Chapter 2

Literature Review

2.1 Status of Automation Research for Forest Products

Over the years the forest products industry has recognized the importance of automation for yield improvement. While a few automated systems for defect detection have been introduced into the industry, most are limited in applications or have fallen short of expectations. Current automated optimizing cut-up systems in industry are based on single sensor technologies which are usually laser or camera based. The introduction of comprehensive and accurate automated defect detection will lead to improvements in lumber recovery and utilization of lower grades which could lead to drastic restructuring of the furniture and dimension industry. To reach the goal of reliable and comprehensive defect detection, a large amount of research has been conducted on various sensor types. The following is a review of the current research that has been accomplished to reach this goal.

The majority of the research has been conducted on applying different types of sensing technologies to wood feature detection in order to test their abilities and limitations. Considerable work has been done over the last 15 years concerning the ability of various non-destructive evaluation methods to automatically detect features in wood (Szymani and McDonald, 1981; Portala and Ciccotelli, 1992). Methods that have been shown to be promising include optical, ultrasonic, microwave, nuclear magnetic resonance (NMR), and x-ray sensing techniques.

2.1.1 Optical

Optical methods include the use of black and white cameras, color cameras, and spectrometers to measure intensity and color of reflected light. These methods are capable of detecting surface features such as knots, checks, splits, wane, stain, color, and grain pattern.

These methods have been shown to be readily automated (Forrer et al., 1989; Conners et al., 1990; Portala and Ciccotelli, 1992; Rowa, 1992). The importance of optical information for defect detection in wood products is well recognized. More recently, optical scanning techniques using color have been developed to accurately distinguish many surface features in wood (Brunner et al., 1990; Maristany et al., 1994; Lebow et al., 1996). However, optical methods cannot detect internal features, have difficulty in differentiating surface features, and are confused by dirt and handling marks. Examples of current optical scanning methods in the forest products industry include the use of color line scan cameras for automatic optimized crosscutting (Lefevre, 1995), and the use of color information in sorting red oak edge-glued pannel parts for improved panel uniformity (Kline et al., 1996).

2.1.2 Ultrasound

Ultrasonic methods involve beams of high-frequency sound waves that are introduced into the material for the detection of surface and internal defects. Ultrasonic methods include resonance, through transmission, and pulsed echo. It has been shown that ultrasound has the ability to detect splits, checks, shake, pitch, decay, and knots (McDonald, 1980; Lemaster and Dornfeld, 1987; Wilcox, 1988; Portala and Ciccotelli, 1992; Schmoldt et al., 1993). The main limitation of ultrasound is that it requires a coupling of the transducer to the surface of the material scanned. Submersion of the sample in water has proved successful but has limited industrial application. The use of dry-couple transducers has been tested and found as a promising means for using ultrasonic methods in lumber inspection (Lemaster and Dornfeld, 1987; Fuller et al., 1995; Ross et al., 1995).

2.1.3 Microwave

Defect detection using microwave-sensing methods is dependent upon the velocity and attenuation of electromagnetic waves through the medium being tested. Microwaves can be air coupled to wood and have been used to detect density, moisture content, and slope of grain in wood samples (Martin et al., 1987). Microwave methods are capable of being used in real-time automated inspection systems (Choffel et al., 1992). The disadvantages of microwave defect detection is that it is not capable of differentiating between visual defect types, and is not effective in detecting checks and pitch pockets (Szymani and McDonald, 1981).

2.1.4 Nuclear Magnetic Resonance (NMR)

NMR imaging techniques subject a material to a high magnetic field and measures the electromagnetic response of the material to certain radio frequency pulses. NMR has been used for defect detection in wood (Chang et al., 1989; Wang and Chang, 1986). Various defect types have been related to moisture variations in wood using NMR methods. NMR applied to defect detection and moisture content monitoring has been successfully demonstrated where green wood is typically processed (Chang et al., 1991). In dry wood, however, the effectiveness of NMR for defect detection decreases.

2.1.5 X-ray

X-ray scanning methods are based upon the attenuation of a radiation beam passing through a material. X-ray scanning has been used to detect decay, knots, checks, pitch pockets, and honeycomb in wood (Szymani and McDonald, 1981; Portala and Ciccotelli, 1992). Methods that utilize x-ray scanning are capable of producing fast and high quality images of defects in wood (Kenway, 1990; Aune, 1991; Portala and Ciccotelli, 1992). X-ray information has been used successfully in conjunction with other methods for automated defect detection in lumber (Conners et al., 1997). Computed tomography (CT) techniques utilize x-rays and have been used to identify defects in standing poles, logs, and lumber (Davis et al., 1996, Taylor et al., 1984; Wagner et al., 1989; Davis and Wells, 1992; Li, 1996). CT imagery differs from direct two dimensional x-ray scanning in that several sections of the material are scanned and reconstructed for a three dimensional image. Three-dimensional CT imagery is useful in finding the location of features inside logs and lumber. The limitations of x-ray scanning methods are that they cannot find those features that have similar density to clear wood and cannot clearly differentiate between defect types.

The above review lists methods where major research effort has been directed to locate and identify features in wood. Other methods to measure wood features such as capacitance (Steele et al., 1991), laser scanning (Soest et al., 1993), and thermography (Sadoh and Murata, 1993), can be found in addition to those discussed above. Although each of these sensing methods can be used to measure particular characteristics of wood, no single sensor has been shown to reliably measure all of the structural, visual, and aesthetic features that ultimately determine the quality of solid wood products. Also, little information has been presented about the effectiveness of the parameters that can be measured using these sensors, or the effect of variability on the measured wood features selected for each scanning method.

2.1.6 Single-Sensor Scanning Methods

The abilities and limitations of single sensor systems have been presented above. While single sensors have shown the ability to accurately detect certain features, no one sensor can accurately and reliably locate and identify all features relevant to the forest products industry. Currently, most scanning systems used in industry are based on single sensor technology and are thus limited in ability. It has been proposed that a combination of sensors will be required to accurately detect all the features required by the industry (Kline, 1993).

2.1.7 Multi-Sensor Scanning Methods

Portala and Ciccotelli (1990) state that full knowledge of features in wood can be realized when three different types of information are known: 1) external dimensional and shape characteristics, 2) appearance characteristics, and 3) internal characteristics. This statement implies that a combination of the sensing methods discussed in section 2.1 is needed to attain an accurate and complete description of wood. For instance, dimensional characteristics can be measured with a laser-based optical ranging system (Rowa, 1992; Rhemrev et al., 1993), appearance characteristics can be measured with black and white or color cameras, and internal or structural characteristics of wood can be measured using ultrasound, microwave, NMR, or x-ray scanning techniques.

While the combination of sensing technologies appears beneficial, little research has been done to investigate the combination of different sensing methods in one system applied to feature detection in wood. Portala and Ciccotelli (1990 and 1992) investigated the combination of x-ray, microwave, and color sensors. While they demonstrate the ability of each method to detect defects in wood, there is no information presented how the sensor information will be combined or what information is required for accurate segmentation and classification of features. Hagman and Grundberg (1993) have studied the combination of x-ray, microwave, and optical sensor information through multi-variate image analysis methods. While their prediction methods for certain features were useful, they were unable to detect all defect types. Åstrand and Åström (1995) combined three lasers and a camera to collect grayscale, surface roughness, trachied effect, and 3-d profile information for defect detection in wood. Their methods were used to study various methods of segmentation; therefore, no information has been presented about classification abilities. Conners et al. (1995 and 1997) are developing a multi-sensor system that utilizes color, laser, and x-ray information. All three imaging technologies contribute information for the segmentation and classification of wood features.

Commercial applications of multi-sensor technology are limited. Rowa (1992) combined various optical sensing methods including color cameras, black and white cameras and a laser-based ranging system; however, no information has been published concerning the abilities or success of the system. Kenway and Stewart (1990) combined both optical sensors and an x-ray scanner to automatically grade structural lumber; however, again no information has been presented the accuracy of this system. The success of these two systems is questionable considering no information has been presented since the publication of the systems design. Most of these multi-sensor investigations have been performed outside of the US and are proprietary. Very little detailed information has been published to advance the state-of-the-art knowledge about features in wood which affect its utilization in value-added processing.

2.1.8 Economics of a Scanning System in Industry

A major concern with automated defect detection is the cost of such a system. Silvén and Kauppinen (1996) estimated that one grading cycle costs approximately 5% of the value of the material being graded, which for a mill producing 100,000 m^3/year, amounts to approximately \$50,000/year. The same authors estimated that a price for a defect detection system for grading softwood lumber would be approximately 100,000-150,000 dollars. This would allow a grading system to pay for itself in three years. Huber et al. (1992) studied the economics of a laser processing system, which utilized an automated defect detection system. This system, known as “ALPS” was demonstrated to save \$1,210 per day when processing red oak. The current high cost of defect detection systems will be reduced in the future as the cost of computers and related components decrease with the rapidly changing technology.

2.2 Image Processing Methods

The first step in identifying features in an object using machine vision is to collect images representing the object. Various sensors are used to collect information that is converted into digital images representing the object scanned. Once an image or images have been collected using various sensors, certain operations must occur to select and identify the various features contained. These operations are generally broken into low-level and high level operations. Low-level processing consists of image filtering, and intermediate processing to extract boundaries and regions of interest. At this level, regions of interest are formed and measures describing these regions are collected. High-level processing utilizes various methods to classify the regions based on the measures extracted by the low-level processing.

2.2.1 Image Formation

When some form of radiation, which has been reflected from or transmitted through an object registers in a sensor, image formation occurs (Ballard and Brown, 1982). When a sensor collects an image, the image is broken up into discrete pieces of data known as pixels, which are the coordinates within the image of the samples and the brightness value(s) associated with it. Limitations of the digitization process are defined by the resolution of the image (Baxes, 1988). Image resolution consists of spatial and brightness resolution. Spatial resolution is the number of pixels representing the entire image. As spatial resolution increases an image usually gains more detail or looks more natural. Spatial resolution controls the minimum size of feature, which can be detected using algorithms. Higher resolutions, however, increase the amount of data that must be processed which slows image processing, segmentation, and classification. Ideally one would like to obtain the minimum resolution required to accurately detect the smallest feature. Brightness resolution is a measure of how accurately the digital brightness compares to the original brightness of the same location in the image (Baxes, 1988). The number of binary levels that are used to represent the conversion in digitization controls the accuracy of that conversion. Increasing the number of bits representing the brightness levels expands the grayscale so that the image pixels blend together better.

Image spatial and brightness resolution depend on the application. It is important that the correct resolution be determined for the application so that segmentation and classification methods work appropriately. For defect detection in wood, it is generally accepted that one needs twice the spatial resolution of the minimum object to be detected and a minimum of 8 bits of brightness resolution.

2.2.2 Low-level methods

Numerous low-level processing techniques have been developed. Image thresholding and segmentation for feature extraction are the most common. These techniques are discussed in detail in Ohta et al. (1980), Haralick and Shapiro, (1985), Nevatia, (1986), and Sahoo et al. (1988). For wood features, thresholding operations typically occur first to remove the background from the object of interest and then new thresholds are used to segment regions of interest from clear wood areas. The differences between low-level methods are usually based on how thresholds are selected and individual regions formed.

Conners et al. (1983) utilized histogram thresholding based on gray level histograms generated from an image collected by a color line scan camera for segmentation. Difficulties were encountered in separating decay and stain from clear wood areas based on black and white histogram information. Later, intensity histograms from all the color channels were used to improve performance (Cho et al., 1990 and Cho, 1991). The thresholds are selected based on valley and inflection points of the gray level histograms from the entire input image. Once thresholds are found, regions are formed and marked. All pixels having the same gray level value between thresholds of the histogram are marked the same. Connected component labeling is then performed where regions are connected and labeled if unique. Very small regions are eliminated as noise and then properties are extracted from the regions for the high level processing.

Klinkhachorn et al. (1993) also used a method of histogram thresholding based on multiple threshold segmentation of black and white gray-level histograms. Thresholding of the entire image is used to separate background, clearwood, and defect regions. The multiple thresholds are obtained with neural networks trained with known inputs using backpropagation. Kothari and Huber (1991) and Lampinen and Smolander (1996) also use neural network based thresholding in a similar manner.

Forrer et al. (1988 and 1989) developed three segmentation algorithms, which are used to eliminate large amounts of clear wood image data from images. These algorithms used morphological data (shape), color-cluster features, and mean and variance features. Color image features used are the intensity, (R+G+B)/3, and a color measure, (R-B)/2. Parameters (mean and variance) were collected for each feature based on an eight by eight pixel tile rather than the entire image. Butler et al. (1989) later increased the algorithm performance by including two threshold values and nearest neighbor information.

Koivo and Kim (1989) also used a pixel window for segmentation. They used the mean, variance, maximum and minimum values measured from a 64 x 64 pixel window. The features were extracted using a two-dimensional time series model constructed on the basis of gray level computer images.

Polzleitner and Schwingshakl (1990) used 4x4 pixel groups for feature texture measures. First pixels were labeled into one of five classes then pixels are assigned a symbolic class based on a 4x4 pixel measure. Finally syntactic rules are applied to the symbolic classed for connected component labeling.

Srikantrswara (1997) used deviations from the mean and variance of the Normal density function to segment defect regions from clearwood regions. The basis of this method assumes that the majority of the image histogram will contain clearwood and that by imposing an estimated distribution function to the data, all deviations represent defects.

While these methods describe the segmentation of backgrounds from regions of interest, defect regions from clear wood, and the reduction of data for classification, few have been used to compare the performance of the color channel used for the segmentation of features. Information used for segmentation is based on previously used methods for pattern recognition and image processing. None are based on *a-priori* knowledge of how wood features are represented by a particular color channel. It is not discussed if a change in species or resolution will affect the performance of the color channel selected. *A-priori* knowledge of how wood features are represented by color would provide a basis from which to determine the best color channel to use in segmentation.

2.2.3 High-level methods

The objective of high-level processing is to label regions delineated in the low-level processing into various classes, otherwise known as classification. Many techniques have been developed in the general field of pattern recognition. In the detection of wood features the main differences between classification methods are the parameters used for classification, (pixel based or region based) and the processing algorithm used (knowledge based or neural networks).

Conners et al. (1983) and Cho et al.(1990) used a knowledge-based approach where initial confidence vectors are computed for all regions. Knowledge sources for each defect type are then used to classify the region. Knowledge sources include calculated confidence vectors, defect verification based on spatial contextual discrepancy, and region label verification. This classification is based on spectral (RGB color), shape (elongatedness, perimeter, and compactness), and location knowledge describing the regions.

Klinkhachorn et al. (1985 and 1993) used a neural network method for classifying defects into one of five categories based on region shape and location. Schmoldt et al. (1997) developed a multilayer feed-forward network based on a 3 x 3 x 3 pixel neighborhood for pixel-wise classification of wood features in CT images. The use of neural networks for classification is also used by Lampinen and Smolander (1996) and has been suggested by (Butler et al., 1993).

A discriminant analysis method is used by Koivo and Kim, (1989). They use a tree classification method based on the gray level mean of features and other statistical parameters calculated from low-level processing methods. They were able to classify red oak boards into nine classes with 92% accuracy.

None of the high-level processing methods described validated the abilities or discussed the selection criteria of the extracted measures used, nor was there discussion of how these measures vary for the individual features or for species. The proper selection of extracted measures (parameters) should increase the accuracy of classification algorithms and reduce the amount of data that must be analyzed.

2.3 Defects in Wood

The natural growth process and environmental influence can lead to features in wood that are undesirable for certain applications and are known as defects. Defects in wood affect the visual appearance and structural properties of wood. The type of defect is based on whether growth, environmental conditions, machining, handling, or processing causes it. The definition and acceptability of defect types can vary between industries. Lumber is usually sold based on its grade. Lumber grade is assigned based on the location, type, and size of defects or defect free areas. Grading agencies exist for both hardwood and softwood lumber and provide the standards by which grades are assigned. These agencies have set standards for the definition of defect types that are accepted throughout the forest products industry. An example of defect definitions as defined by the National Hardwood Lumber Association Grading Rules (NHLA, 1994) in Table 2.1.

Segmenting actual defects into defined classes can be a difficult task. Often definitions are not very detailed and are open ended. Also, defects are often labeled differently by a particular user or user group. A bark pocket may be considered a bark inclusion or an area of where a loose knot has fallen out. Knot definitions are the most difficult to interpret. For example, a knot is entirely intergrown on one face and contains extensive decay on the other.

Knots are formed when a branch base is embedded in wood of the main stem of a growing tree. As the tree grows, successive increments of wood are added around the branch. Intergrown knots are those were the branch remained alive and became intergrown with the main stem (Bodig and Jayne, 1982). A loose or encased knot occurs when a branch dies and the growth increments of the main stem continue to grow around the branch. Often the dead branch has broken and becomes embedded in new growth tissue (Panshin and Zeeuw, 1980).

Knots are considered sound if they contain no indication of decay and are as hard as the surrounding wood. The NHLA (1994) defines sound knots as “ a knot that is solid across its face, as hard as the surrounding wood, and shows no indication of decay”. Unsound knots are considered knots that contain decay, but only within the knot region. The shape of knots is dependent on how the lumber was cut from a log. Flatsawn lumber tends to contain round knots and quatersawn lumber contains more spike knots.

Table 2.1. Definition of defects based on NHLA grading rules (NHLA, 1996).

Defect	Definition
Decay	The decomposition of wood by fungi.
Bark Pocket	A bark-filled blemish in the board.
Sound Knot	A knot that is solid across its face, as hard as the surrounding wood, and shows no sign of decay.
Stain	In hardwoods the word "stain" is used to describe the initial evidences of decay.
Wane	Bark or lack of wood.
Mineral Streak	An olive to greenish-black or brown discoloration of undetermined cause in hardwoods.
Incipient Decay	The early stages of decay that has not proceeded far enough to soften or otherwise perceptibly impair the hardness of the wood. It is usually accompanied by a slight discoloration or bleaching of the wood.
Pin Knot	A knot that does not exceed 1/8" in diameter.

Bark pockets are considered to be any bark filled blemish in the board (NHLA, 1994). Bark pockets are small patches of bark that are embedded in the wood. They are usually caused by some type of damage to the tree where over time the damaged are is covered by new tree growth and thus covering the bark area. Common bark pocket causing injuries include insect damage and bird pecks.

The NHLA (1996) defines stain as the initial evidences of decay. Stain in wood can occur on the surface, or within the wood. Stains can appear as a variety of colors such as blue, black, and brown. Staining in wood does not significantly impact the strength properties of wood, but does lower its commercial value. Stains are usually classified as fungi-based or chemical-based. Fungi-based stains grow on the cell wall and within the cell lumens, but do not deteriorate the cell wall of wood (Haygreen and Bowyer, 1996). Staining fungi live on sugars and starches found within the cell lumen. Staining usually occurs in recently sawn material where the surface is still wet and the sugar-starch content is still high. Most staining can be eliminated by quickly drying the material. Chemical stains are caused by enzymatic oxidation reactions of water-soluble chemicals in the wood (Lamb, 1997).

2.3.1 Occurrence of Defects in Hardwood Lumber

The location of defects in lumber varies with the location of the defect in the tree as it grows and how the log was manufactured into lumber. Several studies have been conducted to determine the distribution of defects in red oak lumber. Wiedenbeck et al. (1995) determined from a data bank of 1,578 red oak boards that wane, unsound knots and bark pockets are the three major defects in red oak lumber. Harding et al. (1993) found in red oak lumber that stain, wane, and decay are major defects with regard to defect size per occurrence. Buehemann (1997) found that unsound knots, bark pockets, and wane have the largest number of occurrences in red oak; however, wane, unsound knots, and splits contained the largest surface area. Widoyoko (1996) determined wane and unsound knots to contain the largest surface area. The results of Buehemann and Widoyoko are presented in Table 2.2.

2.3.2 Defect Parameters that can be Measured

Defects are commonly observed in wood by visual examination; however, other differences occur between clearwood and defects, which can be used to differentiate the two. Most of the sensor methods described in section 2.1 require either visual (color, intensity, shape), or density differences between detected features. It has been demonstrated that wood features can be identified based on these measures. This research will focus on the relationship of these measures for particular features and their importance in post-segmentation feature differentiation.

2.4 Color

Color can be defined as an "attribute of visual perception that can be described by color names such as white, gray, black, yellow, orange, brown, red, green, blue, purple, etc., or by combinations of such names" (Grum and Bartleson, 1980). The color of a material is determined by the spectral makeup of light reflected from its surface. Color measurement standards have been set by an international entity called the Commission Internationale del'Eclairge (CIE). The CIE selected three primary monochromatic (single-frequency) red, green, and blue to create a color coordinate system or "color space". The CIE color measurement method is based upon the idea that it is possible to match any arbitrary color by superimposing appropriate amounts of three primary colors. This idea is known as the trichromatic theory and is represented in equation 1,

$$(C) = A1(P1) + A2(P2) + A3(P3) \qquad \textbf{Equation 2.1}$$

where (C) is an arbitrary color, the values *A1*, *A2*, and *A*3 give the relative proportions of the primary colors (*P1*), (*P2*), and (*P3*).

Table 2.2. Frequency of defects in No1. and No.2 Common red oak as found by Widoyoko, (1996) and Buehemann (1997).

Buehemann							***Widoyoko***	
	1 Common			***2A Common***			***1 and 2 Common***	
Defect type	total no. of defects	total defect area (sq.in)	% of total defect area	total no. of defects	total defect area (sq.in)	% of total defect area	Defect type	total defect area (sq.in)
unsound knot	2228	10842	20.1	3851	13984	21.6		
bark pocket	1556	5907	11.0	2610	8092	12.5	Void	7592
wane	1479	23851	44.3	1375	22749	35.2	Wane	1909
split	1235	5634	10.5	1332	5340	8.3	Unsound Kn	1223
grub hole	196	311	0.6	373	535	0.8	Sap Stain	963
pin hole	208	102	0.2	328	190	0.3	Mineral Stre	794
pith rel. tear/split	93	1334	2.5	367	2927	4.5	Split	442
pith	109	943	1.8	302	2705	4.2	Bark Pocket	354
decay	142	1886	3.5	182	3867	6.0	Machining D	105
shot hole	116	20	0.0	182	120	0.2	Hole	82
sound knot	64	130	0.2	127	247	0.4	Sound Knot	75
shake	50	2045	3.8	96	2236	3.5		
bud trace	40	11	0.0	131	27	0.0		
stain/mineral	45	864	1.6	97	1617	2.5		
incident decay/objectionable	2	3	0.0	5	48	0.1		
total	**7563**	**53883**	**100.0**	**11358**	**64684**	**100.0**		**13539**

Tristimulus values are defined as the number of each primary source value that can be combined to create an unknown color (MacAdam, 1981). They can be obtained from the spectral curve of a color. Tristimulus values of color stimulus are represented by *X*, *Y*, *Z*, and represent the relative amounts of x, y, z curves needed to match arbitrary colors. Tristimulus values can be expressed as dimensionless ratios called chromaticity coordinates. Chromaticity is the evaluation of color quality, and is defined by its chromaticity coordinates or by its dominant wavelength and purity. Chromaticity coordinates *x*, *y*, *z* are derived from the Tristimulus values *X*, *Y*, *Z* using the following equation:

$$\begin{aligned} x &= X/(X+Y+Z) \\ y &= Y/(X+Y+Z) \\ z &= Z/(X+Y+Z) \end{aligned} \qquad \textbf{Equation 2.2}$$

Because the relationship $x + y + z = 1$, only two of the chromaticity coordinates are needed for a chromaticity specification. Chromaticity can be graphically represented by plotting the trichromatic coefficients, *x* and *y*. These two methods are dominant wavelength and purity. Purity is defined as "a measure of the proportions of the amounts of a spectral stimulus and a specified neutral stimulus that, when addatively mixed, provides a color match to a given stimulus in question" (Grum and Bartleson, 1980).

Luminance is used to indicate the intensity of reflected light and is synonymous with brightness. It is measured quantitatively in lumens per square foot. Luminance, dominant wavelength, and purity can be used to create color solid or color space.

2.4.1 Color and the Illuminant

One property that contributes to the color of an object is the illuminant. The CIE developed several "standard illuminants" that have specific theoretical spectral power distribution. Source A approximates normal incandescent indoor light, source B approximates the visible range of daylight, and source C approximates overcast daylight (Brunner et al., 1990). The color reflected from the surface of a material is dependent on the wavelength of the illuminating source; therefore, the illuminant in published results must be stated for color measurement to be meaningful. Much of the early work in color analysis of wood does not include this information and is thus of limited use (Sullivan, 1967).

2.4.2 Color Spaces

Due to the limited understanding of the human visual system, many methods of describing or modeling of color exist. The graphical representation of the modeling approach is considered a color space. One such model is the RGB color model as seen in Figure 2.1. This model uses three primary colors (red, green, and blue) to describe a color within a color range and is considered the simplest color model (Weeks, 1996). The RGB model describes a color image as a set of three independent grayscale images having 256 gray levels. The main disadvantage of the RGB color model is that it produces color components that do not closely follow those of the human visual system.

Other common color models attempt to describe colors in terms of hue and saturation. One common such model is the HSI model that describes colors in terms of hue, saturation, and intensity. Hue is the wavelength of a color, intensity is the brightness of a color, and saturation is the percentage of white in the color. Many other color models exist and are extensively described in literature (Weeks, 1996).

2.4.3 Wood and Color

Various color models have been used to describe the color of wood and are described in detail by Brunner et al. (1990). However, the most common color model used to classify defects in wood is the RGB colorspace. When developing defect detection methods for Douglas-fir, Brunner et al. (1992) concluded that that there is no advantage to converting RGB data into another color space when classifying defects on a pixel by pixel basis. Maristany et al. (1991) concluded that for neighborhood based evaluation of defects in Douglas-fir veneer, CIELAB and CIELUV outperformed other color spaces including RGB. They both suggest that the color space used in any application should be experimentally

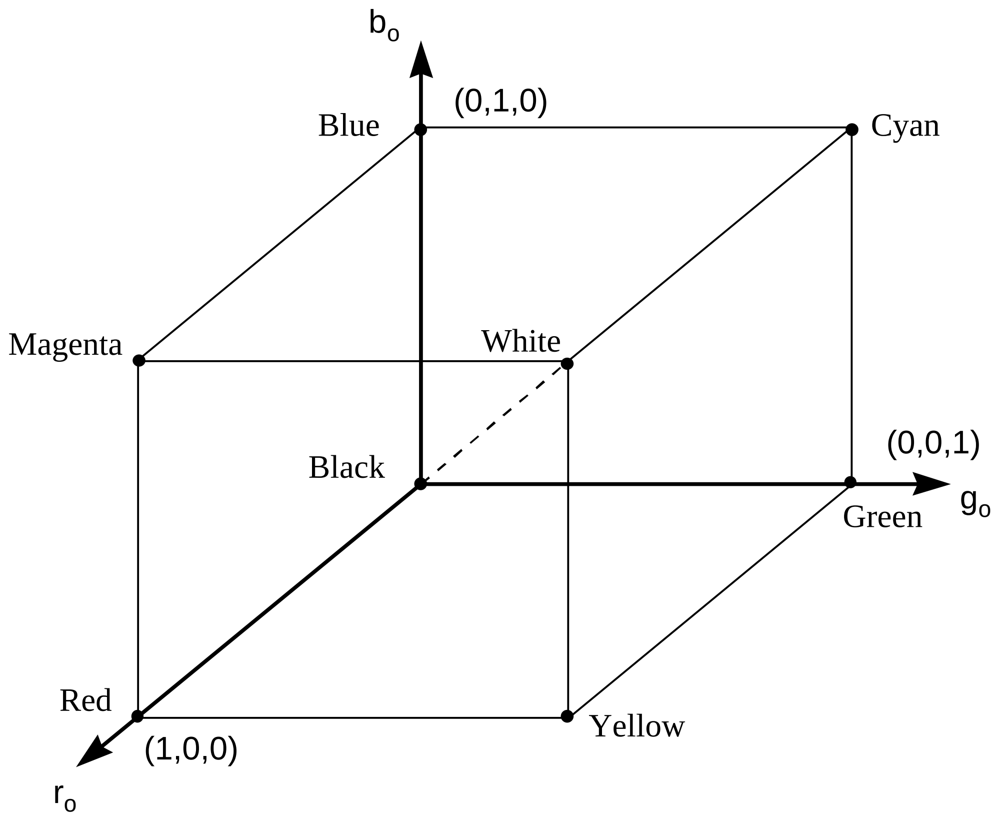

Figure 2.1. Graphical representation of the RGB colorspace.

determined. Adel et al. (1993) determined that out of RGB, HSI, CIELAB, CIELUV, and Ohta's Coordinates, that intensity and a chrominance component such as u* or a* work best for the classification of four defect types in Okoume veneer. Conners et al. (1985) determined that for hardwood species that the red, green and black and white channels provided the best combination for defect classification. Maristany et al. (1991) state that for Douglas-fir only two components of a color space are required for adequate defect classification. Adel et al. (1993) experimented with many color spaces for defect detection in veneer and determined that intensity and one chrominance component were all that were needed for sufficient wood feature classification. While it has been suggested that an intensity and a chrominace component are required for the classification of wood features, the color parameters that best separate features from one has not been determined.

Much work has been done studying the color of clear wood using color spectrometers. The majority of this work was done to determine if there are color parameter differences between the heartwood of various species and how environmental factors effect these parameters. The parameters most commonly used are dominant wavelength, purity, and brightness. It has been shown that there exists color variation both within and between the clearwood of various species.

2.4.3.1 Variation between Species

Between species variation in dominant wavelength, purity, and brightness was studied by Beckwith (1979) for ash, elm, hickory, red oak, white oak, and yellow-poplar. His measurements were taken from wood surfaces without defects, but included both sapwood and heartwood. The inclusion of sapwood increased the variability of his measurements; however, he was able to demonstrate that chromaticity coordinates can be used to separate anatomically similar wood groups. Beckwith also found that when comparing several species there was a very small variation in dominant wavelength and purity for both within and between species-groups, yet luminosity was extremely variable for both groups. These results indicate that color information can be used to differentiate between species.

2.4.3.2 Variation within Species

While the variation in color measures can be used to differentiate between different species, color variation also occurs within species. Color variation within species exists between heartwood and sapwood, growth sites, and the direction of measurement. An example of heartwood and sapwood differences was demonstrated by Phelps et al. (1983) who determined that, black walnut sapwood color parameters are 15% higher in luminance, 2nm lower in dominant wavelength, and 3% higher in purity than those in heartwood.

Growth environment also has been shown to effect the color of wood. In black walnut, darker heartwood was associated with slower growth Rink (1987). Sullivan (1967) discovered that for yellow-poplar and black cherry, significant differences did appear in luminance, dominant wavelength, and purity between groups supplied from different geographic sites. While growth site does effect the color measures of wood, the within-tree and between tree variations in luminance are greater than those between-site variations for those trees studied by Phelps et al. (1983).

Rink (1987) found that luminance was positively correlated to both height and tree diameter. Beckwith (1979) found that there was no significant difference between radial and tangential values for color parameters; however, Maristany et al. (1994) determined that brightness is higher along the grain than it is across the grain.

These results show that certain growth and environmental affects can be distinguished from one another using color information and that variability in color measures within species can be attributed to growth and environmental effects.

2.4.3.3 Color Parameters in Wood

It has been noted that certain color parameters provide more information than others for studying differences in wood. By selecting those parameters that are shown to have feature differences, better defect detection algorithms can be developed. Beckwith (1974) used spectrometer measurements of 21 species at 5% moisture content, and heartwood only to indicate that for both within and between species groups dominant wavelength and purity varied little, but that luminosity was extremely variable. Phelps et al. (1983) also found that luminance was more important than dominant wavelength or purity in describing color differences between-site, between-tree and for within tree differences in wood color.

Stoke et al. (1995) evaluated planed white oak dimension stock based on L*, the psychometric lightness. They found little variation in lightness within each board, but that enough variation existed between boards that color classes could be used to differentiate boards. Phelps et al. (1994) stated that it is possible to sort edge-glued furniture stock of white oak lumber based on L* alone. Based on these results, it can be concluded that the luminance component will be important in differentiating between wood feature types.

2.4.4 Factors Affecting Wood Color

There are several factors that effect the color of wood, which can be controlled. These include moisture content, drying temperature, surface roughness, and exposure to ultraviolet light. These factors add variability to measurements of feature parameters and need to be considered.

2.4.4.1 Moisture Content and Temperature

Sullivan (1967) investigated the effect of moisture content on brightness, color purity, and dominant wavelength in yellow-poplar. He concluded that regardless of surface orientation, brightness increased, color purity decreased, and dominant wavelength remained the same after drying. The variances of these parameters significantly decreased at the lower moisture content. He attributed these results to the presence of water above fiber saturation. The effects of color changes in wood due to moisture content below fiber saturation point have not been closely studied (Brunner et al., 1990).

Kollman and Malquist (1952) concluded that temperature has a darkening effect on wood in the first five to ten hours of exposure, but that high moisture content has a greater effect on darkening.

2.4.4.2 Exposure to ultraviolet light

Ultraviolet light tends to yellow or darken the surface of most commercial timbers with the greatest change occurring in the fist thirteen days of exposure after which time bleaching occurs (Sullivan, 1966). Sullivan (1966) reviewed in detail the work done on the effect of ultraviolet light on the color of wood. These results indicate that moisture content, temperature, and ultraviolet light can effect the color properties of wood; hence, these factors will need to be controlled in the collection of color parameters.

2.4.5 Defects and Color

While much research has been conducted on the color differences between species, sapwood and heartwood of the same species, and earlywood and latewood the color differences between surface features of the same species is more important for imaging purposes (Brunner et al. 1990).

Boardman et al.(1992) used a colorimeter to measure the L* a* b* color properties of heartwood, sapwood, and common defects in black walnut veneer. While able to differentiate defects from clear wood, the methods employed could not detect the entire defect area or clearly differentiate between defect types.

Conners et al. (1985) measured the color properties of several defects in maple using RGB color. Using a Bayesian classification scheme the investigators were able to demonstrate that color information is important for defect detection in wood. Butler et. al (1993) also used RGB data for detecting defects in Douglas-fir veneer. Their method used (R+G+B)/3 for intensity and R-B/2 for color measure. While both investigators demonstrated the usefulness of color information, classification errors still occurred and were unexplained. No information was presented as to how color parameters vary for different defect types.

Sadoh and Takita (1992) studied the ability of color information to separate knots from clearwood in six softwood species. Color information proved a good way to separate the two features for all but the karamatsu species. In this species, the color of knots was not significantly separable from that of clearwood. Sugimori (1993) used color information to recognize the sloped grain around knots.

Silvén and Kauppinen (1996) used color features in the RGB color space to identify defects in spruce. Their selected color features outperformed texture and histogram shape measures for spruce. The color features used were percentile points of the histograms of each of the RGB color channel intensities. No details were presented for the texture and histogram shape measures used for comparisons.

Marszalec and Pietikainen (1993) examined the color homogeneity of spectral reflectance of pine wood and defects. They concluded that while most defects are separable from clearwood, a difficulty exists in differentiating between defect types when the defects have very complex spectral reflectances.

Maristany et al. (1992) studied the use of dicromatic reflection methods to improve the classification of wood features. Body reflectors and total reflectance used for classification were compared. It was found that there was no advantage in determining the body reflection.

Lebow et al. (1996) used spectral reflectance measured from a spectrometer to classify Douglas-fir surface features in veneer. The spectral reflectance curve for each feature type was modeled and classified using principle component analysis. While the method could not be applied to commercial applications, a theoretical method was proposed based on this work.

Srikathyani (1997) used color information to segment defects from clearwood in southern pine, yellow-poplar, and red oak. The use of color in defect segmentation using histogram information was shown to outperform that of black and white segmentation. These results however are limited to a few samples.

In the literature reviewed on the color information of wood features, no detailed information has been presented on the color differences of individual wood features. Most literature is based on the selection of color spaces for the classification of all defects rather than how each feature is represented in the color space. Performance of a color space is based on the classification accuracy of all feature types. By better understanding how each feature is represented by color parameters, improved classification performance could be achieved.

2.5 Density

Density is defined as the mass of an object per unit of volume. It is frequently used to describe an object, and is often related to its structural properties. Differences in density have long been used in the nondestructive evaluation of objects. One common method of evaluating density differences within a material is through the use of x-ray attenuation.

2.5.1 Density and X-ray attenuation

The attenuation of radiation through an object to detect features based on density differences is known as radiography. Two types of radiation common in radiographic inspection include x-rays and γ-rays. X-rays have relatively short wavelength and high energies. The exposure of x-rays is measured in roentgens (R), where 1R is the amount of radiation exposure that produces one electrostatic unit (3.33564×10^{-10}) of charge from 1.293mg of air (ASTM Handbook, 1989). X-rays are produced when fast moving electrons collide with a target material. The quality of x-ray images is determined by contrast, resolution, and radiographic sensitivity. Radiographic sensitivity, or definition, is the smallest sized detail that can be seen in an image. This sensitivity is related to, but is not the same as spatial resolution and contrast resolution.

The attenuation of radiation is governed by the thickness of the material (density) in which it passes and can be determined by

$$I = I_0 \exp(-mt) \qquad \textbf{Equation 2.3}$$

where I is the intensity of the emergent radiation, I_0 is the intensity, t is the thickness of the material, and m is the linear absorption coefficient. The absorption coefficient is often expressed as the mass absorption coefficient as defined by

$$\text{mass absorption coefficient} = {}^{m}\!/_{r} \qquad \textbf{Equation 2.4}$$

where ρ is the density of the material.

Whenever radiation strikes an object, secondary radiation is scattered in all directions. This scattering of radiation can reduce image quality. There are many complex reactions and geometry associations that must be addressed when using real time x-ray imaging. An in-depth review of these is given in ASTM (1992).

2.5.2 X-rays and Wood Density

Much research has been conducted in the field of densitometry, where x-rays are used to measure the density variations within and between growth rings (Polge, 1978; Echols, 1973; Hoge et al., 1974). X-rays have also been demonstrated to be useful in the detection of defects; however, most of these studies are concerned with demonstrating the ability of radiographic methods to detect defect areas rather than a means to automate defect detection.

Gardner et al. (1980) demonstrated that internal defects in wood poles can be reliably detected using techniques requiring film. X-ray fluoroscopy has been used to detect voids as small as one-half inch, decay, and small metal wire in green softwood lumber (Miller, 1964). Computed tomography, a time consuming and expensive process, has been shown to be able to detect defects in logs accurately (Taylor, 1984; Guddanti and Chang, 1995, and Schmodlt et al., 1997).

Clauson and Wilson, (1991) demonstrated that it was possible to use video scanning to determine the density of growth increment cores. The investigators compared video and x-ray densitometer data for growth ring width, location of earlywood and latewood, and for density distribution of small Douglas-fir beams. The results showed that there were no significant differences between the two methods.

Portala and Ciccotelli (1992) demonstrated the abilities of automatic defect detection using x-rays. They demonstrated the ability to evaluate the density of a wood sample by considering the thickness of the material and its attenuation factor relative to its mass.

These results demonstrate the ability of x-rays to be used to locate features in wood that contain density differences and further support the use of x-rays in defect detection methods.

2.5.3 Factors Affecting Wood Density

Wood density has a great variability both within and between trees due to location of wood in the tree, location of species within the range, site condition and genetic source (Haygreen and Bowyer, 1996). Density in wood is usually expressed as specific gravity, which is the ratio of density of a material to the density of water. The average variation of clearwood density within a species in North America is approximately 10% Haygreen and Bowyer, 1996).

2.5.4 Defects and Density

While the importance of color in the segmentation and classification of wood features is well documented (Marszalec and Pietikainen, 1993; Conners et al., 1985; and Brunner et al., 1990) there is a need another feature measure which can be used to improve classification. Lampinen and Smolander (1996) agree that color information is required for classification of many wood features, especially where shape measure will not apply, yet they feel that additional regional information is required for the correct classification of all defect types.

X-ray attenuation can be used to detect all defect types that display density differences. This allows for the detection of internal defects as well as surface defects. A combination of both color and density information not only allows both surface and internal defects to be detected, but can increase classification accuracies by increasing the amount of information which can positively identify defect types. The usefulness of x-ray attenuation for wood feature differentiation has been discussed by Conners et al., (1990) and Portala and Ciccotelli (1992).

2.6 Object Shape Measures

Several methods exist to measure the shape of an object for defect recognition. The most common include area, eccentricity, Euler number, compactness, and the slope density function (Ballard and Brown, 1982). Aspect, or eccentricity, is the ratio of maximum cord A to maximum cord B perpendicular to A as shown in Figure 2.2.

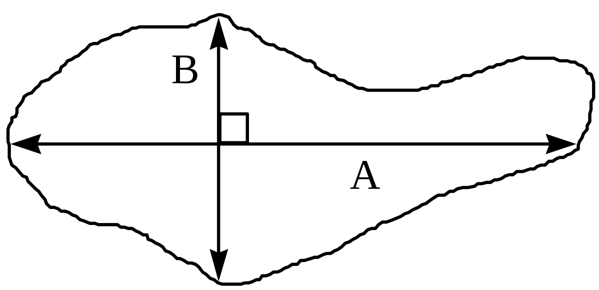

Figure 2.2. Eccentricity measure defined A/B.

The Euler number, *E*, is used to describe the connectedness of a region and is calculated by

$$E = (C)-(H) \qquad \textbf{Equation 2.5}$$

where *C* is the number of connected regions, and *H* is the number of holes. Compactness is the ratio of perimeter squared to the area of the object and is calculated using

$$\text{Compactness} = {r^{2}}\big/{a} \qquad \textbf{Equation 2.6}$$

where ρ is the perimeter, and *a* is the area. Roundness of an object is defined as

$$\text{Roundness} = \frac{r^{2}}{(4\times r\times a)} \qquad \textbf{Equation 2.7}$$

where ρ is the perimeter, and *a* is the area.

Several investigators have applied the use of shape measures in the detection of wood defects. Forrer et al. (1988) used length and direction measures for image segmentation. Pölzleitner and Schwingahkl, (1990) used elliptical approximation, elongation, and orientation in the classification of wood defects. Cho et al. (1991) used elongatedness, perimeter, and compactness information for the classification of wood defects. Kauppinen and Silven (1995) used shape measures for the classification of knots and state that shape measures increase the accuracy of color classification algorithms by 5%.

Lampinen and Smolander (1996) stated that while shape information is of great importance for defect classification of wood features, shape information alone is not sufficient. These results help to show that shape measures can contribute to the differentiation of wood feature types, but when used alone they are not sufficient.

2.7 Concluding Remarks

The scanning methods discussed have been shown to be able to detect wood features, but no one method proves adequate for all feature types. By combining sensors, a more reliable defect detection system can be developed. Sensors locate and identify wood features based on color, shape, and density differences that naturally occur. These differences are recognized to exist and be useful classifying features; however, it is not understood how individual features are represented by these measures. By gaining knowledge of how wood features are represented by color, shape, and density differences, it can be determined what parameters are important for classification, thus improving defect detection methods.