

MEASUREMENT OF WOOD QUALITY PARAMETERS FROM ANNUAL RINGS USING COLOR ANALYSIS WITH DIGITAL IMAGES

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Abstract: In this paper we present an image analysis method which provides wood quality parameters from board and log end images. Our analysis recognizes annual rings in prepared cutting surface despite of varying color pattern or lighting. After locating annual rings accurately, proportions of earlywood and latewood can be measured globally and locally in the image. Our method is based on combining moving window to principle component analysis (PCA). Furthermore, we apply various filtering methods to enhance result matrixes.

Keywords: Image Analysis, Wood Quality, PCA, annual rings.

1. INTRODUCTION

Trees carry their growth history in annual rings. The appearance and properties of individual tree are strongly affected by annual growth, which in turn depends on variations in atmospheric and other conditions. E.g. temperatures, rainfall, fertilization and thinning of forests affect the growth of a tree and hence annual rings. Therefore the cross section of a tree tells much about its history and thus about its quality, too. This knowledge is of high importance in commercial use in forest-based industries, and in forest research. The long-term goal of our research is to make the information carried in the annual ring structure and related wood quality information available for operators at sawmills, pulp mills and in harvesters, and also for the forest researchers in research centers. For this purpose the tree cross-section analyses methods need to be automated.

We have studied both color and texture analysis methods in wood quality analysis. The textural methods on digital images provide average thickness and orientation of annual rings locally. Furthermore, we developed methods to locate tree pith (i.e. center of annual rings) and to measure thickness of bark using textural methods on digital images [1]. Some of these methods have been applied also for board end images, and rather weak, yet useful correlation between textural structures and board firmness and strength measurement at sawmills were established [2, 3]. Typical for those methods is that analyses can be made without tracking individual annual rings.

Currently we are developing color analysis methods to provide indication of rot in wood. This measurement allows modeling the progression of rot inside the tree trunk. The basic problem with color analyses is that lighting is variable and uneven. Color of an object may vary considerably between images. However, we have shown that color variation between images can be corrected with appropriate calibration.

The color variation within an image causes problems when identifying individual annual rings. An annual ring has two parts, lighter area of earlywood and darker of latewood. If annual rings has abnormally high proportion of latewood in a small compact area, the area is called compression wood. Trees produce such hard wood e.g. when growing on the slope. Color of earlywood area may be so dark in one part of the image that it is confused with latewood color at another location. Therefore simple global threshold methods are not applicable. The color of latewood may also vary between and within annual rings. In this paper we describe how to solve these problems with a moving window and principle component analysis (PCA).

The goal of our research is to produce efficient tools for developing measurement system for earlywood and latewood proportions of timber for forest industries. The measurement is made by using digital image analysis. We suppose that the additional information about the amount of latewood inside the log or board increases information about firmness and strength of sawn timber compared to our earlier method of width of annual rings alone. We are currently testing this application, but here concentrate on the measurement aspects rather than on the applications.

2. IMAGE ANALYSIS WITH MOVING WINDOW AND PCA

While developing the analysis method we prepared the board ends to get optimal images. After cutting logs or sawing boards the surfaces were sandpapered and watered for better color contrast. In this paper all examples of images are taken or calculated from prepared board end images, but analyses made for similarly prepared log end image give equally good results. It seems that cutting surface after sharp chainsaw and with watering provides images with adequate quality for these image analyses as well. This makes the

application of the method feasible in production and in harvesters, which is currently being tested.

2.1. Moving window

The variable and uneven lighting makes the analysis of entire images problematic. Therefore we seek local analysis methods with small analysis windows. We have found the moving window a useful method for analyzing and parameterizing locally the properties of log and board ends using digital images. The method provided the basis for thickness field and orientation field of annual rings found in our previous research [1, 2]. In comparison with conventional image analysis methods, the weakness of this method is longer computation time. However, the development of calculation speed has made it possible to apply such solutions even at production lines and in harvesters.

In the moving window approach the analysis procedures are carried out for a small window at a time. The result of the analysis is associated in the area of result matrix (image) to the location of the centre of the current window in the original image.

The size of moving window is optional, but usually the original image sets limits and the final size of window is a compromise. We tested window sizes ranging from 200×200 pixels to 20×20 pixels. We chose in all the analysis presented here (results in Figures 5-7) the window size of 40×40 pixels, to be compared with typical effective image area of 587×1931 pixels. However, in Figures 1 and 2 the window size is 100×100 pixels for better visualizing. The window size should be larger than the thickest single annual ring in the board or log to be measured. The estimate of thickest annual ring within a single log or board end can be measured using the methods developed in our previous research [1, 2]. The window may cover many annual rings, but larger window increases the analysis time. In Fig. 1 the moving window is passing widest annual rings.

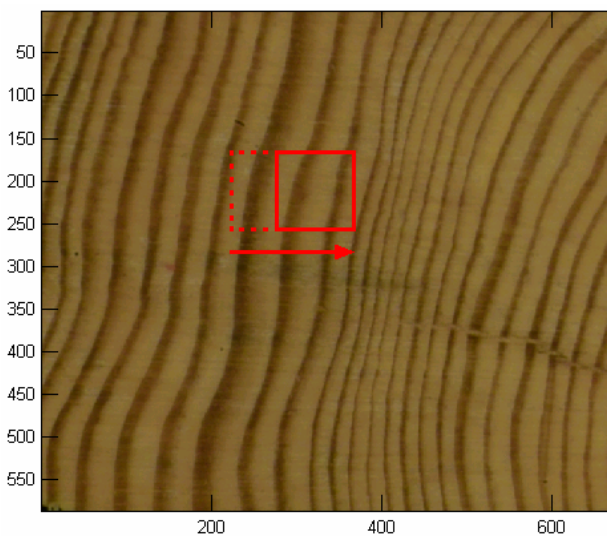


Fig. 1. 100×100 pixel sized moving window sliding across the prepared board end image. The size of window is chosen larger than the widest annual rings (including earlywood and latewood).

The move step size of the window is optional, too. The size of step affects strongly the computation time and the resolution of the result matrix. If the moving step is large, the quality properties are calculated only few areas within the log or board end image and the procedure produces only few quality measures to the result matrix. Thus the computation is rapid, but resolution of the result matrix is poor. With short moving step of window the resolution of the result matrix is good but calculation is very time consuming. We have experimented with move step ranging from one pixel to two hundred pixels.

2.2. PCA for RGB-image

Principal component analysis (PCA) is a well-known and widely-used signal analysis method [4, 5]. PCA arranges the data of several variables into linear combinations, the principal components, so that the components are not correlated. Rearrangement is made through diagonalizing the covariance matrix, and the components are ordered according to their contribution to variance. Major part of variance in entire dataset falls into the first principal component and it can be presented by the first *score* image. The second principal component has more variance than the third component and so on. The amount of principal components is the same as the amount of original variables. In most cases the few first components describe over 90% of variation, and the rest of components are negligible. Thus PCA is commonly used to reduce amount of variables with minimum loss of information. PCA is also used to seek statistically independent combinations of variables. The *loadings* of a principal component describe the contribution of each original variable to the principal component.

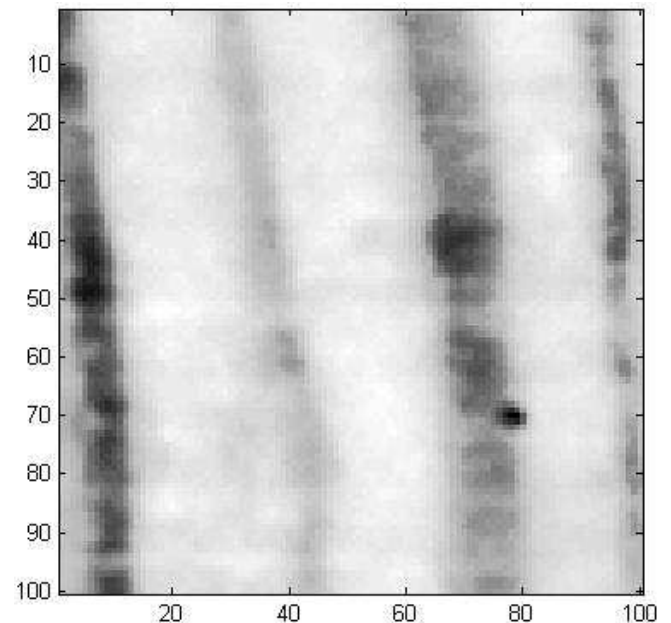


Fig. 2. The first principal component image after calculating PCA for the window of 100×100 pixels. The use of PCA rearranges the data of the image and hence gives better contrast.

We applied PCA to enhance the contrast of images. We have only three variables in an image, red, green and blue

channel intensity, and thus three principal components. The first principal component has the maximum variance. It is related to the annual ring structure, and thus gives the best information and the strongest contrast of the rings. We chose the first principal component, rather than original color channels or their average, to determine the earlywood and latewood proportions within the moving window, and here neglect the other two components. An example of the first principal component of PCA calculated from a 100×100 window is presented in Fig. 2.

2.3. Thresholding the score image of PCA

In the coniferous forest zone softwood species produce one annual ring on the outer surface per year. In springtime trees produce larger cells and grow rapidly. Larger cells cause the lighter color visible in the cutting surface. This part of a single annual ring is called earlywood. In summertime growing slows down, cells become smaller and color gets darker. The darker part of annual ring is called latewood. We should notice that darkening happens little by little and there is no sharp edge between earlywood and latewood. In wintertime trees are not active, because of frozen solids. Next spring trees begin to grow rapidly again and now the sharp edge between dark and light color can be noticed. Therefore, even if we had similarly colored annual rings within the window there would be large variation of color shades. Weather conditions during each spring and summer also have an effect to the growing and the size of the cells. This causes variation between annual ring colors, especially in latewood area. Latewood intensity variations between and within annual rings can be noticed in Fig. 2.

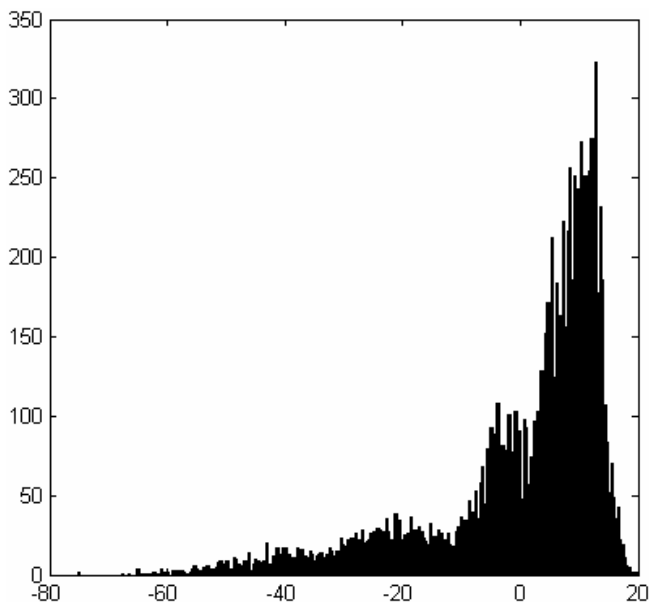


Fig. 3. Histogram of the window in Fig. 2. X-axis describes intensity values after PCA. Y-axis tells the amount of pixels in the window representing each intensity value.

In the case of Fig. 2 thresholding is possible, whereas for original full image or its PCA score image it would not be the case. Fig. 3 presents the histogram of the image in Fig. 2 showing the same intensity variation. There are not only two peaks for high and low valued pixels, but there is also a

large variation of intermediate intensities. The question is which score image levels should be taken into account when identifying latewood areas. We have chosen the threshold in a rather simple way: we calculate the mean of the histogram. The mean sets the threshold near the dominating intensity value of the window, thus it emphasizes minority values. Another simple and feasible way to choose thresholding value is to calculate the mean values for upper and lower 25% percentiles (400 highest and 400 lowest pixel score values in 40×40 window), and then to choose the threshold to be the mean of these two numbers. Hence the thresholds vary from window to window. The method attempts to find clear annual rings from current window by increasing color contrast although there are latewood areas with very light colors.

Thresholding can be made with advanced methods also, e.g. fitting Gaussian mixture models (GMM) into the intensity data, but these methods need more computation time [6]. When applying the methods in prototypes for industrial applications, high requirements are set for thresholding speed and accuracy.

3. BINARY IMAGE OF SEPARATE ANNUAL RINGS

The length of the moving step of the window is the application specific. If it is sufficient to know earlywood-to-latewood proportion of log or board with low resolution only, the moving step both in x- and in y-directions may be chosen even larger than the window size. In such a case there are only few samples taken from a log or board end but this is usually sufficient for obtaining a global estimate of earlywood-to-latewood proportion with the PCA method. Section 4. describes the local and global earlywood-to-latewood analysis.

3.1. Construction of resulting binary image

When the move step of window both in x- and in y-direction is chosen equal to or smaller than the size of moving window, an entire binary image of individual annual rings and the local and global earlywood and latewood parameters can be constructed with PCA score images. If the step is equal to the window size corner anomalies occur in the resulting binary image. The smaller the moving step is the less corner anomalies and the better the resulting binary image. In the following, results and images are presented with maximum resolution.

The corner anomalies, shown in Fig. 4, arise as follows. We choose in the analysis window size of 40×40 pixels according to the widest annual rings in our original board image and the move step of the window the same as the linear size of the window, i.e. 40 pixels. It means then that the original image is divided to 40×40 pixel sized windows and the PCA is carried out for the windows. Result matrix is formed by combining all first component score window blocks into the entire result matrix. Then, typically there will be some corner anomalies in the result images, especially in the areas having considerable darker color than in surrounding colors. Fig. 4 shows a zoomed area of resulting matrix having such corner anomalies. Comparing the area

with the upper left area of original image in Fig. 5 we notice the dark late wood area, which causes anomalies into the resulting matrix. In some cases corner anomalies may cover adjacent annual rings so that the rings can not be discerned at all.

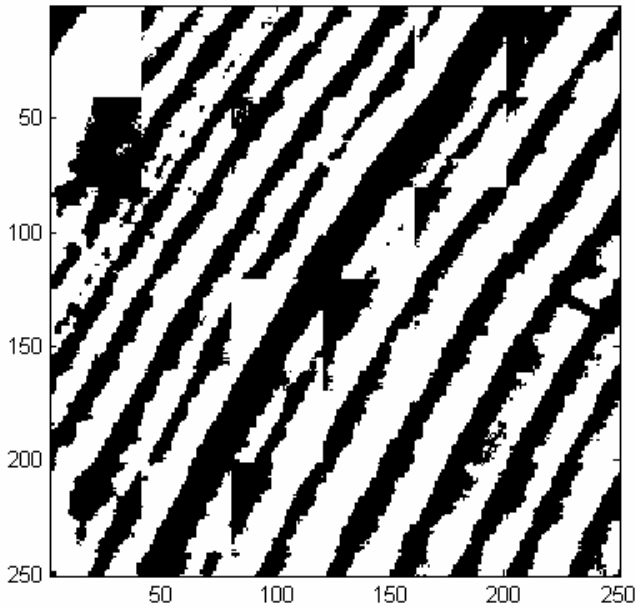


Fig. 4. Zoomed area of resulting matrix. Corner shaped anomalies occur near considerable varying colors in original image. Anomalies cover adjacent annual rings partially.

The problem was overcome as follows. The size of the moving window was maintained at 40×40 pixels and the threshold was evaluated as explained above. Now instead of placing the entire 40×40 pixel sized first component score image into the result matrix, only the center part of the score image was placed. The size of center part is optional, but it determines the length of the step: E.g. center part of size 10×10 pixels requires that the move step size of the window is 10 pixels. The smaller the center part, the better the result, however at the expense of computation time.

3.2. Enhancing the resulting binary image

After building the result binary image, it was enhanced by simple morphological image analysis routines. All small disjoint areas, smaller than 20 pixels, were removed. The small holes within latewood areas were filled similarly.

Fig. 5 presents the original RGB image of a prepared board end. The variations of shades of brown within the image are clearly noticeable. In particular, the upper left corner has very dark and thick late wood part of a single annual ring. There are large color variations between earlywood areas at different annual rings in the center area as well. Lower image in Fig. 5 shows the resulting binary

image combined from PCA first component scores. The move step of the window was 2 pixels for highest resolution possible and correspondingly the center part area was only 2×2 pixels from each 40×40 pixel PCA analysis. The resulting image is quite clear as manifested in the lower image of Fig 5. Even the narrowest annual rings can be discerned in the binary result matrix.

4. EARLYWOOD-TO-LATEWOOD ANALYSES

In timber production there is a need for measuring locally the earlywood-to-latewood proportion, in particular in logs. If the slow and rapidly grown annual rings and their earlywood-to-latewood proportion can be measured, the information helps to optimize the sawing of the log.

The moving window was found a useful tool for obtaining earlywood and latewood estimates from the entire binary image. The window size of 40×40 pixels was chosen still, because of the widest annual rings.

4.1. Evaluating global earlywood-to-latewood proportion

After constructing the binary image with separate annual rings, the global estimate for percentage proportions of early and late wood within entire log or board end is obtained simply by counting proportions of white and black pixels. If the analysis is made for images from both ends of a log (a board), the earlywood-to-latewood proportion inside the log (the board) can be evaluated.

If the binary image of separated annual rings is not needed and the low resolution earlywood-to-latewood proportion field is enough the move step of the window can be more than 40 pixels here. The global earlywood-to-latewood proportion is still available by counting and adding the black and white pixels of individual center parts of windows.

4.2. Earlywood-to-latewood proportion field

The local earlywood-to-latewood proportion was estimated by counting the percentage proportions of black and white pixels within the moving window simultaneously when calculating thresholded PCA score blocks for entire binary image of separated annual rings. These percentage values were inserted into the result matrix as explained above.

Fig. 6 presents the local earlywood-to-latewood proportion as a field calculated simultaneously with the binary image in Fig. 5. The move step of the window has been 2 pixels to obtain the best resolution for the binary image. The darker a point in the image is, the higher the proportion of latewood in the neighborhood of that point.

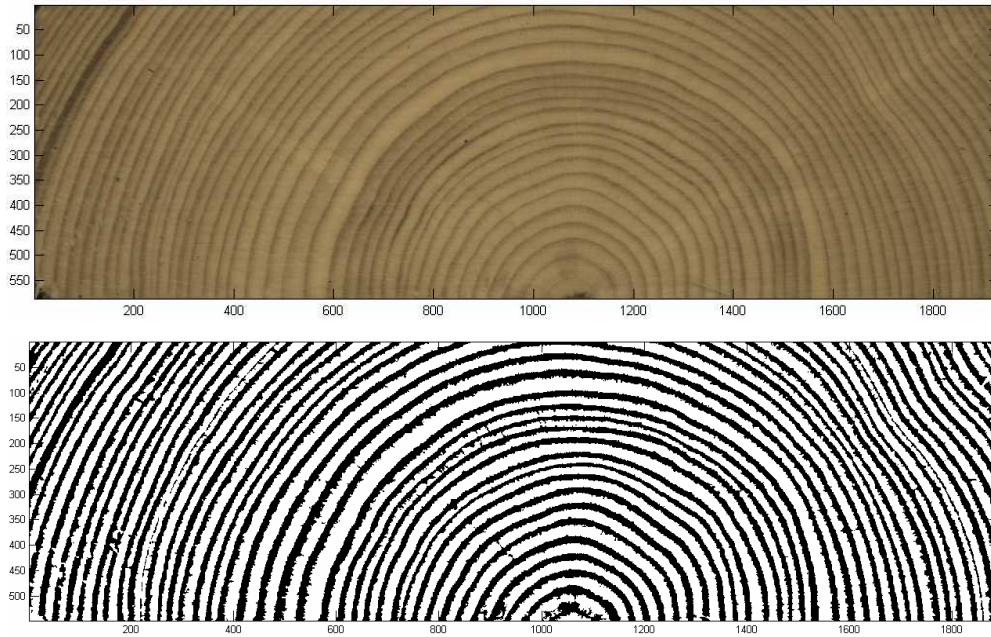


Fig. 5. The original prepared board end image above. Resulting binary image below after combining PCA score blocks and enhancing procedure. Moving window size is 40x40 pixels, center area size 2x2 pixels. Earlywood areas are marked white, latewood areas black. Individual annual rings are clear despite of varying color levels in original image. Axes tell the pixel locations.

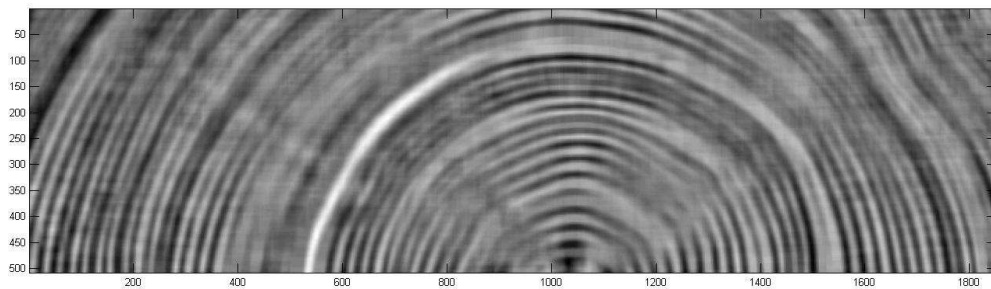


Fig. 6. Earlywood-to-late wood proportion field presented as an image. The areas of high proportions of latewood denoted as dark. Ghost effect of annual rings is noticeable.

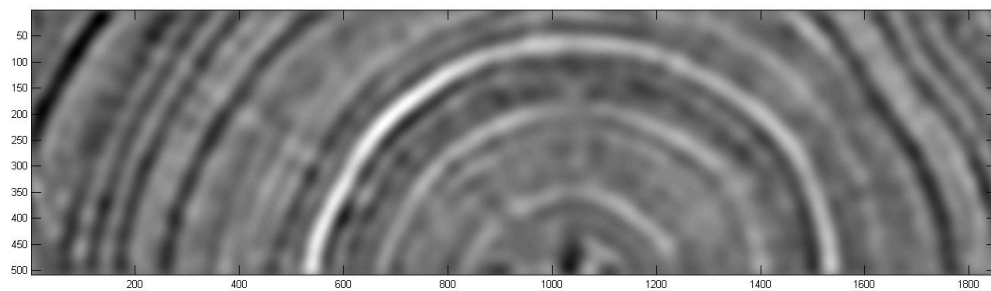


Fig. 7. After spectral filtering earlywood-to-latewood proportion field image, it presents locally the areas of high proportions of latewood as dark points. The ghost effect of annual rings is removed.

4.3. Low-pass filtering in spectral domain to remove variation caused by annual rings

In Fig. 6 the ghost effect of annual rings can be noticed within the earlywood-to-latewood proportion field as short wavelength variation. We removed this variation using low pass filtering in spectral domain [7, 8]. The earlywood-to-latewood proportion image was expanded into a square. Values outside the earlywood-to-latewood proportion field were filled with the mean value of the field. The square was Fourier transformed using Fast Fourier Transform (FFT). The cutoff frequency of the low-pass filter should be at most

the inverse of the width of the widest annual rings, and all variations above this frequency were removed. Our cutoff frequency is 1/40 pixels. The low-pass filtering was simply a sharp cutting edge in the frequency domain. Then the filtered Fourier transform was inverted to spatial domain. Fig. 7 shows the final result after filtering with cutoff frequency 1/40 pixels. Comparing Figures 6 and 7 there can be noticed dark and light areas in corresponding locations, but the high frequency variation caused by annual rings almost vanishes and high resolution earlywood-to-latewood content remains. Resolution can be easily reduced by decreasing the cutoff frequency, if needed.

5. CONCLUSION

In this paper we have presented an efficient way to measure some quality parameters of high industrial relevance from log and board ends. Methods are applied on images of prepared log or board ends, but in our present tests log ends cut with sharp chains saw have been found sufficient as well. Basis of these methods is the PCA in the moving window, which enables local annual ring analyses. PCA was found a particularly good tool for increasing the contrast and for determining the threshold level for deriving binary images.

The binary image in Fig. 5 provides opportunities to measure many new wood quality parameters. We believe that the automated measurement of quality parameters is of high economic potential within forest-based industries and we see the measurement of earlywood-to-latewood proportion globally and locally in the image as one part of the quality measure set available for future wood supply and production chain.

We admit that our present method is still a prototype version, and it is vulnerable for defects in the original image, e.g. knots, rot, or cracks in wood. Our method might recognize those defects as latewood areas and might give too high proportion of latewood. However, we have developed a method for detecting the defected areas in the images and neglecting them from calculation [2].

We see high potential also in our method, as it is able to separate individual annual rings despite of varying lighting and color circumstances. After tracking annual rings accurately, it is feasible to count annual rings within log or board end. E.g. in Sweden the number of annual rings at distance of 2-8cm from the centre of annual rings is an important quality parameter in log classification and should thus be made automatically measurable.

The methods explained above can be developed further. In our previous research based on texture analysis we have developed the method for measuring the orientation of annual rings at any location within log or board ends [1, 2]. When combining the present results with our previous research, it is possible to reduce measurement problems caused by defects. The common problems, - incorrect connection between annual rings and breaks within the single annual ring - can be avoided, when orientation of annual ring is available.

We are also developing our methods more robust to facilitate them for less prepared log end images. We expect that combining the results gives new views for developing an automatic compression wood recognition system. In forest research the question about correlation between the earlywood-to-latewood proportion and thickness and area of annual rings, and annual height growth is addressed. However, a prerequisite for image-based measurement of the quality parameters is that annual rings are visible to the naked eye in the original image.

When developing applications based on these methods, camera calibration is important. For the measurement to be correct the radial and tangential lens errors must be

appropriately compensated. We have developed our analysis methods by using MATLAB developing environment, and we have used camera calibration function library for correction. One calibration tool set for MATLAB is available for free in the web [8].

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