IAWA Journal, Vol. 32 (2), 2011: 233–250

A BRIEF REVIEW OF MACHINE VISION IN THE CONTEXT OF AUTOMATED WOOD IDENTIFICATION SYSTEMS

John C. Hermanson[1,2] and **Alex C. Wiedenhoeft**[1,2]

SUMMARY

The need for accurate and rapid field identification of wood to combat illegal logging around the world is outpacing the ability to train personnel to perform this task. Despite increased interest in non-anatomical (DNA, spectroscopic, chemical) methods for wood identification, anatomical characteristics are the least labile data that can be extracted from solid wood products, independent of wood processing (sawing, drying, microbial attack). Wood identification using anatomical characteristics is thus still a viable approach to the wood identification problem, and automating the process of identification is an attractive and plausible solution. The undisputed increase of computer power and image acquisition capabilities, along with the decrease of associated costs, suggests that it is time to move toward non-human based automated wood identification systems and methods. This article briefly reviews the foundations of image acquisition and processing in machine vision systems and overviews how machine vision can be applied to wood identification.

Key words: Machine vision, wood identification, illegal logging, endangered species, pattern recognition.

MEETING DEMAND FOR WOOD IDENTIFICATION

Of the global timber harvest, it is estimated that as much as 10% by timber volume is in trade illegally (Seneca Creek Associates 2004). Although wood identification is only one of the tools necessary to combat illegal logging (Johnson & Laestadius 2011), it is typically one of the first applied. A field inspector might determine that a shipment of wood may be illegal based upon on *in situ* visual inspection. This first stage of forensic identification is a critical step in law enforcement, and the closer in time and space to the forest we can move the identification component, the better the forest will be protected from illegal timber harvest.

Currently, we rely on human inspectors to examine wood shipments, and compare what is written on a manifest or bill of lading to the wood in the shipment. In an ideal world, all inspectors would be trained in basic wood identification, and would be fully competent to make such determinations. Comparatively few inspectors have the training to definitively distinguish hardwoods from softwoods, and of those, it is likely that over time they will be promoted, lose interest, forget, retire, or otherwise stop performing

1) Forest Products Laboratory, One Gifford Pinchot Drive, Madison, WI 53726-2398, U.S.A.
2) Stump öch Boles, 800 Langdon St., Madison, WI 53706, U.S.A.

identifications, and further will fail to pass on their knowledge. Because anatomical identification is time-consuming and requires training (Miller *et al.* 2002; Koch *et al.* 2011; Sarmiento *et al.* 2011), efforts have been made to identify wood using non-anatomical characteristics (near infrared spectroscopy, Braga *et al.* 2011; identification of species-specific extractives, Kite *et al.* 2010; DNA identification of CITES taxa, Hanssen *et al.* 2011). One aspect unifying these techniques is the comparative lack of training necessary for a field agent to collect a specimen suitable for analysis.

Although appealing for their comparative simplicity, non-anatomical data are labile or expensive to collect and may not always be present in a given specimen. For example, the sapwood of *Dalbergia nigra* is still *D. nigra* (Gasson *et al.* 2010), even if extractives (as are detected in the Kite *et al.* 2010 method) are absent. Conversely, *D. nigra* heartwood is still *D. nigra*, even if DNA is not extractable in sufficient quality or quantity to make an identification. Thus, an argument can be made that barring total destruction of a solid wood specimen (e.g. massive wood decay, burning to ash, *etc.*), the most reliable set of data will be the anatomical data set, despite its limitations in providing a species level identification (Abe *et al.* 2011; Braga *et al.* 2011; Gasson 2011; Hanssen *et al.* 2011; Lowe & Cross 2011).

As has been done in factories and other industrial contexts, medical diagnostics (*e.g.* Arimura *et al.* 2009), and other areas of biology (Cox *et al.* 1998 for fungal mycelia) we suggest using machines to do more efficiently what is usually done by humans, or to accomplish what is left unachieved as a result of human failings. Specifically, we assert that the time is upon us to design and implement machine vision systems for field wood identification; machines do not forget, lose interest, get promoted, or retire. They do not grow tired of processing the same information, and when data are properly managed, have the capacity to learn and store more information than any human could learn or store over a lifetime of wood identification. Ifju (1983) envisioned a future in which this would be possible, using instrumentation and stereology to collect a sampling of quantitative data to characterize woods. Machine vision technologies are now mature enough to be adapted to hand-held units to perform routine field wood identification. The fundaments of this approach are reviewed and discussed here.

In the broadest conceptual sense, machine vision systems for wood identification consist of a light source, the wood, a sensor that collects the reflected or transmitted light, a converter that turns the light into digital signal, a processor that manipulates that signal, a reference data set against which the signal is evaluated, and a software-encapsulated decision process that produces a result. This is fundamentally the same for traditional anatomical wood identification: there is a specimen and its environment, a sensor collecting a signal (human senses), a processor manipulating the signal (a human interpreting patterns and working with reference tools [xylaria, InsideWood, identification keys]), and a decision process (again, human-mediated) that produces a result. Thus machine vision systems are fundamentally analogous to human identification systems. An advantage of machine vision systems, however, is that the various components, because they are engineered by humans, are more fully understood than the analogous processes taking place in the human mind.

MACHINE VISION: OVERVIEW FOR WOOD ANATOMISTS

The core goal of a machine vision system, especially in the context of wood identification, is to achieve a quantifiable, repeatable, and reliable pattern recognition result. For people, pattern recognition is so routine a part of the human experience we seldom recognize that we are continuously engaged in the process. Only when attempting to acquire new skills, such as learning to identify wood, do we consiously experience the workings of our own systems of pattern recognition.

The subconscious or automatic functioning of human pattern recognition systems is something advertisers and businesses rely on, in the context of branding and logos. For example, the average American sees 16,000 advertisements, logos, and labels in a day (Khalsa & Stauth 1997), and recognizes many of them without conscious thought or intent. Pattern recognition in humans is not limited to sight; we can recognize patterns with all of our senses, but for the purposes of this article, sight is the most important sense.

Recognizing patterns is considered both an innate skill and one that is learned (Sutherland 1968). From infancy, humans are able to process vast amounts of input (sights, sounds, smells, physical sensations) and group them and structure them in a way that extracts pattern from the apparent chaos. It is this distillation of meaningful information from an abundance of data that is a core aspect of machine vision and pattern recognition, and this is something humans have begun to offload to computers. When a print document is scanned into an electronic file, optical character recognition converts the representations of test as images into digital text in a file. We likewise employ machine vision for quality control on production lines and in fingerpring recognition. sawmills are using machine vision systems for grading of lumber (Conners *et al.* 1992; Srikanteswara 1997; Pham & Alcock 1999; Bhandarkar *et al.* 1999, 2002; Kline et al. 2001, 2003; Fuentealba et al. 2004). Surprisingly, only one group is publishing on using machine vision for wood identification (Khalid *et al.* 2008; Bremananth et al. 2009; Yuspf *et al.* 2010), although aspects of machine vision are being employed in the detection of certain anatomical features (Pan & Kudo 2010).

Machine vision thus combines optics, electrical engineering, and software engineering to make decisions on information obtained via light captured by a sensor. Numerous tomes have been published on machine vision (see Hornberg 2006) and pattern classification (see Duda et al. 2000) as scientific and theoretical fields in their own right. The objective of this manuscript is to provide a brief technical overview of machine vision suitable for practicing wood anatomists interested in this technology for wood identification. We divide machine vision into two broad categories for review: signal acquisition, and signal processing.

COMPONENTS OF A MACHINE VISION SYSTEM

Because a machine vision system is a real-world assemblage of components (Fig. 1), each with its own function or rold, it is useful to examine each component in turn. The signal acquisition system for machine vision consists of a light source, and object of interest, an objective lens, a sensor, a signal amplifier, and a digital converter. The sig-

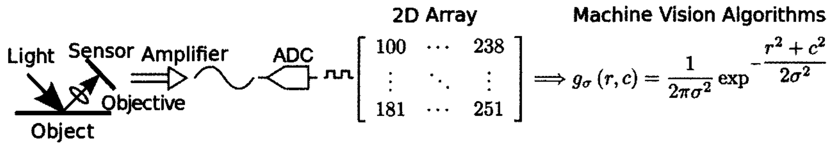


Figure 1. Schematic of the components of a machine vision system. The physical components of the system begin on the left with incoming light, the object of interest, an objective, and further include the sensor, amplifier, and analog to digital converter (ADC). The output of the ADC is an array of numbers (2D Array) representing the object, and this array is fed into the machine vision algorithms (a smoothing function is shown), which are processed by one or more computers (not illustrated). The outputs of these algorithms are decisions based on the information gathered and extracted.

nal acquisition system may perform certain initial preprocessing tasks (formatting the data into an image file format (tiff, jpeg, etc.), and then the digital output of the signal acquisition system is fed into the main signal processing portion of the machine vision system, which is a combination of computer hardware and software for processing the data, as well as some form of interface for a human user, if needed.

Light

The first process-controlling step in any vision system is lighting, and it is the step over which we can exert the greatest direct control. Stating the obvious, if initial information is absent, then no algorithm will be able to detect a pattern in it. No prescribed set of rules exists for configuring lighting because the ways light interacts with an object of inspection varies according to numerous optical (color, reflection, transmission), mechanical (surface geometry and imperfections), and environmental (moisture) factors. Experimentation is required to determine the appropriate lighting regime for any given application. When examining a wood specimen with a hand lens, we often will rotate or move towards or away from the light to highlight the features we are trying to discern. A functional machine vision system must similarly optimize the lighting to maximize the ability to collect meaningful signals.

Object of interest

The second step in the process is the interaction of the light with the wood specimen itself. Because our emphasis in this paper is wood identification in the field rather than in the laboratory, we discuss imaging the object of interest using light reflected from the surface of the wood specimen, rather than light passing through a thin section of wood. Practicing wood anatomists already know that the quality of the surface of the specimen directly influences the observation of anatomical detail. On a transverse surface cut with a dull hand saw, features are obscured compared to those on a transverse surface prepared with a utility knife or a microtome. Artifacts of cutting, such as knife marks or broken intervessel walls, are easily filtered out and ignored by humans, but are not as easily removed by a machine vision system. In the data collection phases of preparing a machine vision wood identification system, it is critical that the reference specimens be prepared with the same techniques to be used when the device is employed in the field. If laboratory-quality images are used as references, but specimens in the field are cut with a utility knife, the cell damage, knife marks, and uneven surface of the latter will be misinterpreted by the system as anatomical features rather than preparation artifacts.

Objective lens

The task of the objective lens is to capture and condition the incoming light (converge or diverge it to a plane) for the sensor. If the objective lens induces chromatic and spherical aberration, they can be removed mathematically from an image in a well-designed system. Filters can be employed to mitigate extraneous information that would otherwise complicate the data. The most important filters are pass filters, which block certain wavelengths while allowing others to be transmitted. An ultraviolet (UV) filter is a form of long-pass filter, eliminating all wavelengths shorter than –380 nm. Although the human eye can be harmed by them, silicon-based machine sensors are not particularly sensitive to UV photons. However, an infrared filter (*i.e.* short-pass filter) is an important component when working with silicon-based sensors, because wavelengths in the near-infrared spectrum penetrate into the sensor and are generally perceived by machine sensors as visible light. Absorbing bandpass filters are utilized extensively in acquiring color digital images (Fig. 2). Commonly used semiconductors for sensors are "color blind"; the sensor cannot differentiate the wavelengths of light we see as colors. Absorbing bandpass filters allow a range (band) of wavelengths to be transmitted while absorbing the other wavelengths. The narrower the band, the more "pure" the color; this is a method of controlling the wavelengths of light that reach the sensor.

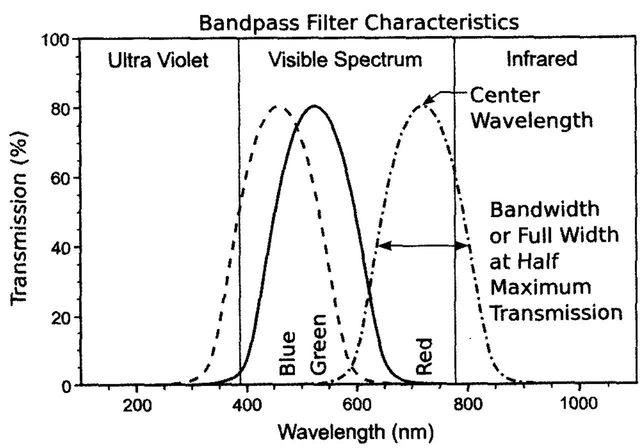


Figure 2. Idealized transmission efficiency and wavelength ranges of Red, Green, and Blue visible light bandpass absorbing filters. Note that although the filter may have a peak transmission at one particular wavelength (center wavelength), a range of light with decreasing percent transmission passes through. The bandwidth or full width at half maximum transmission is the width of the spectrum at half the peak transmission.

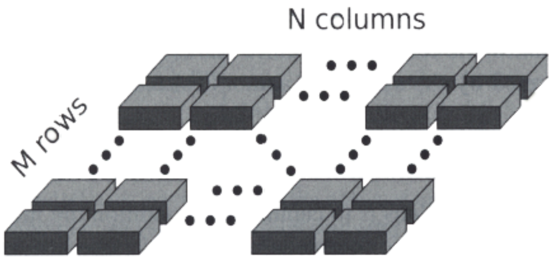


Figure 3. A schematic of the M by N organization of the photodetectors in a digital camera sensor. Each pixel (grey tab) provides one element in an array of directly measured information about the light striking it.

Sensor

Before humans or a machine can process a signal and discern a pattern, a signal needs to be acquired. For vision, this entails a photon being absorbed by a rod or cone in the eye for humans, or photoactive silicon for the sensor in a digital camera. The camera sensor is a semiconductor with an array of M by N photoactive sensors or pixels (Fig. 3), each of which will provide one pixel of data to the final image. In an ideal sensor, every photon would be absorbed by the pixel it encountered, creating a photoelectron that gets counted and placed into the proper row and column in the 2D array as depicted in Figure 1. Unfortunately, real sensors fall short of this ideal, as shown by the quantum efficiency plot versus wavelength in Figure 4. This plot is one example of quantum efficiency for a sensor, and shows a common pattern of nonlinear sensitivity to wavelengths in the visible and non-visible spectrum. The sensor produces or fails to produce a photoelectron in response to the photons striking it, and it records that event independent of the wavelength of the photon striking it, thus there is no color information perceived by the sensor.

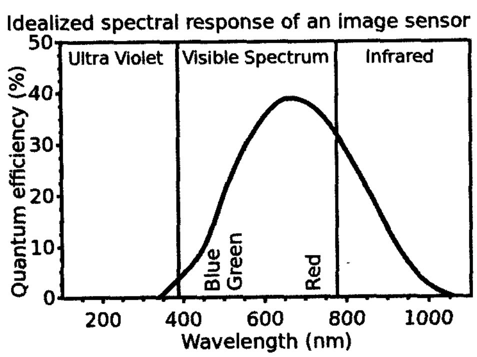


Figure 4. Quantum efficiency of a generic, idealized sensor. Note that the greatest efficiency (percent photons striking the sensor converted to photoelectrons) is found between green and infrared; the infrared photons invisible to the human eye more efficiently generate photoelectrons than do portions of the visible spectrum. For no wavelength is the quantum efficiency higher than 40% for this sensor. Each sensor has its own unique quantum efficiency curve.

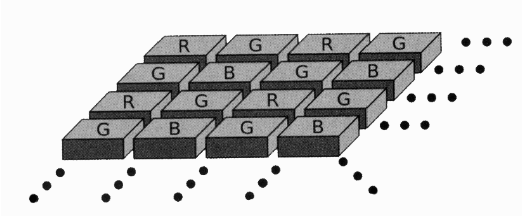


Figure 5. The pattern of light striking the sensor after passing through a Bayer mosaic filter to generate a color RGB image. Note that there is a 1:2:1 ration of Red to Green to Blue pixels in the sensor. Note also that each pixel can record a light intensity for only one color (indicated by R,G,B). The limits of the pattern shown give rise to the need for interpolation or correlation across those pixels for which a given color was not directly measured.

Various workarounds have been implemented to distrnguish colors, but the most common is to use filters to limit the wavelength of light striking an individual pixel. A Bayer mosaic filter is the most common filter for single-chip sensors. The pattern is 25% red, 50% green and 25% blue (Fig. 5). Green is dominant in the pattern because the human eye is the most sensitive to green light and chip manufacturers are trying to capture images of the real world as we see it with our eyes. Because a green pixel contains limited information about the rest of the color spectrum (see Fig. 2), the full-color image is reconstructed by interpolating or correlating the missing values from neighboring pixels for which real data were collected. Thus, for an RGB chip with the 25 % : 50 % : 25 % pixel array, for any given image the minority of the data in the image is actually measured; most of the data is interpolated by the system. For general photography and day-to-day applications this is acceptable; however, for scientific purposes such interpolation or correlation induces chromatic aliases (the reconstructed color differs from that of the actual specimen) and creates a loss of resolution (detail. sharpness, and edge ariifacts - physical details that are caused by the processing of the image and not a legitimate feature of the specimen). With a mosaic color filter over the sensor, we now have an M by N array of data, each pixel of which has one measured pixel value (either red, green or blue) and two estimated pixel values, based on an interpolation or correlation of color values from the nearest pixels for which that color was actually measured. Those intensity values are the output of the final pieces of hardware in the image acquisition phase of the machine vision process, the amplifier and analog to digital converter.

Amplifier and analog to digital converter

The last step in acquiring the image is to “count” the number of photoelectrons created when photon interact with the sensor, after passing through whatever filters are employed. Typically, the signal embodied in the photoelectron is amplified and then converted to a number via an analog to digital converter (ADC). The ADC discretizes a continuous analog signal into steps of digital numbers (Fig. 6). The number of steps is determined by the number of bits in the analog to digital conversion (8 bit - 256 steps, 12 bits = 4096 steps, 16 bits = 65536 *etc.*). The more bits in the conversion the better the resolution and the closer the digital signal approximates the measured signal.

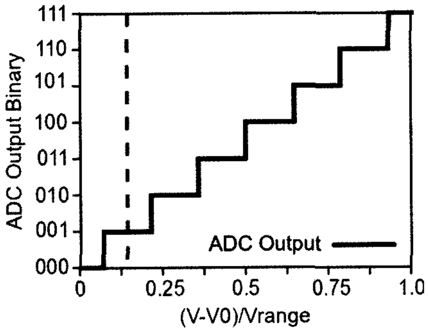


Figure 6. A 3-bit analog-to-digital conversion (ADC) over a normalized voltage range for the sensor; the Y axis is coded with the binary output of the ADC. As a step-function, there are digital equivalencies across the range of measured voltages. As the number of steps (bit depth) increases, the resolution of the sensor increases, but only so long as the sensor is calibrated so that the least significant bit(s) (the dashed vertical line) do not consume bit-depth and thus imply a false resolution. The greater the bit depth the larger the resulting image (in terms of memory) will be, as each pixel has more bits thus more memory is needed to hold those bits.

Increased resolution comes at a cost; doubling the number of bits doubles the storage size of the image and also increases the time to process. Furthermore, a threshold is reached where the resolution of the ADC exceeds the noise of the sensor. If the noise of the sensor exceeds the least significant bit(s) (LSB), it will just contain noise. The effective noise of the sensor is calculated by

$$Bits_{Effective} = \log_2 \left(10^{SNR/20}\right),$$

where *SNR* is the signal to noise ratio. The SNR can be obtained from the manufacturer. Noise comes from the random nature of photon arrival time, dark current of the sensor (thermal noise), the ADC conversion (Steger *et al.* 2008), and any external electromagnetic noise. Thus, more important than the number of bits in the conversion of the signal from the sensor is that the bit depth of the sensor be calibrated to the noise in the system. For this reason, and those listed above in sections on the sensor itself, one should not use just any camera in a machine vision system; the specific details, and the pursuant limitations, of the signal acquisition system should be known and chosen carefully for the application.

While image acquisition is one critical, quality-controlling step in the machine vision process (garbage in garbage out), the typical user leaves all the inner workings of image acquisition to the camera manufacturer. Once an appropriate camera system is purchased, the role of the user is to manipulate the software algorithms to achieve the desired pattern recognition. Assuming that we have an array of quality numbers, software can be used to interrogate these numbers to extract patterns, thus providing the data on which determinations (e.g. wood identification) are based. This process of interrogation and determination occurs in many steps, outlined concisely in Sonka *et al.* (2007), the first of which is to understand the nature of the image itself.

$$\begin{bmatrix} \begin{pmatrix} \mathbf{148} \\ \cdots \\ \cdots \end{pmatrix} & \begin{pmatrix} \cdots \\ \mathbf{116} \\ \cdots \end{pmatrix} & \begin{pmatrix} \mathbf{158} \\ \cdots \\ \cdots \end{pmatrix} \\ \begin{pmatrix} \cdots \\ \mathbf{115} \\ \cdots \end{pmatrix} & \begin{pmatrix} \cdots \\ \cdots \\ \mathbf{98} \end{pmatrix} & \begin{pmatrix} \cdots \\ \mathbf{124} \\ \cdots \end{pmatrix} \\ \begin{pmatrix} \mathbf{152} \\ \cdots \\ \cdots \end{pmatrix} & \begin{pmatrix} \cdots \\ \mathbf{120} \\ \cdots \end{pmatrix} & \begin{pmatrix} \mathbf{160} \\ \cdots \\ \cdots \end{pmatrix} \end{bmatrix} \Rightarrow \begin{bmatrix} \begin{pmatrix} \mathbf{148} \\ 112 \\ 92 \end{pmatrix} & \begin{pmatrix} 152 \\ \mathbf{116} \\ 96 \end{pmatrix} & \begin{pmatrix} \mathbf{158} \\ 122 \\ 103 \end{pmatrix} \\ \begin{pmatrix} 150 \\ \mathbf{115} \\ 94 \end{pmatrix} & \begin{pmatrix} 155 \\ 119 \\ \mathbf{98} \end{pmatrix} & \begin{pmatrix} 160 \\ \mathbf{124} \\ 104 \end{pmatrix} \\ \begin{pmatrix} \mathbf{152} \\ 113 \\ 94 \end{pmatrix} & \begin{pmatrix} 157 \\ \mathbf{120} \\ 98 \end{pmatrix} & \begin{pmatrix} \mathbf{160} \\ 124 \\ 103 \end{pmatrix} \end{bmatrix}$$

Figure 7. A schematic of the M-by-N array of numbers produced by the sensor, amplifier, and ADC. On the left is a representation of the single measured intensities for each pixel, according to the filter that covered that pixel. The top row, from left to right, shows intensity values for R, G, R, the middle row G, B, G, and the bottom row R, G, R. On the right is the same data matrix, with the unmeasured RGB data filled in based on an unknown algorithm from the camera manufacturer. The bold values show those intensities that were directly measured.

Machine vision algorithms (software)

The anatomy of an image

A high-resolution digital image is nothing more than a few million numbers, regardless of how it appears when displayed on a computer screen. After analog to digital conversion, and following the system's interpolation or correlation functions to fill in missing color information, these numbers form an M by N array with an intensity value for each pixel for a grayscale image (Fig. 1) or multiple values per pixel, one for each color (Fig. 7). If the intensity values are plotted as heights, the image can be represented three-dimensionally (Fig. 8), a completely legitimate but altogether foreign way to display the image for most wood anatomists. For example, consider the simple image of a black, RGB [0, 0, 0], circle (idealized vessel) beside a light grey, RGB [Z00, Z00, Z00], line (idealized ray) on a grey, RGB [100, 100, 100], background depicted in Figure 9. Compare this traditional representation to its 3D topographical depiction in Figure 10. Both images represent precisely the same data in terms of pixel values. The intent behind displaying the image this way is to emphasize the format in which the computer stores and processes images and to elucidate some of the tech-

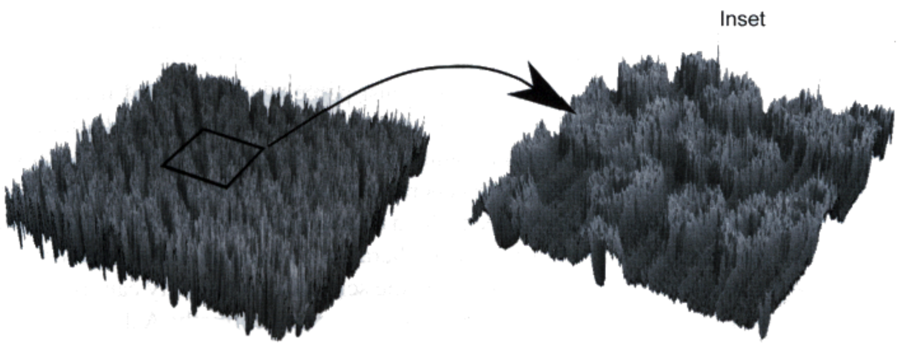
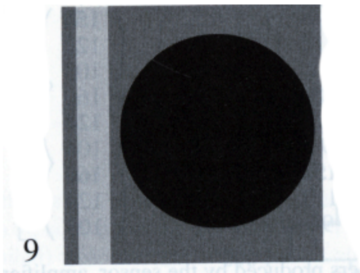


Figure 8. A 3-dimensional topographic representation of the data comprising an image of a transverse surface of *Samanea saman* at hand lens magnification, with the full field of view on the left, and a magnified portion (inset) on the right.



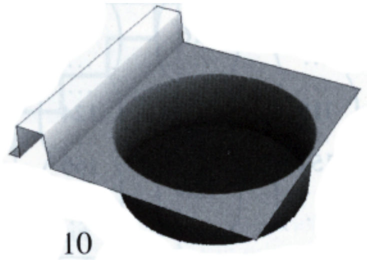


Figure 9. A simple grayscale image with a black RGB [0, 0, 0] circle (idealized vessel) beside a light grey RGB [200,200,200] line (idealized ray) on a grey RGB [100, 100,100] background. — Figure 10. A 3D topological representation of the grayscale image of Figure 9. Both figures represent the same information but Figure 10 depicts how computer vision algorithms interpret the data as a 3D topology to be interrogated.

niques used in machine vision; it forces us to acknowledge the degree to which our biological pattern recognition systems are at play when viewing the traditional way of representing the data (Fig. 11). When an anatomist seeks to define a wood anatomical character for machine vision identification, understanding the numerical nature of the data is critical. Machine vision software extracts useful information (patterns) from such numbers and then applies that information to make a decision.

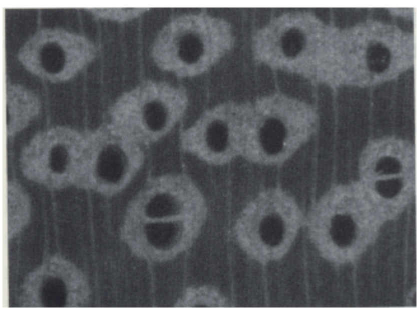


Figure 11. The more typical representation of the image inset from Figure 8 (*Samanea saman*).

Image-based definitions of wood anatomy

The task of translating what a wood anatomist perceives in a digital image into something quantifiable for a computer is a massive one. Robust, flexible, and internally consistent definitions for characters and character states are hard to come by, or possibly even impossible to achieve in anatomy in general (e.g. see the interesting but conflicted literature on imperforate tracheary elements for a case in point), and for machine vision specifically. Anatomists can publish a set of characters, character states, and definitions (IAWA Committee 1989, 2004) and then the scientific community can use those definitions and train its students to interpret and apply them correctly. A disadvantage of such a system is that, if there is need or desire to create or alter a definition, each person in the field must be re-trained with the new or revised definition. One of the advantages of a machine vision system is that, if it stores an original digital image as a reference specimen, it can always re-analyze that image in the light of new or revised definitions supplied by the humans developing the tool. In a machine vision system, character definitions are nothing more than encoded heuristics of the desired patterns to be extracted from the digital image. This is the electronic equivalent of what anatomists do automatically using the human-biological pattern recognition system that they have developed with training and patience.

The gap between traditional wood anatomy and the machine vision signal must be spanned by humans who encode the proper character definitions for the system. These definitions must be based on the information present in the digital images captured by the signal acquisition component of the system. To distinguish the defined patterns, the data must be prepared and manipulated. Although there are many ways to manipulate the image data, below we outline three basic types of operations, and then discuss their use in extracting wood anatomical information from an image of wood.

PREPARING THE IMAGE FOR DISTINGUISHING PATTERNS

Geometric transformation

The M by N array of values is a mapping of a real-world object (wood specimen) with real spatial dimensions to the sensor with its own real world dimensions. This relationship between real space on the wood specimen and pixel space in the image is an important aspect of the information in the image. If the objective did not cause any aberration, then a constant scale adjustment would suffice to describe this mapping. We commonly use scale bars on images to indicate magnification, and the same setting of scale is necessary if we are to use machine vision to incorporate real world lengths, areas, etc., in images of wood. If aberrations (spherical or perspective errors) do occur, then more complex algorithms are required to establish the specimen to pixel relationship, but this can be done relatively easily with software. Calibrated 2D targets are available to establish the degree of aberration in the optical system. The geometric transformation, in this case, is thus mapping the context of the image relative to the real world, and is necessary to a machine vision wood identification system.

Point operations

Point operations take single pixels as input and return a single pixel as output. Mathematically this can be represented as $g'(r,c) = f[g(r,c)]$, where r and c are the row and column respectively of g, the input image array, f[3 is the mathematical operation and g' is the resulting image array. Some examples of point operations are lightening, darkening, negation, equalizing, and simple thresholding of an image. For example, the equation for thresholding an 8-bit image into two segments, separated at pixel level t is:

$$g'(i,j) = \begin{cases} 255 & \text{if } f[g(i,j)] \geq t \\ 0 & \text{if } f[g(i,j)] < t \end{cases} \qquad (1)$$

This gives rise to an image with either black or white pixels, and no grey pixels. Point operations are useful in machine vision for wood identification to prepare or condition the image for subsequent operations.

Area operations

Area operations calculate the value of a pixel based upon a group of other pixels, typically those in the neighborhood of the original pixel. Area operations are the most common method of preparing an image to look for patterns or to ready it for other purposes. Linear and non-linear filters are some of the most used area operations. For example, by examining the area around the pixel, the software can calculate information about the local topography; whether the pixel's intensity values represent a local minimum or maximum, the direction of the steepest incline, or a level traverse. These determinations are made based on the interpretation of the image as a three-dimensional topography. Edge detecting algorithms use this information to determine boundaries within the image, and such algorithms are central to extracting wood anatomical information from an image. An idealized edge would be a cliff wall, topographically (Fig. 10), but edges in real images are less distinctly defined.

FOUR DOMAINS IN HARDWOODS

For the purposes of a general example, let us consider hardwood identification from the transverse plane at hand-lens magnifications. Considering only the information that comes in through the lens (and not what you already know from seeing the wood under the light microscope) characters for certain cell types and patterns disappear (*e.g.* vasicentric tracheids appear as vasicentric parenchyma, diffuse apotracheal parenchyma does not appear at all in many woods). This means that, in general terms, we can distill hardwoods down to four basic domains: vessels, rays, axial parenchyma, and fibers. It is thus our task to define each of these components of a hardwood in a way that the machine vision software can pull out patterns from the numeric data that are similar to the patterns we see with our eyes.

In order to approach this problem in an insightful way, we first reiterate that the data available to the machine vision software occur as an M by N array of numerical values representing light intensities in one or more color ranges. From this array of numbers, we must define vessels, rays, axial parenchyma, and fibers. Our definitions must be independent of any of the features of wood that will vary by taxon. For example, if we use the color and size of the lumen as a feature to define a vessel, vessels much smaller or larger, or with gums or tyloses will not be recognized by the software. The definition we develop for the software must use only characteristics of vessels that are reliable across taxa, and must take into account the nature of the data the machine vision system is processing. Each pixel in the image represents some tiny amount of the wood specimen itself, and the spatial or geometric relationship between a cluster of pixels in the lower left of the image and another cluster in the upper right is directly analogous to the lower left and upper right of the real wood block. This correspondence between what is seen on the wood block and what is represented in the image is the primary goal of the signal acquisition portion of the machine vision system; the machine vision software must be asked to extract pattern from data, and the better the data, the better chance of extracting pattern efficiently. While there are many ways to use machine vision software to extract wood anatomical features (vessels, rays, axial parenchyma, fibers) from images, we outline one possible approach below as an illustration of the machine vision process for wood identification.

Vessels

The first feature in a hardwood we wish to define for our machine vision software is vessels. For the purposes of machine vision, vessels can be defined as having certain edge qualities and certain roundness qualities. In Figure 8, a vessel appears as a well and by applying edge detection algorithms to the data, and selecting for elements of a given circularity ratio, we can select for the vessels. Applying the algorithms just described, we can visualize the resulting data as shown in Figure 12. In this case, the three-dimensional mapping of the data shows the identified vessels. Once the system has identified all the vessels, the pixels that comprise those vessels can be removed from the image; we can tell the machine vision system not to consider any of those pixels in the next step, effectively eliminating the vessels from the image. Now the image has missing data (vessels), but what is left must be, by definition, some combination of rays, axial parenchyma, or fibers.

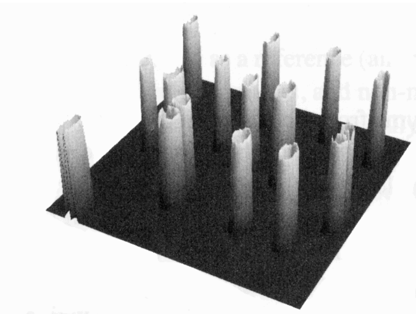


Figure 12. By thresholding and then applying an edge detection algorithm to the inset from Figure 8, the vessels are now standing out above the background.

Note that at this point we have identified the vessels and 'removed' them from the image. Because the image has a scale associated with it, we have geometric information about vessel size (vessel area, but *not* vessel diameter), abundance (vessels per mm^2), relative position in the M-by-N array, and more, but we know nothing about the pattern in which the vessels are arranged; ring-porous, ulmiform, in clusters or radial multiples; the radial and tangential directions are as-yet-unknown. Tangential vessel diameter is likewise unknown. Such information is contextual, and comes only after further analysis.

Rays

Both because we need the contextual information they provide and because they are the next most distinctive features to extract, defining rays is the next step. Rays in hardwood share several general properties: they almost always run parallel to each other (the degree to which they diverge from each other is a function of the distance from the pith); they almost always run from one side of the image to the other without interruption; they are generally spaced relatively regularly; and, they are generally rather straight (*e.g.* compare to banded parenchyma in *Lecythis*). The geometric aspects of rays are critical in defining them for machine vision software. Rays are parallel ridges in our topography of Figure 8, which can be seen upon close inspection of Figure 8, inset. Using techniques analogous to the methods described above for vessels (but with lines, rather than circles), we can distinguish the rays.

With the rays identified, we have accomplished several things. First, we have geometric information about the number, width, total area, and spacing of the rays themselves. Second, we now can re-approach our vessel information with the necessary context to extract additional meaning. With the correct character definitions, we can ask the machine vision system to determine if the wood is ring-porous, or if it has radial vessel multiples. Third, we can remove all those pixels from the image that are defined as belonging to the rays, leaving only fibers and axial parenchyma to define. Note that laying out the criteria necessary to define each character or character state (*e.g.* ring-porosity) for a machine vision system exceeds the purview of our intent, but each character and character state to be used in a machine vision identification system will have to be defined in terms of the machine vision software. This is especially true for systems designed solely to mimic the human process of identification by comparing the presence or absence of discrete features to a coded reference database, such as a system analogous to InsideWood (see Wheeler 2011).

Axial parenchyma and fibers

The primary way to distinguish axial parenchyma from fibers, when the vessel and rays are literally removed from the picture, is by color difference. In most taxa, the axial parenchyma, if present and observable with a hand lens, will be either lighter or darker than the fibers, and thus the system can determine a threshold of color ranges; all the tissue darker than some value will be either fibers or parenchyma, and everything lighter than that value will be the other tissue. This is an application of point transformation, and a way to separate the two cell types. How do we teach the system to decide which set of pixels, the lighter or the darker, should be identified as the axial parenchyma, and which set the fibers? A possible solution might lie in the ways anatomists define parenchyma in general; if a taxon has aliform parenchyma, the geometric information of spatial proximity to the vessels could be used to define the parenchyma. That is to say, we know that fibers are rarely found in aliform-like clusters around vessels, so if an aliform-like cluster of pixels is identified around the space known to be occupied by a vessel in the image, the machine vision system can determine with high probability that the color range of pixels selected represents parenchyma, and thus determine that the other color range represents the fibers.

DATABASE COMPILATION AND MANAGEMENT, AND DECISION AUTHORITY IN THE SYSTEM

With these steps the machine vision system has separated the image into four classes of cells, vessels, rays, axial parenchyma, and fibers. Within each class and between classes data can be extracted and compared to generate the information coded for entry into a database of reference woods, much like the taxa listed in InsideWood. Additionally, the system can store the original image from which the data were extracted, so that, if there are any changes to the system or alterations to the list of characters and definitions, the database can be repopulated with the new data without need to add a new image. As more reference images are added, the system's data set defining the taxa will grow, and the statistical space that each taxon encompasses will change as well. This results in an evolving data set, the evolution of which is completely human-controlled.

The methods by which the system compares the patterns extracted from an image of an unknown wood to its reference database of coded data are beyond the purview of this article, but there are numerous possible combinations of methods; classical keying and comparison to a reference database, statistical methods using similarity calculations, neural networks, and others. This model for generating a database and making decisions is a static model; it waits on the human user to add new data, and it requires human definitions for characters. This is a powerful way to manage the data and operate an identification system, but it is perhaps not the most powerful method, because it relies on human input and does not fully capitalize on the computational power of the computers that comprise the system.

By contrast, an active, self-learning system could: background mine the reference images and their coded data for new characters; have a decision protocol for when to add a new image as a reference (and maintain a hierarchy of "vouchered" images, provisional reference images, and non-matches); and, be able to determine which woods within the database are anatomically similar. Once such similar taxa are identified, a self-learning system could further mine the data with the specific goal of determining a method to separate them, analogous to the work of Esteban *et al.* (2009) in *Juniperus,* or the implied separation methods used in the laboratory-based system of Khalid *et al.* (2008).

A machine vision wood identification system database, whether static or self-learning, will contain unprecedented quantities of data about wood anatomical features, at least partly as a result of the inherently quantitative nature of the data in digital images. There are many possible measurements in wood anatomy that are not typically made (see Ifju 1983 for some examples), and may contain information useful in wood identification. For example, in a wood like *Betula pendula,* some vessels are solitary, some are in multiples of two, some are in multiples of three, etc. When humans see the wood of *B. pendula,* we see a diffuse-porous hardwood with a fairly generic pore pattern. What if, considering only the solitary vessels, there were a specific pattern or distribution useful in identification? A pattern that humans do not readily perceive, because there is too much information present in an image, and we subconsciously smooth out the complexity by assigning the wood to a predefined category (*e.g.* diffuse-porous) in our mind. Machine vision systems will be able to pursue tens of thousands of combinations of "characters" that humans could not hope to codify for non-machine use. The application of high numbers of additional characters for identification is likely to increase dramatically the ability of wood anatomy to separate previously inseparable taxa, in much the same way the large number of characters represented in DNA sequences empowered phylogenetic inference.

CONCLUSIONS

Khalid *et al.* (2008) have demonstrated that a machine vision system is capable of recognizing the differences in some wood species in a laboratory setting. The compounding progress of computational technologies and machine vision methodologies has convinced us that basic field identification by means of a machine vision system is achievable in the short term; especially if the geographic scope or scale of the problem is limited (e.g. the species list of woods coming from Canada into the US is far smaller than those coming from Brazil). To design functional machine vision wood identification systems, wood anatomists must work with machine vision specialists to select the appropriate hardware for signal acquisition, and then must assist in the definition of characters for the signal processing aspects of the system. Such cooperation is facilitated by a basic understanding of some of the core principles and axioms of machine vision theory and application; those details presented here are the ones we deem most directly needed by anatomists to help solve the problem of automated wood identification, and thus extend the expertise of wood anatomy into the field. The process of this synergistic relation between anatomists and machine vision experts is illustrated conceptually in Figure 13, in which the original wood anatomical image is superimposed on the data plotted topographically with the vessels extracted using machine vision algorithms. The broader availability of wood identification tools should facilitate the enforcement of legal logging provisions throughout the world, and empower wood anatomists to focus their attention on problems of wood identification research too complex for a machine vision system.

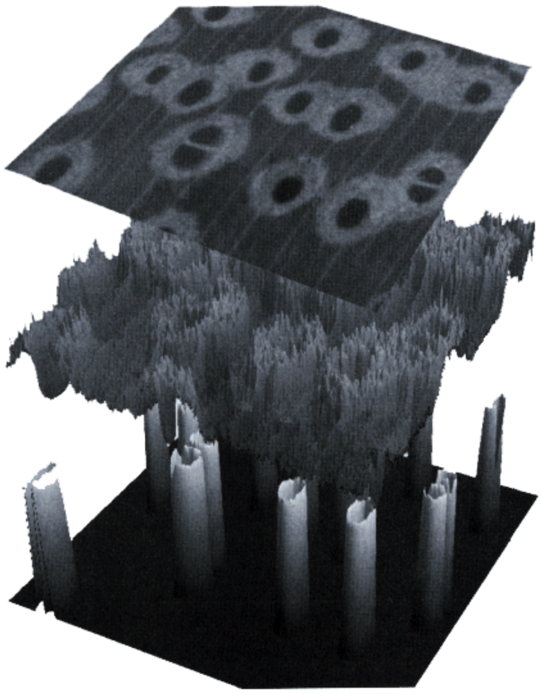


Figure 13. An overlay of the traditional means of viewing an image (top), the 3D topological view of the same data (middle), and a topological view after thresholding and processing the data to identify edges (bottom). Note that by comparing these three representations of the data, it becomes easier to translate the wood anatomical features between them.

REFERENCES

Abe, H., U. Watanabe, K. Yoshida, K. Kuroda & C. Zhang. 2011. Changes in organelle and DNA quality, quantity, and distribution in the wood of *Cryptomeria japonica* over long-term storage. IAWA J. 32 [this issue]: 263–272.

Arimura, H., T. Magome, Y. Yamashita & D. Yamamoto. 2009. Computer-aided diagnosis systems for brain diseases in magnetic resonance images. Algorithms 2: 925–952.

Bhandarkar, S.M., T.D. Faust & M. Tang. 1999. CATALOG: a system for detection and rendering of internal log defects using computer tomography. Machine Vision and Applications 11: 171–190.

Bhandarkar, S.M., T.D. Faust & M. Tang. 2002. Design and prototype development of a computer vision-based lumber production planning system. Image and Vision Computing 20: 167–189.

Braga, J.W.B., T.C.M. Pastore, V.T.R. Coradin, J.A.A. Camargos & A.R. Silva. 2011. The use of near infrared spectroscopy to identify solid wood specimens of *Swietenia macrophylla* (Cites Appendix II). IAWA J. 32 [this issue]: 285–297.

Bremananth, R., B. Nithya & R. Saipriya. 2009. Wood species recognition using GLCM and correlation. In Advances in Recent Technologies in Communication and Computing: 615–619. ARTCom'09 International Conference, Kottayam, Kerala, India.

Conners, R.W., T.H. Cho, C.T. Ng, T.H. Drayer, P.A. Araman & R.L. Brisbin. 1992. A machine vision system for automatically grading hardwood lumber. Industrial Metrology 2: 317–342.

Cox, P.W., G.C. Paul & C.R. Thomas. 1998. Image analysis of the morphology of filamentous micro-organisms. Microbiology 144: 817–827.

Duda, R.O., P.E. Hart & D.G. Stork. 2000. Pattern Classification. Ed. 2. Wiley-Interscience.

Esteban, L.G., F.G. Fernandez, P. de P. de Palacios, R.M. Romero & N.N. Cano. 2009. Artificial neural networks in wood identification: the case of two *Juniperus* species from the Canary Islands. IAWA J. 30: 87–94.

Fuentealba, C., C. Simon, D. Choffel, P. Charpentier & D. Masson. 2004. Wood products identification by internal characteristics readings. In IEEE International Conference on Industrial Technology: 763–768. IEEE ICIT '04. Hammamet, Tunisia.

Gasson, P. 2011. How precise can wood identification be? Wood anatomy's role in support of the legal timber trade, especially CITES. IAWA J. 32 [this issue]: 137–154.

Gasson, P., R.B. Miller, D.J. Stekel, F. Whinder & K. Zieminska. 2010. Wood identification of *Dalbergia nigra* (CITES Appendix I) using quantitative wood anatomy, principal components analysis and naive Bayes classification. Ann. Bot. 105: 45–56.

Hanssen, F., N. Wischnewski, U. Moreth & E.A. Magel. 2011. Molecular identification of *Fitzroya cupressoides, Sequoia sempervirens*, and *Thuja plicata* wood using taxon-specific RDNA-ITS primers. IAWA J. 32 [this issue]: 273–284.

Hornberg, A. 2006. Handbook of Machine Vision. Wiley-VCH. 848 pp.

IAWA Committee. 1989. IAWA list of microscopic features for hardwood identification. E.A. Wheeler, P. Baas & P.E. Gasson (eds.). IAWA Bull. n.s. 10: 219–332.

IAWA Committee. 2004. IAWA list of microscopic features for softwood identification. H.G. Richter, D. Grosser, I. Heinz & P.E. Gasson (eds.). IAWA J. 25: 1–70.

Ifju, G. 1983. Quantitative wood anatomy: certain geometrical-statistical relationships. Wood and Fiber Science 15: 326–337.

Johnson, A. & L. Laestadius. 2011. New laws, new needs: The role of wood science in global policy efforts to reduce illegal logging and associated trade. IAWA J. 32 [this issue]: 125–136.

Khalid, M., E.L.Y. Lee, R. Yusof & M. Nadaraj. 2008. Design of an intelligent wood species recognition system. International Journal of Simulation Systems, Science & Technology 9: 9–19.

Khalsa, D.S. & C. Stauth. 1997. Brain longevity: the breakthrough medical program that improves your mind and memory. Hachette Digital, Inc. 338 pp.

Kite, G.C., P.W. Green, N.C. Veitch, M.C. Groves, P.E. Gasson & M.S. Simmonds. 2010. Dalnigrin, a neoflavonoid marker for the identification of Brazilian rosewood (*Dalbergia nigra*) in CITES enforcement. Phytochemistry 71 (10): 1122–1131.

Kline, D.E., P.A. Araman & C. Surak. 2001. Evaluation of an automated hardwood lumber grading system. Proc. ScanTech 2001, Ninth International Conference on Scanning Technology and Process Optimization for the Wood Industry: 141–151.

Kline, D.E., C. Surak & P.A. Araman. 2003. Automated hardwood lumber grading utilizing a multiple sensor machine vision technology. Computers and Electronics in Agriculture 41: 139–155.

Koch, G., H.-G. Richter & U. Schmitt. 2011. Design and application of CITES*woodID* – Computer-aided identification and description of CITES-protected timbers. IAWA J. 32 [this issue]: 213–220.

Lowe, A.J. & H.B. Cross. 2011. The application of DNA methods to timber tracking and origin verification. IAWA J. 32 [this issue]: 251–262.

Miller, R.B., A.C. Wiedenhoeft & M-J. Ribeyron. 2002. CITES Identification Guide – Tropical Woods. Environment Canada, Canada.

Pan, S. & M. Kudo. 2011. Segmentation of pores in wood microscopic images based on mathematical morphology with a variable structuring element. Computers and Electronics in Agriculture 75: 250–260.

Pham, D.T. & R.J. Alcock. 1999. Synergistic classification systems for wood defect identification. Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering 213: 127–133.

Sarmiento, C., P. Détienne, C. Heinz, J.-F. Molino, P. Grard & P. Bonnet. 2011. Pl@ntWood: a computer-assisted identification tool for 110 species of Amazon trees based on wood anatomical features. 2011. IAWA J. 32 [this issue]: 221–232.

Seneca Creek Associates. 2004. Illegal Logging and Global Wood Markets: The competitive impacts on the U.S. Wood Products Industry. Prepared for the American Forest & Paper Association by Seneca Creek Associates, LLC and Wood Resources International, LLC.

Sonka, M., V. Hlavac & R. Boyle. 2007. Image processing, analysis, and machine vision. Ed. 3. CL-Engineering. 850 pp.

Srikanteswara, S. 1997. Feature identification in wooden boards using color image segmentation. Thesis. Virginia Tech University. 125 pp.

Steger, C., M. Ulrich & C. Wiedemann. 2008. Machine vision algorithms and applications. Wiley-VCH. 374 pp.

Sutherland, N.S. 1968. Outlines of a theory of visual pattern recognition in animals and man. Proc. Royal Soc. London, Series B, Biological Sciences 171: 297–317.

Wheeler, E.A. 2011. InsideWood – a web resource for hardwood anatomy. IAWA J. 32 [this issue]: 199–211.

Yusof, R., N.R. Rosli & M. Khalid. 2010. Using gabor filters as image multiplier for tropical wood species recognition system. In Proc. 2010 12th International Conference on Computer Modelling and Simulation: 289–294. IEEE Computer Society, Washington, DC, USA.