GRAIN PATTERN CHARACTERIZATION AND CLASSIFICATION OF WALNUT BY IMAGE PROCESSING

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ABSTRACT

Grain pattern is an important characteristic of wood materials and it is usually assessed visually by trained workers. This paper presents results from a study to characterize walnut grain patterns by using image processing techniques. Grain streaks of the annual growth rings were segmented and labeled in walnut surface images. Grain pattern features were computed for each streak. The *average elongation* and *average local contrast* were used to classify 48 walnut samples into three visual grades. Three types of classification techniques were tested: linear discriminant analysis, quadratic discriminant analysis, and neural network classification. A hold-one-out procedure yielded correct classification rates of 71.4%, 61.9%, and 69.0%, respectively. The results establish the potential usefulness of image processing techniques in wood grain characterization and grading.

Keywords: Wood grain, image processing, mathematical morphology, discriminant analysis, classification.

INTRODUCTION

Wood grain is a natural phenomenon. In the Handbook of Wood and Wood-Based Materials, wood grain is defined as the direction, size, arrangement, and appearance of the fibers in wood or lumber (USDA Forest Products Laboratory 1987). In this paper, grain refers to the streak pattern of the annual growth rings on a cut wood surface. In many wood products such as furnishings, sporting goods and wood arts, grain is an important attribute. Traditional grain-based wood grading is carried out by human visual inspection. This process needs experienced people and the results are often inconsistent.

Image processing and pattern recognition techniques have been used in wood research in recent years. They are widely used in defect detection, which involves identification, classification, and location of defects such as knots, wane, and stain in wood (Conners et al. 1983; Koivo and Kim 1989; Lebow et al. 1996; Quin et al. 1998; Schmoldt et al. 2000; Butler et al. 2002). Conners et al. (1983) pointed out that the main difficulty in defect image analysis was associated with the natural variation of wood and wood defects. Pham and Alcock (1998) provided a review of automatic wood inspection. Brunner et al. (1990) detailed the use of color in machine vision systems for wood processing. Other applications include hardwood lumber grading (Klinkhachorn et al. 1988); displacement analysis in multiple-bolted wood connections by image correlation (Stelmokas et al. 1997); automatic measurements of radial and tangential lumen diameter in confocal reflected-light microscopic images (Moëll and Borgefors 2001); and water content visualization by magnetic resonance imaging (MacMillan et al. 2002).

The terms texture and grain are often used interchangeably. According to the Handbook of Wood and Wood-Based Materials, texture is used to refer to the fine structure of wood rather than the annual rings (USDA Forest Products Laboratory 1987). Different textures are observed in clear wood and defects (Conners et al. 1983; Pham and Alcock 1998) and in different wood species (Liu and Furuno 2001). By using both tonal measures of gray level moments and texture measures based on co-occurrence matrices, an overall 88.3% correct classification rate on eight types of defects was achieved by Conners et al. (1983). Other texture measures, such as Fourier power spectrum and run-length statistics, were also used in defect detection and a summary was given in Pham and Alcock (1998). Liu and Furuno (2001) characterized textures of the surface of fifteen wood species with a fractal dimension and its distribution pattern. The results showed that a fractal dimension of 2.5 separated a hardwood group from a softwood group. It was unclear, however, whether wood species in the same group (hardwood or softwood) could be identified by this method. Texture measures were computed in subdivisions of an image, and the average value over all subdivisions was used in discrimination or classification (Conners et al. 1983; Pham and Alcock 1998; Liu and Furuno 2001).

No reported work was found on wood grain characterization by image processing, where grain specifically refers to the streak pattern of the annual growth rings. The purpose of this work was to characterize some features of wood grain structures by image processing techniques and to evaluate how such automated quantification agreed with human grading. Walnut grain streaks were segmented and labeled. Features that might characterize grain patterns were computed and evaluated for their effectiveness in discriminating samples of different visual grades. Three classifiers were tested for visual classification of walnut samples. The main challenge roots from the tremendous variability in wood materials.

WALNUT GRAIN IMAGE SEGMENTATION

Samples and image acquisition

Great complexity and tremendous variability exist in wood grain. A species of Persian walnut (*Juglans regia*) was chosen for this study. It was the most used wood by a local sporting equipment manufacturer. Experts graded each walnut sample (hardwood dimension lumber) by evaluating the "fanciness" of grain patterns on a dry, flat wood surface. Because of the highly subjective nature of visual grading, a grader may not be able to articulate the exact characteristics that define each grade. Generally speaking, complex and curved grain streaks are considered fancier than simple, straight grain streaks. This grading is different from the standard wood grading based on clear cutting sizes (USDA Forest Products Laboratory 1987). Three grades of "extra fancy" (EF), "fancy" (F), and "semi fancy" (SF) were used in the factory. Fourteen walnut samples from each grade were obtained and their surfaces were imaged with a digital color camera (Olympus D600) set at a resolution of 640 $\times$ 512 pixels and 256 levels of intensity under fluorescent lighting. The spatial resolution was 0.62 mm per pixel. While color was found valuable in distinguishing defects on wood surfaces (Brunner et al. 1990; Kline et al. 1998), walnut grain color was found to vary independently of the visual grades in this study. The color images were transformed into gray level ones. To exclude the background and stains of soil or oil in some wood images, an area of 320 $\times$ 256 pixels was selected from each image for analysis.

Walnut grain segmentation

To characterize the grain patterns, it was first necessary to isolate the grain streaks in an image—a process called image segmentation. Walnut grain segmentation was accomplished through several steps of processing as described below. These steps are standard operations routinely employed in image processing.

Median Filtering: A 3 $\times$ 3 median filter was employed to reduce digitization, lighting, and other noise effects without visually discernible

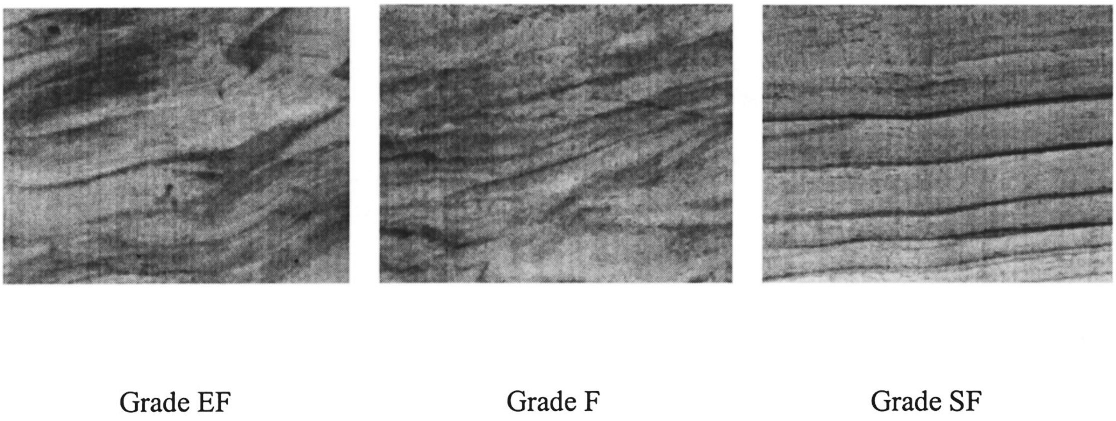


FIG. 1. Noise-reduced sample images.

blurring of the grain streaks. The main advantages of median filters are that they achieve noise reduction without blurring, and the edge sharpness is preserved (Gonzalez and Woods 1992). This step of preprocessing reduced the effects of noise and prepared the images for further analysis (Fig. 1).

Extraction of Streaks: A thresholding approach was found not suitable for segmenting the dark grain streaks from the background. This was because the histograms of all image functions (red, green, blue, and gray level) contained only one principal brightness region, and they cannot be partitioned by a thresholding operation. A morphological black top-hat transformation was used to extract the dark grain streaks. The transformation is defined as,

$$\text{Black top-hat transformation of } I = \mathrm{C}(I) - I \tag{1}$$

where I is the median-filtered image, and $\mathrm{C}(I)$ is the grayscale morphological closing of I with a structuring element (Meyer 1977; Gonzalez and Woods 1992). A structuring element is a set in the 2-D or 3-D integer space $\mathbf{Z}^2$ or $\mathbf{Z}^3$ (Sternberg 1986; Gonzalez and Woods 1992). In this paper, all structuring elements are square matrices with unity entries. The transformation in Eq. (1) can extract the dark objects (low gray values) that are smaller than the structuring element, which was experimentally chosen to be 100×100 with unity entries. This large size was used because there were large grain streaks in some images. The transformation made the streak background reasonably uniform and improved the contrast between the streaks and the background (Fig. 2). A simple thresholding operation was then applied to isolate the streaks into a binary image.

Streak Edge Noise Removal: A morphological binary opening operation (Haralick et al. 1987) with an experimentally chosen 3×3 structuring element of unity entries was applied to remove noises on streak edges in the binary images and to delete some false connections. The resulting binary images approximately represented the dominant grain streaks in the original images (Fig. 3).

Grain Streak Labeling: The segmented grain streaks were labeled by using a connected-component scanning algorithm, which assigns the same label to a set of connected pixels (Gonzalez and Woods 1992). The characteristics of each labeled component can then be computed. Each labeled component should ideally include one and only one streak, but some included two or more. This was because some streaks were not separable or could not be separated by the operations described above.

WALNUT GRAIN FEATURE EXTRACTION

As stated in Tou and Gonzalez (1974), feature extraction is one of the most difficult tasks in pattern recognition. A good discriminatory fea-

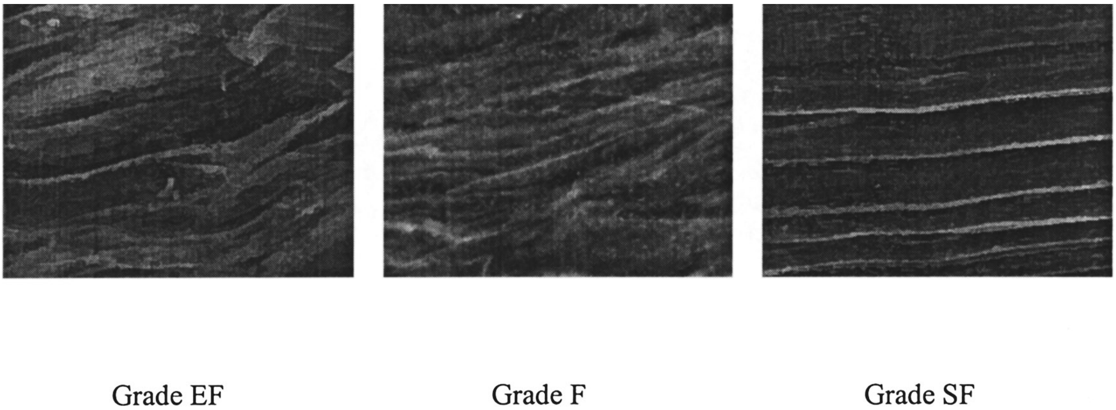


FIG. 2. Grain streaks extracted by the morphological black top-hat transformation.

ture should be consistent within one grade (class) but different between two grades (classes). Feature extraction was naturally the most important and difficult problem in this work for a number of reasons. First, there were tremendous variations in the grains of even the same wood species and grade. Each wood grain streak could be unique in one or more aspects (direction, size, arrangement, and appearance). This made it hard to find consistent discriminatory features. Secondly, often more than one type of grain was present in one sample, and thus it was difficult to characterize grain patterns as a whole. Finally, the segmentation procedure did not produce a streak image that exactly represented grain patterns in the original image.

To deal with these difficulties, many features were computed from the labeled streaks and tested by analysis of variance (ANOVA) (Johnson and Wichern 1998) for their usefulness in discriminating walnut samples of different grades. The following features were found to be ineffective: (1) The *total area of streaks* or the amount of streaks in an area was found not to depend on the grade. (2) The streak width varied significantly along a streak, especially those in the EF samples. The *average streak width* was therefore not a useful grade indicator. (3) The *global contrast* was the difference between the average gray level of all streak regions and that of non-streak regions. It was not related to grade, but it appeared to be influenced by lighting conditions and noise. (4) The

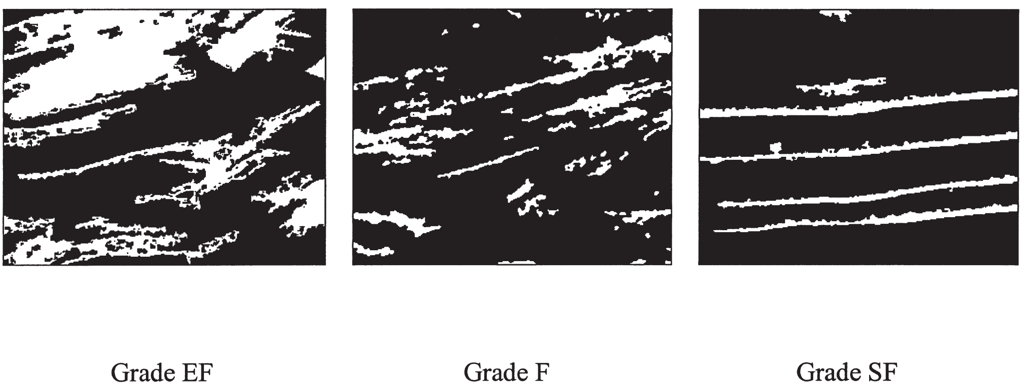


FIG. 3. Binary grain streak images after edge noise removal.

direction of major axis was the orientation of the best ellipse fit to a streak region. Since grain streaks of different shapes may have the same direction of major axis, this feature was not found useful. (5) The *skeleton or medial axis* is a good representation of simple and elongated objects, such as written or typed characters (Haralick and Shapiro 1992). The skeletons, however, failed to represent the streaks sufficiently because wood grain streaks are complex and irregular objects. Two features were found to display significant differences among the three grades ($P < 0.0001$) as described below.

Average elongation

Elongation is defined as the difference between the lengths of the major and minor axes of the best ellipse fit of a region divided by the sum of the axis lengths. Most grain streaks in the EF samples were wide, complex patterns, which would have smaller values of elongation. On the contrary, most grain streaks in the SF samples were narrow and straight line-like patterns, which would have large values of elongation. The *average elongation* E_{Ave} was calculated as,

$$E_{Ave} = \frac{\sum_{i=1}^{n} E_i P_i}{\sum_{i=1}^{n} P_i} \quad (2)$$

where E_i and P_i are, respectively, the elongation and the size of streak i in number of pixels, and n is the total number of labeled components or streaks in an image.

Average local contrast

The sharpness of streaks appeared to be another important property of wood grains. In an image, this sharpness is indicated by the local gray level contrast between a streak and its neighboring non-streak region. The greater the contrast, the sharper a streak appears. To compute the local contrast of a streak, morphological dilation and erosion operations (Gonzalez and Woods 1992) were employed to obtain an external neighborhood and an internal neighborhood of a labeled streak object as,

$$\begin{aligned} &\text{External neighborhood of } S = \mathrm{D}(S) - S \\ &\text{Internal neighborhood of } S = S - \mathrm{R}(S) \end{aligned} \quad (3)$$

where D stands for dilation, R stands for erosion, and S is a streak object. A 2×2 structuring element of unity entries was experimentally chosen for both D and R. The local contrast of a streak was computed as the difference between the mean gray level of its external neighborhood and that of its internal neighborhood in the median-filtered image. The *average local contrast* for all the streaks was computed as a feature for a sample.

The means and standard deviations of these two features are shown in Table 1 for the three grades. Comparisons of individual feature means by ANOVA and the mean feature vectors of the three grades by the multivariate analysis of variance (Johnson and Wichern 1998) showed that both features differed significantly among the three grades ($P < 0.0001$).

WALNUT SAMPLE CLASSIFICATION

Classifiers

Figure 4a shows a scatter plot of the *average elongation* and the *average local contrast* for all 42 walnut samples. It is obvious that there exists a clear linear boundary between grades EF and SF, but the samples of grade F overlap with those of grades EF and SF. Since the scale of the *average local contrast* (8.0–25.0) was much larger

TABLE 1. *Mean and standard deviation (SD) of average elongation and average local contrast.*

	Grade EF		Grade F		Grade SF	
	Mean	SD	Mean	SD	Mean	SD
Average elongation	0.712	0.080	0.749	0.207	0.947	0.049
Average local contrast	12.646	3.093	16.512	3.059	18.199	2.275

than that of the *average elongation* (0.3–1.0), each feature was linearly normalized by using its mean and standard deviation. The normalization transformed the two features into comparable scales without modifying the relative sample distribution. Three types of classifiers—linear discriminant analysis (Johnson and Wichern 1998), quadratic discriminant analysis (Johnson and Wichern 1998), and a multiple perceptron neural network (Haykin 1999)—were tested in classifying a sample represented by the two (normalized) feature values into one of the three grades. The latter two classifiers include, respectively, quadratic terms and complex nonlinear terms in their decision mechanisms.

Linear discriminant analysis: This classifier allocated a sample $\mathbf{x}$ (consisting of two features) to population k (k = 1, 2, 3) if the linear discriminant score $d_k(\mathbf{x})$ was the largest of $d_1(\mathbf{x})$, $d_2(\mathbf{x})$, and $d_3(\mathbf{x})$ with $d_i(\mathbf{x})$ given by:

$$d_i(\mathbf{x}) = \bar{\mathbf{x}}_i' \mathbf{S}_{\text{pooled}}^{-1} \mathbf{x} - \frac{1}{2} \bar{\mathbf{x}}_i' \mathbf{S}_{\text{pooled}}^{-1} \bar{\mathbf{x}}_i + \ln p_i, \quad i = 1,2,3. \tag{4}$$

where $\bar{\mathbf{x}}_i$ was the sample mean vector of population i,$\mathbf{S}_{pooled}$ was the pooled sample covariance matrix, and p_i was the prior probability of population i (Johnson and Wichern 1998). Each population consisted of 14 walnut samples in one grade with equal prior probability of 1/3.

Quadratic discriminant analysis: This classifier allocated a sample $\mathbf{x}$ to population k (k = 1, 2, 3) if the quadratic discriminant score $d_k(\mathbf{x})$ was the largest of $d_1(\mathbf{x})$, $d_2(\mathbf{x})$, and $d_3(\mathbf{x})$ with $d_i(\mathbf{x})$ given by:

$$d_i(\mathbf{x}) = -\frac{1}{2} \ln|\mathbf{S}_i| - \frac{1}{2}(\mathbf{x} - \bar{\mathbf{x}}_i)' \mathbf{S}_i^{-1} (\mathbf{x} - \bar{\mathbf{x}}_i) + \ln p_i, \quad i = 1,2,3. \tag{5}$$

where $\bar{\mathbf{x}}_i$ and p_i were the same as in Eq. (4), and $\mathbf{S}_i$ was the sample covariance matrix of population i (Johnson and Wichern 1998).

Neural networks can be useful classifiers as described by Castleman (1996). One possible advantage of the neural network approach is that it is capable of implementing complex partitioning. A three-layer perceptron model was experimentally constructed for classification. The input layer, hidden layer, and output layer consisted of two, eight, and two neurons, respectively. The inputs to the neural network were the two features. The output was the group membership or grade label. Grades EF, F, and SF were labeled with (0, 1), (0, 0), and (1, 0), respectively. The linear transfer function was used for the input and output layers, and the hyperbolic-tangent-sigmoid transfer function was chosen for the hidden layer (The MathWorks 1998). The model was trained with a backpropagation algorithm (Haykin 1999).

Because the sample size N was small (N=42), a hold-one-out procedure (Johnson and Wichern 1998) was used for validation of each classifier. In this procedure, one sample was withheld from the sample set, a classification function was developed based on the remaining N-1 samples, and the withheld sample was then classified by using the function constructed. This process was repeated for all samples. The correct classification rate was the rate at which the withheld samples were correctly classified.

Classification results

The results from the three classifiers with the hold-one-out procedure are given in Table 2. The correct classification rates for the linear discriminant analysis, quadratic discriminant analysis, and the neural network were 71.4%, 61.9%, and 69.0%, respectively. For all three classifiers, some samples from grade F were misclassified to grade EF or grade SF, or vice versa. No samples were misclassified from grade EF to grade SF, or from grade SF to grade EF. The correct classification rate for the neural network was slightly lower than that for the linear discriminant, but greater than that for the quadratic discriminant. This suggested that the classification did not benefit from quadratic or general nonlinear terms. The linear discriminant analysis should be used as advised by Castleman (1996). The linear boundaries generated by the linear discriminant analysis are shown in Fig. 4b.

TABLE 2. *Classification results by the hold-one-out procedure, sample size* N = *42.*

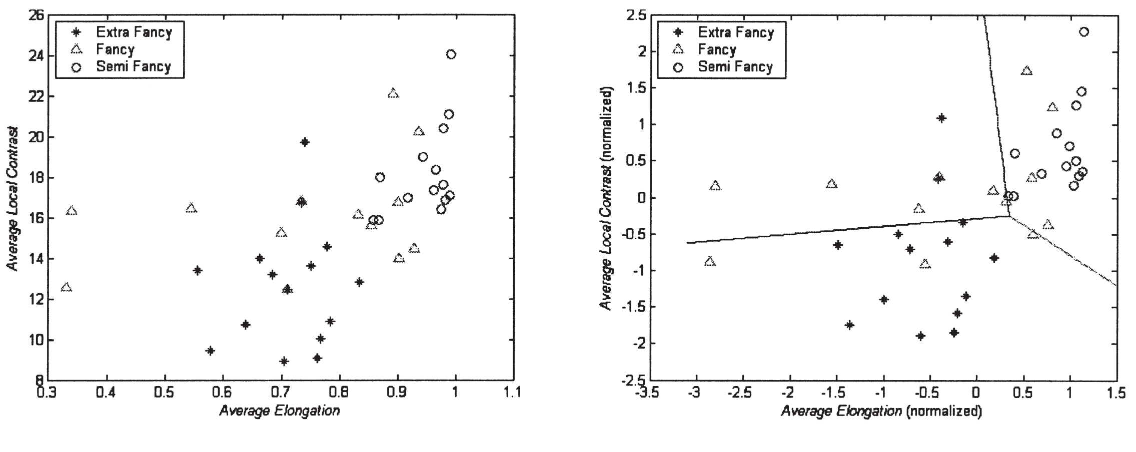
		Predicted grade								
		Linear			Quadratic			Neural network		
		EF	F	SF	EF	F	SF	EF	F	SF
Actual grade	EF	12	2	0	11	3	0	10	4	0
	F	3	5	6	3	4	7	3	8	3
	SF	0	1	13	0	3	11	0	3	11

DISCUSSION

A texture spectrum-based classification method proposed by Wang and He (1990) was tested on the walnut samples plus two oak and two maple samples. This preliminary experiment showed that this textural classification method was useful in distinguishing different species of wood, but failed to distinguish walnut samples of different grades. The shape and gray level features used in this study appeared more useful than the textural spectrum for characterizing walnut grains formed by the annual growth rings. The reason for this was probably because the grain streaks were not fine textures as discussed early in this paper. Other texture features, however, may be useful in characterizing and classifying wood grain patterns. A discussion on textural features for image classification is given by Haralick et al. (1973).

CONCLUSIONS

A segmentation algorithm was developed to extract walnut grain streaks. Two features, *average elongation* and *average local contrast,* were found useful in classifying walnut samples. A hold-one-out procedure yielded correct classification rates of 71.4%, 61.9%, and 69.0% for the linear discriminant analysis, quadratic discriminant analysis, and neural network classifier, respectively. Though the species and samples were limited, the results established the potential usefulness of image processing in wood grain characterization and classification. Further research is needed to find other useful features for charac-



(a) (b)

FIG. 4. Sample distribution and classification results: (a) scatter plot of samples; (b) linear boundaries generated by the linear discriminant analysis.

terizing such complex and variable objects as wood grain patterns.

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