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Circular Hough Transform and Local Circularity Measure for Weight Estimation of a Graph-Cut based Wood Stack Measurement

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Abstract

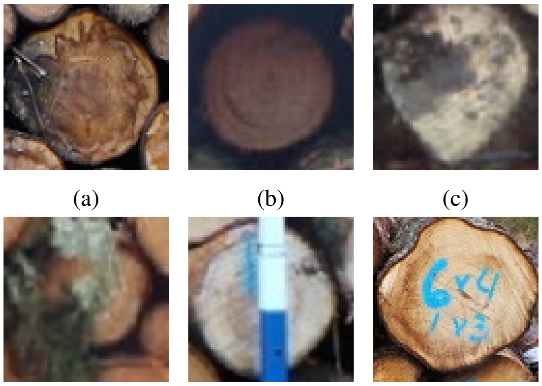
One of the time consuming tasks in the timber industry is the manually measurement of features of wood stacks. Such features include, but are not limited to, the number of the logs in a stack, their diameters distribution, and their volumes. Computer vision techniques have recently been used for solving this real-world industrial application. Such techniques are facing many challenges as the task is usually performed in outdoor, uncontrolled, environments. Furthermore, the logs can vary in texture and they can be occluded by different obstacles. These all make the segmentation of the wood logs a difficult task. Graph-cut has shown to be good enough for such a segmentation. However, it is hard to find proper graph weights. This is exactly the contribution of this paper to propose a method for setting the weights of the graph. To do so, we use Circular Hough Transform (CHT) for obtaining information about the fore- and background regions of a stack image, and then use this together with a Local Circularity Measure (LCM) to modify the weights of the graph to segment the wood logs from the rest of the image. We further improve the segmentation by separating overlapping logs. These segmented wood logs are finally scaled and used to acquire the necessary wood stack measurements in real-world scale (in cm). The proposed system, which works automatically, has been tested on two different datasets, containing real outdoor images of logs which vary in shapes and sizes. The experimental results show that the proposed approach not only achieves the same results as the state-of-the-art systems, it produces more stable results.

1. Introduction

Computer vision techniques have recently found a very interesting application in the timber industry, where these techniques have, among others, been used for detecting and measuring wood logs in piled stacks of wood as in [6], [1], [7], [11], and [8]. These measurements include, e.g., the number of wood logs and their volumes and sizes. Nowadays, most of the forestry companies are measuring and collecting such data manually. This is obviously a slow process, requires a high amount of labor and runs the risk of human error. One alternative reliable industrial technique is using laser scanners for physically estimating length, size and volume of each log in the wood stack [12]. It is however an expensive solution to install and maintain the laser scanners. Moreover, the scanning can not be easily performed outside of factory facilities, which means that the stacks need to be moved for the measurement.

The proposed system in this paper has been developed in collaboration with HedeDanmark A/S company which is collecting and measuring the data from the wood stacks semi-automatically. The reason that HedeDanmark A/S, similar to many other peer companies, is using semi-automatic (if not manual) measurement of wood logs is the sensitivity of the available computer vision solutions to imaging conditions [6], [1], [7], [11], [8]. This is because cut wood logs are located in outdoor environments, i.e., illumination can easily change. Furthermore, the wood logs can vary in size, shape and color. Moreover, they can be occluded by other objects, like debris and mud, in the scene. Figure 1 illustrates some of the observed variations.

In our scenario images are taken by the people of the cooperating forestry with a resolution of 640x480 pixels. These images could be blurred, over- or underexposed, which means the image quality can be far from ideal. Furthermore, the forestry employees of HedeDanmark A/S are required to use some markers of known sizes along with the wood logs to make it possible to transform the extracted information from the pixel domain to real-world measurements in cm (explained more in Section 3.1). These markers will also occlude some wood logs as seen in Figure 1e. Sometimes the employees of the forestry companies are also required to write some manually measured data on some of the logs, for further verification of the semi-automatic system, which obviously changes the texture and



(a) (b) (c)

(d) (e) (f)

Figure 1: Various issues of wood log images: a differently colored log (a), an overshadowed log (b), a log covered by mud (c), a log covered in debris (d) a log occluded by a marker (e), and a log with text written on it (f).

color of the logs as shown in Figure 1f.

The proposed system in this paper develops a system for a real-world computer vision application in timber industry for detection and measurement of wood logs. The proposed system is shown to be more robust against most of the aforementioned degradations, compared to the state-of-the-art systems. The rest of the paper is organized as follows: The related systems in the literature are reviewed in the next section. The proposed system is explained in Section 3. The experimental results and comparison against the state-of-the-art are give in Section 4. Finally, the paper is concluded in Section 5.

2. Related work

Wood log surface segmentation is a less-commonly researched subject, compared to other research topics in wood industry like, wood patterns identification, inspecting bark and classifying trees as a whole. F. Fink [6] is one of the first who did wood log surface segmentation. His proposed algorithm focuses on thresholding an input image until only a contour of the wood stack is present, which is then used for finding the wood cut surfaces. His approach gives precise results, but is not robust against changes in lighting conditions and lower quality input data. These make it impractical for field conditions with drastically changing parameters.

Dahl *et al*. [1] used watershed segmentation for wood logs segmentation which produces good results in constrained environments. However, it also suffers from changing conditions of outdoor environments, as it heavily relies on stereoscopic input data. It also takes the assumption that there are no disturbing factors in the vicinity of the wood stack, such as grass, mud or fallen branches, which is unrealistic.

Graph-cut is another popular method for segmenting based on color information which was first used for wood log segmentation by Boykov *et al*. [4]. The graph-cut algorithm models the input images as weighted graphs and segments them into fore- and background using an energy minimization method. Its frequent usage can be explained with its precision and high optimization working with both high and low resolution images [10] [9]. One of the important prerequisites for obtaining proper segmentation results using this algorithm is to choose suitable graph weights, both inter-pixel weights and pixel-to-terminal weights. There are different ways for doing so. Initially, the inter-pixel weights are calculated using the difference in intensity. Next is determining weights between pixels and the sink- and source-terminal, which can be found with a lot of different approaches. Two approaches for applying graph-cut to wood stack segmentation are suggested in the papers by Gutzeit *et al*. [7] and Gutzeit and Voskamp [8]. The first paper assumes that the wood stack is always located in the middle and the background at the top and bottom of the images. This leads to the creation of three sub-images: one in the middle, which is pre-segmented for finding foreground pixels, and top and bottom images, which are used for background modeling. It is not always easy to satisfy the requirement of this system about the central position of the wood stack, as this imposes a specific distance and position between the camera and the stack, which is not always easy to find due to the cluttered working environment. The second paper relies on pre-segmentation of the whole input image using the Haar-Cascades of Viola and Jones in [14]. From the Haar-Cascades a classifier template for wood logs is found, and then template matching is used to obtain a number of wood log surfaces as foreground, while everything else is considered background. Besides the inherited issues of template matching, like size of the template, the main problem of this work is the need for a large database of wood log for training the Haar-Cascades.

One of the main problems of graph-cut based methods for wood log segmentation is therefore the need for proper fore- and background pixels for training, as these may change very much from one image to another. To deal with this problem in this paper, we propose a graph-cut based wood log segmentation in which Circular Hough transform (CHT) is first applied to the input image to locate circular objects. As wood stacks have a large concentration of wood logs, which have a roughly circular shape, we can conclude that the area in the vicinity of the greatest number of circles is the wood stack. This resolves the limitation of requiring the wood stack to be centered in the image as in [7]. Moreover, the system does not need a very large training databases as those used for the Haar-Cascades approach of [8]. The found wood stack pixels are then used to model

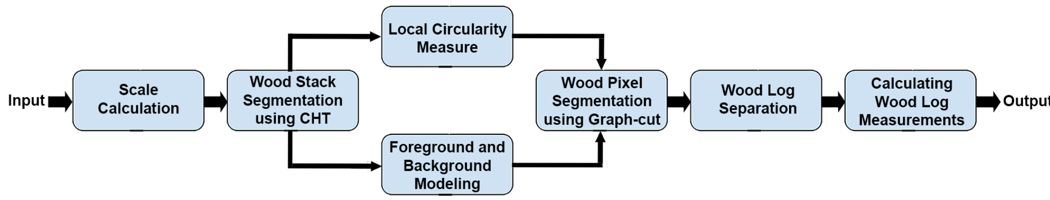


Figure 2: The block diagram of the proposed system.

the foreground, and everything else (with a specific margin from the foreground) is considered background. Then, we go one step further and introduce a Local Circularity Measurement (LCM) for a more precise estimation of the weights of the graph. Then, K-mean clustering is used to model the fore- and background pixels. Finally, morphological methods like those described by Binghan *et al*. [2] are used for separating touching wood logs once the segmentation has been performed.

3. The Proposed System

The block diagram of the proposed system is shown in Figure 2. As mentioned before, the employees of the cooperating company are attaching some landmarks of known sizes to each stack, making it possible to transform the extracted information from the pixel domain to real-world measurements. Therefore, the first step of the system is to calculate the scale of the image by detecting these markers. A circular Hough transform is then used to find the area of the image with the largest concentration of circles, which corresponds to the wood stack. The extracted scale in the previous step is used for limiting the interval of searched radii. The found pixels of the wood stack are then used for modeling the fore- and background. From this we calculate pixel weights for the graph-cut algorithm. The weights are additionally updated using our introduced LCM measurement. The calculated weights are given to the graph-cut, which segments the image into fore- and background pixels. The binary output of the graph-cut, together with the output of the CHT are then used in a recursive morphology method, which approximates a circular area of each wood log. The information for these circles is then used to calculate real world measurements such as the diameter distribution and volume of wood in the stack.
Each of these steps are described in the following subsections.

3.1. Scale Calculation

For this specific application, markers with sections of known length (20cm per blue/white section) are placed physically by the employees of the cooperating company before capturing the image. An example of an image including these markers can be seen in Figure 3a. By segmenting and measuring the length of these markers in pixels we acquire the scale factor, which allows us to map from image-dimensions to real-world dimensions.

Only blue sections of the marker are segmented, as the bottom white section has been observed to be 40cm and often occluded by debris. The number of the marker sections is then found as the number of the detected blue sections together with the detected white ones in between, as the color is always shifting. The blue sections are segmented based on two thresholds: 1) T_{Blue}, which is the blueness and 2) T_{RB}, which is the contrast between the red- and blue color channels. These thresholds, that are found experimentally, are extracted in the normalized RGB colorspace, which is more robust against changes in illumination, compared to RGB. Too large blobs, which are usually sky-pixels, are then removed by morphological operations, the threshold for removing too large blobs is also found experimentally. Figure 3 illustrates a resulting binary image obtained from the marker segmentation.

Linear Hough Transform [5] is then performed on the binary image, in order to find the best fit lines. From the endpoints of the best fit lines, the Euclidean length L_{marker} of each marker is calculated and together with the number of marker sections $N_{sections}$ we calculate the transformation factor ψ as:

$$\psi = \frac{20cm \cdot N_{sections}}{L_{marker}} \quad (1)$$

The final value of the scale factor is the average of the two values of ψ that each have been calculated from each of the markers that are present in the input image. The resulting scale factor is detected with an error $< 1.5\%$ for the majority of input images.

3.2. Wood Stack Segmentation using CHT

The key observation and assumption for detecting the wood stack, is that a large amount of the cut wood logs have a circular shape. This has been observed and verified to be the case by studying a large set of images supplied by the

(a) (b)

Figure 3: Result of marker segmentation. The input image (a) and the resulting binary map after thresholding and applying morphological operations (b)

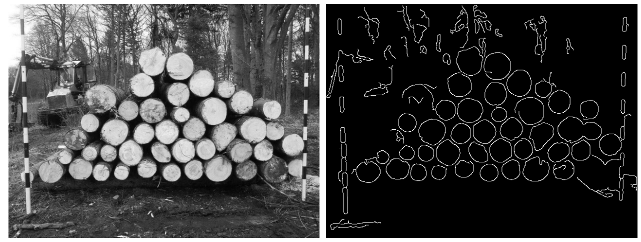
cooperating company. Since not all wood logs are circular, this segmentation can be seen as a coarse-segmentation which aims to roughly detect the wood stack. Naturally, more correctly detected wood logs in this step will yield better results, however, the next steps in the proposed system extend the segmentation, so it can cover all wood logs.

The basis of the CHT, which is widely used due to its robustness against noise, low-contrast objects and occlusion [13], is to create a good edge map with well-represented boundaries of the wood logs and at the same time suppress the edge responses of non-wood logs. Though the overall RGB-color of wood logs vary, it is generally observed that wood logs contain a strong yellow component, as also observed by [7]. An example of subtracting the yellow color component can be seen in Figure 4a.
The Canny Edge detector is used to calculate the edge map as it provides thin edges, preserves small edges nicely and is finally easy to implement. Small connected objects are removed from the edge map. This is useful for removing edge responses created by, e.g., grass-regions, which often is present in the lower part of the input images. An edge map created using this approach can be seen in Figure 4b.

The core step in general Hough Transform is a voting process which maps all the edge pixels to the integral of the Hough Transform often referred to as the $accumulator$., H_c. The CHT uses a parametric description to fit a circle with radius r around each edge point specified by coordinates (x_0, y_0) as in:

$$\begin{aligned} x &= x_0 + r \cdot cos(\theta) \\ y &= y_0 + r \cdot sin(\theta) \end{aligned} \tag{2}$$

In order to create a true circle, θ is to be varied between 0 and 2π, i.e., $\theta \in [0, 2\pi]$. As the wood logs cannot be assumed to be of the same size, r is defined as a vector ranging from the smallest assumable radius to the largest radius: $r \in (r_{min}, r_{max})$. The size of the wood logs in the image naturally depends of the physical size of the wood logs along with the distance of which the image is captured. The last issue makes the CHT scale variant, however, in this



(a) (b)

Figure 4: Gray-level colormap based on the yellow color component (a) and the resulting edgemap (b). Note that wood logs are well represented in the edgemap.

specific application this can be solved by using the fact, that the cooperating company operates with log sizes of 6-40cm in radius. Having obtained the scale of the image, the upper- and lower boundaries for r can be calculated as:

$$\begin{aligned} r_{min} &= 6cm \cdot \psi^{-1} \\ r_{max} &= 40cm \cdot \psi^{-1} \end{aligned} \tag{3}$$

This specifies all the parameters used for performing the voting-process, i.e., creating the accumulator space, H_c. The H_c is a 3D-structure specified by (N_{row}, N_{col}, r), where N_{row} and N_{col} is the size of the input image. Each entry in the H_c specifies the circular-fit at a given image-coordinate for each radius-value in r. A higher value indicates a better circular fit. In another words, the value of each cell indicates the probability of a specific entry representing a true circle.

After the voting-process, the H_c is weighted by a spatial weighing mask in order to grant higher probability of detecting wood logs in the central region of the input image. This is done using a 2D Gaussian function, I_G, as in:

$$I_G = exp(-\frac{(x - N_{col} \cdot 0.5)^2}{2\sigma_x^2} - \frac{(y - N_{row} \cdot 0.5)^2}{2\sigma_y^2}) \tag{4}$$

The size of I_G is the same as the input image and therefore each entry is used to modify the same entry in the H_c for each r-value. By experimentally obtained values of $\sigma_x^2 = 1.18 \cdot N_{col}$ and $\sigma_y^2 = 0.54 \cdot N_{row}$ the resulting appliance of I_G gives approximately 67% higher value for the center entry in the H_c while the four corners are left unaffected.

By performing a global threshold of the H_c, wood logs are detected at a given image-location and radius, (x_0, y_0, r_0), if the value is above a percentage of the highest value in the H_c. This is calculated by considering all entries having a value above $T_{CHT} \cdot max(H_c)$ as representing a true wood log, and discarding the rest. By setting a too low T_{CHT} many non-circular objects will be detected, and by setting T_{CHT} too high an excessive amount

of wood logs will not be detected. Experimentally, a value of $T_{CHT} = 0.6$ is found to bring good results as it brings a low false-positive detection rate, while still detecting sufficient true wood logs.
Because of the voting step being performed with different values of r, the resulting thresholding tends to detect an excessive amount of wood logs, which are often overlapping circles. To resolve this, the wood log candidates are grouped if their inter-distance is too small. The resulting detection is then the average value of (x_0, y_0, r) within the group. This approach can be viewed as applying non-maximal suppression to the H_c prior to thresholding. The result is a set of wood logs, C_{CHT}. Furthermore, outliers are removed by applying a k-nearest neighbors method, removing anything being too far away, i.e. above a specified threshold, from their k-nearest neighbors.

Finally, the region of the wood stack is specified by applying the Convex Hull of the region spanned by the detected circles, resulting in a binary mask $I_{woodstack}$. Figure 5 illustrates wood logs detected by the CHT using red circles superimposed on the input image. The center (x_0, y_0) is marked by a red cross, and the r at which the circle was detected is illustrated by the radius of the superimposed circles, respectfully.

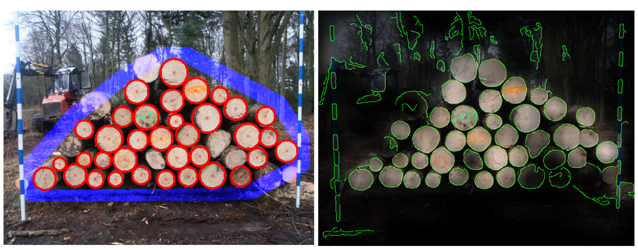


Figure 5: Regions found in the input image: red circles are detected by the CHT, blue indicates the unknown-region (margin) and the outer region is used to model the background, together with found air pixels in the central region. (a) LCM output: The green colors are from the superimposed edge map. (b)

3.3. Local Circularity Measure (LCM)

As mentioned in Section 3.2, the value of H_c at any given entries is proportional to the probability of that entry representing a true wood log. Furthermore, it is observed that most wood logs have a smooth uniform texture, which results in a well-represented edge map where only the outer boundary of each wood log is included, see Figure 4b. By exploiting this, we propose an LCM method to increase the probability of circular objects to be considered foreground. The LCM is calculated as:

$$LCM(x_0, y_0) = \frac{H_{cMax}}{1 + e_c * \alpha} \tag{5}$$

wherein H_{cMax} is the highest value of H_c in a neighborhood specified by r, and e_c is the number of edge pixels counted in the neighborhood specified by (x_0, y_0, r). The value of e_c is used to penalize regions with a high edge pixel count as these regions rarely corresponds to a true wood-log region. This parameter, e_c, is scaled by a scalar $\alpha \in (0, 1)$ which defines the degree of penalization. The values of both e_c and α are found experimentally.

Figure 6 shows how e_c can be used to distinguish between a true wood log region (left) and a noisy-region in the edge map (right). The superimposed green circle illustrates the region included in calculation of e_c .

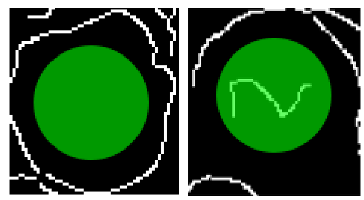


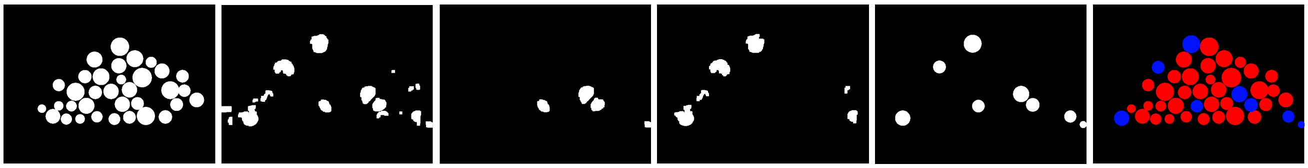
Figure 6: Illustration of calculation of the e_c parameter. In the left image the count is small due to the patch representing a true wood log, whereas the setup in the right image results in a high count due to the patch being located in a non-wood region.

Computing LCM for each pixel of the input image gives a mask, I_{LCM}, that can be applied to the weight maps of Section 3.4. By updating the weights with LCM, pixels with higher values of LCM are more likely to be classified as foreground. Lastly, I_{LCM} is blurred using a spatial Gaussian filter and the mask is normalized. Figure 5, wherein the intensities of the input image are pixel-wise multiplied by I_{LCM}, illustrates the values calculated in the LCM for a representative image - note that this approach of applying the LCM is only for illustrational purposes, see Equation 7 for correct approach.

3.4. Segmentation of Wood Log Pixels

Having found the fore- and background regions of the wood stack, a safety margin needs to be introduced to ensure background pixels contain as few wood logs as possible, as there is no guarantee for CHT to locate wood logs on the edge of the wood stack. This safety margin (blue colored in Figure 5) is simply obtained by dilating the wood stack mask, and then ignoring the pixels in the dilated-region while modeling the fore- and background.

Foreground pixels are wood log pixels inside the wood stack mask. However, there are black spaces between individual logs, which should not to be considered as foreground. To remove these holes, following Gutzeit *et al*. [7],



(a) (b) (c) (d) (e) (f)

Figure 7: Steps for wood log separation. Output from the CHT and graph-cut (a). Pixels found only by graph-cut (b) are separated into two groups - those that do not need additional processing (c) and those that require to be separated (d). After processing all approximated circles found from the graph cut (e) are merged with the ones from CHT (f).

we threshold the yellow color channel in RGB colorspace and the value channel in HSV colorspace, and then intersect the results from these two. Then, a pixel is either classified as: 1) foreground pixel if both the yellow and value channel classified it as foreground, or 2) as unknown pixel if they are classified differently, or 3) as background if both of the classifiers classify it as a background pixel. Background pixels also contain the pixels outside the safety margin. Lastly, unknown pixels are the pixels inside the safety margin and those classified as unknown inside the wood stack mask. Having the tri-map, a k-means clustering is performed to obtain k-color models for both the fore- and background. From these models the graph weights for each pixel towards the sink and source is calculated as in:

$$\begin{aligned} W_{sink} &= 1 - \exp\left(-\gamma \cdot minDistToFG\right) \\ W_{source} &= 1 - \exp\left(-\gamma \cdot minDistToBG\right) \end{aligned} \tag{6}$$

wherein the minimum distance is the calculated minimum Euclidean distance from the pixel to the color models, using the approach proposed by Gutzeit *et al.* [7]. Furthermore, the sink and source weights are updated using LCM, resulting in a lower weight for circular objects to be foreground. LCM is then applied as:

$$\begin{aligned} W_{sink} &= W_{sink} - W_{sink} \cdot I_{LCM} \cdot \beta \\ W_{source} &= W_{source} + W_{source} \cdot I_{LCM} \cdot \beta \end{aligned} \tag{7}$$

where β is a factor determining how much the LCM is weighed. A smoothness cost is also needed in the graph-cut to change the inter-pixel weights. This is created using the tri-map image with different values for foreground, background and unknown. In general foreground pixels require less smoothness, so the segmentation has more detail and in the background the smoothness cost should be higher in order to keep variation low.

Final step is to perform the graph-cut segmentation with the found weight maps and smoothness cost throughout the image. This paper utilized the graph-cut implementation provided by Boykov and Kolmogorov [3]. The graph-cut method used is $\alpha - \beta$ swap. The output of the graph-cut segmentation is a binary mask, $I_{woodpixels}$, containing found wood pixels as foreground and everything else as background.

3.5. Wood Log Separation

In order to obtain measurements for wood logs, the binary mask $I_{woodpixels}$ obtained from the graph-cut needs to be separated into individual wood log blobs. This is done in correlation to the circles found by CHT, as those are already assumed well segmented wood logs. This leads us to the assumption that if circles are found by both the CHT and the graph-cut, they are adequately segmented wood logs and do not need additional separation. Furthermore, their measurements are obtained from the CHT, which means they can be removed from $I_{woodpixels}$. Figure 7a illustrates wood logs found both by CHT and the graph-cut. On the other hand foreground pixels found only by the graph-cut may contain false positives and connected blobs, which means they require additional treatment before they can be considered real wood logs. Some examples of this case can be seen in Figure 7b.

The separation process starts by removing blobs that are too small to be considered wood logs. The features (area and perimeter) of the remaining blobs are then extracted and used to obtain the circularity measure CM as:

$$CM = \frac{P^2}{(4 \cdot \pi \cdot A)} \tag{8}$$

where P and A are the perimeter and the area of each blob, respectively. The lower CM the more circular the blob. This CM is used for grouping the blobs as either roughly circular or non-circular. Non-circular objects are then subjected to a series of morphological operations until they are circular enough. Blobs from the roughly circular and non-circular groups can be seen in Figures 7c and 7d.

The second group is separated into individual blobs using a recursive method. The blobs are first morphologically eroded with a small circular structuring element (SE), then it is morphologically opened with a slightly larger SE. For each iteration each blob's circularity is measured and if the CM is below a given threshold, which is found experimentally, it is considered circular enough, otherwise the erosion

Wood Segmentation Method	Precision	Recall	F-Score
Gutzeit and Voskamp [8]	0.878 (0.08)	0.95 (0.0334)	0.91 (0.043)
The proposed system using both CHT, LCM	**0.880 (0.053)**	**0.949 (0.021)**	**0.912 (0.030)**
The proposed system without CHT	0.879 (0.087)	0.917 (0.058)	0.894 (0.054)
The proposed system without LCM	0.852 (0.068)	0.948 (0.025)	0.902 (0.030)

Table 1: Quality measurements of the segmentation of wood pixel segmentation. Each value is calculated as the average across all images in the data set provided by Gutzeit and Voskamp, with standard deviation in brackets.

and opening is repeated until the blob is either removed or circular enough. Once a blob is considered circular enough it is morphologically dilated again with a small circular SE, making it as large as possible without touching other blobs.

The circular blobs are then approximated into circles by considering a the circle's center being the center of mass of the blob with and a radius of:

$$R = \frac{\sqrt{\frac{4*A}{\pi}}}{2} \tag{9}$$

A binary image of the approximated circles can be seen in Figure 7e. The final output image containing all found circles can be seen in figure 7f. All found wood log blobs are then combined into a binary map $I_{woodlogs}$, and blob measurements from this binary map can be used for calculating the necessary measurements. These measurements are then converted to real-world measurements using the scale factor found previously.

4. Experimental Results

The proposed system has been tested on two different datasets. These datasets and the tests performed on each of them are explained in the following subsections.

4.1. The First Dataset

The first dataset contains 71 input images and their segmentation ground truth data. This dataset which is provided by Gutzeit and Voskamp [8] has been used only to compare the performance of the proposed system against state-of-the-art in segmenting wood pixels from the rest of the image. This dataset does not contain the physical markers, explained in Section 3.1, and the segmented wood pixels can not be therefore translated to the world measurements in cm.

The segmentation results of the proposed system against those of the state-of-the-art system of [8] are shown in Table 1 (the first two rows). The comparison results have been reported using evaluation measurements of precision, recall and F-score. It can be seen from the first column of the table that the two approaches are comparable with respect to performance, however, with less variations, given inside the parentheses, in our proposed system. Our system yields a minor increase in precision while preserving the same recall. This results in an overall better performance, which is indicated by the F-score.

Furthermore, to show the effect of each of the introduced ideas of CHT and LCM on the segmentation results of the proposed system on the first dataset, we have conducted two extra experiments. In the first experiment CHT and in the second one LCM have been removed from the system and the segmentation results have been monitored. The results of these two experiments are shown in the last two rows of Table 1. It can be seen from the table that a better performance is achieved when the proposed system is utilizing both CHT and LCM.

The lack of markers in this dataset imposes the need for an interval for the radius for the CHT. This results in a worse performance of the CHT due to the lack of scale invariance, and it is believed that this lowers the overall performance (forth row).Even then the closely correlated results show that the CHT manages to find a number of initial circles, on average 58% and 60% of all the found circles, which is comparable to the initial method used by the state-of-the-art method of Haar-cascades [8].

4.2. The Second Dataset

Having shown the performance of the system in segmenting wood pixels on the first dataset, we also need to show the performance of the system in translating the measured features from the image domain (in pixel) to the world domain measurements (in cm). The first dataset can not be used for this purpose, because the images in the dataset do not contain the markers explained in Section 3.1. To test this, we have used a second dataset that has been provided by our cooperating company. The 37 images of this second dataset come with the two markers of Section 3.1. The features of interest in this dataset are the number of the wood logs and their volumes. The ground truth data for these two features are generated by the cooperating company. The results of the proposed system in measuring these two features compared against the ground truth data are shown in Table 2. To show the effect of each of the introduced ideas of CHT and LCM on the feature measurement results of the proposed system on the second dataset, we have conducted two extra experiments. In the first experiment CHT and in the second one LCM have been removed from the system and the feature measurement results have been monitored. The results of these two experiments are shown in the last two rows of Table 2. It can be seen from the table that the best performance has been achieved when the proposed system is utilizing both CHT and LCM.

The Method	c1[in %]	c2[in %]
r1	**9,22(9,43)**	**14,22(13,03)**
r2	15.18(11.60)	29.06(19.13)
r3	10,23(9.81)	21,42(17,92)

Table 2: The performance of the proposed system in measuring the number of the wood logs and their volumes applied to the second data set. r1 is the results of the proposed system using both CHT, LCM, r2 is the results of the proposed system without CHT, and r3 is the results of the proposed system without LCM , c1 is the average error in counting the number of the logs, and c2 is the average error in measuring the volume of the wood logs in the stack.

Figure 8 shows the three different cases that have been observed for the performance of the proposed system.

Figure 8: Visualized performance of the proposed system: top-left: good performance, top-right: medium performance, and bottom: bad performance. Detected wood logs are illustrated by the superimposed red circles indicating detected position and radius.

5. Conclusion and Future Work

This paper has presented an interesting application of computer vision in the timber industry. Given an image of a stack, the proposed system uses graph-cut for segmenting the wood logs from the rest of the image. To set the weights of the graph in the graph-cut algorithm we have used Circular Hough Transform (CHT) and Local Circularity Measure (LCM). The experimental results, on two different real-world datasets, show that introducing CHT and LCM to the graph-cut algorithm results in a better performance of the algorithm for wood pixel segmentation and features measurement. The proposed system not only slightly outperforms state-of-the-art, but produces more stable results.

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