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Predicting spiral grain by computed tomography of Norway spruce

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Abstract Spiral grain is a feature of wood that affects the shape of the sawn timber. Boards sawn from logs with a large spiral grain have a tendency to twist when the moisture content changes. The aim of this study was to investigate the possibility of predicting spiral grain based on variables that should be measurable with an X-ray LogScanner. The study was based on 49 Norway spruce (*Picea abies*) logs from three stands in Sweden. The logs were scanned with a computed tomography (CT) scanner every 10mm along the log. Concentric surfaces at various distances from the pith were then reconstructed from the stack of CT images. The spiral grain angle was measured in these concentric surface images, and a statistical model for predicting spiral grain was calibrated using partial least squares (PLS) regression. The PLS model predicts the spiral grain of a log at a distance 50mm from the pith based on different variables that should be measurable with an industrial X-ray LogScanner. The result was a PLS model with $R^2 = 0.52$ for the training set and $R^2 = 0.37$ for the test set. We concluded that it should be possible to predict the spiral grain of a log based on variables measured by an industrial X-ray LogScanner. The most important variables for predicting spiral grain were measures of sapwood content, variation in the ratio between the heartwood and log areas, and the standard deviation for the mean log density in 10mm thick cross slices along the log. The accuracy when sorting the logs into two groups with spiral grain of ≥2.0° and of <2.0°, respectively, was 84% of the correctly sorted logs.

Key words Spiral grain · Stem bank · CT images · PLS regression · Jackknife · Nondestructive measurement

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Introduction

The successful running of a sawmill is dependent on its ability to achieve the highest possible recovery from the sawn logs. Spiral grain is a defect that decreases the quality and thereby the value of the timber. Therefore, it would be of interest to find a nondestructive method for measuring spiral grain before the logs are sawn.

Spiral grain occurs when the cells are not aligned parallel to the axis of the tree; they have grown in a helical structure around the pith.[1,2] Spiral grain is a well-known phenomenon that has been studied by many scientists. It has been shown that spiral grain leads to a reduction of mechanical properties of the timber.[1] An even greater problem is that timber with extensive spiral grain has a marked tendency to twist.[1] An important fact is that the spiral grain often changes its degree of inclination from the pith to the bark (Fig. 1). Most conifer trees in the Northern Hemisphere have a direction of left to right close to the pith, with a change to right to left close to the bark. This pattern is denoted the LR pattern. Indigenous conifers from the Southern Hemisphere have the opposite RL pattern.[3]

Traditionally, spiral grain has been measured using various destructive methods.[1] It is also possible to measure the grain angle on the surface of the log and use this information to predict the spiral grain within the log.[4] For research purposes, it has been shown that computed tomography (CT) is a possible method for measuring the spiral grain in logs nondestructively.[5] When scanning logs with a CT scanner, streaks with high density can be seen in images showing surfaces that are cut concentrically around the pith in the CT image stack. These streaks normally have an inclination relative to the longitudinal axis of the log (Fig. 2). This inclination probably corresponds to the spiral grain.[6]

Today, the fastest CT scanners have a speed of approximately one image per second, which corresponds to a scanning speed of 1cm/s with a resolution of 1cm/pixel in the longitudinal direction. This is much too slow for most softwood sawmills. Using an industrial X-ray LogScanner with two fixed X-ray sources, it is possible to scan logs at 3m/s

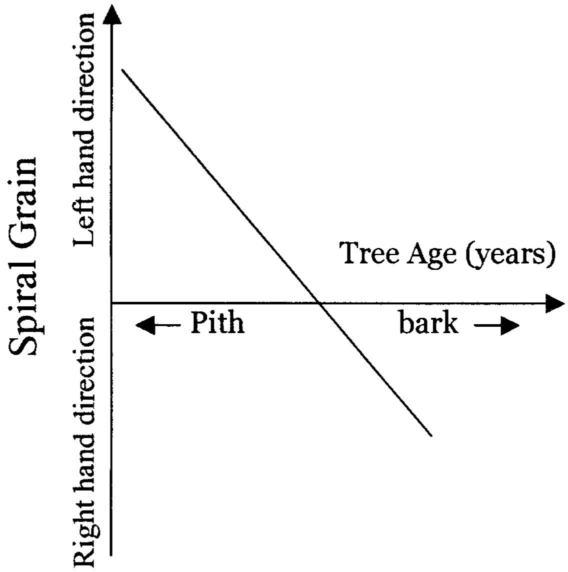

Fig. 1. Variation of spiral grain with age for the left-right (LR) pattern

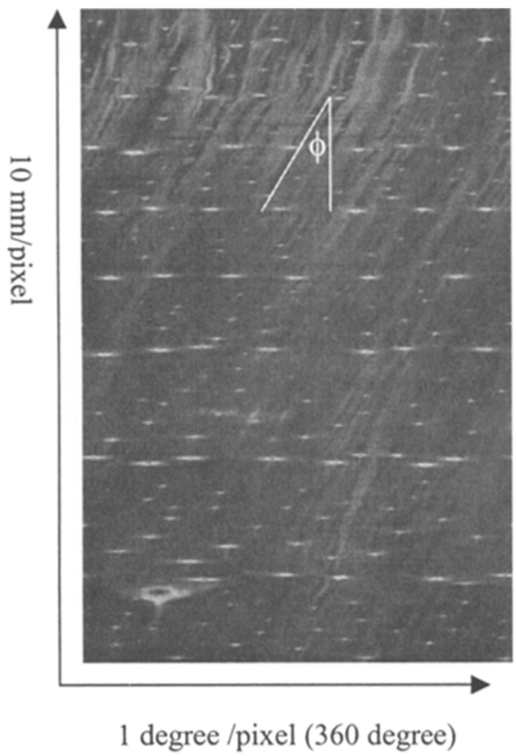

Fig. 2. Concentric surface (CS) reconstructed from a computed tomography (CT) image stack. The horizontal direction (x) corresponds to the tangential direction of the CS, and the vertical direction (y) corresponds to the distance from the butt end to the top end of the log. Resolution in the horizontal direction is 1°/pixel and in the vertical direction 10 mm/pixel. The leaning pattern in the image probably corresponds to the spiral grain. The image was taken 36 mm from the pith, and its gray level is given in kilograms per cubic meter

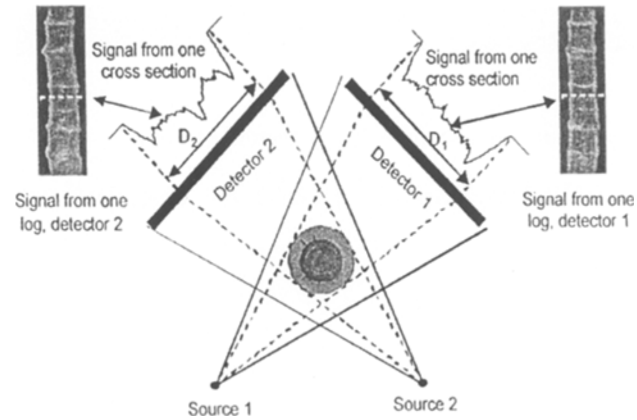

Fig. 3. X-ray LogScanner

(Fig. 3).[7] The output from the X-ray LogScanner is two longitudinal X-ray images of the log. With these images it is possible to measure several important variables, such as knot volume, and percentage of heartwood and sapwood in green density.[8] The spatial resolution of the X-ray LogScanner is too low for a direct measurement of spiral grain. An alternative method would be to find variables that are measurable with the X-ray LogScanner and that correlate with the spiral grain. The aim of this study was to investigate whether it is possible to predict the magnitude of spiral grain based on variables that can be measured with the X-ray LogScanner.

Materials and methods

The study was based on data from the European Spruce Stem Bank, which is a result of the EC project called Improved Spruce Timber Utilization. The basis of the project is CT scanning of 144 carefully selected Norway spruce (*Picea abies* L. Karst) stems from 24 sample plots in Sweden, Finland, and France. The material in this study was taken from three sample plots in Sweden (11, 12, 14) (Table 1).

The study was carried out on 49 Norway spruce logs. The logs were harvested during the winter in Sweden so they would not dry out during transportation and storage. The maximum storage time between felling and CT scanning was 2 months. After felling and crosscutting, the logs were scanned every 10 mm along the log in a medical CT scanner (Siemens SOMATOM AR.T). The X-ray beam width was 5 mm. The logs were fixed at both ends and adjusted to three laser lines so all the logs from a tree followed the same coordinate system during the scanning. All images were stored as 8-bit gray-scale images with a resolution of 256 × 256 pixels. The gray-scale values 0–255 are a linear represention of CT numbers from −1000 (gray-scale value 255) to 700 (gray-scale value 0). A pixel with CT number −1000 corresponds to a material with the same X-ray attenuation as air, and a pixel with CT number 0 corresponds to a material with the same X-ray attenuation as

Table 1. Data for the sample plots from which the test material originated

Parameter	Results, by stand number		
	Stand 11	Stand 12	Stand 14
Country	Sweden	Sweden	Sweden
Location	Siljansfors, Dalarna	Nyköping	Sannarp, Falkenberg, Halland
No. of sampled stems	6	6	6
Altitude (masl)	220	40	170
Stand age (years)	135	51	61
Site index (H100)	G26	G36	G36
Mean height (m)	28	23	24
Stems per ha (no)	53	1970	719
DBH			
Tree 1	285	240	258
Tree 2	274	210	271
Tree 3	356	315	398
Tree 4	358	295	392
Tree 5	394	342	435
Tree 6	404	345	442

masl, meters above sea level; H100, height in meters for the two highest trees of the dominating species at an age of 100 years; DBH, diameter at breast height

water. Light areas in the CT images correspond to high CT numbers (high-density objects), and dark areas correspond to low CT numbers (low-density objects).

For each log the CT images were added to a CT image stack, with one image every 10mm along the log. From the CT image stack, concentric surfaces (CSs) around the pith (Fig. 2) were created with the aid of NIH image software[9] using algorithms described by Grundberg and Grönlund.[10] The number of lines and columns of a CS image correspond to one pixel per degree in the horizontal direction (360 columns) and one pixel per 10mm along the log in the vertical direction (a 5-m long log has 500 lines). Altogether, 10 CSs on different radii from the pith were reconstructed. The five innermost CS images were formed in the heartwood (low moisture content = low green density), and CSs 6–10 were reconstructed within the sapwood (high moisture content = high green density). A high-density streak pattern can be observed in the CS images (Fig. 2). The angle of this pattern in relation to the longitudinal axis was defined as the spiral grain angle in the CS images. For each log the angle was measured manually in CS images 1, 3, 5, 7, and 9 using the NIH image software. Four measurements were made for each CS image, and their mean value was calculated. The following expression was used for the conversion:

$$\phi_{\log} = \mathrm{Arctan}\left[\left(\pi * D * \tan\phi\right)/360\right] \quad (1)$$

where: $\phi_{\log}$ is the spiral grain angle in the log; ϕ is the spiral grain angle in the CS image; and D is the diameter of the CS in pixels.

The relation between the spiral grain and distance to the pith was calculated for each log using linear regression. Finally, this relation was used to calculate the spiral grain at a distance of 50mm from the pith for each log.

The CT images (Fig. 4) for each log were then used to measure several variables such as external shape, knot volume, pith position, and percentage of heartwood and sapwood. These measurements were possible owing to the high correlation between X-ray attenuation and density for wood.[11] Mean values and changes in the longitudinal direction of the log were measured for all variables. Measurements of the average annual ring width were included in the analysis, resulting in a total number of 79 x-variables. The annual ring width was measured with the aid of a CCD camera on a disk cut from the top end of the logs. The aim when choosing these variables was to find variables that correlate with the grain and that should be possible to measure with an industrial X-ray LogScanner.

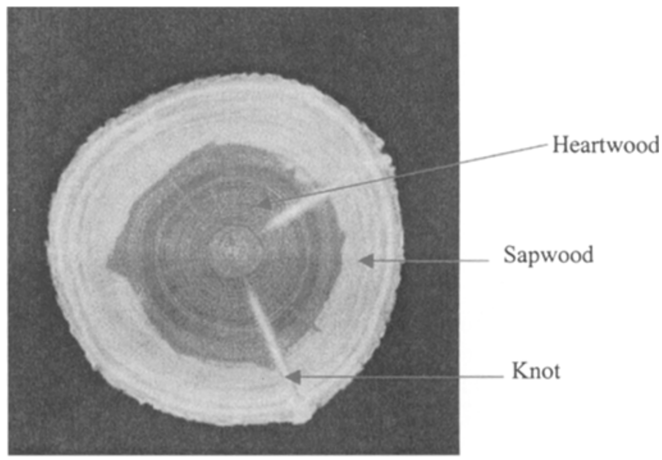

Fig. 4. CT image of a green Norway spruce log

Multivariate models that predict the spiral grain were then calibrated using partial least squares (PLS) regression and the software program SIMCA 8.0 from Umetrics.[12] The reasons for using PLS were that it handles data matrices with more variables than observations very well, and it handles data that are noisy and highly collinear. Of the 49 logs, 10 were chosen as a test set (to be used for validation) and were omitted from the calibration. The logs in the test set were chosen randomly with a controlled, equal distribu-

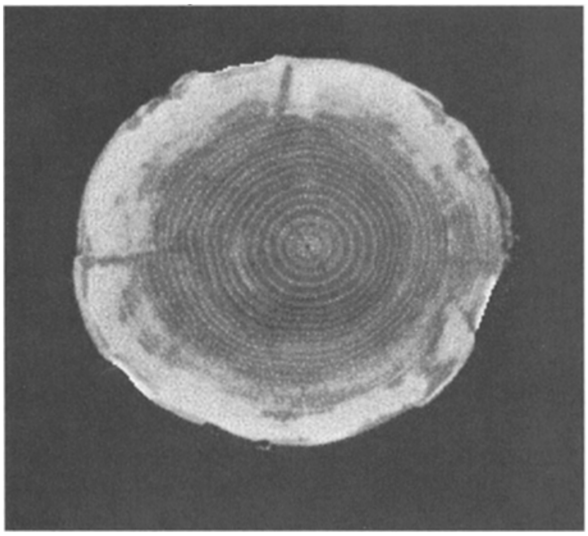

Fig. 5. CT image with a diffuse border between heartwood and sapwood

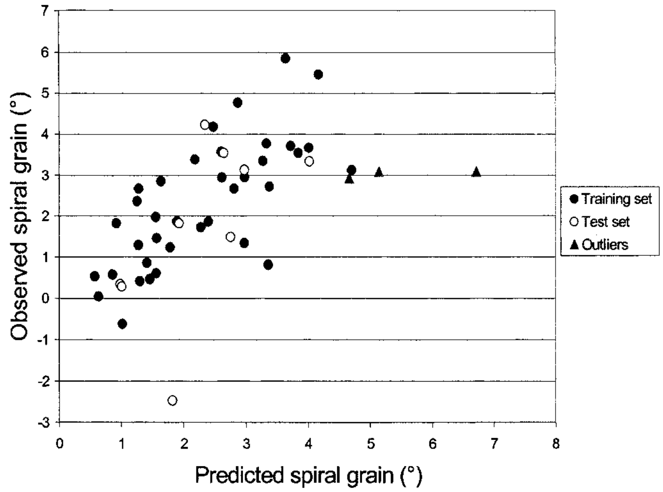

Fig. 6. Predicted (based on CT scanning of the logs) and observed average spiral grain for each log. All logs in both training and test set. The three outliers were excluded when calculating R^2 and RMSE

tion as regards sample plot and tree size. A preliminary analysis showed that of the remaining 39 logs 3 behaved differently. A possible explanation is that it was difficult to define the border between heartwood and sapwood for these logs, perhaps due to the fact that these logs had dried out locally to some extent (Fig. 5). Because of this, these three logs were omitted when calibrating the models, leaving 36 observations to be used for calibration (training set).

When calibrating the final model, the number of variables was reduced based on jackknifing[13–15] and on the magnitude of the linear coefficients. The uncertainty standard deviation Se_{jack} of regression coefficient B was estimated by jackknifing. Then, for each x-variable, the regression coefficient from the original PLS model (B0, calibrated using all 36 observations in the test set, was divided by the coefficient standard deviation (Se_{jack}). The final model was based on x-variables with a large $B0/Se_{jack}$ ratio, a large absolute value for the regression coefficient B0, or both.

Results

Spiral grain was measured at a distance of 50mm from the pith for all 49 logs. The spiral grain varied between 5.9° and −2.5° (average 2.3°). Positive values refer to a direction of left to right (Fig. 1). A statistical model that predicts the spiral grain of logs based on variables that should be possible to measure with an industrial X-ray LogScanner was calibrated using PLS regression. The final model for predicting spiral grain was based on 26 x-variables with a $B0/Se_{jack}$ ratio of >2.0, a scaled and centered coefficient with an absolute value of >0.03, or both. The PLS model was calibrated using 36 logs (training set) and validated on 10 logs (test set). The result when predicting the spiral grain was $R^2 = 0.52$ (RMSE = 1.0°) for the training set and $R^2 = 0.37$ (RMSE = 1.7°) for the test set (Fig. 6). These figures were calculated after excluding the three outliers of the type described in Fig. 5. The most important variables were measures of sapwood content, the standard deviation of the variation between the area of heartwood and the log, and the standard deviation for the mean log density in 10mm thick cross slices along the log (Fig. 7).

The prediction of spiral grain was then used to simulate sorting of logs into two groups with spiral grain ≥2.0° and <2.0°, respectively. The result was 84% correctly sorted logs (Table 2). This means that it is possible to sort out the 43% of the logs with a predicted spiral grain of <2.0°. Among these logs, 85% have an observed spiral grain of <2.0° compared with 47% of the total number of logs in the study.

Discussion

The results indicate that it should be possible to predict the spiral grain of a log based on variables measured by an industrial X-ray LogScanner. The calibrated PLS model is not strong in terms of the value of R^2. ($R^2 = 0.52$ for the training set and $R^2 = 0.37$ for the test set) but can be used to sort logs into two groups ("good" and "bad" logs) with high accuracy (84% correctly sorted logs). The relatively large difference in R^2 between the test set and the training set can be explained by the fact that the test set includes one log with a large negative value, something that is not represented in the training set. When this log is excluded from the test set, the result for the remaining nine logs ($R^2 = 0.54$ and RMSE = 1.0°) is comparable to the result for the training set ($R^2 = 0.52$ and RMSE = 1.0°).

Although the study was based only on 49 logs, the results are promising and motivate future studies on the subject. Such studied should, first, be based on a larger amount of

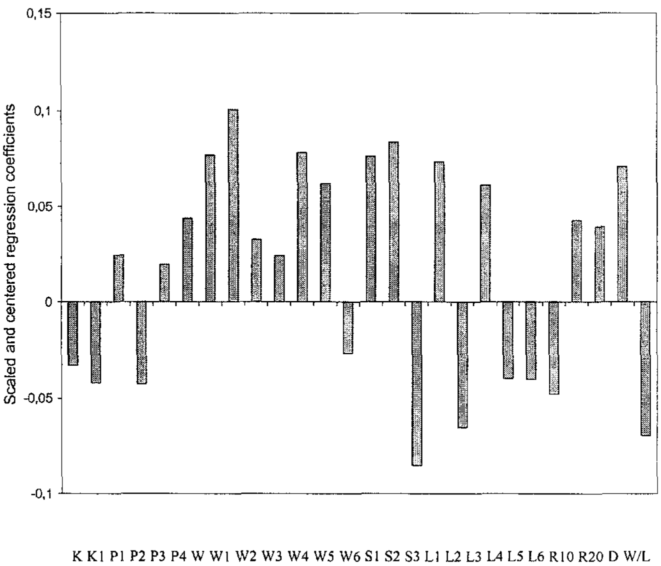

Fig. 7. Scaled and centered regression coefficients for the 26 most important variables on which the PLS model is based. *K*, total number of knots per log; *K1*, total knot diameter; *P1*, standard deviation (SD) of the distance from pith to origin of coordinates (OC) in the *x*-direction; *P2*, mean distance from pith to pith regression line in y-direction; *P3*, SD of the distance between pith and OC in the y-direction; *P4*, mean distance between pith and OC in the *x*-direction; *W*, SD for heartwood density; *W1*, mean heartwood density; *W2*, SD for the length of heartwood major axis; *W3*, SD for the difference between regression line and individual heartwood major axis size; *W4*, SD for the difference between regression line and individual heartwood minor axis size; *W5*, SD for the difference between regression line and individual heartwood minor axis size; *W6*, slope of the regression line for heartwood minor axis size; *S1*, SD for sapwood area; *S2*, SD for the difference between regression line and individual sapwood area; *S3*, slope of the regression line for sapwood area; *L1*, SD for the difference between regression line and individual log area; *L2*, SD for log density; *L3*, SD for the difference between regression line and individual log major axis size; *L4*, SD for the difference between regression line and individual log minor axis size; *L5*, slope of the regression line for log area; *L6*, slop of the regression line for log major axis size; *R10*, mean distance from pith to the 10th annual ring; *R20*, mean distance from pith to the 20th annual ring; *D*, SD for the difference between regression line and individual log diameter; *W/L*, SD for ratio between heartwood area and log area

Table 2. Results for simulated sorting of the logs into two groups with spiral grain ≥2.0° and <2.0°

Observed spiral grain	Predicted spiral grain	
	≥2.0°	<2.0°
≥2.0°	23	3
<2.0°	5	18
Total no. of logs	28	21

Results are based on all 49 logs, including the outliers

material. They should also be based on X-ray LogScanner measurements of the variables that were found important in this study. When calibrating the model for prediction of spiral grain, three logs for which it was difficult to define the border between heartwood and sapwood were omitted. Consequently, future studies also should concentrate on finding variables that are less affected by such difficulties.

Conclusions

The study indicated that it should be possible to predict the spiral grain of a log based on variables measured by an industrial X-ray LogScanner. The most important variables for predicting spiral grain were measurements of variables in sapwood content, variation in the ratio between the heartwood and log areas, and the standard deviation for the mean log density in 10mm thick cross slices along the log. The accuracy of sorting the logs into two groups with spiral grain ≥2.0° and <2.0°, respectively, was 84% correctly sorted logs.

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