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Improving the quality of sorting wood chips by scanning and machine vision technology

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Abstract: Improving the quality of sorting wood waste is the main problem in the timber industry from the point of view of saving energy resources and preserving the environment, associated with the intensity of forest harvesting. Depending on the required quality characteristics, the sorting of wood chips makes it possible to determine their further use in production or utilization as a fuel. This paper presents the results of the development of a novel approach to sorting wood chips on a conveyor belt using machine learning and scanning technology. The proposed methodology includes functions to analyze the fractional size distribution among wood chips and rot detection. It shows that once a defective unit is detected, the quality control system will automatically remove it from the conveyor belt while it is moving. The minimization of wood waste will reduce logging intensity and increase the profitability of lumber enterprises.

Keywords: image processing; laser scanning; machine vision; Otsu method; wood; wood chips

Recycling of wood chips is currently an urgent task from the economic and environmental points of view. Depending on the quality of the product, recycling can range from the production of boards and cellulose to biofuels and fertilizers (Lesar et al. 2018; Borodin, Zhangabay 2019). The quality of wood chips depends on many factors, such as type of wood, log pre-processing, shredding, and sorting. The latter is of particular interest for studies since the effective sorting affects the price category of chips and the direction in which they are disposed of (Aruova et al. 2020).

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Classification of wood chips according to Verheyen et al. (2016) is divided into the following types: raw wood (class A), industrial recycled wood (class B derived from chipboard, cardboard, etc.), fuels (class C), and unsuitable wood (class D). The latter constitutes the wood, hazardous to the environment, which may contain rot, harmful substances, and microorganisms.

At present, the chip industry requires that the purchased wood chips will contain more than 95% of class A wood (Fojtík 2014). Therefore, material quality and dimensional parameters of wood chips are important factors in the evaluation of product sorting.

Sorting wood chips by size (Bian et al. 2017) allows classifying particles by volume and application. For example, for the production of pulp, large wood chips are further processed before application, and fine chips are mainly burned or used as fertilizer (Scharenbroch, Watson 2014).

High-quality wood chips are usually characterized by the type of wood, volume fraction of the chip content of the non-standard size, thick chips, uniform density, absence of bark and rot (Schön et al. 2019; Plankenbühler et al. 2020). The quality of wood chips is also affected by the grinding process. Most industrial shredders use a disc or drum knives to shred wood (Spinelli et al. 2020). As productivity is directly proportional to the power and size of the shredder part, the wear of the blades, cutting length, and drum size also strongly affect the chip quality.

The development of modern laser technology offers completely new possibilities for direct measurement of linear and volumetric wood chips on the conveyor belt. The laser scanning technology enables the continuous measurement of material that is transported at a known speed on the conveyor belt (Ross 2015). For this purpose, a 3D or 2D laser scanner, encoder, and an electronic evaluation unit with the software are required. There are several laser scanning methods and principles that differ in accuracy, speed, measurement range, and price category (Schajer 2016). But the most important and relevant aspect for practical use is the programming of image processing from the scanner and the quick and accurate determination of inconsistencies in products. The purpose of this study was to develop a perfect technique for scanning and sorting wood chips with an assessment of the quality of the material and a quick response to the shortcomings on the conveyor belt in real time. Sorting the product directly in the production process significantly increases its efficiency and reduces the cost of wood raw materials and energy.

MATERIAL AND METHODS

Wood chips are evaluated in a special laboratory equipped with an analyzer, scales, an oven and other devices that help analyze the quality of wood chips. The 3–5 kg portions of wood chips from a debarked log are sorted with a disc screen sorter and transported via a conveyor belt at regular intervals (5, 10 or 15 min). Those chip portions that were collected in 1 hour are placed together in a single pile, which is later mixed. From the resultant mixture, a representative sample weighing about 2.5 kg is selected by quartering. The sample is sorted by size using an ALG-M laboratory chip analyzer (ROTEX, USA) for one minute. The analyzer is equipped with sieves (opening diameters: 30, 20, 10, and 5 mm) and a tray.

Chips from different size groups are weighed and the fractional size distribution is determined. Wood chips that are more than 5 mm but less than 20 mm in size are manually sorted to exclude those with any bark left. Note that if the bark did not separate from the chips during treatment, then the peeling of the part is done manually.

To get immediate updates on the quality of chipped material and to automate a debarking process, participants of the scientific school "Innovations in Lumber Production and Forestry" have designed a new production line for the generation of high-quality wood chips (Grigoriev et al. 2014; Gasparyan et al. 2018).

The system for the automated wood chip quality consists of a laser and a radiation receiver. Together they are a laser distance meter. The laser beam moves at high velocity in a direction perpendicular to the movement of the conveyor belt, is reflected from the surface and enters the receiver. Many distance readings obtained during a single pass of the laser beam along the conveyor give a shear image of the particular location on the conveyor belt. As it moves, the laser repeatedly scans the surface and receives new shear images. A set of many images gives a complete picture of the conveyor performance, specifically the distribution of wood chips on it and their size (Figure 1).

The movement of the laser beam is controlled using a stepper motor. Controlling by pulse-width

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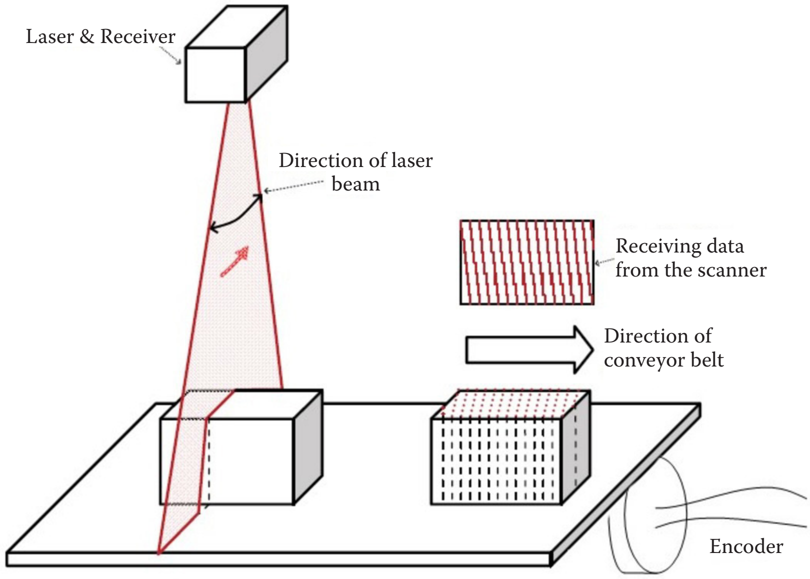

Figure 1. A schematic view of a wood chip quality assessment system in operation

modulation allows you to know the exact location of the laser beam at any given time without additional feedback. The conveyor drive has an encoder to measure the exact speed of the conveyor. Based on the information received from the encoder, the laser scanning protocol can be adjusted.

Readings from the laser scanner and encoder are fed to the computer. Multiple conveyor statuses are sequentially fed to the computer from the scanner as well as distances between them calculated by an encoder will help reproduce the boundaries of each single wood chip, calculate its size and categorize to one of the three groups (i.e., large, small, and acceptable). Based on the statistics stored in the computer, the system measures the proportions of wood chips of different sizes. Further, depending on the laser position and on the goals set, the operator is informed about the progress and signalled if an immediate intervention is needed (Figure 2).

The phase method of measuring distance allows placing the laser up to 15 meters away from the target and taking scans with accuracy to one part in a millimetre, which is acceptable here.

The laser scanning module used in this system is an LS2D laser sensor (NPP Prizma, Russia), with a 10/100 Ethernet interface, which allows connecting it to a computer without using additional equipment. For this system an incremental encoder with measuring wheel and spring arms was used (pulses per revolution, 10.000 or more). Raspberry PI2 sin-

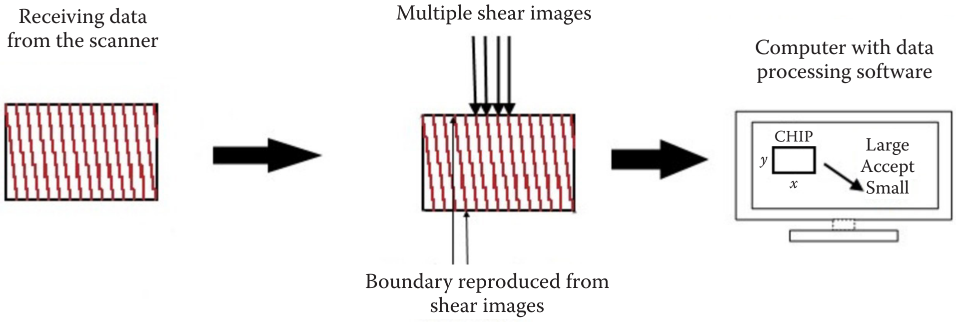

Figure 2. Steps of wood chip quality assessment

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gle-board computer can handle the processing of signals from the sensor and scanner: it has a quad-core ARM processor, 1GB RAM, a 10/100 Ethernet port (for a scanner), a 40-pin GPIO connector (for an encoder).

Advantages of this system:

(*i*) high speed scanning;

(*ii*) high accuracy;

(*iii*) the position of a chip, its shape and size do not affect the result;

(*iv*) no redesign of the conveyor needed.

One of the major disadvantages is that the conveyor must be loaded with only one not deep layer of wood chips.

The proposed system will eliminate the need for chip sampling and laboratory analysis. Scanning wood chips before and after sorting will allow obtaining timely information about the working order of the chipper knives and sorter screens, about the production output and the amount of waste.

To fully automate the assessment of the quality of wood chipping, an independent automation software program was developed. The application is IBM-PC compatible. The major challenge posed by wood sorting automation is linked to machine vision and image processing. To automatically evaluate the quality of wood chips, the laser scanner was set to distinguish wood surface areas that have darker and lighter shades. Darker areas were recognised as defective. The percentage of rot in wood chips was determined in the process of several stages: foreground segmentation; binarisation; image segmentation; area calculation, and class decision. In this study, a graphic-analytical model of core rot recognition was used. Binary image of rot was obtained by the Otsu method. Rotten areas of interest normally either distinguish themselves along the edges or have different brightness. Thus, it is important to obtain high-quality segmented and binary images. Segmentation is the process of partitioning a digital image into multiple pixels. Binarisation is the process of assigning either black or white colour to each segment using a threshold obtained by the Otsu method (Otsu 1979). The threshold value in points varied between 0.5 and 1.5.

The graphic-analytical model of defect recognition. If an image is defined as a function img = I w(x, y) with $x \in [0; W]$ and $y \in [0; H]$, where W refers to the image width and H to the image height, then the graphic-analytical model of this image could be written as follows:

$$G=\left(V,E\right),V=\left\{v_{i1}\right\},E=\left\{e_{i2}\right\},i1\in W\times H,i2\in 1\ldots K \quad (1)$$

where:
G – image;
V – *t*he set of edges;
v_i – i-th edge;
E – the set of vertices;
e_i – i-th vertice;
K – vertice number.

Vertices of this model designate the pixels of an original image, while edges correspond to connections between these pixels. The formula for creating a graph that corresponds to a source image is as follows:

$$\forall P_k\left(x_i,\ y_j\right)\in \text{img}, k=1\ldots\left(W\times H\right),$$
$$G=\left\{V\cup P_c\ \left(x_i,y_j\right)\left(P_{c\ ,}P_{c+r}\right)\right\} \quad (2)$$

where:
P_k – the pixel of an original image;
P_c – pixel of image G;
r – index defining adjacent pixel P_c;
x, y – coordinates of a pixel P_c;
i = 1 … W, j = 1 … H.

The colour of the vertex corresponds to the colour of a corresponding pixel as:

$$G_{\text{sub}}=G\times G^{(n)} \quad (3)$$

where:
G_{sub} – the colour of the vertex;
n – numerical designation of colour.

A zero vertex designates a pixel, the brightness of which equals to zero and follows pure black.

The maximum degree of a graph is a vertex that designates a pixel of image with the highest value of brightness:

$$\max\left(G\right)=\max\left(V\right) \quad (4)$$

Segmentation with mask refers to an overlay of a mask of similar configuration over an arbitrary colour graph to obtain a graph with vertices multiplied in the corresponding positions:

$$G'=G\times B \quad (5)$$

where:
B – a mask.

The multiplication of vertices is the multiplication of brightness values of the corresponding pix-

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els. A mask is a graph with vertices of either black (brightness 0) or white (brightness 1) colour.

The inversion of a vertex is the inversion of a brightness value. Zero vertices are the inversion of non-zero vertices and vice versa:

$$\text{inv}(e)=\begin{cases}1 e=0\\ 0 e>0\end{cases} \tag{6}$$

The inversion of a coloured graph is the inversion of all vertices. The idempotence condition is not fulfilled in this case and applies only to the process of creating a mask:

$$\begin{aligned}&\left(B=\text{inv}(G)\right)\\&\left(G\neq\text{inv}(B)\right)\end{aligned} \tag{7}$$

The union of coloured graphs is the replacement of all zero vertices of the first graph by the non-zero vertices of the second graph in the corresponding positions, if any:

$$G_1\cup G_2=G_3,\forall i\in W\times H,v_i^{(1)}=0:v_i^{(3)}=v_i^{(2)} \tag{8}$$

where:

v_i – the vertex of the graph G.

The quality of segmentation is associated with the image pre-processing procedure. Before binarisation, the image goes through several stages of pre-processing. In the presence of objects other than the object of interest on the image, the segmentation operation was performed on the object by using the thresholding method (the algorithm was set to find a colour-based difference between the background and the object).

The algorithm of determination of the threshold value consists of the following steps:

Step 1. To determine the threshold value in range (0.5; 1.5) and distribute vertices of the graph in two classes, black and white. The resultant graph BG_0 (binary graph) allowed the separation of an object from the background.

Step 2. To obtain a Figure of the object on the black background let us perform a segmentation operation upon the initial graph CG_0 with mask as:

$$CG_0\times BG_1=CG_1 \tag{9}$$

Step 3. Let us build a temporary graph TG_0 that is similar to the initial graph CG_0 and has a maximum degree that corresponds to the maximum degree of the graph CG_1:

$$TG_0=\left\{\forall i\in W\times H: v_1=\max\left(CG_1\right)\right\} \tag{10}$$

Step 4. Let us perform a segmentation operation upon the graph TG_0 with mask created in the previous step:

$$TG_1=TG_0\times\text{inv}\left(BG_0\right) \tag{11}$$

Step 5. The union of graphs TG_1 and CG_1 for the creation of a source object on a non-zero background:

$$CG_2=TG_1\cup CG_1 \tag{12}$$

Step 6. Let us repeat step 1 for the graph CG_2 to highlight the darkened edges of the image. If vertices designating the background pixels continue to be zero, then the binarisation sequence shall be repeated.

Step 7. Let us repeat steps 5–7 for the graph CG_2, for a non-informative part of the image to be excluded. The resultant structures are mask BG_1 and graph CG_3.

Step 8. The graph BG_1 is produced by repeating step 1 for the graph CG_3. It may be segmented by colour to allocate a potentially defective area on the wood surface:

$$BG_1\times G^{(0)}=UG_0 \tag{13}$$

where:

UG_0 – a segmented by colour graph.

Step 9. To evaluate the result let us use graphs BG_1 (for total area calculation) and BG_2 (for defective area calculation).

Step 10. Let us perform a segmentation operation upon graph BG_1 to distinguish the white class of vertices C_1.

Step 11. Let us perform a segmentation operation upon graph BG_1 to distinguish the black class of vertices C_2.

Step 12. To restore the objective picture, it is necessary to introduce a correction coefficient CK, which is calculated as follows:

$$CK=\frac{BG_1\times G^{(0)}}{S_{\text{object}}}=\frac{UG^0}{S_{\text{object}}} \tag{14}$$

where:

$S_{\text{object}} = BG_1 \times CG_0$.

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The need to produce the correction factor *CK* is due to the fact that areas on the wood surface that are rotten may also contain non-rotten wood of low quality. Accordingly, the formula for the percentage of darkened area on the image will be as follows:

$$O_{\%} = \frac{\left(C_2 \times CK \times 100\right)}{C_1} \quad (15)$$

where:

C_2 – the quantity of object's vertices;

C_1 – the quantity of vertices designating a defective area;

CK – a correction coefficient taking into account the darkened edges of the image.

RESULTS AND DISCUSSION

The software application was tested and optimized on the conveyor line developed by the scientific school "Innovations in Lumber Production and Forestry". According to the results of the testing, the average application was established to take only 90 ms to perform a complete classification, set the vision data, and send them to the sorting unit. The results of numerous tests showed that the tested wood chip samples contained up to 4.5% rot of the total chip mass. According to the manual sorting data it was found that only 3% of the chips were removed from the conveyor belt. A comparison of these results allows concluding that the proposed technique of machine vision is more effective and accurate to obtain better quality products. Once a defective unit is detected, the quality control system automatically removes the defective unit from the conveyor belt while it is in motion. Besides, it fully meets the needs of the wood chip industry. Minimizing wood waste will reduce the intensity of logging and increase the profitability of logging companies.

A similar approach to the use of machine vision for sorting wood chips has been used in several works, the results of which are well consistent with the results of this work (Sgarbossa et al. 2014; Rezaei et al. 2016; Wu et al. 2018). In these studies, methods based on machine vision with the analysis of colour images were proposed, which significantly complicates the task. In Bakhshipour et al. (2017), the processing algorithm contained the determination of wavelet texture characteristics for each image class. Image segmentation was based on the neural network solution. After that, a decision was made to sort the image. The use of convolution neural networks and manually created descriptors to classify the fine-grained images in the work of Duissenbekov et al. (2020) showed that neural networks demonstrate good performance but are not reliable or accurate methods for recognizing fixed textures. The sorting program developed in this paper differs from previous methods by its simple architecture, and the use of the Otsu method allows speeding up the process of defect detection, which ensures fast and accurate sorting.

In Tiitta et al. (2020), the authors used electro-impedance spectroscopy in combination with machine learning. According to the results, the method of K-nearest neighbour gives the best result in recognizing the content of the wood core in the chip. Results of the paper published by Eriksson and Gustavsson (2010) showed that the development of the sorting algorithm for wood chips should consider not only the size and grade of the tree, but also the biochemical approach, taking into account the level of primary energy consumption and CO_2 emissions. These findings from the perspective of the given approach suggest further research aimed at improving the software application of wood chip sorting, which will be presented in future works.

CONCLUSION

The developed algorithm of image processing based on machine vision allows detecting rotten fractions and poor-quality wood chips, as well as performing automatic sorting by size. The analysis of the test results showed that the amount of rotten wood chips in the wood mass is up to 4.5%. A comparative study of calculations and observations showed that the existing model provided adequate and up-to-date information on the percentage of rot in the material under consideration. The image processing algorithm is compatible with the used software and existing machine vision systems. It allows improving the quality of wood processing operations by detecting rotten segments in real time. It is assumed that the reduction of wood waste will reduce the intensity of logging and increase the profitability of wood-working companies. As future research, the application for sorting for other wood defects and different types of wood is believed to be improved.

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REFERENCES

Aruova L.B., Ospanova Z.N., Aruov B.B., Alibekova N.T., Shashpan Z.A., Kyrgizbaev A.T. (2020): Cyclic Tests of Joints of Glued Wooden Structures. IOP Conference Series: Materials Science and Engineering, 829: 012017.

Bakhshipour A., Jafari A., Nassiri S.M., Zare D. (2017): Weed segmentation using texture features extracted from wavelet sub-images. Biosystems Engineering, 157: 1–12.

Bian H., Chen L., Gleisner R., Dai H., Zhu J.Y. (2017): Producing wood-based nanomaterials by rapid fractionation of wood at 80 °C using a recyclable acid hydrotrope. Green Chemistry, 19: 3370–3379.

Borodin K., Zhangabay N.Z. (2019): Mechanical characteristics, as well as physical-and-chemical properties of the slag-filled concretes, and investigation of the predictive power of the metaheuristic approach. Curved and Layered Structures, 6: 236–244.

Duissenbekov B., Tokmuratov A., Zhangabay N., Orazbayev Z., Yerimbetov B., Aldiyarov Z. (2020): Finite-difference equations of quasistatic motion of the shallow concrete shells in nonlinear setting. Curved and Layered Structures, 7: 48–55.

Eriksson L., Gustavsson L. (2010): Comparative analysis of wood chips and bundles – Costs, carbon dioxide emissions, dry-matter losses and allergic reactions. Biomass and Bioenergy, 34: 82–90.

Fojtík D. (2014): Measurement of the volume of material on the conveyor belt measuring the volume of wood chips during transport on the conveyor belt using a laser scanning. In: Proc.15th Int. Carpathian Control Conf. (ICCC), Velké Karlovice, May 28–30, 2014: 121–124.

Gasparyan G., Kunickaya O., Grigorev I., Ivanov V., Burmistrova O., Manukovsky A., Zhuk A., Hertz E., Kremleva L., Mueller O. (2018): Woodworking facilities: Driving efficiency through automation applied to major process steps. International Journal of Engineering and Technology, 7: 368–375.

Grigoriev I.V., Kunitskaya O.A., Kunitskaya D.E., Lansky Yu.V., Chuvashev E.S., Perevozchikov A.A. (2014): A device for automatically evaluating debarking efficiency and controlling the return of poorly debarked logs for additional debarking. Utility Model Patent RUS 151533.

Lesar B., Humar M., Hora G. (2018): Quality assessment of recycled wood with and without non-wooden materials from selected recycling companies in Europe. Waste Management, 79: 362–373.

Otsu N. (1979): A threshold selection method from gray-level histograms. IEEE Transactions on Systems, Man, and Cybernetic, 9: 62–66.

Plankenbühler T., Kolb S., Grümer F., Müller D., Karl J. (2020): Image-based model for assessment of wood chip quality and mixture ratios. Processes, 8: 728.

Rezaei H., Lim C.J., Lau A., Sokhansanj S. (2016): Size, shape and flow characterization of ground wood chip and ground wood pellet particles. Powder Technology, 301: 737–746.

Ross R.J. (2015): Nondestructive Evaluation of Wood. 2nd Ed. Madison, U.S. Department of Agriculture, Forest Service, Forest Products Laboratory: 169.

Schajer G.S. (2016): Wood machining: Past achievements, present capabilities, future opportunities. Wood Material Science & Engineering, 11: 127–134.

Scharenbroch B.C., Watson G.W. (2014): Wood chips and compost improve soil quality and increase growth of *Acer rubrum* and *Betula nigra* in compacted urban soil. Arboriculture & Urban Forestry, 40: 319–331.

Schön C., Kuptz D., Mack R., Zelinski V., Loewen A., Hartmann H. (2019): Influence of wood chip quality on emission behaviour in small-scale wood chip boilers. Biomass Conversion and Biorefinery, 9: 71–82.

Sgarbossa A., Costa C., Menesatti P., Antonucci F., Pallottino F., Zanetti M., Grigolato S., Cavalli R. (2014): Colorimetric patterns of wood pellets and their relations with quality and energy parameters. Fuel, 137: 70–76.

Spinelli R., Eliasson L., Han H.S. (2020): A critical review of comminution technology and operational logistics of wood chips. Current Forestry Reports, 6: 210–219.

Tiitta M., Tiitta V., Heikkinen J., Lappalainen R., Tomppo L. (2020): Classification of wood chips using electrical impedance spectroscopy and machine learning. Sensors, 20: 1076.

Verheyen M., Beckers W., Claesen E., Moonen G., Demeester E. (2016): Vision-based sorting of medium density fibreboard and grade A wood waste. In: 2016 IEEE 21st Int. Conf. Emerging Technologies and Factory Automation (ETFA), Berlin, Sept 6–9, 2016: 1–6.

Wu H.H., Hung C.Y., Zeng B.J., Huang Y.Y. (2018): Defect mapping of lumber surface by image processing for automatic glue fitting. In: Chang C.Y., Lin C.C., Lin H.H. (eds.): New Trends in Computer Technologies and Applications. ICS 2018. Communications in Computer and Information Science, Vol. 1013, Singapore, Springer: 376–384.

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