Characterizing nonwoven web structure using image analysis techniques

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ABSTRACT

A discussion of image analysis hardware and software techniques used to characterize the structure of nonwoven webs shows the advantage of modifying electronic images to allow better visualization by humans. Spectral analysis is useful for characterizing web structure globally. The authors examine simple parameters useful for describing web uniformity and discuss other web structural features described by image analysis.

Application:

Modifying an electronic image to provide improved visualization of its contents by humans creates an opportunity for the human brain to evaluate the image better.

THE PROPERTIES OF OBJECTS result from their structure and the properties of their constituent units. Structural knowledge therefore must precede any understanding of the properties of an object. For nonwoven webs, most people would agree that little detailed knowledge of structure generally results. This situation is changing.

The impressive advances in personal computers, video cameras, and related hardware during the last five years have resulted in inexpensive but powerful tools. Many workers in nonwovens now are mastering these hardware tools to learn about web structure. Successful uses of computer vision techniques in diverse areas such as advertising and military applications lead us to expect the successful application of image techniques to nonwovens. The results are detailed information about web structure in the off-line laboratory environment and the on-line production environment.

After imaging a web and digitizing it by computer, many procedures can provide information about web structure. For example, modifying an image to produce other images that reveal more detail to the human eye than it normally discerns is possible. Another example is to describe the contents of an image quantitatively or classify and measure objects in an image. Algorithms are in the development stage that perform these tasks quickly and provide much information in a short time. Image-based techniques also have the advantage of being highly automated to avoid fatigue and errors associated with tedious and repetitious manual measurements commonly used today.

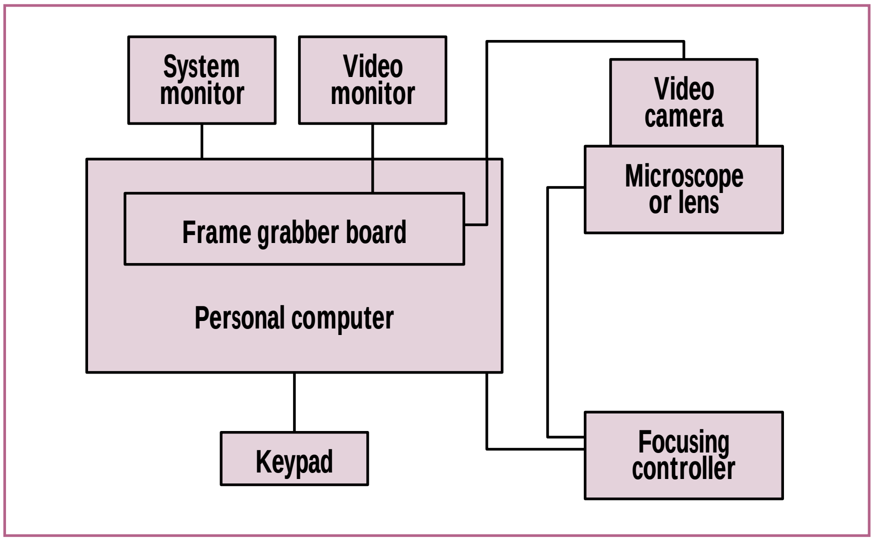
Considering the wealth of structural information usually available in images, one could expect that a single image analysis system would replace several other instruments used to characterize web structure. In this paper, we will review our work toward this goal. We will briefly address hardware used in our laboratory and discuss techniques used to generate detailed information about web structure.

IMAGE ANALYSIS HARDWARE

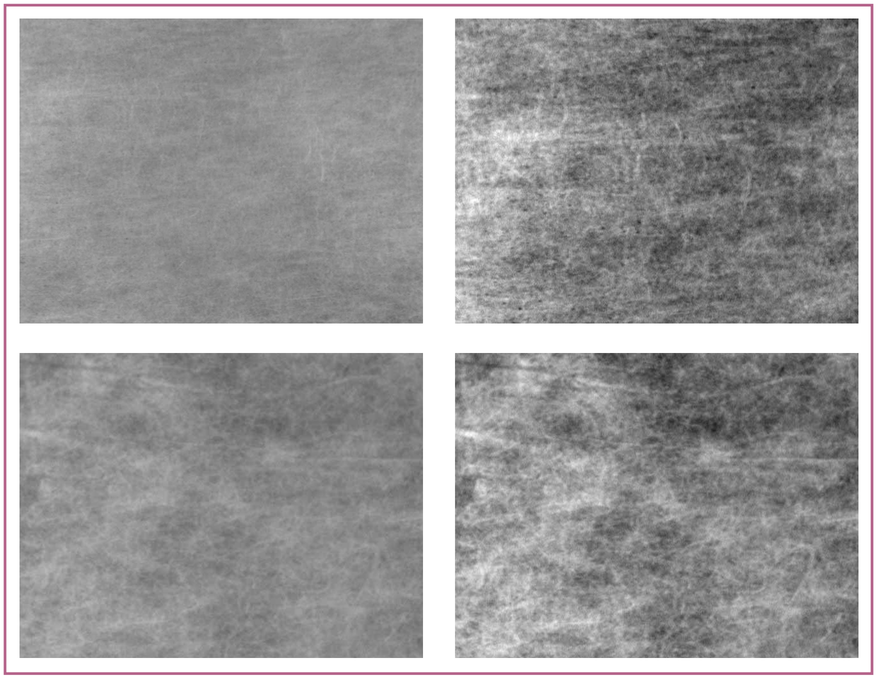
One can assemble an inexpensive yet powerful image analysis hardware system using commercially available components. **Figure 1** shows a schematic illustration of the basic hardware system currently used in our laboratory for web analysis. Major components are a personal computer, frame grabber board installed in the computer, system monitor, video camera, video monitor, microscope, and focusing controller. All these components cost under US$ 12,000. Webs may be illuminated with reflected or transmitted light and focused with the lens of a microscope to produce higher magnification images. Another possibility is to use a separate lens attached to the video camera to produce lower magnification images. A video camera and frame grabber acquire images with a spatial resolution of 640 x 480 pixels and a gray level resolution of 8 bits.

The focusing controller includes a microstepper drive, indexer, and step motor. It connects to a serial port of the computer through an RS-232 interface. The motor shaft couples directly to the microscope fine focus shaft and yields a minimum linear lens movement (focus) of 0.01 μm/step. Focusing is entirely under programming control. We have found this feature very useful, since the software automatically performs focusing before all measurements. This allows increased automation because individual objects within one image can be individually focused or many images may be acquired and individually focused during analysis of large webs. We also have found that automated focusing provides a more objective way to bring objects into focus than human focusing.

Besides the basic hardware system of Fig. 1, we sometimes use a large XY table to analyze webs with dimensions up to 6 in. x 36 in. (>200 in.^{2} of web area). The table has two XY rails—one motor driven and one



1. Basic image analysis hardware system



2. Web images as acquired (left) and after histogram modification (right)

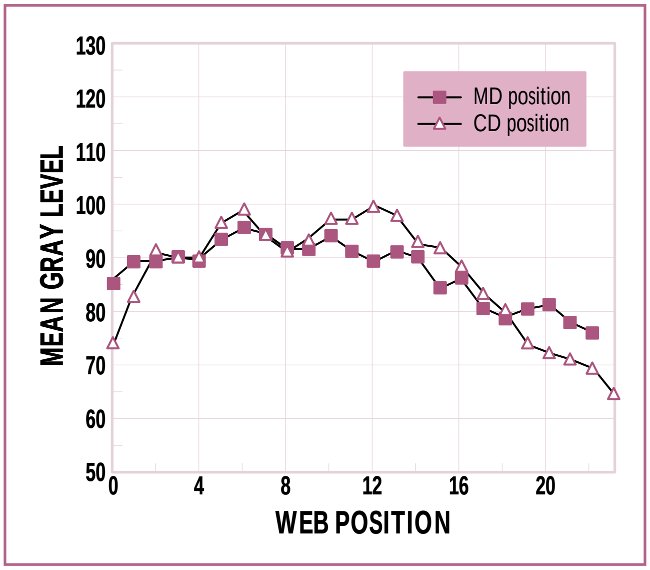
free. The free travel rail is necessary to support large webs to ensure an entirely flat sample. The minimum linear movement of this table is 0.1 mm/step. Like image acquisition, image processing, and image analysis, programming control entirely automates web positioning. The user chooses the number of images acquired and their pattern of selection (random or regular) at the beginning of analysis. We have found the XY table very useful. Automated sample positioning allows performance of time-consuming analysis schemes, more extensive web sampling, edge-to-edge analysis of webs up to 36 in. wide, and searching for objects present only infrequently—defects.

Recent years have seen remarkable performance increases and price decreases for computers and related hardware. One reasonably can expect further impressive advances in hardware performance and a continuing decrease in hardware cost. This will undoubtedly lead to faster and more powerful image analysis hardware in the future. Development of software to operate this hardware should allow more extensive structural analysis of nonwoven webs.

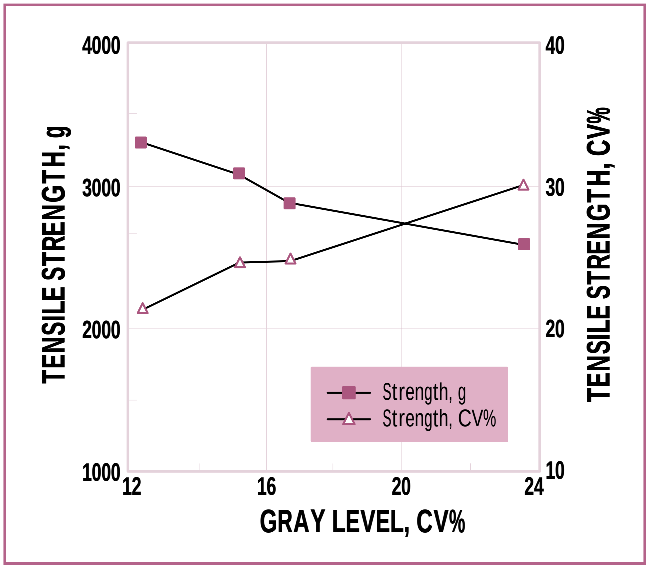
PROCESSING IMAGES INTO OTHER IMAGES

Humans have remarkable visual orientation. Pictorial information probably is their most important source of sensory data. Although humans possess excellent color resolution, they possess poor gray level resolution. Gray level images acquired with a computer vision system usually possess more information than the human eye can discern. Modifying an electronic image to allow better visualization of its contents by humans therefore is useful and creates an opportunity for the human brain to evaluate the image. The brain integrates and analyzes visual information and can provide a complex evaluation of web structure.

Figure 2 shows two images of webs acquired by computer vision hardware. The human eye can perceive little web structure in these images. Figure 2 also shows the same two images after histogram modification has redistributed the image gray levels through a greater range. Structure revealed in the modified images also exists in the unmodified images but is largely undetectable by the human eye. Figure 2 shows that image modification allows the human eye to perceive more structural detail. This figure also shows that a wealth of information is available for analysis in electronic images even when the human eye may not perceive it.



3. Mean image gray level at different positions along the MD and CD of the web



4. Image gray level CV% vs. strength and strength variation for four webs

IMAGE SPECTRAL ANALYSIS

Structural analysis in the frequency domain can be a useful way to characterize image information globally. After two-dimensional Fourier transformation of images from three webs (exhibiting low, medium, and high fiber orientations), we obtained spectral density plots. Both the web of low fiber orientation and its spectral density are isotropic. Images with medium and high fiber orientations and their Fourier spectra exhibit increased anisotropy. Fourier spectral evaluation can provide global measures of web structure. Since hardware or software can rapidly perform Fourier transformations, this measurement can provide a practical means of monitoring web structure.

DESCRIPTION OF IMAGE CONTENTS

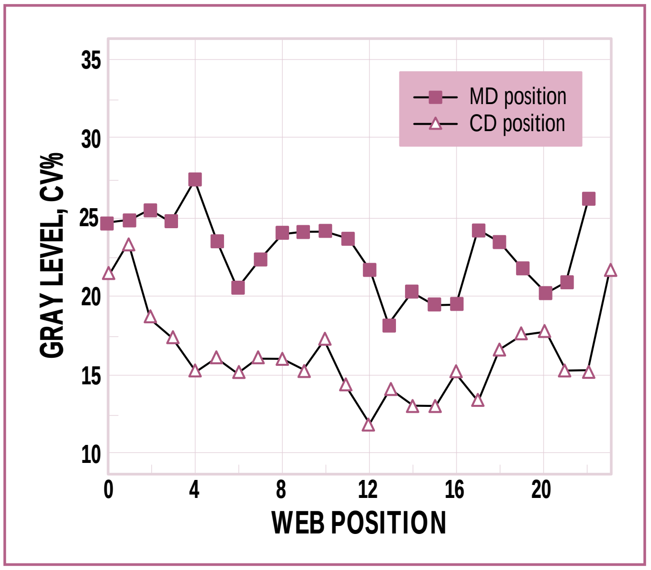
Although electronic images usually contain more visual information than the human eye can discern, image analysis software can analyze their contents. To illustrate the kind of detailed structural information often resulting from applications of simple image analysis concepts, we will discuss the evaluation of web uniformity using only the statistical measures of mean and coefficient of variation (standard deviation divided by the mean). We then will briefly discuss other evaluations of web structure to illustrate the wide variety of structural information available from simple image analysis hardware.

Evaluating web uniformity

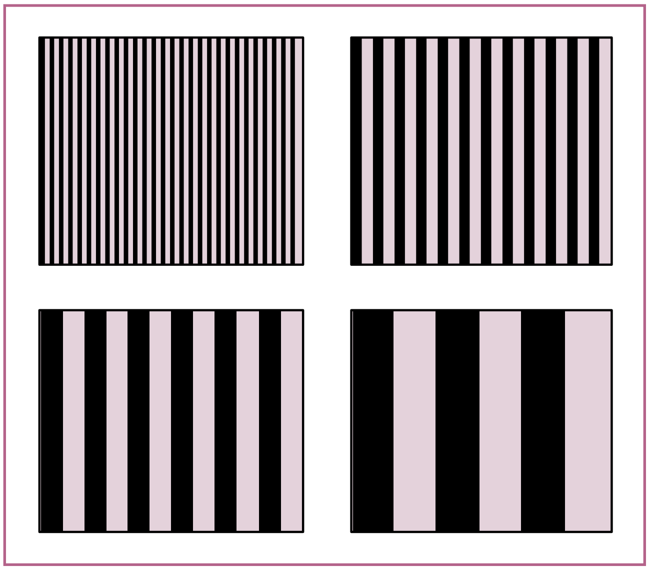
Probably the simplest parameter obtainable from any image is the average brightness. Computing the mean gray level for various pixel groups comprising an image is possible. **Figure 3** illustrates this approach. We placed a web approximately one meter wide on a black surface with its machine direction (MD) aligned along the pixel column direction. Illumination used reflected light. We evaluated the brightness of reflected light. Image brightness or mean gray level is proportional to web basis weight. The gray levels of pixels in small groups of image columns were averaged and plotted for various MD positions to assess basis weight across the web width. These data reveal that the basis weight is less at the web edges than at its center. They also show that the right half of the web exhibits lower basis weight than its left half. Similarly, gray levels of pixels in small groups of image rows were averaged and plotted for various cross direction (CD) positions to assess basis weight along the web length. Comparing these data with the MD position data shows that basis weight varies less along the web's length than across its width.

Another simple parameter easily obtained from any image is the coefficient of variation among gray levels of all pixels in an image. This parameter can assess the overall uniformity of webs since more variable web structure leads to more variable image gray levels and a larger coefficient of variation. **Figure 4** illustrates this approach where the coefficient of gray level variation expressed as percentage (CV%) was computed for four webs. This is plotted with measurements of web tensile strength and tensile strength variation. The figure illustrates how tensile strength decreases as web uniformity decreases (gray level CV% increases). The figure also illustrates how the uniformity of tensile strength measurements for different web specimens decreases (tensile strength CV% increases) as web uniformity decreases (gray level CV% increases).

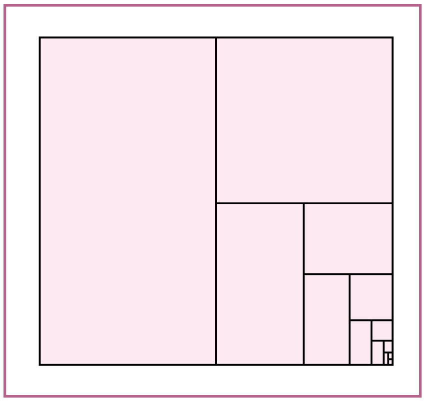
Besides computing the coefficient of variation among gray levels of all pixels in an image, computing



5. Image gray level CV% at different positions along the MD and CD of the web



7. Different column widths identifiable in an image



6. Different cell sizes in an image

the coefficient of gray level variation among specific pixel groups within an image is possible. This allows an assessment of web uniformity at different web positions. **Figure 5** illustrates this approach for the same web represented in Fig. 4. Coefficients of variation among the gray levels of pixels in small groups of columns or rows of the image were computed and plotted for various MD or CD positions to assess basis weight variation at different positions across the web width or along its length. Whereas Fig. 4 revealed the web was thinner at its edges, Fig. 6 shows that web structure is more variable (less uniform) at its edges than at its center. When comparing the two curves in Fig. 6, one can see that web structure variation changes less along the web length (MD position data) than across its width (CD position data).

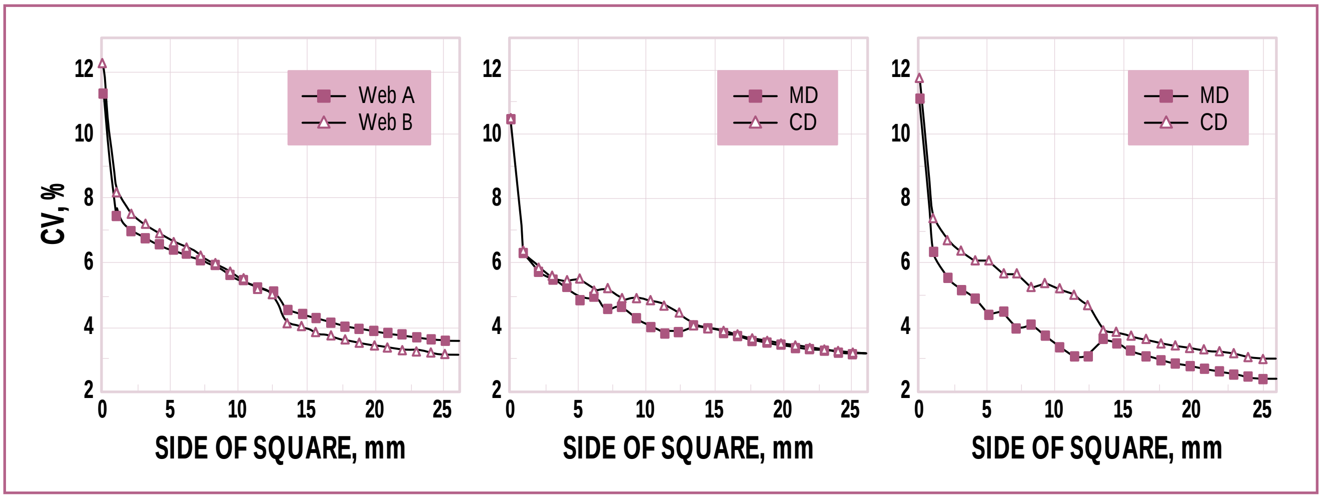
There is yet another way to compute the coefficient of gray level variation among specific pixel groups. Instead of fixing the size of pixel groups in images as in the analysis for Figs. 5 and 6, varying pixel group size to evaluate web uniformity at different size resolutions is possible. Image division in this manner allows data evaluation for cell-area-dependent CV%—the coefficients of variation among mean gray levels of cells computed for various cell sizes. To accomplish this, an image is divided into many cells of the same size with each cell consisting of n x n pixels. Then the coefficient of variation among the mean pixel gray levels of the cells is computed. This yields a value of the web CV% for cells of size n x n. As the number, n, changes (cell size changes), one obtains data consisting of gray level CV% vs. cell size. Presenting this information in a plot called a uniformity spectrum efficiently displays the uniformity of a web at many size resolutions. The user may pay particular attention to the most appropriate size resolution for the intended application of the web.

Figure 6 schematically shows how one image can be divided into cells that differ in size through a substantial size range spanning individual pixels to an entire image. This figure shows one cell for each of several size resolutions. This procedure is rapid with electronic images because a computer can divide data into various groups very quickly.

If webs are positioned in the imaging system with their MD aligned parallel to the image column direction and their CD aligned parallel to the image row direction, one can obtain separate MD and CD uniformity spectra. To accomplish this, pixel groups are columns of varying width as **Fig. 7** illustrates schematically. A CD web uniformity spectrum (CD web uniformity evaluated for various size resolutions) consisting of CV% vs. column width may be easily computed. Similarly an MD web uniformity spectrum consisting of CV% vs. row width may be easily computed.

KEYWORDS

Fabric, image analysis, microstructure, nonwovens, procedures, test methods, webs.



8. Uniformity spectra for two webs showing total web uniformity spectra for both webs (left), MD and CD spectra for web A (middle), and MD and CD spectra for web B (right)

Three different web uniformity spectra can describe the uniformity of any web: total web, MD uniformity spectrum, and CD uniformity spectrum. **Figure 8** shows these for two webs. These spectra show that measured web uniformity depends on sample size because smaller structural features are physically averaged when size increases. This observation indicates that web uniformity conducted for only one specimen size can be misleading. Unfortunately, uniformity measurements performed by most techniques such as the cut-and-weigh method are too time consuming to prepare many specimen sizes. Preparing small specimen sizes—often the most pertinent to an application—by many techniques is difficult. Image processing "prepares" specimens of various size rapidly by electronically dividing web images into various cell sizes. This allows one to obtain uniformity spectra quickly using image analysis techniques.

Characterizing web uniformity comprehensively by uniformity spectra can provide useful information. The total uniformity spectra in Fig. 8 indicate that Web A is more uniform than Web B when considering small cell sizes. Web A is less uniform when considering large cell sizes. The MD and CD uniformity spectra for each web indicate that both webs are more uniform in their MD than in their CD. The spectra also show that uniformity in the MD and CD of Web A are more similar to each other than for Web B.

Evaluating other web features

Image analysis techniques can evaluate many structural features besides web uniformity for nonwoven webs. In our laboratory, we have investigated the feasibility of using a simple hardware system and image analysis techniques to characterize most major structural features of nonwoven webs. Software operates with high automation to provide quick and convenient measurements *(1-4)*. The software provides information about pore structure, orientation directions of fibers, fiber diameters, web uniformity, and web defects. This comprehensive set of web structural measurements uses only the simple hardware system of Fig. 1. Software to describe other web structural features is under development for use with the current hardware system without adding to hardware cost.

Table I summarizes specific structural parameters currently measured by our software. The software incorporated various image processing steps. Steps necessary to identify objects of interest within images included image smoothing to reduce the effects of random uncorrelated noise that is invariably present in electronic images, edge detection to identify object boundary locations, thresholding to locate possible objects of interest, and image clean-

Feature	Output
Pores	Size distribution Shape distribution Orientation distribution Number per unit web area Pore cover ratio
Fiber orientation	Fiber orientation indexes: mean orientation angle fiber ratio in MD to CD Fiber orientation distribution
Fiber diameter	Mean fiber diameter Coefficient of diameter variation Fiber diameter distribution
Web uniformity	Optical uniformity spectra: MD, CD, and total basis weight estimation Basis weight uniformity
Bright and dark defects	For each kind of defect: Size distribution Intensity distribution Number per unit web area Defect cover ratio

I. Structural features measured by image analysis

ing. After identifying objects of interest within an image, we obtained measurements that describe the objects. Object description included number, size, shape, orientation, cover, and intensity. The wealth of quantitative information obtainable by image analysis can be difficult to evaluate if not presented concisely. Means for simplifying data are usually beneficial. Procedures we use to reduce data include computation of basic statistical descriptors and graphical output of data. We also have developed convenient procedures for calibration, storage of commonly used settings, and common file utility functions.

After developing software, considerable work is necessary to evaluate its usefulness. While developing software for image analysis applications is easy, it is challenging to develop software that is computationally efficient and provides accurate results. To allow software performance assessment, developers should evaluate and report the performance of important algorithms by comparing results with those from other techniques. Since the usefulness of any analytical technique relates to its accuracy, it is necessary to describe and quantify errors associated with real applications of software. Considerable effort is necessary for these tasks. We have conducted extensive evaluations of our software and reported these results *(1–4)*. Using this experience, we can say that the time required to evaluate software is approximately equal to the time required to develop the software. These efforts are a necessary part of software development.

CONCLUSIONS

To understand better the properties of nonwoven webs, increased knowledge of web structure is necessary. Computer vision techniques are beginning to provide this knowledge. Image processing and analysis can provide images containing more information than the human eye can discern, characterize web structure in a global way using spectral analysis, and detect and describe web structural features comprehensively. We expect continued performance advances and price decreases for image analysis hardware in the future. Software developed to operate this hardware should provide more detailed structural analysis of nonwoven webs. **TJ**

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