On-Line Characterization of Slurry for Monitoring Headbox Performance

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ABSTRACT

We are developing an intelligent, vision-based apparatus for the paper industry, who has had a long-standing need to better understand and to robustly control its papermaking process up-stream, specifically, in the forming section. This unique apparatus is a state-of-the-art vision system that automatically measures and interprets the pertinent paper web parameters at the wet end. Unlike the currently available sensing systems that are intended to operate down-stream, our vision system provides the capability of generating timely measurements of the important web parameters at the crucial stage of paper formation. Having this capability can create both short-term and long-term changes in the paper industry and dramatically impact product quality and production yield. In the short term, the ability to characterize the web at the wet end will provide the machine operators with the necessary feedback they need to make definitive adjustments to the headbox and, hence, minimize the undesirable effects of formation variations. In the long run, the industry can expect significant advances in headbox design and control as their researchers use this same capability to better understand and quantify the headbox flow dynamics.

The wet-end characterization of the paper web by our vision system involves a four-dimensional measurement of the slurry in real-time. These measurements include the two-dimensional spatial information, the intensity profile, and the depth profile of the slurry. To infer the pertinent web parameters from these measurements, the system employs a suite of sophisticated image processing and pattern recognition algorithms. Automatically inferred parameters, such as web homogeneity, and location and topography of the web streaks will then be used to quantify paper formation characteristics or to monitor production events. In addition to the detection and characterization of the slurry features, the system will also make the determination of whether or not these features persist over the section between the headbox and the dryline. At this point in time, one of the two subsystems of this apparatus has been designed, tested, and deployed to a paper mill for on-line evaluation. The second of the two subsystems (i.e., the depth profiling system) is presently under development, and the overall system is expected to be completed towards the end of 1999. This paper describes our general approach and presents some of our early results.

INTRODUCTION

A number of sensors, including vision systems, have been developed for measuring paper properties both on-line[1,2] and off-line [3]. However, nearly all are intended for the dry end and typically scan across the web resulting in less than 100% web coverage. A few wet-end sensors have been proposed. Niemi has used a camera and illumination to determine the location and shape of the dry line at the wet end of a fourdrinier machine [4]. Whitaker has developed a nuclear backscatter gauge to measure consistency at the wet end [5]. This gauge samples the stock at the nip of a fourdrinier machine. Kiviranta, using stroboscopic imaging and a charge-coupled devices (CCD) camera, has investigated the role of table activity on formation in fourdrinier machines [6]. Viewing the wet end with the aid of a strobe light as a diagnostic tool is a fairly common practice in the industry. Generally, by observing the web in this form, nonuniformities, flocculation, and the table action of the slurry on the wire may be discerned. Aidun has used high-speed imaging to investigate the dynamics of the headbox in relation to the production of streaks and other nonuniform physical properties in paper [7]. Nomura has also used stroboscopic imaging to show the varying nonuniformities in the sheet due to variations in headbox design [8]. The headbox flow conditions have been shown to directly affect fiber orientation and other formation properties [9, 10]. While stroboscopic imaging is established as a viable on-line...
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technique for paper web sensing, structured lighting techniques have only been used in off-line applications, such as measuring the surface roughness of paper and board [11]. In other application areas of computer vision, however, depth or range measurement using laser-based structured lighting is a well-established method [12, 13]. Image analysis and pattern recognition methodologies are also areas that have been underutilized by the paper industry researchers, especially here in the United States.

In this work, we describe the design and development of a CCD-based vision sensor for the 4-D characterization of the paper web at the wet end. The characterization of the web in this region involves a 4-D measurement of the slurry in real time. These measurements include spatial information in the \( x \) (machine direction) and \( y \) (cross direction) coordinates; the intensity profile, \( f(x, y) \); and the depth profile, \( z(x, y) \). Image analysis techniques are employed to extract those parameters that correlate with key paper web properties in directly affecting production yield and product quality. The work to date has concentrated on the development of two subsystems to acquire these measurements. The first, the stroboscopic subsystem, acquires intensity images of the web using a CCD camera and a strobe light to freeze motion. The second is the depth-profiling subsystem whereby the depth profile of the slurry is measured in real time using a CCD camera and structured lighting.

This project extends the use of strobe lighting techniques to real-time 100% web measurements with sophisticated image processing approaches to extract the desired information. The addition of depth profile measurement in real time provides a new approach to investigating the formation properties. The following describes the technical approach used in the design and development of the stroboscopic subsystem and in the depth-profiling subsystem, as well as providing the results obtained from initial testing.

**TECHNICAL APPROACH**

The hardware and software components of the stroboscopic and the depth-profiling subsystems are described in the next two sections. Furthermore, novel image analysis techniques for the extraction and identification of pertinent web structures are discussed. The performance of each system and algorithm is evaluated and the results are included.

**Stroboscopic Subsystem**

The stroboscopic subsystem has been developed by Oak Ridge National Laboratory (ORNL) during 1997 and successfully field-tested. This subsystem employs a CCD camera and high-intensity strobed illumination to capture intensity images of the moving slurry at the wet end. A computer-based image storage unit is used to record the images at real-time frame rates. These images form a database for use during development of the image analysis software. The image analysis portion of the subsystem will develop automatic measurements of nonuniformities and flocculation using robust image processing techniques.

**Image Acquisition.** A complete subsystem for stroboscopic image acquisition has been developed and implemented for use as a field test device to acquire and store images of the wet end just downstream from the headbox. This subsystem has been tested at a paper mill where a large number of images were acquired from the wet end at various distances from the headbox. This system includes the following components:

- Pulnix TM-9701 CCD camera
- 25-mm focal length C-mount lens
- Circular polarizing filter
- Unilux Hi-Lighter Strobe Light model HI-RR-6.0-VC
- Datacube Maxvideo MV200 and Motorola MVME167 image acquisition and processing system

A block diagram of the stroboscopic subsystem is given in Fig. 1. The Pulnix camera is a progressive scan device with 768 horizontal pixels and 484 vertical pixels. The camera outputs images at 30 frames per second with manually selectable electronic exposure control. Exposure control was found necessary even with a strobe due to ambient light causing a significant background signal with large variations over the image. This effect was observed in the lab when the integration time was equal to the frame acquisition time of 33 ms. Reducing the exposure time down to 500 \( \mu \)s
eliminated the interference even at the high ambient light levels present in a paper mill.

The strobe light is a rugged unit designed for harsh environments such as a paper mill. It is built to withstand high temperatures as well as high humidity. This particular model uses a Xenon flash tube with a flash rate of 6000 flashes per minute and a maximum energy of 4.7 joules per flash. Flash duration is approximately 20 µs. A remote control unit allows manual control of intensity, flash rate, and phase. In order to acquire images at the time the strobe flashes, the strobe light also includes a video input that is used to synchronize the strobe to the camera. The strobe triggers on the vertical sync from the camera so that the relative time between the strobe flash and the CCD readout is fixed. The manual phase control is used to adjust the time delay between the sync signal and the firing of the strobe so that the integration time window for the camera of 500 ps falls within the strobe flash.

The computer system with image capture hardware consists of a Datacube MV200 and a Motorola MVME 167 CPU in a self-contained VME rack. For this task, the MV200 is used for real-time acquisition and for storage of the images from the camera. During testing at ORNL, the local memory in the MV200 was used for image storage, but this memory is limited to about 160 frames or less than 5 s of image data. For the actual test, the image capture hardware was provided by Lawrence Livermore National Laboratory (LLNL). This hardware also used an MV200, but with the addition of an MD1 disk array capable of recording up to 8 gigabytes of real-time image data. This amount of storage corresponds to about 12 min of data. A backup tape drive was also provided by LLNL so that between tests, the image data could be backed up to the tape, permitting reuse of the MD1 storage.

A frame was also designed and fabricated at ORNL to provide a support for the camera and the light during testing. This frame is shown in Fig. 2. The frame was mounted to the catwalk on the paper machine and permitted extension of the camera and the strobe light for several feet over the web during operation without danger to either the machine or to personnel.

During normal operation, the camera field of view is approximately 1 m wide. This width corresponds to a pixel resolution of about 1.6 mm. A web at 480 m/min will move 0.16 mm during the strobe time of 20 µs. This gives a ratio of 10 to 1 for the resolution to motion distance and ensures that the acquired image will be sharp with negligible blur because of motion. For initial testing, the system was assembled and checked out on a web transport in the laboratory at ORNL. Figure 3 shows the equipment setup in the lab. To demonstrate the operation and to verify the calculations, tests were conducted on the web transport using paper. A thin ink line was drawn in the cross direction on a web of plain brown paper. With the web running at approximately 300 m/min, an image of the line was acquired using the test hardware. Observing the profile of this line along a section in the direction of motion demonstrated that the acquired line from the stroboscopic system was sharp (i.e., only 2 to 3 pixels wide) with no blurring evident.
I. VISION INSPECTION TEST STAND

Fig. 2. CAD drawing of the frame that was used to support the components of the stroboscopic subsystem during the field test.

Fig. 3. Laboratory setup of the stroboscopic subsystem.

Image analysis. The objective here is to analyze the images collected with the stroboscopic subsystem and to extract those pertinent features that relate to and correlate with known paper web parameters. Thus far, we have concentrated on characterizing the collected images based on their apparent homogeneity. This feature is believed to be
related to paper formation properties and perhaps even to the formation index, which is most widely measured off-line with the aid of a densitometer. Of course, validation of this claim requires a controlled, on-line trial, which we intend to undertake during the upcoming performance period. In what follows, we present two different algorithms that are used to adequately detect and characterize the unique structures that typically show up in stroboscopic images of slurry (e.g., streaks). Obviously, characterizing the streaks is directly related to measuring the apparent homogeneity of the paper at the wet end. Note that although the functionality of these algorithms is adequately described, a detailed discussion of their theoretical underpinnings is beyond the scope of this paper, so wherever necessary, the reader is referred to appropriate articles for detailed information.

**Wavelet transform and correlation dimension.** A combination of these two techniques (i.e., discrete wavelet transform and correlation dimension) gives rise to a powerful tool for measuring the apparent homogeneity of texture images. Below, we describe each of these techniques.

By wavelet transform, we are in fact referring to a specific class of the 2-D discrete wavelet transform called the multiscale wavelet representation (MSWAR) [14]. The primary difference between MSWAR and the standard discrete wavelet transform is that the generated signals (or images) in the former case remain at full resolution, whereas in the latter case their resolution is reduced (through decimation) with every iteration of the transformation process. For object recognition and feature extraction (as with this work), this distinction becomes especially significant because loss of resolution means that measurements must be made with fewer data points.

The MSWAR of a 2-D discrete signal (image) \( f(x, y) \), \((x, y) = 1, 2, ..., N\), with \( M \) levels of scale reduction is a set of \((3M + 1)\) signals. These are the detail signals at all levels of scale reduction:

- \( f^j_{d1}(x, y) \) (no vertical edges),
- \( f^j_{d2}(x, y) \) (no horizontal edges),
- \( f^j_{d3}(x, y) \) (no horizontal or vertical edges), for \( j = 1, 2, ..., M \),

plus \( f(x, y) \)’s blurred version at the lowest scale level, \( f^M(x, y) \). An efficient algorithm for the generation of these images has been devised [14], and is given below for easy reference.

1. Given a low-pass and a high-pass filter, and assuming that these filters are represented as column vectors \( LP \) and \( HP \), respectively, generate four 2-D kernels as follows:

\[
LP(LP)^T, \quad HP(LP)^T, \quad LP(HP)^T, \quad HP(HP)^T, \quad \text{where} \quad (,)^T \quad \text{is vector transposition.}
\]

2. For \( j = 1, 2, ..., M \),
3. For \( x = 0, 1, ..., N-1 \),
4. For \( y = 0, 1, ..., N-1 \),
5. Allocate \( u \) row pointers, \( p_0, p_1, ..., p_{u-1} \), and \( u \) column pointers \( q_0, q_1, ..., q_{u-1} \), where \( u \) indicates the support of the selected filters.
6. Initialize the above pointers as follows:

\[
p_0 = x, \quad p_1 = p_0 + 2^{j-1}, \quad ..., \quad p_{u-1} = p_{u-2} + 2^{j-1}
\]

\[
q_0 = y, \quad q_1 = q_0 + 2^{j-1}, \quad ..., \quad q_{u-1} = q_{u-2} + 2^{j-1}
\]

7. Conolve the generated kernels with the elements of the signal \( f^{j-1} \), where \( f^0 = f(x, y) \), as addressed by the above pointers. The results are the \((x, y)^{th}\) elements of the four output signals \( f^j, f^j_{d1}, f^j_{d2}, \text{and} \ f^j_{d3} \), respectively.
8. Next \( y \).
9. Next \( x \).
Fig. 4. Input image (a) and its MSWAR (b) after one level of scale reduction (i.e., \( j = 1 \)). Starting with the top, left-hand corner and moving clockwise, the output images in (b) correspond to \( f^j, f_{d1}^j, f_{d3}^j \), and \( f_{d2}^j \).

10. Next \( j \).

The choice of the above-mentioned low-pass and high-pass filters is application-dependent. Thus far in this work, we have utilized Daubechies’ filters [15] for their compact support and orthogonality. An example of the application of this algorithm for the generation of MSWAR of an arbitrary image is shown in Fig. 4. Note the automatic decomposition of the high-frequency components (edges) of the input image into horizontal and vertical edges. Simply put, the wavelet transform and MSWAR, because of their multiscale nature, allow a choice of the appropriate scale of operation (i.e., a specific level of scale where the desired image features are accentuated and/or the image clutter is attenuated). Following is a brief description of the correlation dimension and its measurement from digital images.

Fractal-based measurements, such as the fractal dimension, lacunarity, and the correlation dimension, have been utilized extensively, with varying degrees of success, for quantifying surface characteristics of texture images. In this work, two new measurements, which are derived from the correlation dimension, are utilized [16]. The first of these is a local measurement that quantifies the surface roughness, while the second gives a measure of the surface homogeneity in a global sense. Let us start by introducing the correlation dimension.

Let a grey level image, \( f(x, y) \), be represented by a point in 3-D space as \( \hat{X}_i[x, y, f(x, y)], i = 1, 2, ..., N \). The correlation dimension, as introduced by Grassberger and Procaccia [17], is defined as

\[
\nu = \lim_{\varepsilon \to 0} \frac{\log [C(\varepsilon)]}{\log [\varepsilon]},
\]

where \( C(\varepsilon) \) is the correlation integral and \( \varepsilon \) is the scale of observation.
where $\varepsilon$ denotes scale. The correlation sum, $C(\varepsilon)$, is given as

$$
C(\varepsilon) = \lim_{N \to \infty} \frac{1}{N^2} \sum_{i, j = 1}^{N} \Theta(\varepsilon - \|\mathbf{x}_i - \mathbf{x}_j\|),
$$

where $N$ is the total number of points in the set; $\Theta(x)$ denotes the unit step function; and $\|\mathbf{x}_i - \mathbf{x}_j\|$ is the distance between vectors $\mathbf{x}_i$ and $\mathbf{x}_j$. Generally, the correlation dimension is estimated as the slope of the line that is fitted to the data points $\{\log(\varepsilon), \log[C(\varepsilon)]\}$. In this work, however, two new measurements are derived directly from the correlation sum.

The first of these reflects the local roughness of the input image surface and is given as

$$
R(m, n) = \sum_{\varepsilon = 1}^{\varepsilon_u} C^2(\varepsilon, m, n),
$$

where $\varepsilon_u$ is the upper limit for $\varepsilon$, and $C(\varepsilon, m, n)$ is the correlation sum computed within nonoverlapping subregions of the input image. The second measurement quantifies global image homogeneity and is computed as follows:

$$
V = \frac{1}{Q} \sum_{m} \sum_{n} [R(m, n) - M]^2,
$$

where

$$
M = \frac{1}{Q} \sum_{m} \sum_{n} R(m, n),
$$

and $Q$ is the total number of subregions into which the input image is divided. Given the above expressions, the following statements can be made. High values of $R(m, n)$ signify high correlation among the pixel values in the subregion (corresponding to a smooth surface), while low values of $R(m, n)$ indicate a rough surface. Furthermore, small values of $V$ (i.e., surface is either mainly rough or mainly smooth) denote a homogeneous image.

Combining MSWAR with the above measurements provides a powerful tool for quantifying the surface characteristics of texture images. By applying the local roughness and global homogeneity measures to the output of MSWAR (specifically, the detail signals), one can quantify these features in a scale-dependent fashion. Note how the natural texture of the input images in Fig. 5 has been removed by MSWAR to allow for the dark streak in Fig. 5(b) to greatly impact the homogeneity measurement. This approach has been tested on the stroboscopic images of the slurry for the detection of streaks and the quantification of web homogeneity. Before discussing these results, however, we will introduce yet another algorithm for a more accurate detection and characterization of the web streaks.

**Classification of topographic structures.** While the methodology described above helps us achieve a scale-dependent quantification of the web homogeneity, it does not provide an accurate characterization of the surface topography. Below, we describe an algorithm based on the facet model [18] that aids in the characterization of topographic structures (e.g., streaks), which are visible in the intensity images of paper slurry. Also, the same algorithm is intended to be applied to the true 3-D data that is to be gathered with the depth-profiling subsystem.

The facet model principle assumes that the intensity image can be characterized as a piecewise continuous gray level intensity surface. To actually carry out the characterization and processing with the observed digital image requires a model that describes the general form of the surface in the neighborhood of any pixel. The commonly used general forms for the facet model include piecewise constant, piecewise linear, piecewise quadratic, and piecewise cubic. Assuming, for now, that the images are not degraded by noise or geometrical transformations (e.g., defocusing), and utilizing one of the above mentioned forms, one must first estimate the parameters of the underlying surface for all the pixels and their respective neighborhoods. Subsequently, these estimates can be utilized in a variety of ways,
Fig. 5. (a), (b) Input images. (c), (d) $f_{d1}^2$ for the images in (a) and (b), respectively. (e), (f) $R(m, n)$ for the images in (c) and (d), respectively. The global homogeneity measures, $V$, for the input images are 1.11 for (a) and 58.14 for (b). This suggests that the dark streak present in (b) renders this image nonhomogeneous.

including the labeling of every pixel into one of a variety of topographic structures, such as peak, ridge, valley, saddle, flat, and hillside (see Fig. 6).

In this work, we compute the best fit (in a least-squares sense) cubic facet for each pixel and its neighborhood in the input image. The neighborhood is chosen to be $7 \times 7$, and the cubic facets are cubic polynomials of the form

$$F(x, y) = Ax + By + Cx^2 + Dxy + Ey^2 + Fx^3 + Gy^3 + Hxy^2 + Iy^3 + J.$$ 

Once the 10-element vector of coefficients has been estimated for each pixel, the topographic labeling can proceed by computing the gradient and the Hessian of the facets. These are defined as:

$$\begin{bmatrix} \frac{\partial F}{\partial x} \\ \frac{\partial F}{\partial y} \end{bmatrix} \quad \text{and} \quad \begin{bmatrix} \frac{\partial^2 F}{\partial x^2} & \frac{\partial^2 F}{\partial x \partial y} \\ \frac{\partial^2 F}{\partial y \partial x} & \frac{\partial^2 F}{\partial y^2} \end{bmatrix},$$

respectively. This is followed by determining whether various quantities are negative, zero, or positive. For example,
a flat region has zero gradient and zero Hessian eigenvalues. The specific arrangements for the other labels are presented in Table 1 below. In reading the table, the following definitions apply:

- $\| \nabla F \|$ is the gradient magnitude.
- $\lambda_1$ and $\lambda_2$ are the largest and the smallest eigenvalues of the Hessian.
- $\nabla F \cdot E_1$ and $\nabla F \cdot E_2$ are the first directional derivatives in the direction of $E_1$ and $E_2$, which are the eigenvectors associated with $\lambda_1$ and $\lambda_2$, respectively.
- "0" means close to zero; "+" means significantly different from zero on the positive side; "-" means significantly different from zero on the negative side; and "*" means it does not matter.

### Table 1. Properties of topographic structures

<table>
<thead>
<tr>
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<th>$\lambda_1$</th>
<th>$\lambda_2$</th>
<th>$\nabla F \cdot E_1$</th>
<th>$\nabla F \cdot E_2$</th>
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Fig. 7. (a) Test image, (b) 3-D representation of the intensity image in (a), and (c) the labeled topographic image. Each intensity value in (c) represents a label (e.g., black means a flat region). Two out of a total of 11 labels are identified on the image.

The described algorithm was applied to a synthetic image, and the result is shown in Fig. 7. The results of the application of both of the above described algorithms to acquired images of slurry are presented in the next section.

Results. The stroboscopic subsystem described above, was deployed at the paper mill in early 1997. In this trip, we were accompanied and assisted by our colleagues from LLNL. The apparatus was installed on a machine producing linerboard at a speed of approximately 500 m/min. To avoid interfering with production, the frame was mounted on a catwalk seldom accessed by plant employees. The view of the paper machine from this catwalk, which was extended in the machine direction, along with a picture of the mounted apparatus are shown in Fig. 8. This two-day field test proved to be quite valuable both in terms of image collection for analysis and in getting a firsthand feel for the challenges that are faced in a paper mill environment.

The collection of images shown in Figure 9 provides examples of the acquired images. The image in Fig. 9(a) is among the first images acquired by our stroboscopic system. This is an overhead shot (1 m away) of the slurry with a 1m $\times$ 1.2 m field of view, the center of which was approximately 2 m away from the headbox and 0.8 m away from the edge of the web. This image, like all the others, has a resolution of 1.6 mm per pixel. Although some structure is visible in this image, what is immediately apparent is the specular reflections caused by the water beads. We devised two means of eliminating this problem: (1) as shown in Fig. 9(b), through the utilization of median filtering [18] after acquisition, or (2) by using polarizing filters, which help to reduce the specular reflection prior to acquisition, Fig.
The images shown in Fig. 10 are typical results obtained from the wavelet-based algorithm for the measurement of apparent homogeneity. The image in Fig. 10(a) represents a subregion of an overhead shot taken during our field test. Because of the presence of the streak, the MSWAR of this image [Fig. 10(b)] exhibits nonuniformities in the machine direction [i.e., in the detail image $f_{d1}(x, y)$], whereas in the cross direction, represented by the detail image $f_{d2}(x, y)$, the web appears more homogeneous. Comparing the estimated values of the global homogeneity for the first image ($V = 751.3$) with that of the second image ($V = 166.3$) confirms this fact as well. It is also interesting to compare these results with those computed for the image in Fig. 10(c) (i.e., an image of fiberless water). Note that not only the MSWAR of this image [Fig. 10(d)] appears more uniform than that of the slurry, but the computed value for its global homogeneity (i.e., $V = 38.9$) is much smaller.

The described algorithm based on the facet model has also been applied to the collected images, and typical results are shown in Fig. 11. Observing the topographic structures (in this case, ridges and ravines only) shown in Figs. 11(b) and 11(d), indicate how accurately the web streaks are characterized by this model and how different the structure of the slurry appears from that of the fiberless water.

**Depth Profiling Subsystem**

The depth profiling subsystem has also been developed by ORNL and tested in the laboratory to demonstrate feasibility. This subsystem is designed to measure the depth profile of the wet end slurry in the cross direction at a particular location downstream from the headbox. Structured lighting is employed through the use of an infrared laser for illumination and a CCD camera to capture images of the laser profile. A computer-based image acquisition and analysis system is used to record the images at real-time frame rates. The image analysis portion of this subsystem will develop automatic techniques to characterize nonuniformities in the moving slurry from the sequence of depth profiles.

**Data acquisition.** The data acquisition subsystem being developed measures the depth profile along a cross sec-
Fig. 9. Example of images collected during our field test. See text for details.
Fig. 10. Typical results obtained from the wavelet-based algorithm for the measurement of homogeneity. (a) Slurry and (b) its MSWAR. (c) Fiberless water and (d) its MSWAR.
Fig. 11. Labeling of topographic structures in images of (a) slurry and (c) fiberless water. For clarity, only ridges and ravines are identified in (b) and (d).

This subsystem uses structured lighting and a standard CCD camera as the method of depth measurement. The setup in the lab at ORNL is shown in Fig. 12. An infrared laser with optics to spread the beam into a plane of light is placed directly above the web. The light plane is perpendicular to the motion direction and is parallel to the cross direction. A CCD camera is mounted at an angle to the laser, viewing the slurry as it moves underneath. The equipment for this test is listed below.

- Pulnix TM-9701 CCD camera
- 25-mm focal length C-mount lens
- Screw-on mount linear polarizing filter
- Infrared pass filter
100-mW, 830-nm, IR diode laser with 45 degree fanout line projector

Datacube Maxvideo MV200 and Motorola MVME167 image acquisition and processing system

Note that the camera, the lens, and the image acquisition computer system are the same as those used on the stroboscopic subsystem. The major addition is the laser. An infrared laser at 830 nm wavelength is invisible to the eye, but the silicon in the camera is highly sensitive to energy at this wavelength. The infrared pass filter is used to exclude visible light so that external lighting does not interfere with the algorithm used to locate the laser line position. The laser projects a single line of light onto the surface at a fanout of 45 degrees. For a 1 m line width at the surface, the laser height above the surface is about 1.1 m. With the camera at an angle $\theta$ from the laser, the change in image height as seen by the camera is related to actual depth change by $dy = \sin \theta \, dz$, where $dy$ is the change in $y$ coordinate relative to the camera and $dz$ is the change in depth (Fig. 13). As this expression shows, the sensitivity of the depth by the camera increases as the angle increases up to 90 degrees. The result is that the depth resolution is improved. However, a larger angle potentially produces more occlusions by surfaces not in the laser light plane, giving no data where the occlusion occurs. For the feasibility testing in the laboratory at ORNL, good results were obtained when this angle was set to about 45 degrees. At this angle, the sensitivity is about 70% of the maximum.

During operation, the laser sheet of light intersects the surface of the web, producing an irregular line. The camera acquires an image of this line and transfers the image data to the MV200 for processing. A portion of the image processing is done by the MV200 while the CPU performs the primary processing to calculate the line position. During image acquisition, the MV200 applies a threshold to the data and calculates the upper left and lower right coordinates of the bounding box that surrounds the laser line area above the threshold. Then only the data within the bounding box is read by the CPU. This process significantly reduces the amount of data that must be transferred to the CPU as well as reduces the local storage requirements. Testing has shown that this computer system cannot both acquire data and perform the depth calculations in real time. To prove the feasibility in the lab, however, an alternative method was implemented to demonstrate the operation. The system initially acquires in real time up to 90 frames of line data extracted from the bounding box image. This data represents three seconds of web sampling. After acquisition, the line data is processed by the depth estimation algorithm to produce the actual depth profile. For actual field testing, a
new computer system will be required that has the processing capability to perform both the acquisition and depth calculation in real time.

**Depth estimation algorithms.** Once the laser line has been detected, the next step is to estimate the center of this line within each column of the image. As discussed before, the estimated centers, or more specifically, their displacement from a reference point, correspond to the depth profile of the object under study. Two algorithms for the estimation of the laser line centers were implemented, and their performances were compared.

The first of these, referred to as the binary centroid algorithm, is a straightforward technique that operates as follows. Within each column of the bounding box, the intensity values of the contained laser line are thresholded to produce a one-dimensional blob. Then, the depth profile of the object in each location is computed as the centroid of the obtained blob according to

\[ z = \frac{1}{A} \sum_i r_i, \]

where \( r_i \) represents the coordinate (row position) of the pixels whose intensity values fall above the threshold, and \( A \) is the total number of such pixels.

The second algorithm, referred to as the weighted centroid algorithm, is a more sophisticated technique, and one that is computationally more complex [19]. As was the case above, the procedure that is to be described is repeated for each column of the bounding box that contains the laser line. The distinct characteristic of the weighted centroid algorithm is a smooth mapping function, \( P(g_i) \), that is used to represent the likelihood that a pixel with intensity \( g_i \) is a member of the laser line. This is in contrast to the binary centroid algorithm, in which, through the utilization of a threshold, the decision of whether or not a pixel is a member of the laser line is one that is crisp rather than fuzzy. In this work, a truncated error function (erf) was chosen for the smooth mapping function. The shape of the Gaussian, which is integrated to compute the values of \( P(g_i) \), was chosen so that 3\( \sigma \) below the mean were intensity values clearly belonging to the background. Then, the depth profile of the object in each column is computed as follows:

\[ z = \frac{\sum P(g_i) r_i}{S}, \]
where $S = \sum P(g_i)$. It will be shown in the next section that depth information estimated in this fashion, though computationally more intensive, is far more robust than the binary centroid algorithm.

**Results.** To test the apparatus and the algorithms described above, a scene comprising rows of cotton balls glued to the transported paper was fabricated [Fig. 14(a)]. This test scene was scanned by our depth-profiling system at various web speeds. The 3-D plot of Fig. 14(b) represents the estimated depth profile of the test scene at 30 m/min. The 2-D contour plots in Figs. 14(c)-14(e) give an interesting view of the rows of cotton balls at 15, 30, and 150 m/min, respectively. Note how the lengths of the rows are shortened as the number of samples in the direction of motion decreases with increased speed of the web. The contour plots seem to provide a revealing way of presenting web non-uniformities.

The same test scene was also utilized to evaluate the performances of the binary and the weighted centroid algorithms, Fig. 15. It is observed that the profile obtained through the usage of the binary centroid algorithm [Fig. 15(a)] is far more susceptible to noise than that obtained by the weighted centroid algorithm [Fig. 15(b)]. One can further observe that the rows of cotton balls and their peaks are much better defined in the latter case.

**CONCLUSIONS AND FUTURE WORK**

This work involves the design, development, and deployment of a cost-effective vision system that uses the described components to characterize the paper web at the wet end. The characterization of the web in this region involves a 4-D measurement of the slurry in real time. The stroboscopic and the depth-profiling subsystems are used to measure spatial information, the intensity profile, and the depth profile of the slurry. The sensed quantities are subjected to image analysis and pattern recognition algorithms for extraction of web parameters. Automatically extracted parameters, such as homogeneity of the web, and location and topography of the web streaks, may then be used to predict paper properties (e.g., formation) or to monitor production events (e.g., table activity and web breaks).

The following provides a list of the main tasks that are to be accomplished in the future:

1. Real-time implementation of the described analysis algorithms, followed by a second field test of the stroboscopic subsystem.
2. Real-time implementation of the depth estimation algorithms, followed by an initial field test of the depth-profiling subsystem.
3. Design and implementation of image analysis algorithms for the depth data.
4. Integration of the two subsystems into one, followed by the deployment of the alpha system.

**REFERENCES**


Fig. 14. (a) Test scene sensed by the depth-profiling subsystem. (b) Depth profile of the scene. (c), (d), and (e) Depth profiles of the test scene scanned at 15, 30, and 150 m/min, respectively, and represented as contour plots.
Fig. 15. Depth profile of the test scene represented as 2-D contour plots using (a) the binary centroid algorithm and (b) the weighted centroid algorithm.


