USING COLOR IN MACHINE VISION SYSTEMS FOR WOOD PROCESSING[1]

Charles C. Brunner

Associate Professor
Department of Forest Products
Oregon State University, Corvallis, OR 97331

Gilbert B. Shaw[2]

Former Research Associate
Department of Forest Products
Oregon State University, Corvallis, OR 97331

David A. Butler

Professor
Department of Statistics
Oregon State University, Corvallis, OR 97331

and

James W. Funck

Associate Professor
Department of Forest Products
Oregon State University, Corvallis, OR 97331

(Received April 1989)

ABSTRACT

Color information, already shown to be valuable in distinguishing wood surface features, should prove especially useful for future applications of machine vision in the wood products industry. This review provides investigators interested in such applications with the information necessary for understanding the benefits—and associated difficulties—of using color. Various standard color-measurement systems ("color spaces") are discussed. No one system has been completely successful, at least partly because simple physical measurements are difficult to correlate with a human observer's complex perception of color. Color video camera systems, designed with human viewers in mind, have the potential for machine vision applications, but certain system "features" (white balance, gamma or contour correction) could cause problems. Future applications, including detecting and classifying hard-to-identify defects and matching colors of wood components, will require careful choice of lighting geometry and source, camera system, and color space for the purpose at hand.

Keywords: Optical scanning, machine vision, automation, spectral reflectance, color models.

INTRODUCTION

Visual inspections are central to many wood-processing decisions. Their purpose may be to assess overall wood quality, as in grading, or to locate specific defects, including cosmetic ones like pitch streak or structural ones like open

---

[1] This research was supported by a special grant from the United States Department of Agriculture. This is Paper 2497, Forest Research Laboratory, Oregon State University.

[2] Currently a private consultant with GBS Consultants, 325 N.W. 9th St., #4, Corvallis, OR 97330.

Wood and Fiber Science, 22(4), 1990, pp. 413–428

holes. Substantial efforts have been made to develop machine vision systems capable of automatically making these types of inspections. Existing applications of machine vision in the wood processing industry tend to be relatively simple. They work with binary or gray-scale images and ignore the intricacies of human vision, especially its ability to perceive color. This simplifies system design and reduces the amount of data to be manipulated. However, for future applications, e.g., color matching of wood components or detecting and classifying certain difficult-to-identify defects, the use of color information and understanding how humans perceive color will be desirable or even critical. For example, Conners et al. (1985) concluded that color information could help reveal surface defects on maple (*Acer* spp.) lumber. In another study, Butler et al. (1989) found that color information was critical for detecting pitch streak in Douglas-fir [*Pseudotsuga menziesii* (Mirb.) Franco] veneer.

The purpose of this paper is to provide investigators interested in applying machine vision to wood manufacturing processes with the information necessary to understand the benefits and associated difficulties of using color. The discussion describes how standard measurement systems characterize color and how machine vision systems sense and process color. Two other components of the discussion—how humans see color and how video camera systems render color—are considered vital for at least two related reasons. First, where the objective is to monitor or control product appearance, it is imperative that the machine vision system be able to closely duplicate the perception of a human observer. Second, the most available and least expensive way to implement color-based machine vision systems is to use standard color video cameras. However, because the video industry is driven by commercial television standards and because its products are designed for human viewers, understanding commercial systems' limitations is prerequisite to using them in machine vision applications.

HUMAN COLOR VISION

Although human color vision has been intensively investigated, it is not well understood (Levine 1985). A common misconception is that colors have a simple association with light frequency. The association exists, but is far from simple. For example, there is no single frequency of light that will produce the color we call purple. Moreover, a particular yellow may result from a single light frequency, from a mixture of two distinctly different frequencies (red and green), or from a mixture of many frequencies. Color can be defined as that "attribute of visual perception that can be described by color names: white, gray, black, yellow, orange, brown, red, green, blue, purple, and so on, or by combinations of such names" (Billmeyer and Saltzman 1981). This definition implies that color is a psychological phenomenon involving considerable processing of the eye's retinal inputs by the human optic nerve and brain. This psychological component greatly complicates any measurement standard for quantifying color.

Sight is the result of the brain's processing the eye's retinal inputs, which depend on the spectral power distribution of the light source (the energy at each light frequency in the source), the spectral reflectance of the objects under view (the light reflected at each frequency), and the retina's spectral response. Humans can sense color because their retinas contain three different types of photoreceptors, called cones, each of which has its own pattern of response when exposed to any

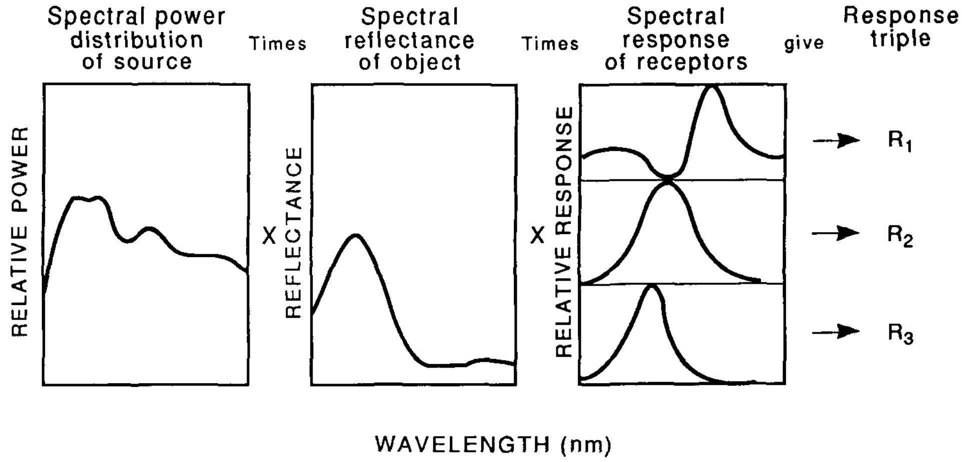

FIG. 1. How a response triple is produced from three different response curves. Adapted from Billmeyer and Saltzman (1981, p. 112).

particular mixture of light frequencies. Color video cameras (discussed later in this review) also use three different types of photoreceptors. For both the eye and the camera, a single basic sensor is fitted with different color filters to produce the three different response curves (Fig. 1). Each curve is used to integrate the incoming light into a single response value. Together, the three values constitute a "response triple" that characterizes a single perceived color. This process is not reversible; that is, from knowing an object's response triple, it is impossible to determine its spectral reflectance. Consequently, two objects with very different spectral reflectances can have identically perceived colors. (They are then said to be metamers.) This property depends upon lighting conditions as well as reflectances, e.g., two surfaces that appear to be identical under incandescent light may have obviously different colors in daylight.

"Color constancy," another important feature of human vision that must be considered when developing color-based machine vision systems, is the property by which humans perceive only a small change in an object's color with relatively large changes in the light source used to illuminate it (illuminant color), as when a cloud covers the sun. This phenomenon is not fully shared by color video systems, which are not as adept at compensating for changes in illuminant color. This difference emphasizes the importance of lighting control with machine vision systems.

STANDARD COLOR MEASUREMENT SYSTEMS

To use color information in any application, including machine vision, it must be stated in quantitative terms. Many such systems have been devised. The number of systems reflects the difficulty of the task and the lack of complete success for any one system.

The first quantitative measurement standards for color were established by the Commission Internationale de l'Eclairage (CIE), a Paris-based international body formed for this purpose. The CIE began by arbitrarily selecting three "primary" monochromatic (single-frequency) lights of wavelengths 700.0 nm ("red"), 546.1

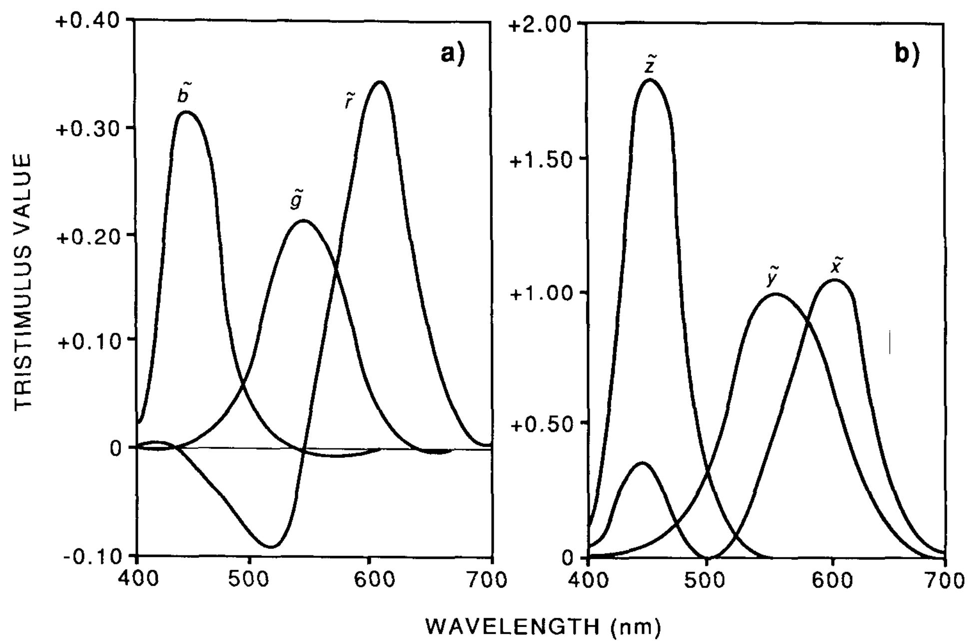

FIG. 2. a) $\bar{r}$, $\bar{g}$, $\bar{b}$ color matching functions (the "standard observer's" functions), adopted by the Commission Internationale de l'Eclairage (CIE) in 1931 and resulting in the CIE RGB color space. b) ($\bar{x}$, $\bar{y}$, $\bar{z}$) color matching functions, transformed from the CIE "standard observer's" functions to the CIE XYZ color space. Adapted from Billmeyer and Saltzman (1981, pp. 39 and 40).

nm ("green"), and 435.8 nm ("blue") to create an R, G, B (CIE RGB) color coordinate system, or "color space." Although the choice of exact frequencies was arbitrary, they were required to obey Grassman's "laws" of color mixture, one of which states that any colored light can be exactly matched by a mixture of the three primaries. Psychophysical experiments were performed to determine the mixture of the three primaries that matched the color of a given monochromatic light. Plots of the relative amounts of the three primary colors (tristimulus values) required to match monochromatic light of any given wavelength (Billmeyer and Saltzman 1981; Wyszecki and Stiles 1982; Sproson 1983) appear in Fig. 2a. These "standard observer's" color matching functions, adopted by the CIE in 1931, result in the CIE RGB color space. The functions take on negative values when a primary must be added to the test color to obtain a match.

One characteristic of color matching functions developed from different sets of primaries is that they can be transformed one to the other with simple linear combinations (Hunter and Harold 1987). One such linear transformation was developed by the CIE to produce a new set of primaries and corresponding color-matching functions ($\bar{x}$, $\bar{y}$, $\bar{z}$) with the following desirable properties. The coefficients $\bar{x}$, $\bar{y}$, and $\bar{z}$ never take on negative values; $\bar{y}$ follows the human visual response for luminosity (overall brightness); $\bar{z}$ is nearly zero over as much of its range as possible; and the coefficients take on equal values when evaluated with any light source having equal energy at every wavelength. Figure 2b shows the resulting CIE $\bar{x}$, $\bar{y}$, $\bar{z}$ color matching function used to create the X, Y, Z (CIE XYZ) color space.

Because the color of an object depends in part upon the illuminant, the source of illumination must be specified before colors of objects can be meaningfully compared. Therefore, the CIE developed several "standard illuminants" with specified theoretical spectral power distributions. (A standard illuminant may or may not have a corresponding physical "standard source" capable of producing it.) CIE source A approximates normal incandescent indoor light; source B approximates the visible range of direct daylight; and source C approximates scattered (overcast) daylight. The illuminant D_{65} also approximates scattered daylight, but includes an appropriate range of ultraviolet light. This illuminant is useful for analyzing materials that fluoresce and has been widely employed as the reference white for color television monitors.

The color of an object is measured by illuminating it with a CIE light source (which *must* be specified in reporting results), then measuring its tristimulus values. These values may be measured directly by using three photodetectors having spectral response functions that match the CIE ($\bar{x}$, $\bar{y}$, $\bar{z}$) functions. They may also be indirectly determined by using a spectrophotometer to measure the entire spectral curve of the reflected light, then integrating it against each of the ($\bar{x}$, $\bar{y}$, $\bar{z}$) functions. The resulting tristimulus values are the CIE XYZ standard color coordinates of the object. Each of them contains information concerning both the object's luminance (brightness) and its chromaticity (color). However, humans tend to perceive the chromaticity of an object independent of its brightness; that is, making an object appear dimmer does not usually change its color. A number of color spaces have been developed from the basic CIE coordinates that better separate luminance and chromaticity.

The most closely related system to CIE XYZ is the "reduced" CIE Y, x, y system (CIE Yxy), where $Y = Y$, $x = X/(X + Y + Z)$, and $y = Y/(X + Y + Z)$. This system retains the Y coordinate for overall brightness. The reduced coordinates x and y (chromaticity coordinates) are considered "purer" measures of color because they contain only chromaticity information and are unaffected by changes in the level of the illumination. However, the x and y coordinates do not easily convey the sense of color perception common to human experience.

An attempt to use these coordinates to introduce such a sense produced the CIE xy chromaticity diagram (Billmeyer and Saltzman 1981). Although the concepts in this diagram are valuable, it has several shortcomings. Its description of hue can be ambiguous; there is no specifically defined point corresponding to black; and differences between colors are not accurately reflected by the distances between coordinate values. For example, "greens" whose points are separated by a given distance are generally much more alike than "reds" of the same separation.

A color space that preceded the CIEs and that lacks some of these irregularities is the Munsell color system for hue, value, and chroma (Munsell Color Company 1929; Fig. 3a). With this system, the colors produced by a prism differ largely in hue, the colors produced by using brighter or dimmer light sources differ largely in value, and the colors produced by combining varying amounts of white light with the pure color differ in chroma. However, the Munsell system is not easily related mathematically to the CIE color spaces because it is based on physical samples with equal intervals of visual perception.

One attempt to relate the Munsell and CIE RGB color spaces is Smith's (1978) hue, value, saturation (HVS) transformation, used in the computer graphics in-

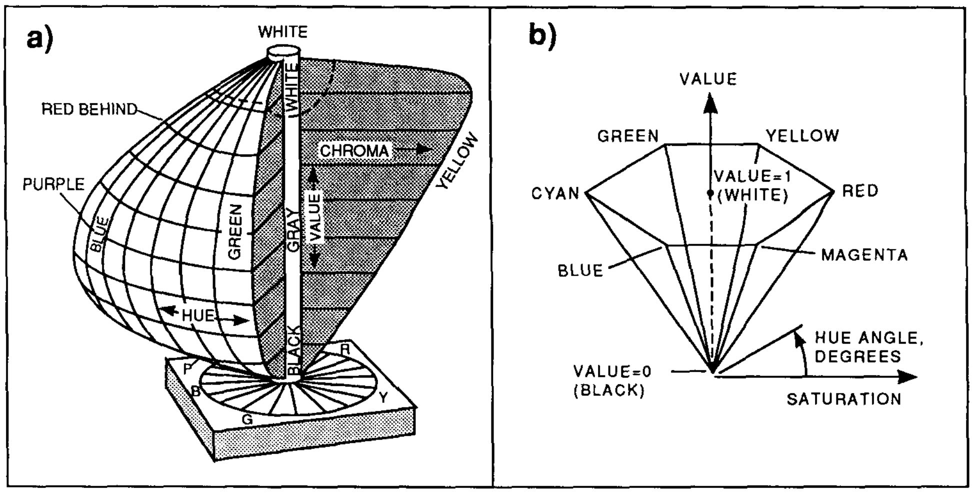

FIG. 3. a) Munsell color solid (Munsell Color Company 1929), defining color by hue, value, and chroma; from Billmeyer and Saltzman (1981, p. 52). b) Smith's (1978) HVS color space, defining color by hue, value, and saturation and represented by a hexcone; from Foley and Van Dam (1983, p. 614).

dustry, in which hue (H) and value (V) are defined as in the Munsell system, and saturation (S) corresponds to the Munsell chroma. The HVS system transforms the rectangular primary-color space into a polar coordinate system represented by a single hexcone (Fig. 3b). Unlike the CIE xy chromaticity diagram, it has a defined point for black and unique values for all hues. However it, too, does not produce equal intervals of visual perception between coordinate values.

There have been a number of attempts to create more uniform color spaces from the basic CIE measures. Although no true uniform space has been developed, the CIE in 1976 adopted two nonlinear systems that more nearly model human color perception: the L^*, u^*, v^* (CIE LUV) and the L^*, a^*, b^* (CIE LAB). These color systems are especially useful for determining perceptual color differences. Neither system has been found to be significantly better than the other (Pointer 1981).

The color systems discussed so far are generally used to describe color for applications such as color matching and are not well suited to use in color video systems, where issues of efficient information encoding (bandwidth), compatibility with black-and-white television standards, and simplified hardware design are dominant. Thus, two special systems derived from CIE specifications were developed by the National Television System Committee (NTSC). The NTSC YIQ system is used in broadcast television to make color transmission compatible with black-and-white transmission. The NTSC RGB system is used to encode information from the camera and is used in closed-circuit applications. Together, the three RGB signals have approximately three times the dynamic range of the YIQ signal. The NTSC RGB system is comparable, but not identical, to the CIE RGB system. For a more complete discussion of NTSC standards, see Pritchard (1977).

Other coordinate systems are in use as well. See Wyszecki and Stiles (1982),

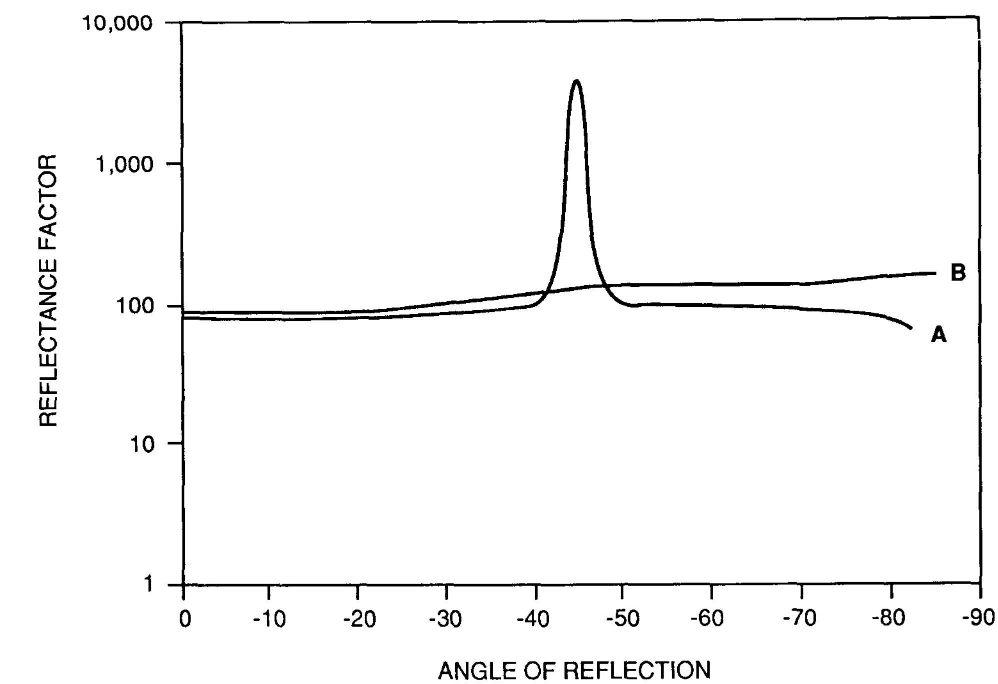

FIG. 4. Typical specular reflection curve for a) metallic (shiny white) surface and b) diffuse (matte white) surface. Adapted from Hunter and Harold (1987, p. 43).

Billmeyer and Saltzman (1981), Hunter and Harold (1987), Sproson (1983), and Smith (1978) for a more complete discussion of color spaces and formulas for transforming between them. Although the various color coordinate systems provide an objective mechanism for making physical measurements that can be related to human color perception, they generally do not provide a reliable guide to the "color" of things. For example, the correspondence between a CIE XYZ response triple such as (0.9, 0.1, 0.1) and a color name such as "deep red" is a hazy one. Human perception of colors is indeed more than a simple association of colors with retinal responses on a point-by-point basis. The composition of the entire visual scene, or of parts of it (e.g., the background), can substantially alter the perceived color of an object. The fact that our eyes and brain make automatic adjustments to correctly interpret a scene makes it very difficult to establish concrete connections between simple physical measurements such as CIE or NTSC color coordinates and a human observer's interpretation of a color scene.

CIE COLOR MEASUREMENTS OF WOOD

Wood color research using the CIE standards has been performed for more than four decades. Descriptions of past wood color research and its methods have been presented elsewhere (Loos and Coppock 1964; Sullivan 1967a; Beckwith 1979). The CIE color measures have been used primarily to quantify natural wood colors, which were previously described only in qualitative terms such as light reddish brown or yellowish gray (Moon and Spencer 1948; Gray 1961; Loos and Coppock

1964; Lakatosh 1966; Sullivan 1967b; Resch et al. 1968; Moslemi 1969; McGinnes and Melcarek 1976; Beckwith 1979). Other researchers have reported CIE values as part of investigations into color changes in wood due to various treatments (Shibamato et al. 1961a, b; Webb and Sullivan 1964; Brauner and Loos 1968; Moslemi 1969; Nelson et al. 1969; Hiller et al. 1972; McGinnes 1975; Phelps and McGinnes 1983; Phelps et al. 1983; Rink 1987).

Sullivan (1967a, b) noted that wood color is basically two-dimensional within the standard CIE color space. He observed that differences in hue appear to be relatively small, but those in brightness and saturation much larger. This observation led Beckwith (1979) to suggest that some other measure might be more appropriate for characterizing wood color.

Researchers have also investigated viewing conditions that affect wood-color measurements. Surface orientation is one such condition. Investigations of the CIE values for radial, tangential, and transverse faces in the same species have indicated little or no difference between the radial and tangential faces (Sullivan 1967b; Resch et al. 1968; Beckwith 1979). Webb and Sullivan (1964) found similar results for redwood [*Sequoia sempervirens* (D. Don) Endl.] and Engelmann spruce (*Picea engelmannii* Parry ex Engelm.), except that radial redwood sections were brighter; probable explanations for the similarity of these two surface types are the presence of rays on the radial face and the possibility of a larger proportion of earlywood being exposed on the tangential face. Lakatosh (1966) reported radial and tangential color values for 31 species but drew no conclusions about differences. Beckwith (1979) generally found dominant wavelength and color purity to be the same for longitudinal and transverse faces, but brightness to be significantly lower on the transverse face.

Because the amount of light reflected from a wood surface depends on the wood fiber angle with that surface (Matthews 1987; Soest 1987), the orientation of incident light relative to the wood surface is another variable affecting color measurement. Spectrophotometers typically use a 45/0 geometry (i.e., the light source is at a 45-degree angle to the surface to be viewed), with the detector normal to, and directly above, the area being illuminated; this arrangement helps reduce the specular reflection to the instrument. The reduction is important because diffuse reflection is generally considered to contain "truer" color information than specular reflection, which contains more of the illuminant's color. Raw wood, a semidiffuse reflector, has specular reflection values that fall between those shown in Fig. 4 for a shiny metallic and a diffuse surface. Because fiber angle is so important to reflectance, the alignment of the incident light with or across the grain affects colorimetric measurements. However, as previously suggested, investigations have found no significant difference in CIE values except for the brightness coordinate, Y, which is greater when the surface is illuminated along the grain (Nakamura and Tackachio 1960; Gray 1961; Moslemi 1969). Therefore, researchers generally average two readings, one along the grain and a second across the grain, or they take all readings in a specified direction, usually along the grain.

Another variable affecting color measurement is moisture content (MC). Sullivan (1967b) investigated the differences in brightness, color purity, and dominant wavelength between the upper (saturated) and lower (dry) levels of MC in yellow-poplar (*Liriodendron tulipifera* L.). He chose 40% MC for the saturated condition, 10% for the dry. The results showed that regardless of the surface orientation

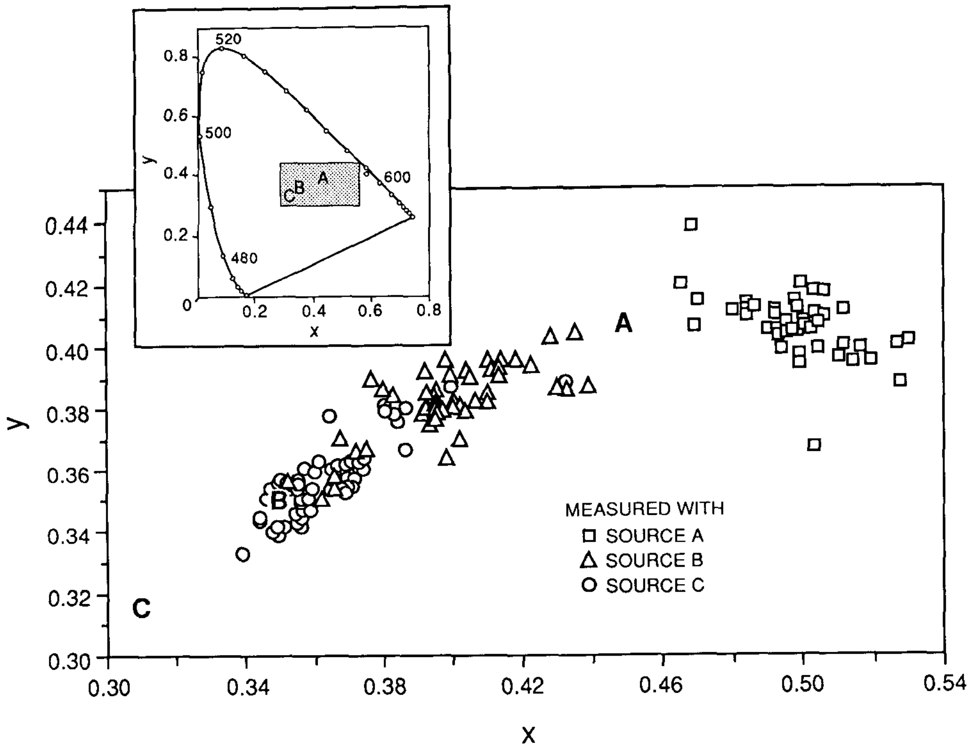

FIG. 5. CIE chromaticity diagram plotted with color coordinates for various wood species, as reported in the references cited in the accompanying text section. Samples measured with the same CIE standard source (A, B, or C) occupy relatively small areas that, though slightly overlapping, are distinct.

(radial, tangential, or transverse), brightness increased, color purity decreased, and dominant wavelength remained the same after drying. The variances for the three parameters were found to significantly decrease at the lower MC. These results are attributed to the presence of free water above the fiber saturation point (FSP); however, the effects on color of changes in MC below the FSP have not been closely studied. Measuring the spectral reflectance of a wood specimen's surface while controlling its surface moisture content is difficult. Researchers have generally used specimens in equilibrium with the laboratory's environment or have ignored this factor's variance below the FSP because its contribution is small compared to that of other variance components, e.g., color differences between samples from the same board. The fact that Sullivan (1967b) found greater uniformity in CIE values for the dry yellow-poplar appears to support the idea that MC below the FSP can be ignored. Brauner and Loos (1968) cited this uniformity as their reason for making spectrophotometric readings at 0% MC in their study of induced color changes in black walnut (*Juglans nigra* L.) sapwood.

Wood's spectral reflectance is the single inherent physical property involved in producing its color and is not completely described by the CIE coordinates. McGinnes and Dingeldein (1971) reported changes in reflectance at each of 10 wavelengths spaced throughout the visible spectrum when studying the effect of light, solvent extraction, and storage conditions on the color of eastern redcedar (*Juniperus virginiana* L.); using the same technique, McGinnes (1975) reported changes in reflectance at 14 wavelengths when assessing the influence of incandescent and fluorescent light on the color of unfinished black walnut and eastern redcedar heartwood. Both studies found that wood exposed to light yellowed because of changes in the reflectance of light in both the red (longer) and blue (shorter) wavelength portions of the spectrum. Findings from these two studies suggest that information can be lost when only CIE color values are used to describe surface reflectance. A CIE chromaticity diagram plotted with wood color coordinates from the references cited in this section illustrates the relatively small area occupied by the values from numerous wood species (Fig. 5). Because the reflectance curve cannot be recreated from CIE values and some information about a wood surface can be lost in converting to CIE color space, it may be beneficial to report results in terms of the original reflectance curves, as some researchers have done, rather than as standard CIE values. Full reflectance curves are especially important for understanding how wood will appear to a human, or in a video image, under unusual lighting conditions.

The research discussed so far has focused on differences between species, or sapwood and heartwood of the same species, for which the surface area investigated was considered homogeneous. Although this information is important, the color differences between surface features of the same species are far more important for imaging purposes. A limited amount of work has been done in this area, most of it comparing earlywood and latewood. Moslemi (1969) investigated the color differences of loblolly pine (*Pinus taeda* L.) earlywood and latewood before and after exposure to sunlight. Webb and Sullivan (1964) found no color differences between Engelmann spruce earlywood and latewood; redwood earlywood and latewood did not differ in dominant wavelength, but the latewood was brighter and had a lower color purity than the earlywood. Lakatosh (1966) reported values for brightness, dominant wavelength, and color purity for a comprehensive list of surface features for five different genera (no species names given): spruce (*Picea*), pine (*Pinus*), beech (*Fagus*), birch (*Betula*), and oak (*Quercus*). Although not described in standard CIE terms, the illuminant used is assumed to be CIE standard source B. He also reported coefficients of variation of 3% or less, which is very low compared to coefficients of variation for most wood properties, and suggested that this might make color useful for detecting and locating defects.

APPLICATION OF COLOR TO MACHINE VISION

The additional data present in a color image greatly increase the computations needed for analysis, so where color is not strictly required, it is usually avoided. This is one reason why the use of color in machine vision is only now being extensively explored. However, color is a critical feature of many products, either as an aesthetic attribute or an indicator of product quality. Machine vision systems have been used to monitor color for aesthetics and quality (Aus et al. 1983; Zuech and Miller 1987; Daley et al. 1988), wherever possible with a monochrome system filtered so that the image is created and analyzed using only a narrow region of the spectrum (Daley et al. 1988). Of course, systems with such narrow spectra are not "true" color systems and have only limited application. Actual color systems—

for example, video camera systems—use most of the visible spectrum, much like the human eye.

Recall that the human eye senses color through three different types of photoreceptors in the retina. Similarly, a color video camera processes a color image comprising at least three separate, spatially aligned images of the same scene, each in a different primary color. The primary images can be taken sequentially, using a single monochrome camera and three separate filters, or simultaneously, using a color camera with one to three sensors. The monochrome camera allows many different types of filters and potentially has perfect image registration, but is slow by most application standards. Color cameras directly separate simultaneous R, G, and B signals for each pixel, but ones that are defined by broadcast television standards. Three-sensor color cameras have only a single filter on each sensor, but one- and two-sensor cameras must be fitted with masks of alternating stripes of filter material. The two- and (especially) three-sensor cameras require a rather complex image-splitting and registration system, which makes them more expensive but also helps them produce a higher quality image.

The type of sensor used also influences the image. The two basic sensor types, which have different spectral sensitivities, are the photoconductor-based image tube and the silicon solid-state sensor. Image tubes typically are more responsive in the green or blue portions of the spectrum, depending on the photoconductive material used in their construction, whereas solid-state sensors are most responsive in the red and least in the blue. Thus, if the blue portion of the spectrum is of special interest, then the image tube would give a better signal-to-noise ratio; but if the far-red portion of the spectrum is of interest, a solid-state sensor would be preferred. Some cameras also use linear masking or matrixing to better reproduce the NTSC color matching functions for each of the R, G, and B signals by mixing appropriate amounts of individual signals with each other. This feature is most important when making colorimetric measurements of a scene, but requires a more expensive camera with a high signal-to-noise ratio.

Because color video systems are designed to please human observers, some features may cause concern for machine vision applications. A color camera's white balance is one such feature. The color of a scene changes with the chromaticity of its illuminant (e.g., from tungsten to daylight), yet the color perceived by a human observer remains remarkably constant, especially for white surfaces (see color constancy, discussed earlier). Achieving constancy, within limits, is the function of a camera's white balance. While focused on a white surface, the camera adjusts the gain of the R and B signals so they equal the magnitude of the G signal. For example, if CIE illuminant A is used to white-balance a camera, the camera will increase the B signal's gain to compensate for the low levels of blue light found in this light source. These signal levels become the reference white point for the camera (CIE illuminant C for NTSC cameras), and are then mapped by the display device to its reference white point (CIE D_{65} for most color monitors). Chromatic points are similarly mapped in relation to these white points. This feature is necessary to produce usable color rendition for color television, but is critical with some color-based machine vision applications (Aus et al. 1983). For machine vision applications, it might be helpful to white-balance the camera using a colored surface that will cause the signal's gain to be increased, or at least not decreased, for that portion of the spectrum of interest, or to disable the white-balance circuit entirely and set the signals' gains manually. Even though the camera's white balance is meant to compensate for changes in light sources, care must always be used in selecting light sources because increasing gain to compensate for low light levels will decrease the signal-to-noise ratio.

Another feature that can adversely affect machine vision applications is gamma correction. Recent video cameras have sensors that produce a nearly linear response between the incident light flux and the output voltage, whereas the phosphors in display monitors fluoresce nonlinearly with the input energy (Sproson 1983). To eliminate the need to include a nonlinear amplifying circuit in every television receiver, a gamma correction circuit in the camera modifies the signal to the monitor so that it displays the proper color intensity. This approach makes sense if a human is viewing the image from a monitor, but not if a computer is analyzing it; if the R, G, and B signals are at different input levels, the relationship between them will be distorted by the gamma circuit.

Yet another feature that could adversely affect machine vision applications is contour correction. This signal distortion is used to accentuate the edges of an image (make an image appear "sharp") by adding an impulse to the R, G, and B signals when a high frequency change occurs in either direction in the G signal. In some machine vision applications, this may distort the computer's analysis of the image if no such edges are present in the R or B signals.

Given the potential for white balance, gamma correction, or contour correction to cause problems in machine vision applications, users should probably investigate their effects on a specific application before selecting a camera. The effect of these "distortions" on systems that detect or segregate may be minimal, but can be considerable on systems meant for colorimetry, such as color matching (Wandell 1986; Lee 1988).

Once a color machine-vision system has created an image, it can use a variety of techniques to analyze it. As with gray-scale systems, there is no single method that performs adequately for all applications. However, many of these techniques ignore image brightness and concentrate instead on image chromaticity (e.g., I and Q) to produce a one- or two-dimensional space for image analysis, which minimizes data manipulation while preserving essential image information (Keil 1983; Kelly and Faedo 1985; Shearer and Holmes 1987; Slaughter and Harrell 1987). Where the application involves a small set of distinctively different colored features with virtually no variation, pattern matching techniques can be used (Ito 1976; Romanik 1988). If variability associated with the measured colors is small, then multispectral classification methods, such as minimum distance or maximum likelihood, can be employed (Fukada 1980; Showengerdt 1983). Even texture analysis, similar to spatial gray-level dependency, can be used for color image analysis (Shearer and Holmes 1987). All of these techniques, but especially the multispectral methods, work best when the image input signals have considerable spectral separation (Estes et al. 1983). However, the standard color matching functions overlap extensively and are somewhat correlated (see Fig. 1). The effect of this correlation can be minimized by selecting the color space whose values for the image features of interest are most different.

Several researchers have indicated the need to determine the best color space for a specific machine-vision application (Nelson et al. 1969; Yachida and Tsuji 1971; Hiller et al. 1972; Ohlander 1975). Ohlander (1975) and Ohta (1985) have investigated the most appropriate one for outdoor natural scenes. Ohta et al. (1980) used a dynamic Karhunen-Loeve (K-L) transformation to select the linear combinations of the R, G, and B signals to be used in segmenting an image. These combinations are selected so that they are mutually orthogonal and produce maximal variance. This method assumes that the linear combination with the largest variance has the best discriminant power in separating segments—an assumption valid for Ohta et al.'s (1980) investigation because the entire image was being segmented into all its possible parts. These researchers found the linear combinations $(R + G + B)/3$, $(R - B)/2$, and $(2G - R - B)/4$ common to their image set of outdoor natural scenes, with most of the information contained in the first two transforms. Comparing the linear combinations to a set of seven standard color spaces, they determined that the combinations were as effective and more efficient to implement.

Using color systems to detect defects in wood has been investigated. Conners et al. (1983, 1984a, b) extended their work with gray-scale vision systems by reviewing the literature relating to wood color and how color might be used with machine vision (Conners et al. 1985). This work also included some experiments with a gray-scale system and color filters to determine the effect of adding color information to their defect-classifying algorithm, which used Bayesian decision theory to classify 0.5- by 1-inch areas of boards into clear and defect categories. Using only the red and blue data was nearly as effective as using the red, green, blue, and brightness data.

Funck et al. (1987), Butler et al. (1989), and Forrer et al. (1988, 1989) have also used color data with a number of algorithms to identify likely defect areas in images of Douglas-fir veneer. These algorithms differ from those of Conners et al. (1985) in their use of the color data. First, they employ two linear combinations, $(R + G + B)/3$ and $(R - B)/2$, proposed by Ohta et al. (1980) for segmenting outdoor natural scenes because preliminary investigations with K-L analysis of wood images produced similar combinations. Ohta's third combination was not used because it provided little additional information about defects. Second, the algorithms use adaptive statistical methods instead of Bayesian theory. Conners et al. (1987) also proposed an adaptive method for classifying image segments with the red and blue data. These investigations (Conners et al. 1987; Funck et al. 1987; Butler et al. 1989; Forrer et al. 1988, 1989) further reinforce Sullivan's (1967a) observation that wood color is two-dimensional.

RECOMMENDATIONS

Even though this discussion has been fairly general, some specific recommendations can be made for using color-based machine vision in wood manufacturing:

1) Given the importance of fiber angle on specular reflection and the fact that this angle cannot generally be carefully controlled, a highly diffuse light source should be preferred to a collimated one.

2) Rough surfaces should be avoided wherever possible. They not only create shadows, but also increase the amount of specular reflection, which may complicate image analysis. A change in process steps may even be warranted to ensure a smooth, fresh surface, as Conners et al. (1985) have indicated.

3) Special consideration should be given to selecting a light source with the appropriate spectral power distribution. Because many wood species typically

have high reflectance in the yellow-red portions of the spectrum, as indicated by either direct spectrographic studies (Moon and Spencer 1948; McGinnes and Dingeldein 1971; McGinnes 1975; Funck et al. 1987) or dominant wavelength measurements (Gray 1961; Loos and Coppock 1964; Lakatosh 1966; Sullivan 1967b; Resch et al. 1968; Moslemi 1969; Beckwith 1979), selecting a light source with adequate energy in those areas seems to be a good first choice (incandescent lights have high energy levels in this range). However, if, for example, the blue portion of the spectrum were important for imaging a specific feature, then a light source with adequate energy in that portion would be desired (high-frequency fluorescent lights might be a good choice in this instance). Even though a camera's white balance is partly intended to compensate for deficiencies in lighting, care must be taken to avoid decreasing signal-to-noise ratios to the point where they affect image quality.

4) Possible adverse effects associated with gamma or contour correction must be minimized whenever a standard color video camera is used. A camera system's gamma correction should probably be disabled for most, if not all, machine vision applications; it *must* be disabled for colorimetry purposes such as color matching. Similarly, contour correction should be disabled for most wood-manufacturing applications because it tends to accentuate the grain patterns in clear wood, which often confuses image analysis.

5) Finally, the best color space for the purpose at hand should always be determined. The most appropriate color space for image analysis may differ from that initially produced by the camera's signals. Although further research is required for generalization, workers should keep in mind that wood color, like color in outdoor natural scenes, appears to be two-dimensional in most color spaces—a fact that could greatly simplify machine vision applications in the wood industry.

REFERENCES

Aus, H. M., H. Harms, M. Haucke, B. Gerlach, A. Kriete, and S. Thieme. 1983. Computer color vision. Pages 225–229 *in* Intelligent Robots: Proceedings, 3rd International Conference on Robot Vision and Sensory Controls, Cambridge, MA. SPIE Vol. 449, Bellingham, WA.

Beckwith, J. R., III. 1979. Theory and practice of hardwood color measurement. Wood Sci. 11: 169–175.

Billmeyer, F. W., Jr., and M. Saltzman. 1981. Principles of color technology. John Wiley & Sons, New York.

Brauner, A. B., and W. E. Loos. 1968. Color changes in black walnut as a function of temperature, time, and two moisture conditions. Forest Prod. J. 18(5):29–34.

Butler, D. A., C. C. Brunner, and J. W. Funck. 1989. A dual-threshold image sweep-and-mark algorithm for defect detection in veneer. Forest Prod. J. 39(5):25–28.

Conners, R. W., P. Klinkachorn, C. W. McMillin, J. P. Franklin, and C. N. Ng. 1987. A computer vision system for grading hardwood lumber. Pages XV-1 to XV-7 *in* Proceedings, 2nd International Conference on Scanning Technology in Sawmilling. Miller Freeman, San Francisco, CA.

———, C. W. McMillin, K. Lin, and R. E. Vasques-Espinosa. 1983. Identifying and locating surface defects in wood: Part of an automated lumber processing system. IEEE Trans. Pattern Anal. Mach. Intell. PAMI-5(6):573–583.

———, ———, and C. N. Ng. 1985. The utility of color information in the location and identification of defects in surfaced hardwood lumber. Pages XVIII-1 to XVIII-33 *in* Proceedings, 1st International Conference on Scanning Technology in Sawmilling. Miller Freeman, San Francisco, CA.

———, ———, and R. E. Vasques-Espinosa. 1984a. A prototype software system for locating and identifying surface defects in wood. Proceedings, 7th International Conference on Pattern Recognition, Montreal, Canada 7(1):416–419.

———, ———, AND ———. 1984b. A prototype software system for locating and identifying surface defects in wood. Scanning technology for the eighties. Spec. Publ. No. SP-21:107–114. Forintek Canada Corp., Vancouver, B.C., Canada.

DALEY, W., R. MILLET, C. SOULAKOS, AND C. THOMPSON. 1988. A novel application: Machine vision inspection, grading and parts identification of chicken parts. Pages 13–33 to 13–49 *in* Robots 12 and Vision '88 Conference Proceedings, vol. 2. Society of Manufacturing Engineers, Dearborn, MI.

ESTES, J. E., E. J. HAJIC, AND L. R. TINNEY. 1983. Fundamentals of image analysis: Analysis of visible and thermal infrared data. Pages 987–1124 *in* Manual of remote sensing, vol. 1: Theory, instruments and techniques. American Society of Photogrammetry, Falls Church, VA.

FOLEY, J. D., AND A. VAN DAM. 1983. Fundamentals of interactive computer graphics. Addison-Wesley, Reading, MA.

FORRER, J. B., D. A. BUTLER, C. C. BRUNNER, AND J. W. FUNCK. 1989. Image sweep-and-mark algorithms: Part 2: Performance evaluations. Forest Prod. J. 39(1):39–42.

———, ———, J. W. FUNCK, AND C. C. BRUNNER. 1988. Image sweep-and-mark algorithms: Part 1: Basic algorithms. Forest Prod. J. 38(11/12):75–79.

FUKADA, Y. 1980. Spatial clustering procedures for region analysis. Pattern Recognition 12:395–403.

FUNCK, J. W., D. A. BUTLER, C. C. BRUNNER, AND G. B. SHAW. 1987. Evaluation of image analysis routines for defect scanning on wood surfaces. Pages XIII-1 to XIII-19 *in* Proceedings, 2nd International Conference on Scanning Technology in Sawmilling. Miller Freeman, San Francisco, CA.

GRAY, V. R. 1961. The colour of wood and its changes. Res. Rep. C/RR/10. Timber Development Association Ltd., St. John's Rd., Tylers Green, High Wycombe, Buckinghamshire, England.

HILLER, C. H., F. FREESE, AND D. M. SMITH. 1972. Relationships in black walnut heartwood between color and other physical and anatomical characteristics. Wood Fiber 4:38–42.

HUNTER, R. S., AND R. W. HAROLD. 1987. The measurement of appearance. John Wiley & Sons, New York.

ITO, T. 1976. Pattern classification by color effect method. Pages 833–837 *in* 3rd International Conference on Pattern Recognition. IEEE Computer Society, Los Angeles, CA.

KEIL, R. E. 1983. Machine vision with color detection. Pages 503–512 *in* Intelligent Robots: Proceedings, 3rd International Conference on Robot Vision and Sensory Controls, Cambridge, MA. SPIE Vol. 449, Bellingham, WA.

KELLY, R. B., AND W. FAEDO. 1985. A first look into color vision. Pages 96–103 *in* Intelligent Robots and Computer Vision: Proceedings, International Society for Optical Engineers. SPIE Vol. 579, Bellingham, WA.

LAKATOSH, B. K. 1966. (Translated 1970). Defectoscopy of wood. Indian National Scientific Documentation Center, New Delhi.

LEE, R. L. 1988. Colorimetric calibration of a video digitizing system: Algorithm and application. COLOR Res. Appl. 13(3):180–186.

LEVINE, M. D. 1985. Vision in man and machine. McGraw-Hill, New York.

LOOS, W. E., AND W. A. COPPOCK. 1964. Measuring wood color with precision. Forest Prod. J. 14(2): 85–86.

MATTHEWS, P. C. 1987. Wood, light and objective scanning. Pages XI-1 to XI-13 *in* Proceedings, 2nd International Conference on Scanning Technology in Sawmilling. Miller Freeman, San Francisco, CA.

MCGINNES, E. A., JR. 1975. Influence of incandescent and fluorescent light on the color of unfinished heartwood of black walnut and eastern redcedar. Wood Sci. 7:270–279.

———, AND T. W. DINGELDEIN. 1971. Effect of light, extraction, and storage on color and tackiness of clear-finished eastern redcedar. Forest Prod. J. 21(1):53–60.

———, AND P. K. MELCAREK. 1976. Equipment for studying the color characteristics of wood at the cellular level. Wood Sci. 9:46–50.

MOON, P., AND D. E. SPENCER. 1948. The color of unstained wood. J. Opt. Soc. Am. 38:405–408.

MOSLEMI, A. A. 1969. Quantitative color characterization for loblolly pine veneer. Wood Sci. 2: 61–64.

MUNSELL COLOR COMPANY. 1929. Munsell book of color, Standard ed. Baltimore, MD.

NAKAMURA, G., AND H. TACKACHIO. 1960. Reflection of light and roughness on sanded surfaces of wood. J. Jpn. Wood Res. Soc. 6:237–242.

NELSON, N. D., R. R. MAEGLIN, AND H. E. WAHLGREN. 1969. Relationship of black walnut wood color to soil properties and site. Wood Fiber 1:29–37.

OHLANDER, R. 1975. Analysis of natural color scenes. Ph.D. thesis, Department of Computer Science, Carnegie-Mellon University, Pittsburgh, PA.

OHTA, Y. 1985. Knowledge-based interpretation of outdoor natural color scenes. Pitman, Marshfield, MA.

———, T. KANADE, AND T. SAKAI. 1980. Color information for region segmentation. Comput. Graphics Image Process. 13:222–241.

PHELPS, J. E., AND E. A. MCGINNES, JR. 1983. Growth-quality evaluation of black walnut wood. Part III—An anatomical study of color characteristics of black walnut veneer. Wood Fiber Sci. 15:212–218.

———, ———, H. E. GARRETT, AND G. S. COX. 1983. Growth-quality evaluation of black walnut wood. Part II—Color analysis of veneer produced on different sites. Wood Fiber Sci. 15:177–185.

POINTER, M. R. 1981. A comparison of the CIE 1976 color spaces. COLOR Res. Appl. 6(2):108–117.

PRITCHARD, D. H. 1977. U.S. color television fundamentals—A review. IEEE Trans. Consum. Electron. CE-23(4):467–478.

RESCH, H., E. T. CHOONG, AND H. H. SMITH. 1968. Sorting incense cedar types for drying. Forest Prod. J. 18(4):40–44.

RINK, G. 1987. Heartwood color and quantity variation in a young black walnut progeny test. Wood Fiber Sci. 19:93–100.

ROMANIK, P. B. 1988. High-speed color image analysis for machine vision. Pages 13–17 to 13–31 *in* Robots 12 and Vision '88 Conference Proceedings, vol. 2. Society of Manufacturing Engineers, Dearborn, MI.

SCHOWENGERDT, R. A. 1983. Techniques for image processing and classification in remote sensing. Academic Press, New York.

SHEARER, S. A., AND R. G. HOLMES. 1987. Plant identification using color co-occurrence matrices. Paper No. 87-1534. American Society of Agricultural Engineers, St. Joseph, MI.

SHIBAMOTO, T., Y. INOUE, AND Y. KENJO. 1961a. Studies on water-borne wood preservatives XVII: Color change of treated wood by weathering procedure. J. Jpn. Wood Res. Soc. 6:122–128.

———, ———, AND ———. 1961b. Studies on water-borne wood preservatives XVIII: Color change of wood treated with colorants caused by weathering. J. Jpn. Wood Res. Soc. 6:147–151.

SLAUGHTER, D. C., AND R. C. HARRELL. 1987. Color vision in robotic fruit harvesting. Trans. ASAE 30(4):1144–1148.

SMITH, A. R. 1978. Color gamut transform pairs. Comput. Graphics 12(3):12–19.

SOEST, J. F. 1987. Applications of optical measurements of slope of grain. Pages XII-1 to XII-10 *in* Proceedings, 2nd International Conference on Scanning Technology in Sawmilling. Miller Freeman, San Francisco, CA.

SPROSON, W. N. 1983. Colour science in television and display systems. Adam Hilger Ltd., Bristol, England.

SULLIVAN, J. D. 1967a. Color characterization of wood: Spectrophotometry and wood color. Forest Prod. J. 17(7):43--48.

———. 1967b. Color characterization of wood: Color parameters of individual species. Forest Prod. J. 17(8):25–29.

WANDELL, B. A. 1986. Color rendering of color camera data. COLOR Res. Appl. 11 (Suppl.):S30–S33.

WEBB, D. A., AND J. D. SULLIVAN. 1964. Surface effect of light and water on wood. Forest Prod. J. 14(11):531–534.

WYSZECKI, G., AND W. S. STILES. 1982. Color science: Concepts and methods, quantitative data and formulae, 2nd ed. John Wiley & Sons, New York.

YACHIDA, M., AND S. TSUJI. 1971. Application of color information to visual perception. Pattern Recognition 3:307–323.

ZUECH, N., AND I. MILLER. 1987. Machine vision. The Fairmont Press, Lilburn, GA.