

Bark Abrasion Evaluation on Birch (*Betula Spp.*) Round Timber by Using Machine Learning Algorithm

Jānis Magaznieks
VMF LATVIA SIA
Riga, Latvia
janis.magaznieks@gmail.com

Mareks Millers
VMF LATVIA SIA
Riga, Latvia
mareks.millers@inbox.lv

Abstract— Birch has an exceedingly high potential from the point of view of cultivation, respectively, now in Latvia more and more new factories are being opened that produce birch plywood and the demand for birch round timber is increasing every year. Latvian legislation, as well as business relations between different trading parties, require accurate determination of the volume of round timber without bark. Automatic measuring devices mainly determine the diameter with bark and then reduce it using bark algorithms. Machine learning has great potential in labour shortage. During machine learning, a computerized system could analyse large amounts of data and diverse properties [1]. Convolutional neural network can ensure the system's resistance to image defects due to various types of lighting conditions, image shifts and changes in their shapes, which can be caused by the characteristics of the camera lens [2]. One of the tasks of timber measurement process is to assess the amount of bark abrasion, as well as the thickness of the bark. Within the framework of the project, we have investigated the possibilities of determining the area of bark abrasion of round timber using machine learning algorithms. To assess the accuracy of the model, we have randomly selected 90 round timber samples from the system, which have been marked by a timber scaler in a computer program, as well as the computer program itself. On software with image processing and analysis capabilities, visual data of the side surface of round timber were evaluated, manually assessing the areas of bark abrasion. The obtained results were compared with the bark mass obtained using the prepared computer vision algorithm. Machine learning algorithm, on average, calculates smaller bark mass – 76 %, compared to the manually obtained results – 84 %. Bark abrasions and most of the remaining bark can be assessed without difficulty for round timber with a darker and more crusty bark, for example, for cuts prepared from the thick end of the trunk. For birch round timber with a white colour, in some cases, part of the white colour is perceived as bark abrasion and,

therefore, a smaller majority of remaining bark is assessed. To assess the volume of round timber without bark, the proportion of bark must be assessed, which must be calculated from the total volume of the measured diameter with bark. When assessing the coincidence of the determined bark types, it can be observed that the bark type according to the computer vision algorithm coincides in 79 % of cases with the bark type obtained after manual processing of visual data.

Keywords— Birch, bark detection, machine learning.

I. INTRODUCTION

In many European countries, the price for each log is determined based on log volume and quality. Reason for retaining the bark until the moment before sawing is improved log properties with respect to preservation and processing efficiency [3]. Latvian legislation, as well as business relations between different trading parties, require accurate determination of the volume of round timber without bark [4].

The log price depends on log volume and log quality. Both for log quality (which is not discussed any further here), and for log volume, there are different assessment methods, depending on the targeted use and on country specific regulations. Therefore, the determination of the log volume for sawlogs is often based on individual log diameter and length measurements [5]. In some countries, the top diameter is used (e.g. in Sweden) [5], while in other countries, the middle diameter is the basis for calculating the log volume [6].

In Latvia both methods are used, additionally with section wise method - when diameter is measured in every section, starting from 1 cm length [7]. For harvested timber, bark is a good insulating or wrapping material and the most

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important feature in determining the tree species, which preserves the moisture of freshly harvested wood, prevents the occurrence of lateral drying cracks and the development of fungi for a limited time [8].

Mostly, bark is excluded from the diameter or volume or weight measurement, either by removing the bark prior to the measurement, or by reducing the measured values according to some estimate of the involved bark. For sawlogs, roundwood diameter measurement usually is done in the sawmill, directly after log delivery. The logs are loaded onto a conveyor, where one by one they are singled out. If the bark is to be removed before log measurement, it is usually done at this point [9]. There are several approaches for determining the diameter (or the volume) under bark if the measurement has been done on bark. One common method is to infer bark thickness from the log diameter, based on tabled values or formulas [5].

Other way is bay using X-ray computer tomography. If there are fresh round timber it is possible to determine log diameter with and without bark [10], [11]. There is also possibility to use convolutional neural networks for image recognition. Convolutional neural networks are widely used in image and pattern recognition as they have several advantages compared to other techniques. A neural network is a system of interconnected artificial “neurons” that exchange messages between each other. The connections have numeric weights that are tuned during the training process, so that a properly trained network will respond correctly when presented with an image or pattern to recognize [2]. Assessing the quality of round timber by measuring with automatic measuring devices and using artificial intelligence technologies includes a variety of approaches, including deep learning algorithms and computer vision systems. Deep learning algorithms enable wood defects to subtly segment and acquire various characteristics, as well as create a resource collection with wood defect features for large amounts of data. Deep learning algorithms usually require a relatively large amount of data, but it is also possible to apply them to small amounts of data by training algorithms [12], [13].

Bark detection algorithms can be based on colour, texture, and a combination of colour/texture. Natural colour variations of the bark can negatively affect the pixel colour algorithm, which in turn negatively affects the bark detection algorithm [10].

II. MATERIALS AND METHODS

To assess the possibilities of evaluating bark abrasion, 90 birch veneer log samples were selected at random sampling method from timber sorting line from production environment in JSC "Latvijas Finieris" log yard "Bolderāja" in Riga, Latvia. Samples were collected from 23rd of October till 13th of November year 2024. In this research all taken samples were clean from ice, mud or any other impurity which could affect bark recognition. Top diameter distribution is shown in Table 1.

TABLE 1 TOP DIAMETER DISTRIBUTION OF VENEER LOG SAMPLE SET

Top diameter, mm		Amount, pieces
From	Till	
160	179	12
180	209	30
210	249	33
250	299	12

This particular plywood factory in using individual measurement method by measuring the diameter at small intervals. For this method it is necessary to obtain results for bark abrasion on all assortment side surface for under bark diameter calculation. In the same location special camera setup were created to record data on timber sorting line and by using the computer program developed within the framework of the project, birch round timber was processed automatically using the developed bark assessment machine learning service. The following raw and unprocessed images were obtained and shown in Fig. 1. This type of pictures was obtained for all sample set.



Fig. 1. Samples of birch round timber without bark filters on the left and automatically recognized bark amount on the right.

In this type of image processing, it is possible to obtain the exact volume of the remaining bark, which is applicable in the further calculations of the bark thickness. In this study main task is to understand precision for bark abrasion amount. In Fig. 1 it is possible to see also difficulties on the left side of the figure where part of the bark is marked as debarked. White colour pattern for birch in some cases is giving difficulties to correctly recognize the amount of bark abrasion. Images of birch round timber logs are obtained in motion on the conveyor of the sorting line, without stopping the conveyor. Same birch round timber logs were measured manually by using ImageJ program for computer vision precision comparison (see Fig. 2 and Fig. 3).

To understand machine learning service capabilities to assess bark abrasion, the amount of the bark abrasion on round timber were compared to bark type codes which are used in Latvia. Bark type 0 is used when bark abrasion is 0 %, bark type 1 is used when bark abrasion is 50 %, bark

type 2 is used when bark abrasion is 75 %, Bark type 3 is used when bark abrasion is 100 % [14].

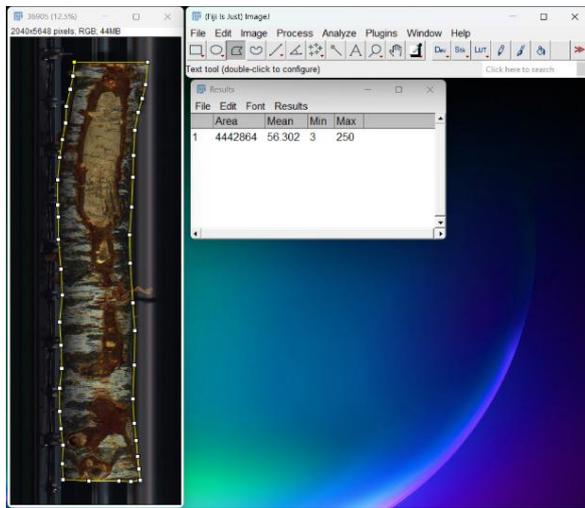


Fig. 2. Full surface area detection manually by using ImageJ program.

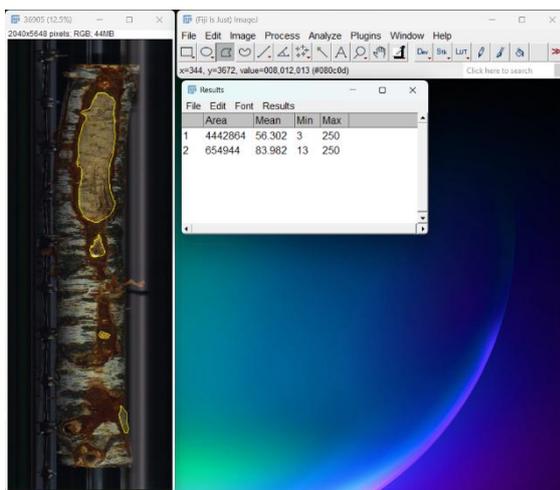


Fig. 3. Bark abrasion area detection manually by using ImageJ program.

In determining the volume of round timber, only the volume of wood is considered, so the proportion of bark should be calculated from the total volume or the measured average with the bark [7]. Since the thickness of the bark varies widely, and in the process of logging it is partially abraded in each working operation, significant difficulties arise in assessing the correct volume of timber. The deduction of bark in further calculation shall be made by applying a particular type of abrasion [15].

III. RESULTS AND DISCUSSION

To correctly determine the volume under the bark using the bark algorithms, it is important to know the actual abrasion of the bark for each cut-off, in cases where the individual measurement method is used. To improve the accuracy of determining the volume of round timber using computer vision technologies, the amount of the bark is also evaluated. Using the visual data of cameras with the help of computer vision technology, it is possible

to evaluate bark abrasion on the side surface of the round timber.

On software with imaging and analysis capabilities, visual data of the side planes of round timber is evaluated, manually evaluating the abrasion areas of the bark are determined. The results obtained manually with ImageJ are compared with the amount of the bark, obtained using the prepared computer vision algorithm developed in project framework. Without difficulty, bark abrasions and most of the remaining bark are appreciable round timbers dominated by darker and more crested bark, such as cutoffs prepared from the butt part of the trunk. For birch round timber, where white colour predominates, in some cases, part of the white colour is perceived as an abrasion of the bark and, as a result, a smaller majority of the remaining bark is valued. For this purpose, according to the estimated proportion of the bark, certain types of bark are used (Table 2).

TABLE 2 COMPARISON OF MANUALLY DETECTED BARK AND BARK DETECTED BY COMPUTER VISION

Parameter	Bark amount, % (manual measurement)	Bark amount, % (computer vision)
Total		
Average	84,0	76,2
Standard error	1,8	2,0
Standard deviation	16,7	19,3
Minimum	25,0	18,0
Maximum	100,0	100,0
Samples	90,0	90,0
Bark type 0		
Average	27,0	20,0
Standard error	2,0	2,0
Standard deviation	2,8	2,8
Minimum	25,0	18,0
Maximum	29,0	22,0
Samples	2,0	2,0
Bark type 1		
Average	52,5	45,5
Standard error	3,6	3,8
Standard deviation	8,8	9,3
Minimum	38,0	29,0

Parameter	Bark amount, % (manual measurement)	Bark amount, % (computer vision)
Maximum	60,0	53,0
Samples	6,0	6,0
<i>Bark type 2</i>		
Average	78,2	68,6
Standard error	1,1	1,5
Standard deviation	7,1	10,1
Minimum	65,0	48,0
Maximum	90,0	85,0
Samples	44,0	44,0
<i>Bark type 3</i>		
Average	98,7	92,7
Standard error	0,4	1,6
Standard deviation	2,3	9,6
Minimum	92,0	63,0
Maximum	100,0	100,0
Samples	38,0	38,0

Bark abrasion level in Latvia in autumn is quite low, so most of the data is bark type 2 or bark type 3. The difference for bark type 2 is 10 %. Computer vision is giving slightly smaller bark abrasion value. In bark type 3 the difference is around 8 % and the same pattern that computer vision algorithm gives smaller abrasion value.

In Fig. 4 it is possible to analyse that correlation between actual bark and bark amount determines by computer vision has close correlation ($R^2 = 0,8475$).

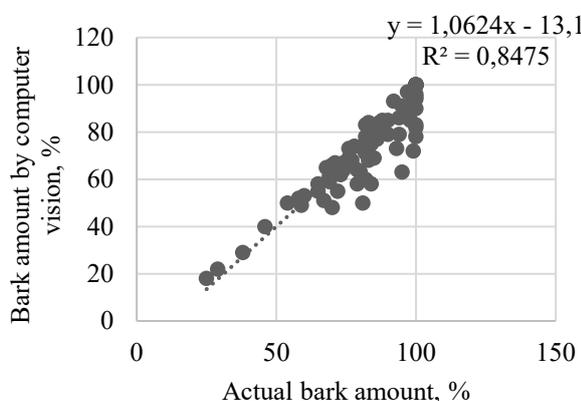


Fig. 4. Actual and computer vision calculated bark amount, %.

In production environment timber scaler is choosing bark type by visual so in this research we wanted to evaluate precision of coincidence of bark types has also been assessed based on manually processed visual data, in the actual assessment of bark abrasion. When comparing the coincidence of bark types according to most bark evaluated by the actual and computer vision algorithm, the type of bark determined by timber scalers is also considered.

When evaluating the coincidence of the identified bark types, it can be observed that the type of bark according to the prepared computer vision algorithm in 79 % of cases coincides with the type of bark obtained after manual processing of visual data. On the other hand, the type of bark determined by the scaler in 62 % of cases coincides with the type of bark after manual processing of visual data (Fig. 5).

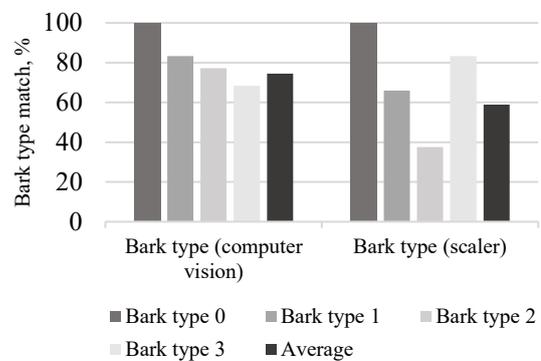


Fig. 5. Bark type match in comparison of computer vision and timber scaler.

When evaluating the coincidence of bark types separately for each type, according to the prepared computer vision algorithm, a trend is observed – as the majority of bark increases, the mismatch of bark types also increases. On the other hand, according to the bark type recorded by the scaler, it can be concluded that the highest coincidence is for bark type 3 (most bark above 90 %) and bark type 0 (most bark below 30 %).

When assessing the coincidence of bark types, scalers should take into account that in the performance of their duties it is possible to see the side surface of the round timber at a rate of 100 %, but using visual data from cameras it is possible to see a maximum of up to 75 % of the side surface, which may contribute to the mismatch of bark types.

In order to improve the coincidence of the bark type according to the computer vision model, it is necessary to improve the recognition of bark abrasion on birch round timber, which is strongly dominated by white colour, but in general if we analyse the bark type match, the results are promising for testing the bark recognition service in production environment.

IV. CONCLUSIONS

Using the prepared computer vision algorithm, on average, a smaller majority of bark is systematically determined in the assessment of most bark – 76%, compared to manually obtained results – most bark – 84%. The reason for this trend is the analysis of the images of the bulk of the prepared bark evaluation algorithm, in which the colour of the peel is evaluated first, and then the texture. To improve the coincidence of the bark type recognition the bark according to the computer vision algorithm, it is necessary to improve the recognition of bark abrasion on birch round timber, which is mostly dominated by white colour.

When evaluating the coincidence of the identified bark types, it can be observed that the type of bark according to the computer vision algorithm in 79 % of cases coincides with the type of bark obtained after manual processing of visual data. On the other hand, the type of bark determined by the scaler in 62 % of cases coincides with the type of bark after manual processing of visual data. Here, however, it should be noted that scalers have the opportunity to see the side surface of the round timber at 100% when performing their duties but using visual data from cameras it is possible to see a maximum of up to 75 % of the side surface, which can contribute to the mismatch of bark types.

The precision of bark type match for computer vision in comparison to timber scaler gives average is 15 % better results.

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