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Identification of selected internal wood characteristics in computed tomography images of black spruce: a comparison study

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Abstract The feasibility of identifying internal wood characteristics in computed tomography (CT) images of black spruce was investigated using two promising classifiers: the maximum likelihood classifier (MLC) and the back propagation (BP) artificial neural network (ANN) classifier. Nine image features including one spectral feature (gray level values), a distance feature, and seven textural features were employed to develop the classifiers. The selected internal wood characteristics to be identified included heartwood, sapwood, bark, and knots. Twenty cross-sectional CT images of a black spruce log were randomly selected to develop the two classifiers. The results suggest that both classifiers produced high classification accuracy. Compared with the MLC classifier (80.9% overall accuracy), the BP ANN classifier had better classification performance (97.6% overall accuracy). Moreover, statistical analysis reveals that the heartwood of the black spruce log used in this study is the easiest to identify by either classifier compared with the other three log features. The results also suggest that the separability of one wood characteristic from the other wood characteristics in black spruce CT images is mainly related to moisture content.

Key words Artificial neural network (ANN) · Black spruce · Computed tomography (CT) images · Internal wood features · Maximum likelihood classifier (MLC)

Introduction

A crucial part of lumber manufacturing is the initial log breakdown. The sawyer needs to select feasible log break-down strategies to preserve large areas of clear wood on board faces. Different sawing methods may greatly affect the lumber economic value.[1,2] However, for decades the decision in the initial log breakdown has been mainly based on external log geometry and appearance in practice.[3,4] This type of sawing method does not usually lead to maximum value for the products because the sawyer uses only the external log information and past experience in sawing logs. The internal log information, such as sizes of defects, also determines the value of the products.[5] The key is to acquire internal log information nondestructively so that an optimum log conversion process can be determined with the objective of maximizing the values of the wood products.

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Several nondestructive evaluation (NDE) technologies have been investigated to extract internal log information. They include thermal imaging and microwave imaging, nuclear magnetic resonance (NMR) and ultrasound imaging, and also computed tomography (CT) scanning based on X-rays.[6–10] Among these NDE technologies, CT scanning is promising. This is mainly because the high energy associated with X-rays provides CT scanning with the ability to penetrate through inspected logs easily.[11] The produced log cross-sectional CT image is composed of pixels. Each pixel has a brightness measured in terms of gray level (GL) values converted from CT numbers, which are proportional to attenuation coefficients of X-rays as they pass through the corresponding wood zone. Lindgren[12] investigated the relationships between moisture content (MC), oven-dry wood density, and X-ray attenuation coefficient for pine. According to his study, X-ray attenuation coefficient (CT numbers or GL values) is proportional to moisture content and oven-dry wood density. Besides detecting wood defects, the information acquired from CT images has also been used to estimate the volume of resin pockets and to determine moisture flux and diffusion coefficients in wood drying.[13,14]

Various image classification methods have been investigated to develop reliable approaches to detect internal wood characteristics using log CT images.[3,15] Among them, back propagation (BP) artificial neural networks (ANN) and maximum likelihood classifier (MLC) are promising methods because they appear to have good classification performance. Schmoldt et al.[16] and Nordmark [17] applied the BP ANN classifier to detect knots and clear wood in oak and Scots pine logs. A 96% overall classification accuracy was achieved.[16,17] Rojas et al.[18] employed the MLC classifier to identify sapwood, heartwood, and knots in sugar maple logs and an overall accuracy of 80% was achieved. Although some progress has been achieved using these two methods for detecting log features, they have not yet been fully investigated. With respect to BP ANN, the steepest gradient descent with momentum algorithm is widely used as the training algorithm of BP ANNs for identifying wood characteristics, but this algorithm is time consuming. A faster-converging BP training algorithm: the resilient BP training algorithm, has not yet been used in BP ANNs for detecting log features.[19] For MLC, it has not been applied to other wood species except sugar maple. Meanwhile, the input image features for both methods are limited to gray level (GL) values and distance information.

In this study, both BP ANN and MLC classifiers were applied to identify internal wood characteristics in black spruce. The resilient BP training algorithm was used as the training algorithm for the BP ANN classifier. Image information used as input for both classifiers included not only the GL values and the distance, but the textural features. The classification performance of the two types of classifiers in detecting internal wood characteristics in the same black spruce log was also compared.

Materials and methods

Both MLC and ANN classifiers were applied to detect selected internal wood characteristics in a black spruce (*Picea mariana*) log. The selected wood characteristics included heartwood, sapwood, bark, and knots. The black spruce tree was collected from Thunder Bay, Ontario, Canada. The tree was 48 years old with a diameter at breast height (DBH) of 17.1 cm and tree height of 16.8 m. The butt log from the tree was collected for this study. The log was scanned by a Siemens Somatom Plus 4 Volume Zoom CT scanner. The scanning conditions were those recommended by Hou et al.:[20] 140 kV and 178 mA; slice plane (each corresponds to a CT image and represents each scanned log cross section) 5–10 mm in thickness; and room temperature (ca. 20°C). Twenty CT images of the black spruce log cross sections were randomly selected to develop the MLC classifier and the BP ANN classifier. Comparison of the classification performance of the two different classifiers was then considered reliable because both classifiers were established using the same 20 images. Each CT image had an 8-bit radiometric resolution and a size of 512 columns × 512 lines.

Removal of image background and selection of input image features

Each raw CT image has a background that represents the air surrounding the log. The background was removed by means of two thresholds. One is the GL value of 45, and the second threshold is a Euclidean distance between a pixel of interest and the pith of the log cross section of 150. This second threshold avoids flagging heartwood pixels (for which most of the GL values were less than 45) as background. Any pixels in the black spruce CT images having a GL value of less than 45 and a Euclidean distance greater than 150 were removed.

The image features extracted from the CT images that are used as inputs for the classifiers play an important role in the classification accuracy.[21] Therefore, it is important to select feasible image features, which can produce higher separability between the selected wood characteristics, as the input for the two classifiers before developing the classifiers. Following the previous study,[22] nine image features were used as the input for the two classifiers. They included one spectral feature: gray level (GL) values; the Euclidean distance between a pixel of interest and the pith of the log cross section; and seven textural features: homogeneity, contrast, dissimilarity, mean, standard deviation, entropy, and angular second moment. Refer to Wei at al.[22] for more details about calculation of the textural features.

Development of the MLC classifier and the BP ANN classifier

Maximum likelihood classifier

Maximum likelihood classifier (MLC), also called optimum statistical classifier, is based on Bayes probability theory.[23] The algorithm of MLC is briefly given as follows: for instance, there are two different wood characteristics, that is, two classes i and j to be identified. A pixel of interest with image feature vector $\boldsymbol{X}$ is classified as one of these two classes. The image feature vector $\boldsymbol{X}$ contains nine components and each component corresponds to one value of the selected image features. The pixel is classified to class i if the conditional probability to observe class i from pixels with image feature vector $\boldsymbol{X}$ is greater than the probability to observe class j from pixels with the same image feature vector. The corresponding decision rule is given as follows:[23]

$$\text{Pixels (with image feature vector } \boldsymbol{X}) \in i \quad \text{if} \quad P(i/\boldsymbol{X}) > P(j/\boldsymbol{X}), \quad \forall \quad j \neq i \tag{1}$$

The decision rule is modified as follows according to the Bayes probability theory:

$$\text{Pixels (with image feature vector } \boldsymbol{X}) \in i \quad \text{if} \quad g_i(\boldsymbol{X}) > g_j(\boldsymbol{X}), \quad \forall \quad j \neq i \tag{2}$$

where $g_i(\boldsymbol{X})$ is the discriminant function for class i and computed as in Eq. 3:

$$g_i(\boldsymbol{X}) = \ln(P(i)) - \frac{1}{2}\times(\boldsymbol{X}-\boldsymbol{M}_i)^{\mathrm{T}}\times\Sigma_i^{-1}\times(\boldsymbol{X}-\boldsymbol{M}_i) - \frac{1}{2}\times\ln(|\Sigma_i|) - \frac{k}{2}\times\ln(2\pi) \tag{3}$$

where $\boldsymbol{X}$ is the image feature vector of the pixel of interest; $\boldsymbol{M}_i$ is the mean image feature vector for class i; Σ_i is the covariance matrix for class i; $|\Sigma_i|$ is the determinant of the matrix Σ_i; Σ_i^{-1} is the inverse of the matrix Σ_i; $(\boldsymbol{X} - \boldsymbol{M}_i)^{\mathrm{T}}$ is the transposed matrix $(\boldsymbol{X} - \boldsymbol{M}_i)$; and k is equal to nine in this study corresponding to the nine selected image features. Four discriminant functions (each corresponds to one selected wood characteristic, Eq. 3) were then established to develop the MLC classifier mainly using the corresponding image feature vectors. These image feature vectors were derived from sample areas in the 20 CT images selected from the log. The sample areas were manually selected using the PCI Geomatica software (PCI Geomatics).

Artificial neural network classifier

The artificial neural network (ANN) is a computer model that was originally developed to model the way in which human brains perform particular tasks and is now applied widely for pattern matching and other image analysis work. Among all the ANN types, back-propagation (BP) ANN is commonly used because it is effective for pattern-matching problems and is easy to implement.[16]

A BP ANN classifier generally consists of one input layer, one or more hidden layers, and one output layer. Each layer contains a given number of nodes, which are the fundamental processing elements of the BP ANN classifier. The number of layers and nodes in each layer define the classifier's topology. The development of the BP ANN classifier includes three major steps: defining the training data set that will be employed to train the classifier; selecting the classifier's topology; and training the classifiers, that is, let the classifier "learn" information from the known image feature vectors of various classes. In this study, the BP ANN classifier was developed using Matlab software. The same 20 images employed to develop the MLC classifier were also used to develop the BP ANN classifier.

Defining the training dataset. The training data consisted of a set of 8000 vectors. Indeed, for each of the 20 images, a randomly selected sample was created with 100 vectors for each of the four wood characteristics. Each vector consisted of nine components corresponding to the values of selected input image features of a pixel belonging to the sample.

Classifier's topology selection. The topology has a significant influence on the convergence speed and also on the classification accuracy. In this study, the network topology consists of one input layer, with nine input nodes corresponding to the nine input features; and one output layer, with four output nodes corresponding to the four wood characteristics to be identified. With respect to the number of hidden layers, according to Mas and Flores,[24] one hidden layer with an appropriate number of hidden nodes can produce good classification. Log-sigmoid function was chosen as the transfer function because it is a monotonic differentiable function and easy to use. Based on the previous study of Wei et al.,[25] the hidden node number was chosen as 25 for the BP ANN classifier.

Training. The steepest gradient descent with momentum algorithm is widely used as the training algorithm of BP ANNs for detecting wood characteristics. However, in practice this weight-updating procedure is slow and may fail to converge. Riedmiller and Braun[19] show that for the same BP ANN classifier, the resilient BP training algorithm only took 25 iterations to make the classifier converge (meet the target minimum error) compared with 120 iterations achieved by the steepest gradient descent with the momentum algorithm. The resilient BP training algorithm was then selected as the training method[19] in this study. After training, the BP ANN classifier is ready to be used for classification. For each pixel of interest, the nine input feature values of the pixel were input into the BP ANN classifier to compute the outputs (four outputs in total at a time). The pixel was classified into the class for which the corresponding output node produced the maximum output.

There were occasionally isolated pixels remaining in the image after classification using the two classifiers. A 5×5 pixel median filter was then used to remove these pixels and defragment the classified image.

Classification accuracy analysis

The calculation of classification accuracy requires comparison of two types of images: that of the classified image with the corresponding reference image through a confusion matrix. In this study, areas of each selected wood characteristic in the CT images were also manually labeled and delineated with PCI Geomatica software. They produced the reference images for the corresponding classified images and contained the information of the true class belonging to each pixel. A more accurate way to produce the reference images would be to cut the corresponding disks from the previously CT-scanned log, manually delineate each wood characteristic on the disks, and take digital photos of the discs.[17] These digital photos of cross sections of the log can then serve as the reference images for the corresponding classified CT images. Two types of classification accuracy were computed based on the confusion matrix:[26]

1. Producer's class accuracy. For one class i, the producer's class accuracy is defined as the number of pixels labeled as class i in both the reference image and the classified image divided by the total number of pixels of class i in the reference image. It assesses the classification accuracy for each individual class. Hereafter, it is called "class accuracy."
2. Producer's overall accuracy. The producer's overall accuracy is defined as the number of correctly classified pixels divided by the total number of pixels classified. It is an average classification accuracy for all the classes together. Hereafter, it is called "overall accuracy."

The accuracy analysis was mainly undertaken to compare the classification performance of the two classifiers and also to assess which wood characteristics are easily separated from the others. Classification accuracy was estimated using the fivefold cross-validation method[27] given as follows: for the maximum likelihood method, the 20 sampled CT images were divided into 5 groups of 4 images each. At each stage of the fivefold cross-validation process, one of the 5 groups was reserved for testing the developed MLC classifier (testing group). The classifier was developed using the remaining 4 groups and the developed MLC classifier was employed to identify the wood characteristics on the testing group. Class accuracy and overall accuracy were then computed. This process was repeated five times. Therefore, five estimates of the overall accuracy and five estimates of the class accuracy of each wood characteristic were obtained. For the artificial neural network method, the same process was also applied. The accuracy estimates were then used as samples in the following statistical analyses.

The mean overall accuracies of the two classifiers were compared to assess which one had the better overall classification performance. The class accuracy of a wood characteristic indicates, to some extent, whether the characteristic can be easily separated from others. A one-way analysis of variance (ANOVA) with Tukey's test[28] was conducted to examine this issue for each classifier. ANOVA was performed first to determine if there were statistical differences among all class accuracies in the log. A P value of less than 0.05 (α-level) indicated significant difference. ANOVA used the 20 estimates of class accuracy (5 estimates for each wood characteristic) as the statistical samples. If the P value was less than 0.05, Tukey's test was then applied to determine which wood characteristics could be separated easily from the others by comparing class accuracies between each pair of wood characteristics. This test generated several sets of multiple comparison confidence intervals, which represent ranges of values, derived from sample statistics that are likely to contain the value of an unknown population parameter. There is no statistical difference between the class accuracies for each pair of the wood characteristics if the confidence interval for the subtraction between the class accuracies of the two wood characteristics includes zero. The statistical analyses were performed using Minitab software (version 15, Minitab, State College, PA, USA).

Results and discussion

An example of classified CT images is given in Fig. 1b for the MLC classifier, and Fig. 2b for the BP ANN classifier. Both classified images were then filtered by a 5×5 pixel median filter (Figs. 1c, 2c). The classification accuracies of the two classifiers acquired through the fivefold cross validation are listed in Table 1 (each stage of the fivefold cross validation corresponds to one group). For the MLC classifier, the overall accuracy was 80.9%. The class accuracy for heartwood was 87.5%, which was higher than those for sapwood (73.0%), bark (81.6%), and knots (78.3%). For the BP ANN classifier, a higher overall accuracy of 97.6% was achieved. The class accuracy for heartwood was 100%, which was greater than those for sapwood (98.1%), bark (96.8%), and knots (95.5%).

For each classification method, the corresponding P value of ANOVA was 0 indicating that there were signifi-

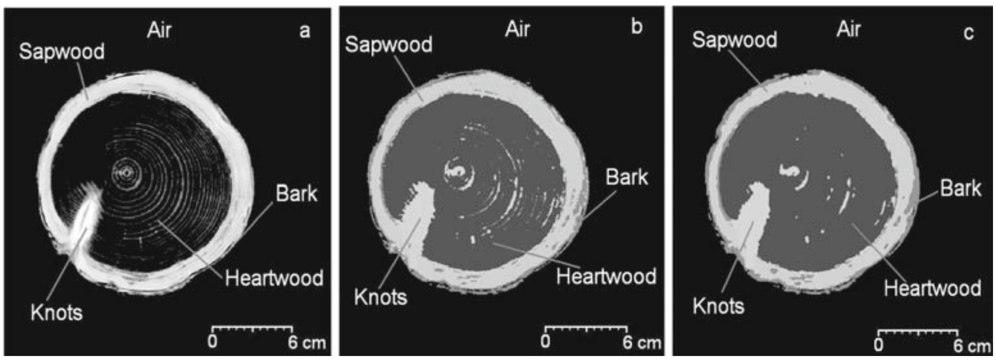

Fig. 1a–c. Examples of computed tomography (CT) cross section images for the black spruce log. **a** Raw CT image, **b** image classified by maximum likelihood classifier (MLC), and **c** classified image filtered using a 5×5 pixel median filter

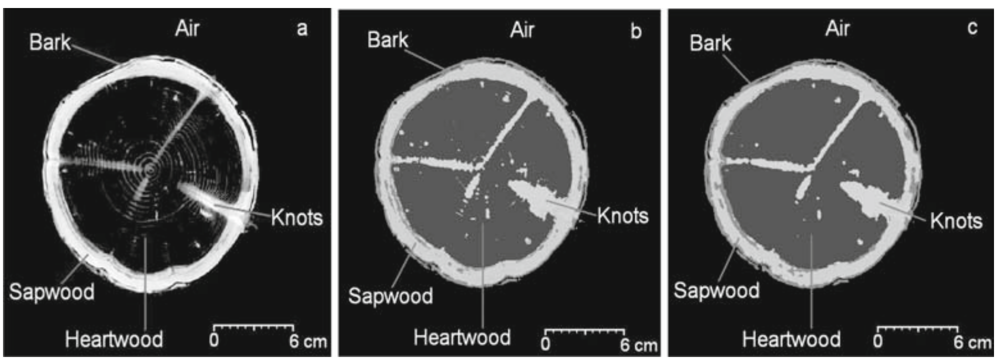

Fig. 2a–c. Examples of CT cross section images for the black spruce log. **a** Raw CT image, **b** image classified by the back propagation artificial neural network (BP ANN) classifier, and **c** classified image filtered using a 5×5 pixel median filter

Table 1. Classification accuracy achieved by the maximum likelihood classifier (MLC), and the back propagation (BP) artificial neural network (ANN) classifier in identifying the four wood characteristics in the 20 sampled CT images of the black spruce log

Classifier	Group no.	Overall accuracy (%)	Class accuracy			
			Heartwood (%)	Sapwood (%)	Bark (%)	Knots (%)
MLC	1	78.0	85.3	70.4	81.0	73.6
	2	82.0	86.9	78.8	81.0	78.6
	3	84.0	91.2	73.8	85.1	82.1
	4	78.5	88.8	63.4	81.0	79.2
	5	81.8	85.5	78.5	80.0	77.8
	Average	80.9	87.5	73.0	81.6	78.3
BP ANN	1	97.6	100	96.6	97.1	96.3
	2	97.3	100	98.3	97.4	93.6
	3	97.7	100	98.3	95.3	97.0
	4	98.0	100	99.5	97.1	95.6
	5	97.4	100	98.0	97.0	94.9
	Average	97.6	100	98.1	96.8	95.5

Table 2. Confidence interval of the subtraction between class accuracy values of each wood characteristics pair as estimated by Tukey's test

	MLC classifier				BP ANN classifier			
	Heartwood	Sapwood	Bark	Knots	Heartwood	Sapwood	Bark	Knots
Heartwood	–				–			
Sapwood	(0.075, 0.216)	–			(0.167, 3.554)	–		
Bark	(–0.130, 0.011)	(0.016, 0.157)	–		(–4.913, –1.527)	(–3.054, 0.334)	–	
Knots	(–0.163, –0.022)	(–0.018, 0.123)	(–0.104, 0.037)	–	(–6.214, –2.8265)	(–4.354, –0.967)	(–2.994, 0.394)	–

cant differences among the class accuracy values. For both classifiers, Tukey's test results show that the difference between the class accuracy values of most pairs of the wood characteristics was statistically significant because the corresponding confidence intervals excluded zero. There were exceptions for the sapwood–knot and bark–knot pairs; the heartwood–bark pair was also included for the classification performed by the MLC classifier (Table 2). The heartwood class accuracy, which was produced by either classifier, was the greatest (Table 1). All these results suggest that the heartwood of the black spruce log tested in this study is the easiest to identify compared with the other three wood characteristics.

The easy separation of heartwood in black spruce may be mainly due to the moisture content (MC) influence. According to previous studies,[11,12,29] X-ray attenuation coefficients (corresponding to GL values in gray scale images) of a wood characteristic is proportional to its moisture content and wood density. In general the wood density continuously increases from pith to bark in black spruce.[30,31] However, the difference in density between heartwood and sapwood is usually small. On the other hand, the heartwood in black spruce generally has a much lower MC than the sapwood. For green wood, the average MC of heartwood and sapwood is estimated to be about 52% and 113%, respectively.[32] Low MC values correspond to low GL values. Therefore, heartwood pixels in black spruce CT images generally have much lower GL values than sapwood pixels. The CT image contrast between sapwood and heartwood in black spruce is then mainly influenced by the moisture content, which makes the heartwood easily separable from sapwood. This also indicates that for black spruce it would be better to scan logs as soon as they are felled. This is because the difference in MC between sapwood and heartwood in green wood of black spruce is huge, which means it is easy to distinguish these two wood characteristics. Some parts of the bark and sapwood had higher GL values, similar to knots. It was also noted that variation in GL and textural values of bark and sapwood regions is high. This may be also related to the MC influence. When a knot is close to these parts of the bark or the sapwood, it becomes difficult to identify because its GL values and Euclidean distances are generally similar to the corresponding values for bark and sapwood. Incorrect classification may therefore occur mainly among bark, sapwood, and knots.

For the tested black spruce log, both classifiers produced the highest class accuracy in the heartwood of the log. The BP ANN classifier produced a higher overall accuracy (mean value of 97.6%) than the MLC classifier (80.9%). This suggests that the BP ANN classifier developed in this study provides a better classification performance than the MLC classifier. One possible reason is that the maximum likelihood approach assumes normality in the image feature data, while the BP ANN approach does not require any assumption regarding statistical distribution. Each discriminate function of the MLC classifier is generated from a normal distribution. However, in practice, image feature data deviates from the normality assumption to some extent. Compared with the MLC classifier, the ANN classifier does not require any assumptions regarding the underlying probability density function or other probabilistic information for the classes under consideration.

Conclusions

This study investigated the feasibility of identifying internal wood characteristics in black spruce CT images using two classifiers: the maximum likelihood classifier (MLC), and the back propagation (BP) artificial neural network (ANN) classifier. Nine image features including one spectral feature (GL values), a distance feature, and seven textural features were used as the inputs for both classifiers. The results suggest that the BP ANN classifier appears to have better classification performance than the MLC classifier. This conclusion was reached after experiments on a single black spruce log. Because wood is an anisotropic material, variations in density and moisture content within a single log could be distinct. Therefore, this conclusion should be tested in a more rigorous manner in future work by using a larger number of black spruce logs.

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