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Improving OSB Wood Panel Production by Vision-Based Systems for Granulometric Estimation

Ruggero Donida Labati, Angelo Genovese, Enrique Muñoz, Vincenzo Piuri, Fabio Scotti, and Gianluca Sforza

***Abstract*—Oriented Strand Board (OSB) is a kind of engineered wood particle board widely adopted in manufacturing, construction and logistics. The production of OSB panels requires rectangular-shaped wood strands of specific size, arranged in layers to form the so-called "mattress" (mat) and bonded together with glue. The structural properties of the panel rely directly on the layer forming. In particular, the size distribution – namely granulometry – of the strands should fulfill standard measures to reach the mechanical properties expected from the panel. Off-line granulometry of particle materials is the most commonly procedure used to evaluate the production process, but it is prone to several drawbacks owing to the manual intervention of human operators. Vision-based systems, instead, allow for performing granulometric analyses in an automatic and contactless manner. We propose a computer vision approach to estimate the granulometry of wood strands. The designed framework analyzes images of a mat of strands placed over a moving conveyor belt, and provides useful information and measurements to enhance the production of OSB panels. Because of the very large amount of wood strands on the mat, particle-overlapping is frequent and represents a main issue for measurement algorithms. In order to overcome this problem, our framework joins image processing and computational intelligence methods, such as edge detection and fuzzy color clustering. We tested the framework with real and synthetic images, useful to variate the conditions of the material's shape. The obtained results demonstrate the ability of our approach to evaluate the granulometry of the strands in real conditions, and robustness against the simulated variations of the production process.**

***Index Terms*—Oriented Strand Boards, Particle image analysis, Granulometry, Fuzzy clustering.**

I. Introduction

Engineered wood board is a product manufactured from wood strands or other kinds of wood fibers, bonded together with glue to form a large and efficient composite product. Thanks to its mechanical properties, weight, versatility and excellent quality/price ratio, Oriented Strand Board (OSB) is a kind of engineered wood board widely adopted in manufacturing, construction and logistics. This panel is typically uniform, does not have internal gap and voids, and is water-resistant. OSB production is now advancing towards lightweight panels at lower cost and reduced environmental impact. This is possible thanks to the use of the upper part of the tree – commonly neglected – as well as different types of recycled wood [1], [2], and also the reduced use of glue.

The production of OSBs employs rectangular-shaped wood strands of predetermined dimensions, arranged in three layers or more to form the so-called "mattress" (mat), and bonded together with glue under pressure and heat [3]. During mat forming, for the outer layers the machine aligns the strands parallel to the direction of the production line. For the core layer instead, the strands often smaller have random orientation. The manufacturer has to check the specific orientation and size of the strands on each layer in order to guarantee the desired mechanical properties of the panel. Also, an optimal strand measurement allows for lowering the amount of needed glue, thus reducing the panel cost and the environmental impact [4]. Hence, it is of capital importance to provide suitable tools for evaluating the size distribution in the granular composition of the panel, namely its granulometry.

Nowadays, it is still common to perform off-line granulometric analyses using vibrating sifters that mechanically classify particle samples. The final granulometric measurement comes by weighing the obtained partitions. This process has some drawbacks: the analysis is time consuming and the measurement lacks of a standard accuracy, because human operators can differently or incorrectly apply the measurement procedures. A possibility to avoid the aforementioned problems is to employ vision-based systems to estimate the granulometry of the wood strands in a region of interest captured by the camera. Following this approach, it is possible to perform the measurements in a fully automatic way and without contact. This kind of systems can operate in two ways: working on samples extracted from the production line (spin-off approach) or directly on the production line (in-line approach). In the latter case, typically a camera placed above the surface of a conveyor belt acquires images of the particles. This setup is simple and effective, but its main drawback is the great amount of overlapped particles in the images acquired. An alternative but more complex setup is necessary to capture free-falling particles [5]: in this way it is possible to avoid potential particle-overlapping, but other problems can appear, such as motion blur, poor focus quality and uncontrolled three-dimensional orientation of the particles.

Along with assessing the quality of a wood particle panel during the production [6], [7], machine vision is applicable also for quality assessment of the final product, such as in automatic visual inspection of the panel's surface for defect detection [8], [9].

This work presents a framework for the in-line visual monitoring of the mat layers in different measuring points of the production line. The proposed framework performs a granulometry estimation of the strands on the mat, which is useful to improve the mechanical properties of the final OSB panel and to reduce the amount of employed glue.

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This paper presents a threefold contribution:

- We designed the first computer vision approach for evaluating the granulometry of a very large amount of wood strands.
- Our method uses innovative clustering and post-processing methods.
- We tested our method using both real and synthetic images, useful to simulate several conditions of test.

The paper is organized as follows: Section II describes the state of the art related to computer vision techniques for granulometric analysis. Section III presents the proposed framework for granulometric evaluation, and Section IV describes the tests conducted and the obtained results. Finally, Section V proposes the main conclusions and the future research.

II. Related Work

Studies examining the distribution of shape and size in granular composite materials strongly relate it to the characteristics of the final products [10]. This happens in the wood panel production [6] as well as in many other industrial applications, like pharmacy [11], papermaking [12] or mining [13]. The analysis of particle distribution allows for detecting problems that occurred in production, like bias in the working point of the machines, wearing of the tools, wrong or poor quality in the basic materials [6].

The application of granulometric analysis based on vision systems started more than 30 years ago [14]. However, the market does not offer a general solution yet, because of the alternating success of the proposed solutions [13]. Typically, vision-based systems employ a single camera and follow a two-step process in order to estimate the size distribution of the objects present in the image. The first step is image segmentation, to locate the depicted objects; the second step consists in evaluating and aggregating the properties of the identified objects to estimate their size distribution. In order to obtain high confidence on the obtained results, it is important to measure as many objects as possible [6]. Testing and validation of the designed algorithms represent two main issues in image-based granulometry. The solution proposed in [15] attempts to tackle this problem, introducing an environment for the supervised generation of synthetic image databases containing realistic particle distributions for testing the algorithms.

A great variety of research and industrial applications exploit the two-step approach described. Research in biology considers the granulometric analysis to test the health of human tissue/cells, for instance by applying successive structural openings of the segmented image [16] [17] or multiresolution texture analysis [18]. Further, this approach is efficacious in the mining industry to characterize the shape distribution of the extracted materials. Employed techniques ranges from edge detection to mathematical morphology [19], watershed, area boundary [20], and the analysis of images captured under different light conditions [21]. Two-step granulometric analysis is useful also for the classification of powders: the paper [22] proposes clustering to automatically characterize the properties of the powder, and the work in [23] uses classical image processing to characterize morphology and size distribution of wood dust particles [23].

Segmentation represents the most important source of estimation errors in unconstrained setups [24], especially when the particles overlap or the illumination is not correct. In addition, the segmentation of a complex and densely populated scene is typically a computationally intensive task and subject to errors. To avoid the segmentation step, the work presented in [25] uses the Fourier analysis and scale-space decomposition to estimate the granulometry of rocks, while the work in [26] combines Fourier analysis and mathematical morphology. More recently, the work in [27] used morphological opening operations to estimate the granulometry of aquaculture fish feed pellets, and the paper [24] proposed neural networks to classify the extracted set of features in a general acquisition setup.

Another approach to granulometric analysis employs more complex setups to generate 3D models of the particles. In the paper industry for instance, the work in [12] makes use of 3D laser scanners to detect the surface of wood chips, used for making wood-pulp. Also, the works in [13], [28] take advantage of the same technology to measure rock fragments. From a different perspective, the work in [29] studied rock granulometry using stereophotogrammetry, demonstrating its capability to obtain more precise measurements than traditional 2D approaches. However, in the case of OSBs, the particles employed are very thin (strands are less than 1mm thick typically), which make it difficult an improvement of the granulometry results using additional 3D information.

With regard to the granulometric analysis of wood particles, the paper [30] introduces one of the first studies in the field, using statistical evaluation of dimensional features extracted from images of ring-cut flakes to categorize the strands into two quality classes. More recently, [7] analyzed the influence of temperature on the quality of wood particles. The analysis exploits the shape features extracted from grayscale images of the strands acquired using a CCD camera and two light sources.

III. A framework for estimating particle size distributions in wood particles

This work focuses on the in-line visual inspection of the strands of a raw OSB mat from single images, introducing a framework for the automatic analysis of particle size distribution in different measuring points of the line. The process to obtain the granulometric information exploits the traditional two-step approach: first, segmenting the image to locate as many strands as possible; then, measuring the strands and aggregating the measurements. Aggregated results makes it easier the interpretation of the measurements. The most challenging step is segmentation; in fact, estimating the strand size distribution in images of OSB mats poses some important image processing challenges:

- Due to the particular shape of the strands having one side particularly elongated, images tend to present many occlusions that visually interrupt the edges of the whole strands.
- Most of the strands present very similar colors, making it difficult to differentiate them.

To obtain more reliable measurements of the strands, we consider the lightest parts of the image to segment. Basically,

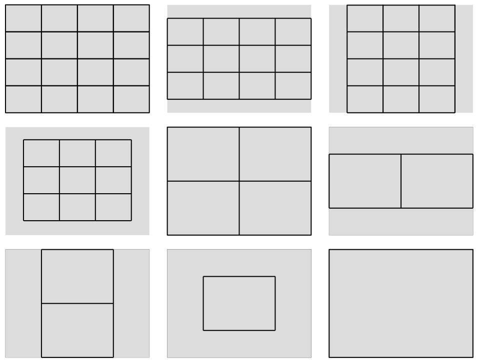

Fig. 1. Blocks partitioning schema used to perform the segmentation: small blocks favor the retrieval of smaller objects and large blocks the retrieval of bigger strands.

these regions depict the strands located on the surface of the mat, which tend to present less occlusions because the strands are not shaded or covered by other strands. Our method adopts fuzzy color clustering to locate the lightest parts of the image.

To maximize the number of segmented strands and increase the estimation accuracy, our method partitions the image into n blocks $B_i, i = 1, \ldots, n$. The method considers blocks of three different sizes. Figure 1 presents the partition. This partition aims at catching objects (strands) at different levels of detail, following the rationale that smaller strands fall into smaller blocks, and larger strands fall into larger blocks. These blocks present many inter-overlaps that permit to detect the strands that fall in the borders of other blocks. Fusing the information extracted by each block gives the size distribution of the strands, as described below.

For each block B_i, the segmentation process involves the following steps:

1) Application of a Laplacian filter to highlight edges and favor the separation of the strands. The resulting image is $L_i = B_i + k[\nabla^2(B_i)]$, where $\nabla^2(B_i)$ is the Laplacian of image B_i, and $k = 1$ or $k = -1$ depending on the derivative implementation.
2) Histogram equalization for contrast enhancement. The output image is H_i.
3) Edge subtraction. The method uses Canny algorithm [31] to detect and dilate the edges, obtaining E_i. In particular, the edges are dilated using a circular kernel of one pixel of radius and successively subtracted from the original image. The result of this step is $S_i = H_i - E_i$. This step helps the clustering algorithm to differentiate strands that are close together and share similar colors.
4) Application of Fuzzy C-Means (FCM) [32] clustering algorithm to the RGB components of S_i. The FCM algorithm is based on the minimization of the following objective function:

$$F_m = \sum_{i=1}^{n} \sum_{c=1}^{C} u_{ic}^{f} \parallel \mathbf{x}_i - \mathbf{v}_c \parallel^2,$$

where f indicates the "fuzziness" of clustering, n the number of pixels, u_{ic} is the degree of membership of the pixel $\mathbf{x}_i$ to the c-th cluster, $\mathbf{v}_c$ is the center of the c-th cluster. We empirically selected three clusters. Among the three clusters obtained, the one presenting the lightest color is chosen as output. In this way, most of the background can be eliminated from the image and segmenting the strands on top of the mat becomes easier. The final output of this step is an image that represents the degree of membership of each pixel to the lightest cluster, T_i.
5) Binarization of T_i using Otsu's algorithm to calculate the threshold [33], the results is O_i.
6) Elimination of the connected components in O_i that do not correspond to strands, obtaining G_i. In particular, the method discards each component $CC_j, j = 1, \cdots, m$, where m is the total number of connected components, whose shape is much different from that expected from a OSB's wood strand. The following four tests determine if a connected component CC_j is discarded:

- CC_j is eliminated if $A(CC_j) < 0.3 \times \max_{l=1,\cdots,m}(A(CC_l))$, where $A(CC_j)$ represents the area of CC_j. This test eliminates the smallest connected components, which generally correspond to noise.
- CC_j is discarded if $M(CC_j)/m(CC_j) < 2$, where $M(CC_j)$ and $m(CC_j)$ represent the major and minor axis of CC_j. The basis for this test is the fact that the majority of the strands are much longer than wider.
- CC_j is eliminated if $|P(CC_j) - IP(CC_j)|/\max(P(CC_j), IP(CC_j)) > 0.5$, where $P(CC_j)$ is the perimeter of CC_j and $IP(CC_j)$ is the ideal perimeter of a rectangle with long and short sides equal to $M(CC_j)$ and $m(CC_j)$. The reason that justifies this test is that the majority of strands have a rectangular shape.
- CC_j is eliminated if $|A(CC_j) - IA(CC_j)|/\max(A(CC_j), IA(CC_j)) > 0.5$, where $A(CC_j)$ is the area of CC_j and $IA(CC_j)$ is the ideal area of a rectangle with long and short sides equal to $M(CC_j)$ and $m(CC_j)$. The reason that justifies this test is that the majority of strands have a rectangular shape.

To aggregate all the results obtained for the different blocks, the final output is calculated as $\text{OR}_{i=1,\cdots,n}(G_i)$. In this process, partitioning the input image into blocks of different sizes has the positive effect of enabling the detection of both small and big strands.

Once the segmentation is completed, the major and minor axes of every particle in the segmentation mask are measured. The real size of each strand (in mm) is calculated considering the ratio between the given resolution of the camera and the metric reference acquired on the mat. Individual results are finally aggregated in a histogram, representing the estimate of the strand size distribution, which is the output of the proposed framework. The bins used for calculating the histograms have been chosen in compliance with the productive procedures.

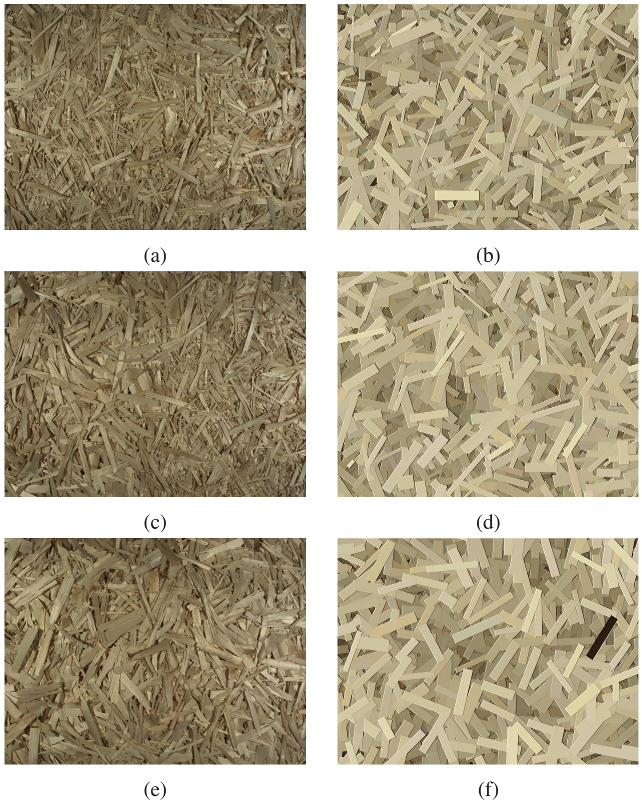

Fig. 2. Examples of the images used in the tests. Images in the first column are from the real mat, respectively from dataset *Small* (a) *Medium* (c) and *Big* (e). We selected these datasets of images to test the opposite granulometry ranges of one layer in operative conditions. We carefully processed them manually, to identify and measure the real length of the strands and to produce a ground truth for checking on the designed algorithms. Relevant for segmentation is the fact that color hues appear to be almost uniform across the strands. Moreover, shadows and different illuminating apparatus can cause sensible differences in the color of the strands. Second column presents synthetic images respectively from datasets $\widehat{Small}, \widehat{Medium}$ and $\widehat{Big}$ with simulated size distributions. These images are useful to test the correctness of the method on all the size parameters of the strands, as well as to realize images of critical conditions of functioning difficult to acquire in-line.

IV. Experiments

This section analyzes the performance of the proposed framework, tested with both real and synthetic images of resolution 1600×1200 pixels. Fig. 2 shows some examples of these images. We used a DFK 23G274 The Imaging Source® camera to acquire real images. The GigE interface of this camera guarantees that the acquisition point can be located far from the image processing server, a usual requirement in real productive environments. We generated synthetic images using different normal distributions of the strand size. In order to intuitively assess the validity of the obtained results, we aggregated the performed measurements using histograms and the related quartiles.

A. Tests using real images

This section analyzes the results obtained by processing images captured from a real mat. We collected three datasets corresponding to three different granulometry conditions revealed by the production system. The datasets, consisting of 10 images each, contain respectively:

- mainly small strands, namely *Small* dataset (Fig. 2a).
- mainly big strands, namely *Big* dataset (Fig. 2c).
- a mixture of small and big strands, namely *Medium* dataset, as referred to the average size of the strands in the image (Fig. 2e).

Fig. 3 presents the histograms for the major and minor axes of the strands extracted from the three datasets. To assess the ability of our framework in distinguishing between different strand distributions, we carried out a statistical study using Student's t-test. The study consisted in a pairwise comparison of the quartiles, considering each quartile for every couple of distributions. The results indicated significant statistical differences with $\alpha = 0.02$ in all cases, except for the comparison of the $2nd$ quartile between images in the *Small* and *Medium* datasets. This illustrates the capability of the framework of detecting significant changes in the strand particles size, being comparable to the job that would be made by a human expert who visually inspects the mat of wood strands moving in-line. Hence, the framework fulfills the requirements and purpose that motivated its development.

B. Tests using synthetic images

This section evaluates the performance of the framework using synthetic images. The purpose of this study is to test the robustness and accuracy of the system against variations in the materials. This kind of study is not feasible in real conditions, where the shape of the strands cannot be controlled. Besides that, synthetic images only enable to perform an in-depth analysis of the relationship between superficial strands and the unknown size distribution of the mat layers under the surface. The synthetic image generation allows the control of different parameters with high precision, like the size of the major and minor axes, or the chromatic palettes, for simulating different ambient lights and non-uniform lighting. Fig. 2(b,d,f) shows examples of images used in these tests.

We tested our framework using three synthetic datasets, built on different normal distributions of the size of the strands, namely $\widehat{Small}, \widehat{Medium}$ and $\widehat{Big}$ datasets. To simulate the distributions of small, medium and big sized strands, we chose the mean and the standard deviation accordingly for each distribution. Each rectangle picked its color randomly from a color palette extracted from a real image. Each dataset contains 100 images. Table I presents the obtained results. The table indicates the measurements of the major and minor axes of the strands given by the proposed method, and the actual values of the generated strands. These values show that our method is capable to detect changes in the size distribution with satisfactory accuracy. We performed Student's t-test on the synthetic data, as with the real images. The statistical test assessed the effectiveness of our framework in distinguishing between different strand distributions.

V. Conclusions and future work

This work presented a vision-based framework for the granulometric estimation of wood particle-size distributions. Our framework can contribute to enhance the production of

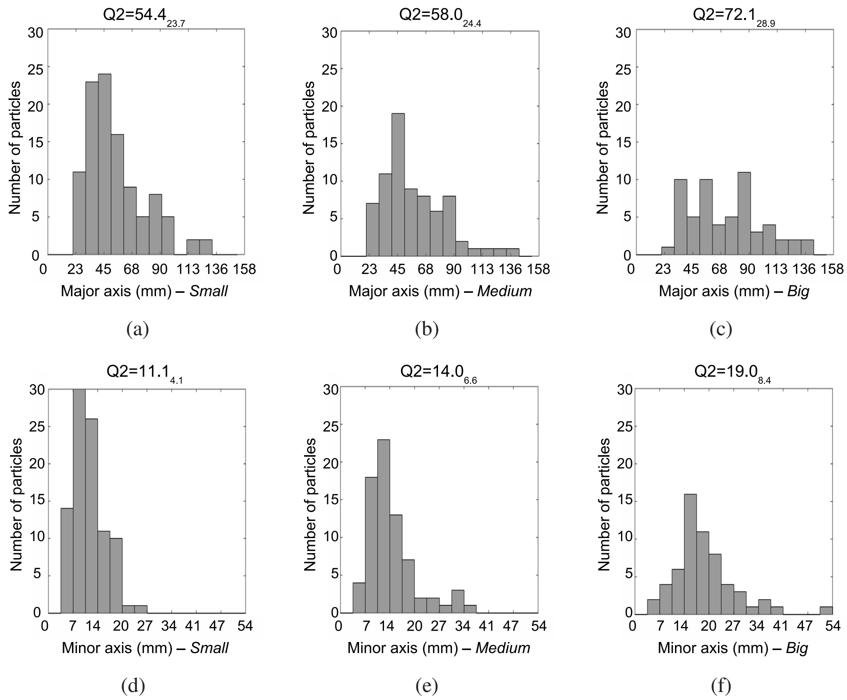

Fig. 3. Assessment of granulometric estimation in real images of the mat. The figure shows histograms of the major and minor axes of the strands. Histograms (a,d) present the results of the proposed method for an image of dataset *Small*, histograms (b,e) for an image of dataset *Medium*, and histograms (c,f) for an image of dataset *Big*. The results show how, as the proportion of big strands in the image increases, the proposed method detects a lower number of strands with a small minor and major axis, and a higher number of strands with a big minor and major axis. Q2 indicates the 2$^{\text{nd}}$ quartile of the distribution measured by the proposed method (standard deviation subscript).

TABLE I
ASSESSMENT OF GRANULOMETRIC ESTIMATION IN SYNTHETIC IMAGES

		Major axis			Minor axis		
		Q1	Q2	Q3	Q1	Q2	Q3
$\widehat{Small}$	AD	$50.9_{0.36}$	$71.0_{0.44}$	$94.2_{0.49}$	$10.4_{0.08}$	$14.6_{0.07}$	$18.8_{0.08}$
	PM	$52.0_{3.76}$	$71.7_{5.35}$	$97.5_{6.47}$	$12.1_{1.04}$	$16.4_{1.08}$	$21.3_{1.28}$
$\widehat{Medium}$	AD	$64.8_{0.32}$	$82.9_{0.32}$	$102.1_{0.37}$	$14.1_{0.06}$	$17.5_{0.06}$	$20.9_{0.07}$
	PM	$58.4_{4.03}$	$79.4_{5.33}$	$105.1_{6.74}$	$14.3_{0.79}$	$18.4_{0.84}$	$22.9_{1.20}$
$\widehat{Big}$	AD	$86.6_{0.26}$	$100.1_{0.23}$	$113.6_{0.26}$	$17.3_{0.05}$	$20.0_{0.04}$	$22.7_{0.05}$
	PM	$66.8_{5.03}$	$94.2_{6.15}$	$119.8_{6.41}$	$16.8_{0.85}$	$20.7_{0.94}$	$24.6_{1.32}$

Note: AD stands for Actual Dimensions and PM stands for Proposed Method. The table reports both the mean values and their std deviations (subscript), which indicate the average differences between the AD and PM quartiles (values in mm).

OSB panels, by improving the mechanical properties of the panels and reducing the used glue.

The proposed framework employs an innovative image processing approach, based on the segmentation of image partitions through an optimized algorithm of fuzzy color clustering. The approach is especially adapted to the characteristics of the application, and it demonstrated its ability to detect a trend in the granulometry of the strands. Discovering such a trend is helpful to prevent deviations from the optimal operating point of the factory and consequently favor the quality of the panels.

Future works are foreseen on the following research lines:

- The detection of strand fragments incorrectly identified as whole strands, which may subsequently be further improved to yield more realistic final results.
- The reconstruction of the strands divided into pieces for possible occlusions, which could help in performing more accurate granulometric analysis.
- The study of a measurement method that avoids segmentation, which could complement the obtained results and make the system more robust against changes in the ambient conditions.

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