AN APPROACH FOR AUTOMATED INSPECTION OF WOOD BOARDS

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ABSTRACT

This paper presents a machine vision methodology for automated quality inspection of the wood boards. A pilot real-time system has been developed. It performs four-face inspection and detects and classifies the main biological and mechanical defects using standard area-scan cameras and the PC computer with off-the-shelf frame grabber.

1. INTRODUCTION

The need for automatic visual inspection is becoming critical in the wood industry in order to maintain and improve productivity and quality. In practice, a system capable of sensing, recognizing and measuring the sizes and relative positions of individual defects and finally classifying the piece of wood is required.

Frequently, the major problems of grading wood boards are: very high rate of production, large number of defect classes and high inherent variability. On a typical line, the boards travel at speeds of *0.5-2m/s.* The main standards of the major European countries list over *400* different quality classes. As a consequence, there are no two boards or defects that have exactly the same properties such as color and texture.

Most of the current automatic inspection systems are used for controlling the edging process that removes the wane from the plank and minimizes the number of knots on the edges [1], [2], [3]. The recent solutions for grading [4], [5] are not suitable for commercial applications for one of the following reasons: a) they are very expensive as they are based on complex hardware and software, b) they use heterogeneous sensors for data formatting and c) they use gray-scale image data that do not contain enough information.

In this paper, the proposed methodology for wood defect detection is presented through the description of developed machine vision system. The system uses standard area-scan cameras and the PC computer with off-the-shelf frame grabber. It performs four-face inspection and detects and classifies the main biological and mechanical defects such as knots, checks, wane edges, resin pockets, width, thickness, curvatures, flaws, splits, cracks, etc, using the proposed inspection method. Also, it deals with monochrome and color data and allows 2D and 3D processing on the same platform.

2. SYSTEM OVERVIEW

The automated wood inspection system consists of an experimental setup and corresponding software, as is shown in Fig. 1. The experimental setup consists of six area-scan cameras having *4-16mm* millimeter variable lens and resolution of *768 x 576* pixels, one four-channel image grabber with fifty frames per second capture rate, adequate lighting, computer controlled feeding mechanism, one synchronization controller and a Pentium computer as a platform for image processing and system control and coordination.

Two illumination techniques are employed; front lighting and structure lighting. The front lighting is obtained using fluorescent lamps, which operate at *32KHz* in order to avoid flicker. They illuminate top and bottom faces of the sample in order to highlight biological and surface defects as is shown in Fig. 1. A laser-line generator is used as a structured light to extract range information, employing the triangulation theory. This information presents the inputs to the *Laser Profile Controller (LPC)*.

An image acquisition is performed using the multi-channel, low cost, PCI frame grabber Picolo Pro from Euresys S. A. For synchronization of frames capture with board motion, a special *Synchronization Controller* (SC) is implemented. The software part, named as *"APELWOOD"*, is developed in Visual Basic and C++ using libraries from the *eVision* Tool (*Euresys S.A.*) and special Dynamic Link Libraries (DLL) developed by us (see: *www.apel.ee.upatras.gr/MachineVision/mvg.htm*).

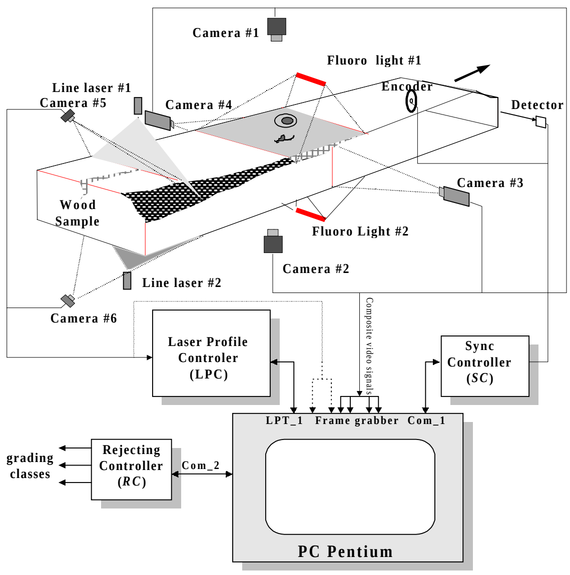

Fig. 1: System overview.

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3. INSPECTION METHOD

Roughly, the inspection method consists of defect detection and defect classification procedures and is achieved through a number of image processing algorithms applied on each captured image of the sample under test as is shown in Fig. 2. The defect detection is achieved through two parallel operations, detection of biological (surface) defects and detection of mechanical deformations.

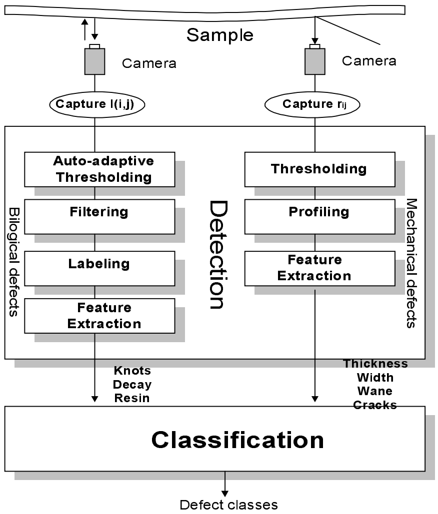


Fig. 2: Inspection steps.

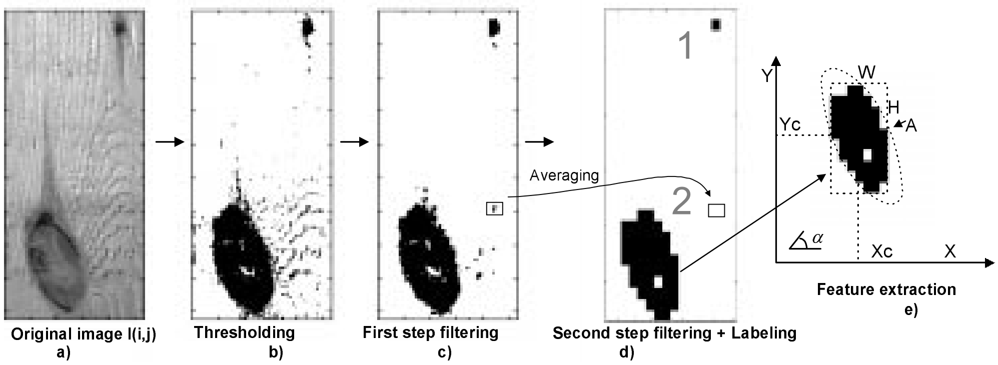
3.1. Detection of Biological Defects

A gray-level image *I(i,j)* of the sample under test is acquired with background. An appropriate gray-level threshold is used for the segmentation of the image into wood and background. It is calculated automatically by performing a histogram analysis of the image. After evaluating the threshold "goodness" for many known algorithms such as the *ISODATA*, *Otsu Thresolding*, *Fuzzy-logic Based Thresholding* and *Local Neighborhood Based Thresholding*, we have selected the ISODATA techniques as an optimal solution. This technique has a very good speed performance as well as simple code realization. Fig. 3(b) shows a segmented image of Fig. 3(a), where an optimal threshold is auto-adaptively selected by using the chosen approach.

After thresholding, the binary image may have noise introduced, as is shown in Fig. 3(b) and 3(c). The basic assumption used in our analysis is that all data in the binary image that do not represent defects or background are due to noise. To filter out the noise from the binary image two filtering steps are implemented. In the first step a nonlinear morphological filter is applied as is illustrated in Fig. 3(c). The template for this filter is chosen to emphasize oval defects like knots, while line defects, i.e splits and cracks, will be distinguished using a ranging method. In the second step the averaging is performed on disjoint rectangular regions inside the image obtained after the morphological operation. This results in a reduced binary image and possible defects are isolated as non-connected binary objects inside it, as is shown in Fig. 3(d).

In order to extract features from the individual components it is necessary to have a component labeling algorithm that identifies each component, as is shown in Fig. 3(d). The objects labeled as *"1"* and *"2"* in Fig. 3(d) represent the first and second defects in Fig. 3(a). A classical way to handle it is to use sequential or recursive labeling algorithms. The recursive algorithm requires large memory stack that can produce problems in our case, especially in labeling of large samples with a great concentration of defects. For these reasons we turned our attention to the sequential labeling algorithm given in [6], in which we incorporated certain improvements

During the connected components analysis of image, the shape features can be collected and stored for the blobs. These include dimension of the defects, area of the defects, number of thresholded pixels, moments and the features derived from them, like lengths of principal axes, aspect ratio and angle, etc. The moment-based features are useful in determining the dimensions of the defects. For the knots the dimensions are needed for the minimum and maximum diameters. The angle parameter is not so important in knot analysis because the knot can be oriented practically in any angle. On the other hand, it is a very important parameter in detection of split orientation. In order to increase the speed of the overall processing for biological defects, we have selected the following five features for their description: *length of the defect (**H**), width of the defect (**W**), position (**X_c,Y_c**), aspect ratio of ellipse fitted* (***R**=major_exe/minor_axe*) and *compactness*, i.e. filled ratio, (***C**=H*W/A*, *A=area*), as is shown in Fig. 3(e).



Fig, 3: Inspection of biological defects – algorithmic steps.

3.2. Detection of Mechanical Defects

As seen, we use the vision methods to measure the geometrical properties of the plank sample such as thickness, deformations and shape of surface. In this case a single intensity image, as is *I(i,j)* proves of limited use. Furthermore, reconstructing the 3D shape from a single intensity image is difficult and often impossible. Using the range sensors we can acquire images by encoding shape directly. In this case we are dealing with the range images that can be considered as a special class of digital images. Each pixel of a range image r_{ij} expresses the distance between a known reference frame and a visible point in the scene [7].

There exist several ways for producing range images. Here we concentrate on triangulation-based range sensors realized by an area-scan camera, as is shown in Fig. 4. To obtain better trace distinction from the background and to minimize useless light variations, an optical band-pass interference filter is used. It is mounted in front of the camera lens and its center frequency is adjusted to *670nm*, which is the wavelength of red-laser light.

Our objective is not the whole range image, r_{ij}, but only the line vector, *Y(i),* that follows the laser trace. It means that additional post processing must be performed on the r_{ij} image in order to extract the vector *Y(i)*. This operation is known as “profile extraction”, usually performed by using weighed centroid technique. Since the cracks and the splits can be considered as a shape deformation, the range technique can be used for their detection, as is shown in Fig. 5. Our experiments say that the binarization of the image by thresholding before the profile extraction can increase the scanning speed guaranteeing a good resolution performance. Due to the fact that a laser trace is well distinguished from the noise by implementing optical filtering, the choice of the threshold value is not of crucial importance as in the case of biological defect detection and it can be implemented by hardware as is used in our approach.

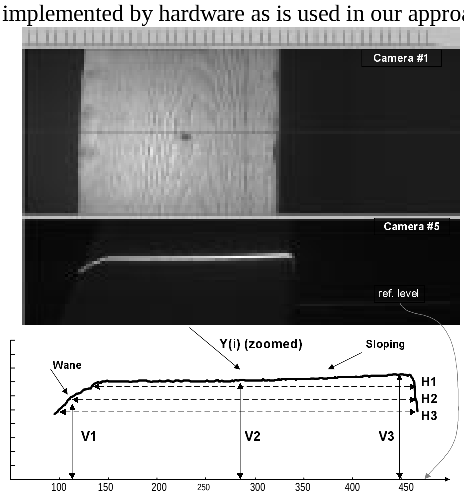


Fig. 4: Laser triangulation in function of wood board inspection and profile extraction.

In order to inspect mechanical defects in samples, appropriate features must be extracted from the profile vector *Y(i)*. We use the features such as *thickness in different points, width in different levels* and *number of cracks or splits* along the trace. The first feature sets are interpreted in Fig. 4 – bottom. The sample under test contains one wane defect and one curvature defect (sloping). To estimate thickness a vector *Y(i)* is checked at three points, left end point (V_1), middle point (V_2) and right end point (V_2). The width is checked in three planes H_1, H_2 and H_3 using the intersection points of the vector *Y(i)* with straight lines $y_1=V_2-h$, $y_2=V_2-2*h$ and $y_3=V_2-3*h$, where h is a numerical constant adjusted by the system set-up. Analyzing the plank profile in three horizontal and three vertical positions, at a minimum, is sufficient for a rough geometric estimation because the profile of a plank sample does not change drastically.

Splits and cracks can be seen as impulses in the profile vector, as is shown in Fig. 5. To emphasize these peaks, different techniques such as *Windowed Standard Deviation* (*WSD*) and *Windowed Contrast in Horizontal Direction* (*WCHD*) can be employed, as is shown. After filtering out the cracks, the automated thresholding is implemented. The resultant binary vector gives the number of detected cracks counting the groups of separated strings of “ones”. As is shown, the *WCHD* gives a better distinction of peaks.

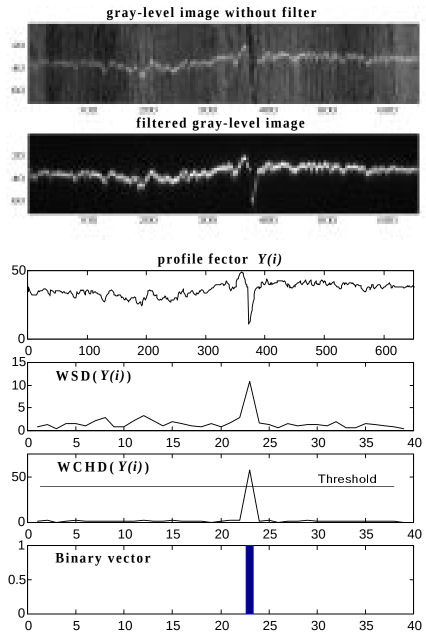


Fig. 5: Splits and cracks detection.

The operations of profiling and range feature extraction can be performed by a PC or independently by the special *Laser Profiling Controller (LPC)*. We have implemented the controller solution because it increases processing speed and eliminates the need for more than one four-channel frame grabber for full side inspection.

3.3. Classification

Real-time processing requests fast and accurate classification. Although a general best choice for a classifier does not exist, it should be selected according to the requirements and the nature of the classification problem. In our case, the classification is performed using the mixed fuzzy-logic approach and rule-based technique. This type of classification corresponds more closely to "human classification" and has good speed performance and simple hardware realization. The fuzzy-logic is used for biological defects grading, while the rule-based technique emphasizes crack/split defects and mechanical deformations. The limitation factors, given in Section 1, caused unsatisfactory results using neural network based classifier.

Our membership functions could, for example, look like the ones shown in Fig. 6. They illustrate length of the defect (*H*), width of the defect (*W*) and transversal position of the defect X_c inside the plank. Their shapes are obtained experimentally.

Our rules, for example, for one biological and one mechanical defect can be described as: 1) *If the blob's* ***location*** *is in the CENTER of the plank and its* ***length*** *is MEDIUM and its* ***width*** *is MEDIUM, then it belongs to the category* ***medium knot***, 2) *If* V_1 *is much less than* V_2 *and* V_2 *is equal to* V_3*, then the profile has a* ***left wane***.

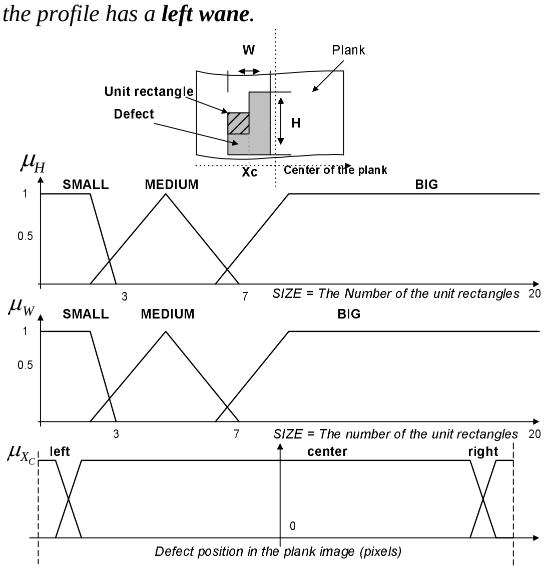


Fig. 6: Membership functions used for board defect description.

4. EXPERTIMENTAL RESULTS

In order to evaluate the system performances the following experiment is performed. In the first stage, two sets of the defects are collected in secondary wood industry. First, *set_1* (268 samples), used for test purposes and the second, *set_2* (160 samples), used for membership functions designing and rules forming. The human inspector analyzed the both sets, off-line, and all related information was stored in a *"manual inspection data base"*. In the second stage, the system performance was evaluated on criteria such as specific accuracy rate, overall acuracy rate and inspection speed using the *set_1*. The specific and overall acuracy rate are defined as:

$$R_{ri} = \frac{C.D.|i\_type}{T.D.|i\_type} \times 100\% \; ; \quad R_R = \frac{C.D.-F.A.}{T.D.} \times 100\%$$

where: *C.D.*|*i_type* = the number of *"i"* type defects correctly detected, *T.D.*|*i_type* = the total number of defects of *"i"* type, *T.D.*= the total number of all defects, *C.D.*= the total number of all defects correctly detected and *F.A.*= the number of false alarms.

The results were stored in an *"automated inspection data base"*. After adequate statistics calculations the results given in Table 1 and Table 2 were obtained. For specific accuracy examination the defects such as black knot, red knot, resin pocket, decay, cracks and splits are considered. The inspection speed performances were examined in two cases: for ROI (*Region of Interest*) size of *32x32* and *16x16* pixels

Table 1 - Specific accuracy (ROI size of *32x32* pixels).

Defect	Accuracy
Black knot	90%
Red knot	76%
Resin pocket	78%
Decay	82%
Crack	96%
Split	91%

Table 2 - Overal accuracy.

Speed	Accuracy	ROI size (pixels)
0.75 m/s	83.6%	32x32
0.63 m/s	88.6%	16x16

5. CONCLUSION

A pilot approach for plank defect inspection has been demonstrated. It uses off-the-shelf components and takes advanatge of a suitable inspection technique that is based on the concept of binary image processing, range imaging and fuzzy-logic classification. The results obtained in the evaluation and testing phases indicate that a machine vision system for industrial requirements, based on the given approach, can be implemented.

6. REFERENCES

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