THE FRACTAL EVALUATION OF WOOD TEXTURE BY THE TRIANGULAR PRISM SURFACE AREA METHOD

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(Received February 2000)

ABSTRACT

Textures of the surfaces of fifteen wood species were characterized by fractal dimension of the triangular prism surface area method. Fractal dimension ranged from 2 to 3, and sharp lightness variation caused high fractal dimension, whereas low values related to smooth variation. Based on this index, wood specimens were generally divided into a hardwood group with value greater than 2.50 and a softwood group with value less than 2.50. Six types of fractal dimension distribution were explored in our experiments, including plane, inclined plane, concave, convex, zigzag distribution, and hilly distribution. From these both the features of local textures and the general variation tendency of the whole surface could be illustrated. It was strongly proposed that fractal dimension should be adopted to quantitatively evaluate wood texture with coarseness and evenness, because such variation was related to the number of grains, surface orientation, and location. For wood color matching, fractal dimension is of great importance in ensuring texture matching to achieve a constructed surface texture close to the features of natural variation. These distribution patterns were considered as a good reference previous to matching. Little variation of fractal dimension along the grain was observed, and this could be used to simplify texture matching by a very limited number of the indices. No significant relationship was found between fractal dimension and lightness, further implying that fractal dimension was independent of lightness.

Keywords: Fractal dimension. lightness, texture, color matching.

INTRODUCTION

Grayscale scanning systems have been widely considered capable of efficiently improving product quality in the wood industry. For color matching of wood components, those systems that have the potential to reliably and efficiently characterize the surface of wood products are required. Understanding how to appropriately evaluate the information on wood lightness is both desirable and critical.

Lightness plays an important role in the appearance of most wood features. Several algorithms have been applied to identify knots, holes, and pitch streaks in Douglas-fir veneer, based on manipulating the intensity to extract defect features in wood images (Forrer et al. 1988, 1989; Butler et al. 1989). Maristany et al. (1994) proposed that the dichromatic reflection model could be used to describe the surface appearance of wood. In addition, spectral-reflectance curves were suggested to classify surface features of Douglas-fir veneer via principal-component analysis (Lebow et al. 1996). Since very little lightness variation has been observed within each board, it has been suggested that lightness can be used to sort oak dimension stock with better lightness uniformity for color matching (Phelps et al. 1994; Stokke et al. 1995; Pugel et al. 1995).

Since color variation endows the wood surface with inhomogeneity, characterizing lightness variation becomes far more important for color matching of parts. Efforts should be made to guarantee that the measurements are identical with the observer's perception of color. Up until now, a limited number of investigations have been done focusing on the relationship between visual characteristics of wood and psychology. Masuda (1992) mentioned that wood surface color, gloss, and texture affect human psychological images. It has been further proven that color variation, rather than wood color itself, plays a powerful role in perceiving warmth and naturalness by distinguishing wood textures from artificial ones. Pattern anisotropy has been used to deal with the psychological difference of wood vs. stone and to compare flat grain and edge grain. Local area contrast has been demonstrated to be as good an estimator of texture roughness (Nakamura et al. 1994, 1996; Nakamura and Masuda 1995).

It is possible to use fractal geometry to characterize surface features from wood images. Fractal was first introduced to describe the complexity of natural objects that could not be evaluated by traditional Euclidean geometry (Mandelbrot 1982). Pentland (1984) distinguished perpetually smooth and perpetually textured surfaces, based on a three-dimensional fractal model. The fractal dimensions of surface areas have been calculated by using an ϵ-blanket method suggested by Mandelbrot (Peleg 1984). Keller et al. (1987) employed fractal dimension as a scale-insensitive ruggedness measure of the texture of grayscale images. Stochastic fractal dimensions of image textures and local fractal dimensions were induced to analyze the textures of grayscale images (Kaneko 1987). Subsequently, that idea was applied to evaluate wood gloss (Nakamura et al. 1999). Similarly, capable of including more detailed characteristics than Kaneko's method, the triangular prism surface area method (Clark 1986) was successfully employed to characterize topographic surfaces that are quite close to the wood image textures. Liu (1999) adopted this model and quantitatively estimated the wood surfaces of small specimens of eleven species of Japanese native wood.

The purposes of this paper are to evaluate the texture of wood grayscale images by fractal dimensions of the triangular prism surface area and to further investigate the distribution patterns of those fractal dimensions, including comparisons among species and within species. This method may easily be extended to actual application in machine vision.

MATERIALS AND METHOD

Materials preparation

Fifteen species of wood stocks (boards), one specimen for each species, from East Asia, South Asia (tropical species), Siberia, North America, and Africa were selected for a relatively wide range of investigation, as listed in Table 1. Different ring patterns and grain orientations for different species, e.g., radial, tangential, and mixed, were chosen to explore as many texture distribution patterns as possible. Specimens were at least 30 ~35 cm long, 21 cm wide, and 2 cm thick. A constant plane setting was chosen to guarantee uniform surface quality for all specimens before scanning.

Image acquisition

The surfaces of all specimens were scanned by Scanner Sharp JX-610 with the resolution of 100 dpi, and the color images were digitized to $827 \times 1181 \sim 1378$ pixels with 256 levels of intensity (8 bit). And then all these original images of wood surfaces were converted into grayscale images (shown in Fig. 1) to characterize their lightness, based on the following formula (1):

$$L = 0.3R + 0.59G + 0.11B \qquad (1)$$

where L, R, G, B are lightness, red, green, and blue, respectively.

TABLE 1. *Wood specimens used for the study.*

Species	Source	Code	Scientific names	Lightness
			Hardwood	
Moabi	Africa	MA	*Mimusops djave* Engl.	106 ± 3
Kihada	Japan	KH	*Phellodendron amurense* Rupr.	117 ± 12
Mizunara	Japan	MN	*Quercus crispula* Blume	160 ± 2
Yachidamo	Japan	YD	*Fraxinus mandshurica* Rupr. var. japonica Maxim.	162 ± 6
Mersawa	Malaysia	MW	*Anisoptera* sp.	166 ± 4
Red oak	Japan	RO	*Querus acta* Thumb. ex Murray	169 ± 9
White ash	USA	WA	*Fraxinus americana* L.	210 ± 3
			Softwood	
Agathis	Indonesia	AT	*Agathis* sp.	146 ± 2
Laos cypress	Laos	LC	*Cupressus fokienia*	164 ± 4
Western hemlock	USA	WH	*Tsuga heterophylla* (Ruf.) Sarg.	168 ± 5
Sawara	Japan	SW	*Chamaecyparis pisifera* Endl.	171 ± 2
Douglas-fir	USA	DF	*Pseudotsuga menziesii* (Mirb.) Franco	172 ± 5
Hinoki	Japan	HK	*Chamaecyparis obtusa* Endl.	198 ± 3
Scotch pine	Siberia	SP	*Pinus sylvestris* L.	200 ± 3
White pine	USA	WP	*Pinus strobus* L.	205 ± 5

Lightness represents the average lightness with the deviation of each species.

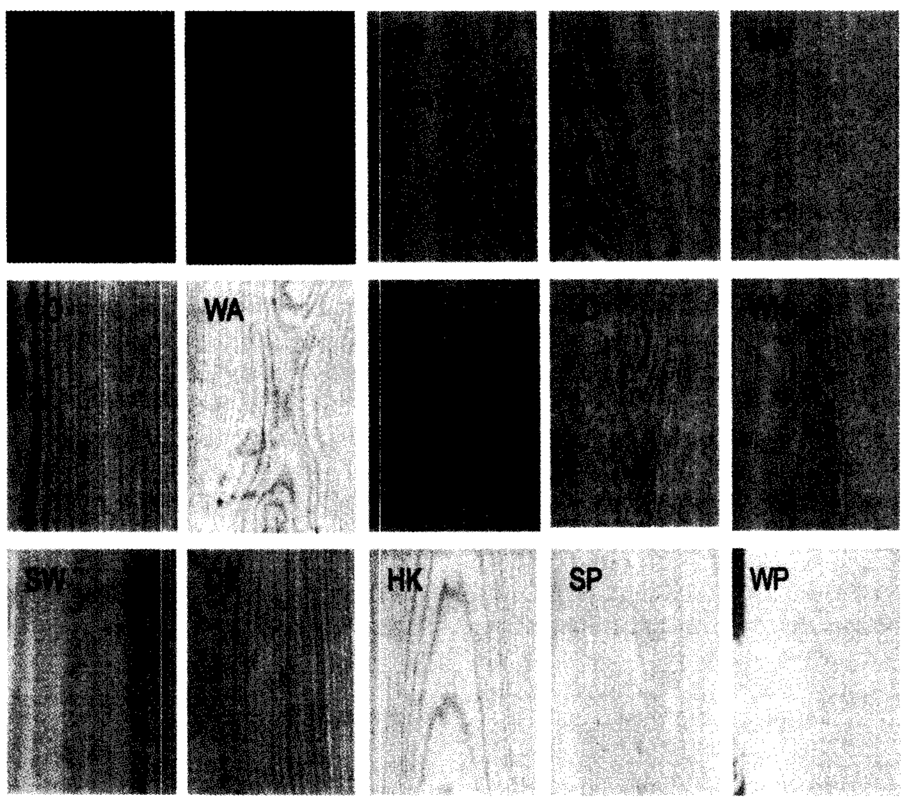

FIG. 1. Grayscale images of wood specimens listed and coded in Table 1.

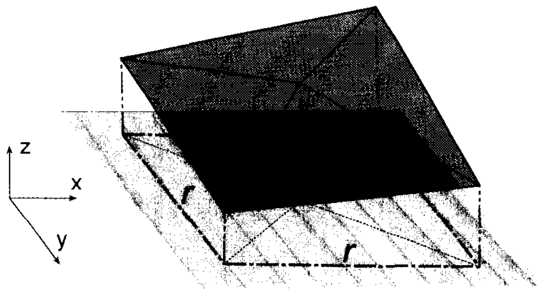

FIG. 2. Triangular prism surface area method.

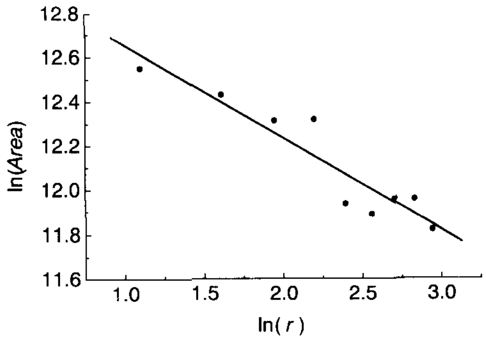

FIG. 3. Plot of ln(*Aear*) vs. ln(*r*) used to obtain the fractal dimension. Species: hinoki, the slope of straight regression line: $K = -0.42$.

Analysis method

For each species, the image was automatically divided into 6 by 9 ~ 12 blocks (integer only) with the size of 128 × 128 pixels, from top to bottom and from left to right inside. Consequently, the fractal estimation of wood surface features was dealt with, based on those individual blocks, as described below. To correlate fractal dimension with lightness later, lightness (between 0 and 256) was also investigated (Table 1).

Consider a representation of discrete intensity of a wood image, which is the observation of the intensities spaced at the intersections on a regular grid of uniform spacing, in a three-dimensional coordinate system. For a square of given size r (as scale), a triangular prism is constructed by the four intensities at corners and the intensity at the center with average values of the four corners, as described in Fig. 2. Compute and aggregate the triangular areas of the top surface of the prism. This procedure should be carried out from top to bottom and from left to right in an individual block of interest. Consequently, the sum of the whole surface areas of the triangular prisms with the same scale can be obtained. In order to guarantee calculation accuracy and efficiency, scale r is odd in our experiments, ranging from 3 to 19, and correspondingly, a series of surface areas can be obtained. Based on the Eq. (2), the *log-log* plot between $Area(r)$ and r can be drawn (Fig. 3), from which the slope of straight regression line (K) can be achieved by the least squares regression method.

$$\ln(Area(r)) = K \ln(r) + c \qquad (2)$$

where c is the intercept.

Finally, fractal dimension D_{TPSA} of the triangular prism surface area method can be calculated by the following formula Eq. 3:

$$D_{TPSA} = 2 - K \qquad (3)$$

Fractal dimensions are between 2 and 3 in two-dimensional images. D_{TPSA} tends to approach 3 as its intensity varies greatly, whereas it approaches 2 as its intensity becomes less variable.

RESULTS AND DISCUSSION

Visual property of grayscale image

Lightness or grayscale values of wood surfaces demonstrate nonuniformity anywhere growth variation of wood structure exists. Both genetic factors and living conditions control the anisotropy of wood cell distributions. The differences in dimensions of wood cells (including pores and rays) differentiate lightness in hardwood. As shown in Fig. 4, lightness of both ring-porous and diffuse-porous woods varies sharply at the location of vessels. Such variation in softwood occurs mainly at the interface from latewood to earlywood (growth ring boundary), with relatively small fluctuation. Uniform texture, like that of white pine, has a more uniform lightness distribution than does Douglas-fir with uneven texture. Nakamura and Takachio (1960) found that the

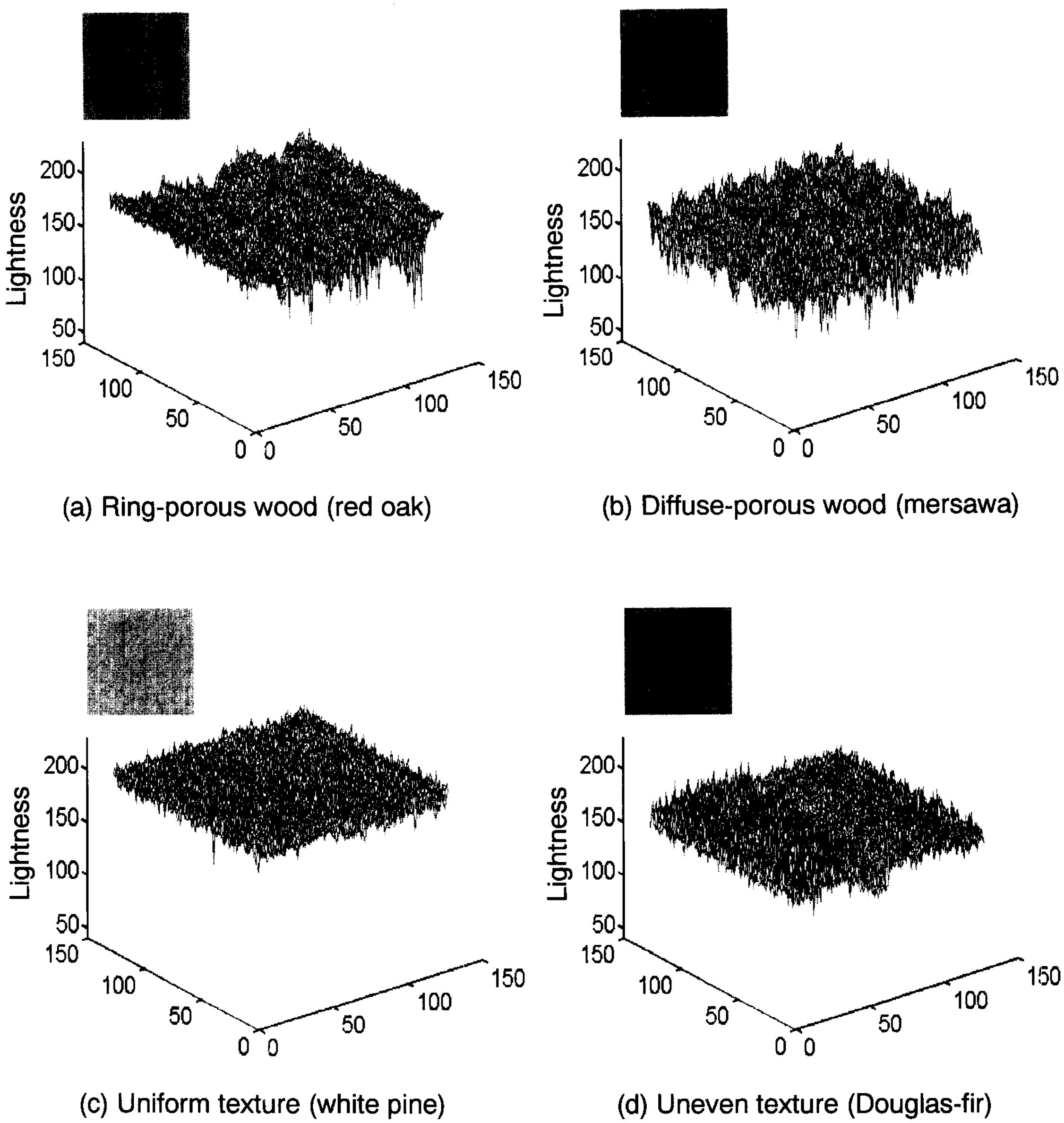

FIG. 4. Visual properties of the lightness of wood surfaces. Above figures are their corresponding images with the block size of 128 × 128 pixels.

lumen size affects the maximum reflection of a wood surface. In addition, the quantity of pores and rays of hardwood should be observed, since lightness in mersawa changes more frequently than that in red oak. Similarly, the number of growth rings in softwood becomes important.

Fractal dimension of texture

Grayscale images of wood surfaces of fifteen species were investigated by fractal dimensions of the triangular prism surface area method and the results are listed in Table 2. The mean value of each species was calculated

TABLE 2. *Fractal dimensions of wood texture.*

Code	Fractal dimensions (FD)				Coefficient FD vs. lightness	FD distribution patterns
	Mean	Maximum	Minimum	Difference		
			Hardwood			
MA	2.51	2.55	2.46	0.09	0.70	Plane
KH	2.51	2.66	2.34	0.32	0.54	Concave
MN	2.63	2.68	2.57	0.10	0.10	Plane
YD	2.56	2.64	2.48	0.17	0.61	Inclined plane
MW	2.64	2.70	2.59	0.12	0.59	Plane
RO	2.52	2.63	2.46	0.17	0.51	Inclined plane
WA	2.45	2.60	2.29	0.31	0.02	Hilly distribution
			Softwood			
AT	2.67	2.74	2.62	0.12	0.67	Plane
LC	2.49	2.59	2.34	0.26	0.22	Concave
WH	2.42	2.58	2.32	0.26	0.62	Concave
SW	2.47	2.56	2.26	0.30	0.55	Convex
DF	2.45	2.56	2.35	0.21	0.58	Inclined plane
HK	2.30	2.48	2.19	0.29	0.34	Concave
SP	2.42	2.50	2.32	0.21	0.07	Zigzag distribution
WP	2.44	2.48	2.37	0.10	0.09	Plane

Difference demonstrates the result of Maximum minus Minimum, indicating variation range of fractal dimensions.

from fifty-four ~ seventy-two of the 128 × 128 blocks within. Based on such averages, softwoods were in the group of low fractal dimensions (less than 2.50) except agathis, while hardwoods were found in the group of high fractal dimensions (greater than 2.50) except white ash. In our experiments, these values ranged from 2.30 (hinoki) to 2.49 (Laos cypress) for softwood (not including 2.67 for agathis) and from 2.51 (moabi) to 2.64 (mersawa) for hardwood (not including white ash, 2.45). Since fractal dimension indicates lightness variation of texture, high value implies strong lightness fluctuation and low value represents weak variation. Consequently, evaluating wood texture by fractal dimension conforms to the general visual impression that softwood is even and hardwood is coarse (Lincoln 1996).

It should be emphasized that detecting an individual block of wood texture is of local significance. Coarse textures cause high fractal dimensions, and fine textures lead to low fractal dimensions. The variation of fractal dimensions reflects uniformity of texture, that is, large variation relates to uneven texture and little variation corresponds to even surface. Ring-porous species and softwood had large differences of fractal dimensions (> 1.50), indicating large variation of textures. Textures of diffuse-porous species (moabi and mersawa) and those with faint grains, like mizunara, agathis, and white pine, caused small differences of fractal dimensions (< 1.50). For the whole image, low mean values of fractal dimensions with small variation can be used to induce a fine and even texture, e.g., white pine (mean dimension is 2.44 with variation of 0.10).

Distribution pattern

Lightness variation depends principally on wood surface characteristics. The number of grains in both softwood (growth rings) and ring-porous species affects fractal dimensions of the textures. The density distribution of pores and rays in diffuse-porous species is of the same importance. Based on these surface features combined with processed selection, six types of fractal dimension distributions were explored and are depicted in Fig. 5.

Fractal dimension distribution not only furnishes uniformity information and coarseness

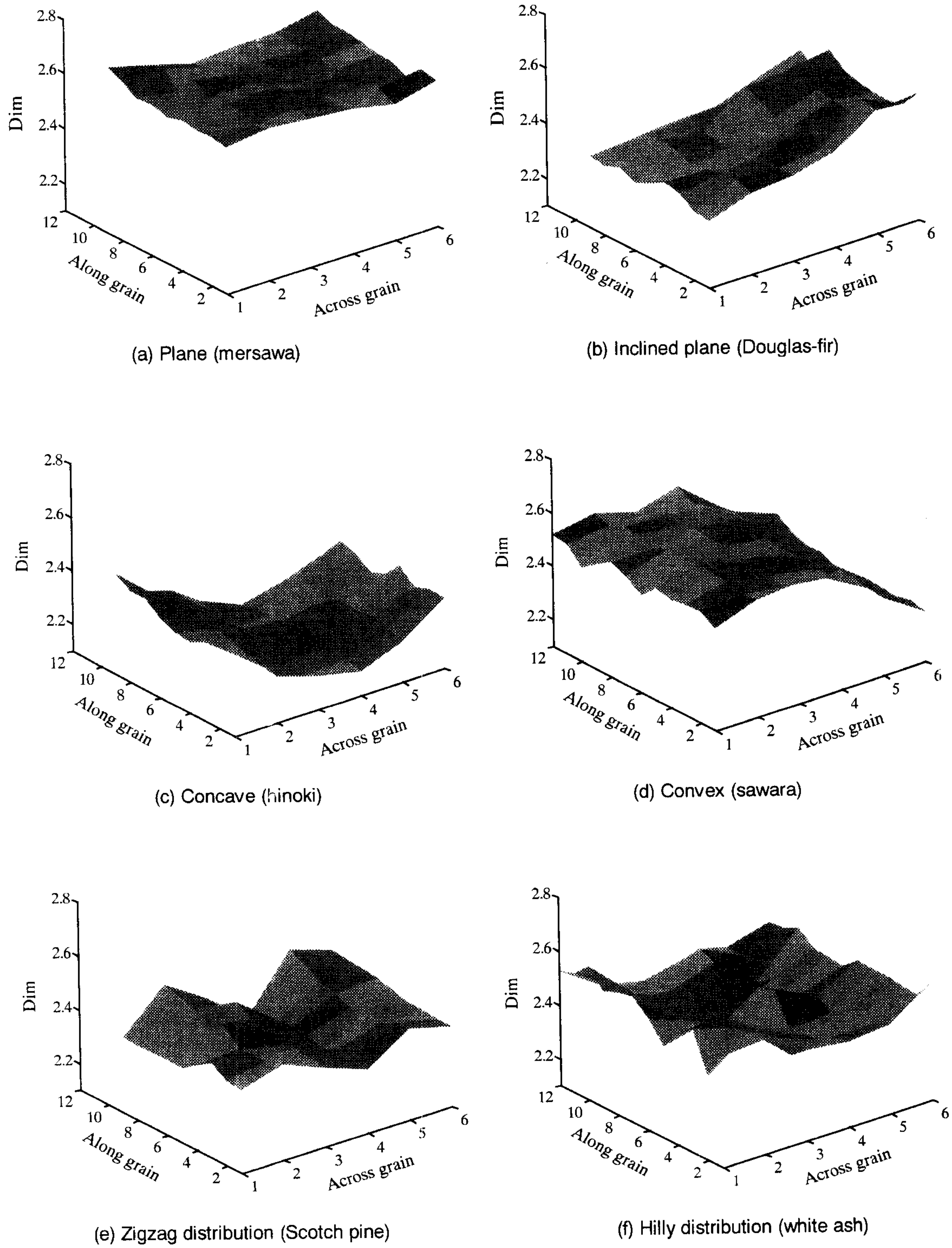

FIG. 5. The distribution patterns of fractal dimensions of lightness variation of wood surfaces. The numbers along and across the grain represent corresponding locations of the whole blocks in each original image in Fig. 1.

of local texture (blocks) but also demonstrates the tendency of lightness variation within the surface for each species. Variation features across the grain indicate diversity. Textures with approximately the same fractal dimensions cause a plane distribution (Fig. 5(a)). Such types include diffuse-porous species (mersawa, MW), the portion of edge-grain near sapwood with almost the same width of rings (white pine, WP) both of which lead to the lightness variation with even amplitude. Moabi (MA), agathis (AT), and mizunara (MN) also show a similar tendency.

Inclined plane is correlated with the gradual increase or decrease of fractal dimensions caused by the same trends of grain numbers, as shown in Fig. 5(b). Such distribution normally appears in half of flat-grains, like Douglas-fir (DF), yachidamo (YD), and red oak (RO), in Fig. 1.

In the textures of typical flat grain, such as hinoki (HK), kihada (KH), Laos cypress (LC), and western hemlock (WH) in Fig. 1, the width of grains gradually increases and then decreases with the transition from radial to tangential orientation. This even change consists of the combination of two inclined planes with smooth connection at the bottom and is named concave (Fig. 5(c)).

Only sawara (SW in Fig. 1) indicates a convex distribution (Fig. 5(d)). This is mainly because its texture goes from fine to coarse and finally back to fine.

In the texture of Scotch pine (SP in Fig. 1), the density of grains suddenly turns from gradual increase or decrease into gradual decrease or increase, and then this process repeats at least once, which forms a zigzag distribution as illustrated in Fig. 5(e).

Since there are great portions of curved grains in the texture of white ash surface (WA in Fig. 1) and the numbers of grains in each individual blocks vary, the local irregularity of fractal dimensions randomly appears in the whole image, and this type is called a hilly distribution (Fig. 5(f)).

Fractal dimensions are able to accurately and quantitatively evaluate wood surface texture. Under most circumstances, wood surfaces are subjectively described as coarse or fine textured for hardwood, even or uneven textured for softwood (sometimes also for hardwood) (Lincoln 1996). Such a general description easily misleads users and neglects specific properties of texture. This confusion can be overcome and wood surface features can be digitized by fractal dimension. As shown in Fig. 5, except for the plane type, most of surfaces are characterized as both the fine and even textures with low fractal dimensions with little variation and the coarse and uneven textures with high fractal dimensions with large variation, which are specifically dependent on their corresponding locations. For example, textures in or near heartwood are relatively fine and even, and conversely, those in or near sapwood are comparatively coarse and uneven (Douglas-fir, hinoki). In addition, grain orientation should be considered as a determinant factor. From Fig. 5(b) to Fig. 5(f), gradual transition from radial to tangential orientation formed inclined plane, concave, convex, and zigzag distribution, and the abrupt transition in the texture of white ash caused irregular hilly distribution. As contrasted to the traditional visual estimation method, this digitized evaluation further broadens the concept of coarseness to softwood. Agathis is the example, whose texture is coarse with high fractal dimensions.

Distribution patterns of fractal dimensions should be carefully considered before color matching of wood components. Distribution patterns are determined on wood species, surface orientation, and location. Following one pattern of the same species in part, matching can best guarantee the perception of natural texture in matching surfaces. On the other hand, matching only by color evaluation can only ensure the color uniformity of wood components but ignores its natural nonuniform texture. Consequently, texture evaluation should also be used along with color evaluation for wood color matching. It is the distribution pattern of fractal dimension that supplies both the indices for wood texture and the reference in this practice.

Little variation of fractal dimensions was observed along the grain (Fig. 5). The reason is that the number of grains in blocks remain constant in the longitudinal direction, even for textures with a large portion of curved grains, and the evenness can last within at least a certain short length. This implies that few fractal dimensions can be used to characterize wood textures like those with wide wood specimens in our experiments. Brunner et al. (1990) emphasized that surface features of the same species play vital roles in image processing. For color matching, besides color information, fractal dimension evaluating lightness variation becomes essential in guaranteeing longitudinal uniformity of texture. In dealing with narrow components of the same species in practice, it may be that few fractal dimensions are sufficient. This needs to be further investigated in the next step.

Fractal dimension vs. lightness

The coefficients of all wood species were calculated between mean lightness and fractal dimensions of the individual blocks, and they are listed in Table 2. A great difference appears among species, varying from 0.02 (white ash) to 0.70 (moabi). Such low values imply that to some degree, lightness and fractal dimensions are relatively independent. And this further indicates that evaluating wood texture cannot be replaced by color evaluation in color matching of parts. In other words, evaluation of wood surface texture using fractal dimension becomes essential.

CONCLUSIONS

Fractal dimensions obtained by the triangular prism surface area method can be used to characterize textures of wood surfaces. It is essential that wood texture be quantitatively evaluated by fractal dimension with sufficient local features beyond species. The texture with great lightness variation causes high fractal dimension, and the average fractal dimension of hardwood (>2.50) is generally larger than that of softwood (<2.50), which conforms to an observer's perception of wood texture.

Fractal dimension distribution of wood texture demonstrates the uniformity of textures and the tendency of lightness variation. There exist six types of distribution, namely, plane inclined plane, concave, convex, zigzag distribution, and hilly distribution. Fractal dimensions across the grain change greatly, whereas those along the grain become relatively steady.

Better color matching of wood components requires not only color uniformity, but also the texture matching with at least approximately natural variation tendency. The distribution pattern of fractal dimensions furnishes those variation trends as a good reference for matching. In addition, the relative stability of fractal dimensions along the grain simplifies this process with only few fractal dimensions, which can efficiently ensure a better texture-matching quality even with approximately the same number of grains.

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