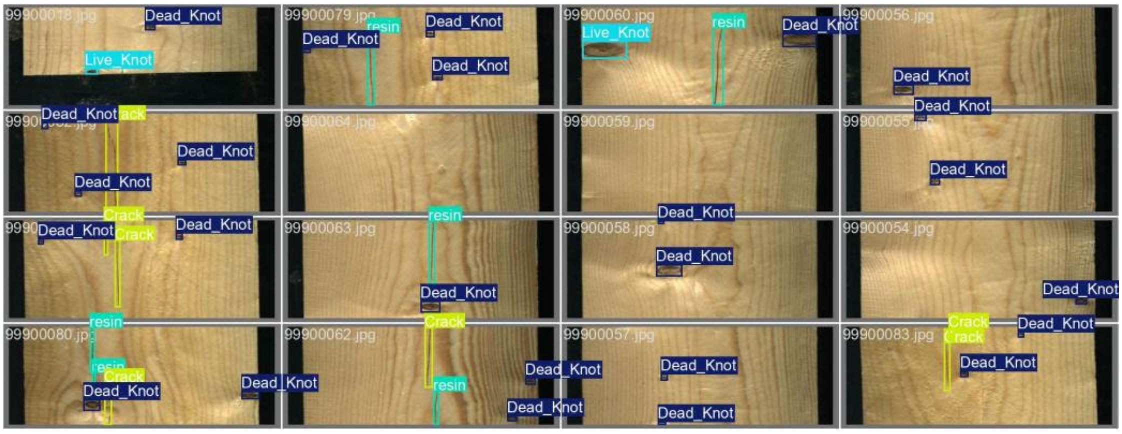

Figure 4: Defects detecting on the validation set.

5. Conclusions

Milling is a complex process, and therefore requires a comprehensive approach. Defects in wood directly affect the efficiency of processing, therefore, determining the type of defect plays a key role and has a direct impact on product quality.

The research proposed a method of detecting wood defects in real time using the YOLOv8 model. The evaluation of the metrics allows to conclude that the application of image analysis technology can significantly improve the milling process. The proposed model allows to determine Live Knot, Dead Knot and Resin. At the same time, there is a need for further research to improve the accuracy of identifying individual defects as Quartzity, Marrow, Crack and other.

The limitations of the conducted research are determined by the lack of images for certain types of defects in the dataset. However, sufficiently high indicators of metrics for classes that are present in sufficient numbers in the dataset testify to the effectiveness of the chosen approach and the feasibility of further research. In future work, we consider it advisable to conduct research with an expanded dataset to classify a larger number of defects.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: grammar and spelling check; DeepL Translate in order to: some phrases translation into English. After using these tools/services, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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