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Development of a 3D and Line-Scanning Camera for Automatic Wood Defect Marking

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***Abstract*— The industrial sector is focused on efficiency of an industrial vision through automation as one of the most popular solutions as in recent decades. The main bottleneck of the process is image processing due to high speed and precision. Graphic processing units (GPUs) and Field-Programmable Gate Array (FPGAs) have been proposed for real-time detection, where tasks are now performed repeatedly by machines assisting or replacing humans, reducing the occurrence of errors. New frameworks are trying to be in pace with Industry 5.0 advancements and to rely heavily on real-time sensor systems, with integration to Smart Factory which are essential for assessing dynamics of industrial data. In the paper, the research project focuses on developing an application of innovative combined 3D and line-scan camera system capable of simultaneously capturing visual and 3D information and identifying wood properties such as fiber direction and resin pockets. The camera employs laser triangulation and controlled LED illumination for precise wood structure analysis, while high-speed Field-Programmable Gate Array (FPGA) with High-performance computing (HPC) technologies enables real-time image analysis in-camera. Additionally, the research will focus on presenting fully functional prototype with discussion on modular system architecture scalability and parallel development of FPGA and AI components in simulation, moving closer to industrial implementation in subsequent stages. As the critical step for framework elaboration, the development of a functional application in manufacturing environment of FPGA firmware, laser triangulation, line-scan imaging, controlled illumination, trigger boards, and AI modules and evaluation of technological options that would ensure effective recognition of wood defects, as well as creation of a basis for further technological development are performed.**

Keywords*— *Computer Vision, Deep Machine Learning, defect detection, FPGA, HPC, labelling, quality control, wood processing.

I. Introduction

The implementation of a high speed inspection system for the wood processing industry is not a novel [1], yet very promising direction since it is bringing improvements in production process, higher quality of delivered coated board and reduction of waste [2]. Modern wood trimming optimization lines using marking devices and laser scanners of the wood surface do not provide high accuracy in determining the location of defects and are quite expensive [3]. Contemporary market competition and applications of Smart Factories with Industry 4.0 are increasing the entry into the industry. Companies are trying to implement fragmental modules into new paradigm and looking for cheaper and easier option to integrate into complete framework with scalability options [4], [5]. The wood processing sector faces modern challenges coming from the natural variability of wood and the demand for rapid, reliable inspection to reduce waste, improve product quality and increase sustainability [6]. With increasing industrial automation and environmental regulations in Europe, optimizing wood defect detection through real-time imaging and processing is of practical and economic [5], [7], [8].

Despite progress, the problem of a low understanding of automation opportunities, unclear requirements specifications, small production volumes and suitable automation solutions are hindering technology transfer [9], [10], [11]. The accurate and efficient detecting due to

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diverse wood defects based on wood species in real-time remains unresolved, since the existing approaches vary widely, from traditional image segmentation and texture analysis [12], [13], [14] to deep learning models requiring substantial computational resources [15], [16].

The biggest knowledge gap exists in balancing detection accuracy with processing speed, especially under industrial conditions involving high-speed conveyors and complex defect types [17], [18], [19].

Recent trend in Machine Learning application in data processing algorithms through convolutional neural networks (CNNs) and integration with high-performance computing (HPC) in 3D and line scanning camera systems for real-time wood processing has emerged as a critical area of inquiry due to its potential to enhance efficiency and accuracy in defect detection, quality control, and automation within the wood industry [17], [20]. However, these defection methods based on single image data have difficulty when distinguishing the wood broken defects with the interference similar to the defects due to the limitation of feature representation [14], [21]. Most of conventional systems were based on common image processing techniques in combination with supervised learning algorithms, however, over the last decade deep learning has achieved remarkable success in the forestry and wood products industry [22], [23]. Deep learning (DL) techniques are very efficient tool for wood anomaly detection, feature detection (segmentation), object classification, instance segmentation, point localization, and character recognition [24], [25], [26], [27], [28].

As one of the most popular solutions as in recent decades, the industrial sector was focused on efficiency of an industrial vision through automation. The main bottleneck of the process is image processing due to high speed and precision. Graphic processing units (GPUs) and FPGAs have been proposed for real-time detection, where tasks are now performed repeatedly by machines assisting or replacing humans, reducing the occurrence of errors [29], [30], [31], [32]. FPGAs are used to reduce the processing time in vision systems, and consequently, to reduce their cycle time. FPGA processing times are on the order of nanoseconds, while the other platforms have times in the order of milliseconds. It can also be concluded that the use of the GPU is only advantageous when the number of sequential filters is high, under these circumstances, the FPGA is advantageous. Unlike conventional processors or microcontrollers, FPGAs do not have predefined functions. Instead, they contain many small logic elements, the interconnections and operating principles of which are defined by the user as needed, using programming languages. Moreover, the bottleneck exists regarding the optimal hardware platform: FPGA-based systems offer low latency and power efficiency but may lack flexibility, whereas GPU-based and traditional CPU methods provide programmability at the cost of higher power and latency [29], [33], [34], [35], [36]

The purpose of this paper is to present Machine Vision, ML, FPGA and HPC elements interaction to define the system's capability to perform real-time defect marking, where imaging provides raw data, FPGA enables rapid processing, and ML detection algorithms ensure precise identification. This framework guides the evaluation of technical challenges and benefits within industrial wood defect marking applications.

II. Specifications of environment

The three critical factors were identified for concept: the laser triangulation method, as it provides high accuracy and is able to detect changes in fiber direction based on the dispersion of the laser point. Line scanning technology with controlled LED illumination that ensures stable acquisition of visual information, which allows accurate defect identification of wood surfaces. And the use of FPGA chips for real-time data processing that significantly increases the scanning speed, allowing the integration of both 3D and visual data processing in one system. A dual-encoder switching mechanism was implemented to select appropriate trigger signals based on board motion speed, ensuring reliable image capture timing under variable conveyor speeds. Line-scan and 3D image rectification algorithms were developed using homography transformations to reconstruct undistorted images of moving boards. Additionally, surface defect pixelation algorithms (combining laser profile and visual data) were prototyped in C++ for compatibility with FPGA translation. An adapted state-of-the-art segmentation models (including Transformer-based architectures) to project-specific wood defect data. Using the newly established annotation pipeline with the Segment Anything Model (SAM) and a human-in-the-loop workflow, a large segmentation model was fine-tuned on wood defect dataset. e.g. detection of knots, cracks, and blue stain with up to 95–99% accuracy, depending on defect type), greatly outperforming previous methods. The AI annotation workflow was revamped by integrating SAM for automatic pre-labelling in the CVAT platform, enabling faster dataset generation and refinement.

Surface defect "pixelation" algorithms: Initial algorithms have been developed to combine laser 3D information and visual RGB/NIR images that detect defects on the wood surface at the pixelation level. For example, for crack detection, the algorithm simultaneously analyzes laser profile distortions (depth changes) and visual image contrast changes; while for "blueing" (blueing of wood), the NIR channel absorption characteristics are combined with visible light color information. These algorithms were implemented in C++, in modular components, using the company's existing image processing software code. The choice of C++ ensures easier portability to FPGAs using high-level synthesis (HLS) or by integrating the code into the ARM processor subsystem. This maintains compatibility with existing competencies and at the same time provides the opportunity to gradually "port" the algorithms to FPGA logic. All changes and new modules were thoroughly tested in the Questa simulation environment (compatible with Xilinx Vivado). Test vectors were created that emulate different scenarios of encoder pulses (uniform movement, acceleration, stop and reverse) and the trigger logic response was checked in each case. The operation of the rectification algorithms was also validated in the simulation using synthetically generated deformed images and known homography parameters and practical tests were performed in laboratory conditions with real wood sample data (Figure 1).

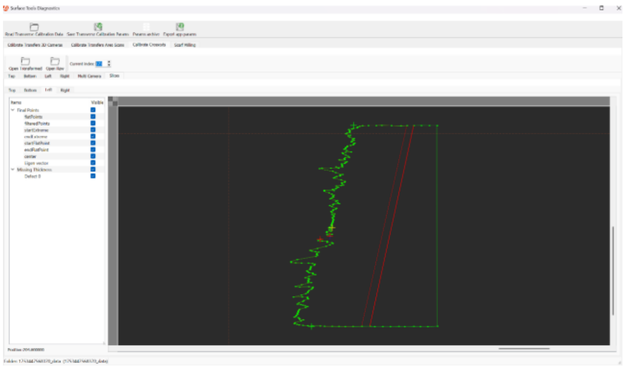

Fig. 1. Magnetization as a function of applied field. 3D algorithm testing example (Zippy Vision SIA property).

The trigger circuits were integrated into the existing test stand (Figure 2). The camera was connected to the board's trigger output, and the encoder to the board's inputs (channels A and B). Configuration was performed: the pulse division was set in the board software so that in normal mode (at maximum speed) the camera would capture approximately 2000 frames per second, which corresponds to a ~0.2 mm spatial step between the lines of the line scan image.

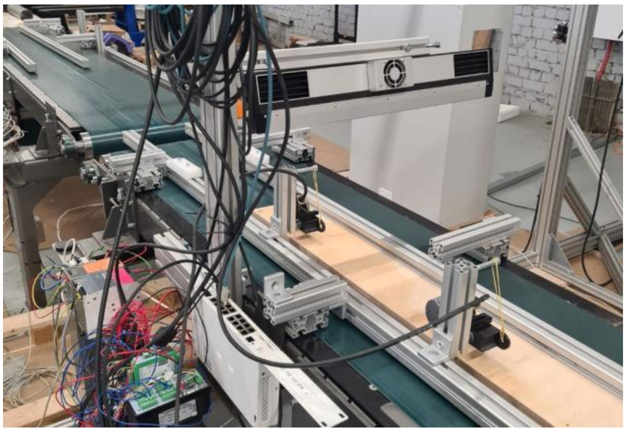

Fig. 2. Testing stand (Zippy Vision SIA property).

The trigger zone boundaries were also defined according to the board's length and the camera's field of view to ensure that the camera would not be triggered until there was material underneath it. During the integration process, compatibility with the existing system was checked - signal timing and voltage levels, as well as response time (from the encoder pulse to the trigger pulse edge).

After testing in real environment with the help of the integrated SAM approach and Human-in-the-Loop (HITL) process, annotation productivity increased several times. The time required to annotate one image (full board) has decreased from, for example, 5 minutes manually to ~1–2 minutes with ML support, depending on the number of defects. The segments proposed by SAM are often 70–90% accurate and require only minor adjustments. Consequently, the data set grew faster during the project, allowing the model to be trained with more variations. In addition, workflow automation (Docker containers, scripts) eliminated many manual steps – data flows through the processing pipeline almost completely automatically. The training cycle of a new model (from raw images to a trained model) now takes much less time and is repeatable with a single command. The quality of annotations has also improved, as SAM helped maintain a consistent treatment of defect contours across all data (Figure 3).

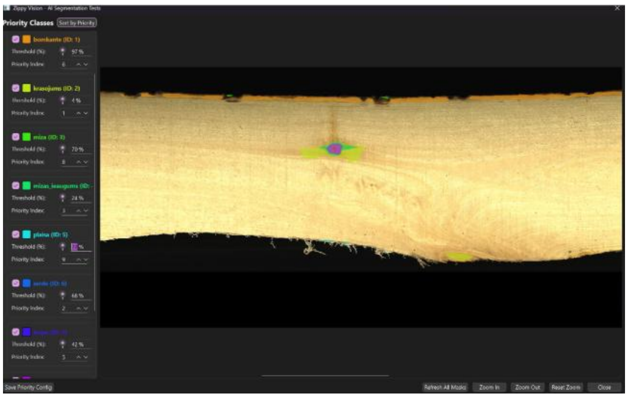

Fig. 3. Wood defect identification example (Zippy Vision SIA property).

The results achieved in the testing phase confirm that the chosen artificial intelligence approach with Transformer architectural segmentation models is extremely promising for detecting wood defects. A specialized synthetic data generation program was developed for model training, based on the physical properties and geometric parameters of laser profilers. This approach allowed for the preparation of training datasets with more than a million samples, which sufficiently accurately reflect the shape and measurement characteristics of real-world objects.

During model development, 14 different lightweight model configurations were tested, assessing their suitability for training, inference, and integration into systems with a limited time budget. Training was performed in the PyTorch environment, while inference execution was optimized using TensorRT to ensure maximum efficient execution at the GPU level and reduce the data exchange load between the GPU and the central processor. Comparative analysis with previously used methods showed that the new approach significantly reduces lateral artifacts and projection errors, which are characteristic of simplified homography methods (Figure 4). This improves the quality of the obtained data and ensures more stable results for further analysis.

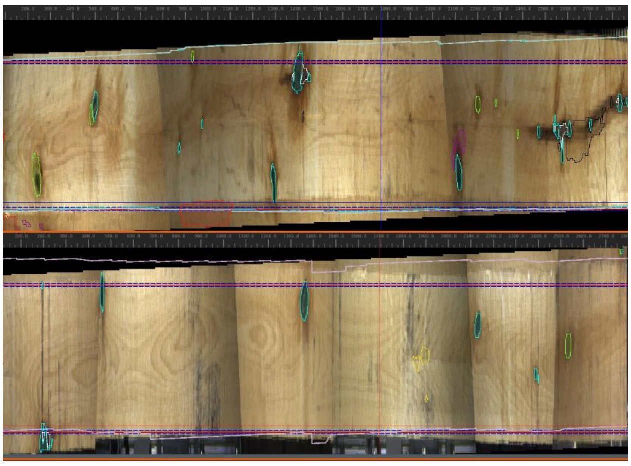

Fig. 4. Comparison of the previous methods (Zippy Vision SIA property).

From the comparative data it is easy to see that the new method eliminates lateral artifacts – edges that inevitably appear with simple homography) it is intended to focus on increasing the robustness of the model against variations in illumination, surface structure and material properties, as well as on performance optimization for the target industrial equipment.

The experiment used an industrial laser triangulation line scanner system Teledyne DALSA Z-Trak 4K, which simultaneously provides high-resolution profile measurements and a laser intensity value associated with each point. Wood samples with known resin pockets were transported through the scanning area at a constant speed, maintaining a stable working distance and laser power. This ensured that intensity variations were mainly related to material properties and not to geometric factors of the measurement.

III. Final Results

Integrated all hardware and software components developed in previous stages into a single functioning prototype. This included FPGA firmware, laser triangulation, line-scan imaging, controlled illumination, trigger boards, and AI modules. The assembled prototype was tested to validate system synchronization, triggering stability under variable conveyor speeds, quality of fused image data, and real -time execution of AI models. Test results confirm that all major subsystems now operate cohesively and are ready for industrial-environment. Laser cameras generate sequential 3D cross-sections that directly represent the object's geometry, while visual cameras acquire 2D intensity or color information without a direct depth component. As a result, each line scan step produces a heterogeneous data set, in which the same area of material corresponds to multiple 3D profiles, multiple visual lines or frames, as well as motion and positioning parameters. Transverse line scanning is one of the most methodologically complex types of multi-sensor line scanning. Combining sensor spaces in this case is significantly more complex than in classical line scanning, since the data to be combined differ in spatial semantics, sampling structure, temporal association, and interpretation. Small temporal or spatial discrepancies can accumulate along the entire scanning direction and cause systematic shifts in the spatial localization of defects, it was one of the anticipated issues for industrial application (Figure 5).

Fig. 5. The image of a downward shift of three separate images. The physical displacement of the object along axes that are perpendicular to the conveyor line of motion (Zippy Vision SIA property).

In order to overcome this challenge the project developed a sequential, deterministic transversal line scan data fusion flow. Its goal is to obtain a single, spatially coherent and suitable for further analysis data structure from heterogeneous, asynchronous sensor data. In the first stage of the flow, parallel sensor data acquisition takes place: laser profiling line scan cameras generate 3D profiles, visual cameras acquire image data, while trigger and encoder signals provide information about material movement. At this stage, the data is not yet directly merged. In the second stage, time and motion normalization is performed. All sensor data are linked to a common motion description, ensuring an exact match between 3D profiles, visual lines and material position. In the third stage, all data are transformed to a single coordinate system. Laser profiles are spatially arranged as sequential cross sections, while visual data are projected into this same space using the spatial relationships between the sensors. This stage is one of the most algorithmically complex. In the fourth stage, the spatially aligned data is joined and projected into representations suitable for analysis, such as cross-sections, surface projections, or structured grids. In the fifth stage, a single transverse line scan data unit is created, containing the combined 3D geometry, visual information, motion parameters, and derived features (Figure 6).

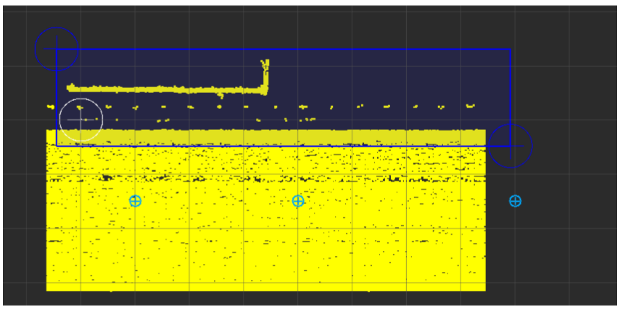

Fig. 6. Corresponding YZ plane projection. (Zippy Vision SIA property).

In addition to geometric information, laser triangulation systems also obtain laser reflectance or intensity data, which characterizes how much of the emitted laser energy is reflected back to the sensor. Resin pockets in wood differ significantly from the surrounding wood material in terms of their optical behavior – they have a smoother, often semi-transparent or shiny surface, which causes a higher and more localized intensity of reflected light. As a result, resin pockets appear as distinctly contrasting areas in the laser intensity map compared to the more uniform reflectance of the wood fiber (Figure 7).

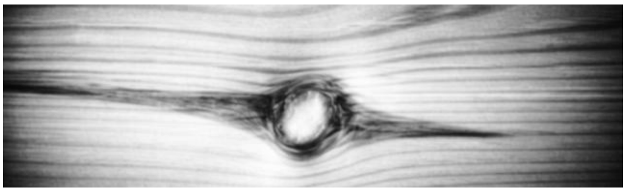

Fig. 7. Laser triangulation sample (pine) (Zippy Vision SIA property)

The acquired intensity data showed that resin pockets often produce not only a local geometric anomaly, but also a rapid increase or saturation of the laser reflectance that persists over several adjacent scan lines. This combination allows to distinguish resin pockets from other defects, such as branches or fiber direction changes, for which the intensity signature is usually weaker or structurally different.

IV. Conclusions

The results showed that the implementation of specialized trigger synchronization logic was critically necessary - now the camera works reliably even in difficult operating conditions (variable speed, reverse). The solution with two encoder switching allows covering the entire range of possible conveyor speeds without losing image resolution. The inclusion of rectification algorithms ensures that subsequent image processing steps (defect analysis, AI) can operate with geometrically correct data, which increases the accuracy of defect recognition. The implementation of the defect pixelization concept confirms the usefulness of the combined 2D/3D approach and serves as a basis for further improvements. Testing of the integrated prototype provided significant feedback on the system's weaknesses and challenges, especially regarding synchronization accuracy and performance. Anticipated issues with industrial applications were approved and successful solutions applied. The experiment showed that laser triangulation reflectance data is a valuable addition to the classic 3D profile for detecting resin pockets. By using intensity thresholds, spatial filtering and correlation with height data, it is possible to create a robust algorithm that works in a real-time industrial environment. This allows for early identification of resin pockets, improved wood quality grading and reduced risks in subsequent processing stages.

The chosen solution optimally combines the necessary hardware programmability, processing power and flexibility in real-time data flow management. Such a base allows in the next stages to implement both experimental 3D profile processing, AI model data preparation, and further optimization of laser triangulation and line scanning systems - linking visual line scan data with 3D laser profiles in a single coordinate space. In the following stages, it is recommended to analyze in depth how different data combinations (texture, depth, reflectance intensity) affect the accuracy of defect recognition. Special attention should be paid to whether, for certain types of defects, it is possible to reduce the dependence on the full 3D profile by using ML models based on enriched visual information.

This activity result directly corresponds to the goal of the project application to create an effective camera platform base capable of realizing combined visual and 3D information acquisition for a wood defect recognition system. The developed solution showed that training a lightweight model under the supervision of large models is a viable approach for real-time industrial systems. In the next stages, it is recommended to focus on improving the robustness of this model, especially with regard to variations in lighting, surface structure and material properties. In addition, it should be evaluated how the lightweight model can be adapted to different wood types and production lines, while maintaining high performance and stability.

Initial FPGA firmware version fully confirms the compliance of the selected platform with the technical requirements of the scalability. Experemntation has shown that developing hardware (FPGA, trigger systems, data acquisition) and AI workflows in parallel is an effective approach. The requirements of AI models for data quality and structure can serve as guidelines for hardware optimization, while the capabilities and limitations of the hardware determine the practical applicability of AI solutions.

The achieved results directly correspond to the defined main goal of the paper to develop a new generation of combined camera system that integrates elements of laser triangulation, line scanning and artificial intelligence in wood quality control automation. The conducted research has provided a solid foundation for adapting artificial intelligence algorithms to the specific problem of wood defect identification. The choice of Transformer architecture provides significant advantages for companies by delivering higher accuracy in processing irregular defect contours; accelerated development time of specialized models; accelerated and refined implementation of annotations using SAM models at all stages of the workflow. Modern architectures trained using the new workflow model are able to model structural and visual aspects of the wood surface simultaneously with better adaptation capabilities to increase data volume. The prepared methodology and solution is allowing to start further practical applications for model training in the subsequent stages of the development in corresponding field.

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