

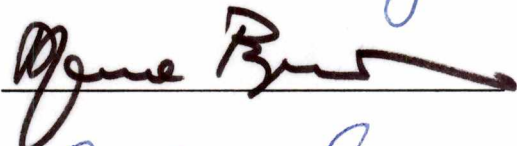
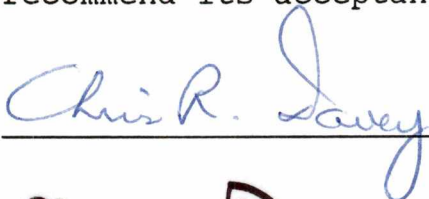
To the Graduate Council:

I am submitting herewith a thesis written by Chang-Huei Hsi entitled "The Application of Digital Image Processing Using FFT to Monitor Web Structure." I have examined the final copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Textiles and Apparel.



Randall R. Bresee, Major Professor

We have read this thesis and
recommend its acceptance:



Accepted for the Council:



Vice Provost
and Dean of The Graduate School

**THE APPLICATION OF DIGITAL IMAGE PROCESSING
USING FFT TO MONITOR WEB STRUCTURE**

**A Thesis
Presented for the
Master of Science
Degree
The University of Tennessee, Knoxville**

**Chang-Huei Hsi
December 1991**

ACKNOWLEDGEMENT

Instruction from my major advisor, Dr. Randall R. Bresee, has always been a substantial help for the thesis. I am appreciative of his assistance. For portions relative to digital image processing and pattern recognition, I greatly appreciate Dr. Dragana Brzakovic's guidance in these techniques. Without her help, the project would not be successful. Also, support from Exxon Chemical Company which provides the image processing system and the melt-blown pilot line is greatly appreciated.

ABSTRACT

The goal of this project was to develop a new PC-based tool to monitor important structural features in thin nonwoven webs and classify unknown webs based on these features.

First, a 512 X 512 pixel image is snapped by a video camera and displayed on a monitor screen. Then, a 2-D Fourier transform is applied to a fixed area of 256 x 256 pixels to convert data from the spatial domain into the frequency domain; that is, a web image is replaced by a FT spectrum. Energy is accumulated in the FT spectrum in response to the spatial arrangement of fibers over the background. Consequently, analysis of spectral energy provides a feasible path to monitor web structure. Total spectral energy was measured. In addition, the spectral energy distribution was measured using bi-linear interpolation. Several models using simple arrangements of lines were used to study the influence of web structural features on the 2-D FT spectrum. Several indices were extracted from the Fourier spectrum in order to classify webs with regard to structure. This process was illustrated for the case of webs having different fiber orientation and weight where unknown patterns were classified using 3 different training models.

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PART 1

INTRODUCTION

A fundamental element determining web performance is web structure, i.e., how fibers are assembled. Several instrumental techniques have been developed to monitor individual web structural features. For online web monitoring, a quantitative measurement which simultaneously monitors several important web structural features might be useful. Therefore, two questions were asked in this thesis:

- (1) Can digital image processing be used to monitor several important structural features of a thin web simultaneously?
- (2) Is it possible to classify a web with the technique of pattern recognition?

Due to the low cost of available hardware, digital image processing is a promising tool for characterizing web structure. When a two-dimensional Fourier transform (2DFT) is applied to a web image, the ability to monitor several web structural features simultaneously seems possible. The investigation of this seems desirable since many scientists and engineers are familiar with the FT, a fast algorithm (FFT) already exists for obtaining the FT, and many web structural features would be expected to contribute to the FT spectrum.

After static image measurements conducted for this thesis, the FT technique has the potential to be applied on line, if desired. Most other analytical methods, however, seem to be confined to a conditioned laboratory. Improved web properties and increased productivity are desirable goals. These goals as well as routine product monitoring involve frequent measurements by producers. Ideally, these measurements are obtained rapidly and are sensitive to many product structural features. By using several pieces of information derived from the FT spectrum, a web can be assigned to a class based one or more structural features. This provides a means to monitor web structure changes and assess the influence of processing changes on web structure.

For this thesis, a procedure was developed to

characterize the FT energy distribution, to monitor several important web structural features, and to classify webs. The basic techniques employed included image acquisition, Fourier analysis, data interpolation, and pattern recognition.

PART 2

**REVIEW OF TECHNIQUES
FOR
ASSESSING FIBER ORIENTATION**

In most cases, numerous analytical techniques are available for characterizing a particular web structural feature. Several items of equipment are usually required to characterize the most important structural features. Equipment purchase, maintenance and training are required for each item of equipment.

A single measurement which is sensitive to several web structural features would seem to offer an advantage with regard to these factors. The image-based tool described in this thesis was proven to be sensitive to fiber orientation, fiber diameter, fiber density (number of fiber per unit area), and fiber spacing.

No convenient analytical method currently exists for determining fiber spacing or the number of fibers per unit area. Reliable methods of measuring fiber diameter currently exist, but these usually are based on tedious and time consuming measurements using the scanning electron microscope or optical microscope. Although many methods exist for measuring fiber orientation, none are convenient to use. To illustrate the extensive equipment purchase and training that often must be invested to characterize a single structural feature, a brief review of techniques used for characterizing fiber orientation in nonwoven webs will be given.

2.1 Microscope Counting

The classical method for determining the fiber orientation distribution of webs involves counting the number of fibers aligned in various web directions when a sample is viewed under a microscope. This method yields a number-average distribution which may not be adequate for webs composed of fibers having variable cross-sectional area. In addition, it is difficult to specify the orientation of fibers with bent or curled shapes. Other limitations of this technique are that the work is tedious and time-consuming.

A slight modification of this technique has been used.

The lengths and directions of fibers are input into a computer which sums the total length in each defined direction so the distribution of fiber length in various web directions is obtained [3].

Another way of applying this technique is to divide a fiber into segments and assign the segments to angles [4]. It is claimed that webs require a few dyed fibers, although this method is said to be used on line. When dyed fibers are required, however, the use of this technique for analyzing most commercial webs is quite limited.

2.2 Light Reflection and Refraction Intensity [5]

When a fiber with a circular cross-sectional shape is illuminated, the reflected or refracted light forms a cone of rays coaxial with the fiber. Only fibers which are perpendicular to the plane of incidence deflect light in a direction perpendicular to their axes. The total intensity of light normal to the web plane thus is proportional to the total length of fiber perpendicular to the plane of incidence. The web is rotated in its own plane or the plane of incidence is rotated and a photocell is used to measure light intensity. An orientation coefficient is given by

$$\text{coefficient} = \frac{\text{max. photocell output}}{\text{min. photocell output}} - 1 \quad (2.1)$$

The orientation coefficient is zero when a perfectly random fiber distribution occurs. This method is restricted to very loosely packed webs.

2.3 Zero-span Tensile Testing [6]

A web is gripped by a pair of jaws close together so there is essentially a "zero span" at the start of the test. The function, $f(\theta)$, describes the fiber orientation distribution of a sheet.

$$f(\theta) = \frac{1}{\pi} + e \cos 2\theta \quad (2.2)$$

$$e = \frac{3}{2\pi} \frac{(1 + Z_{md} : Z_{cd})}{(1 - Z_{md} : Z_{cd})} \quad (2.3)$$

where Z_{md} = zero span tensile strength in machine direction,
 Z_{cd} = zero span tensile strength in cross direction, and
 e = eccentricity defined as a degree of fiber bias.
 Plots are obtained for $e=0$ for a random network, and $e=-1/\pi$ for the most highly oriented network. This technique is said to be suitable for characterizing most papers with $Z_{md} : Z_{cd}$ in the range 1.0 - 5.0. However, one must question the validity of determining the fiber orientation distribution from only two tensile measurements.

2.4 X-ray Diffraction [7]

The fiber orientation distribution in papers is obtained from the distribution of measured x-ray diffraction intensity. However, an independent measurement of the crystallite angle distribution function is required. In addition, it is necessary to assume that the distribution possesses a specific functional form.

2.5 Infrared Absorption [8]

An anisotropic ratio based on machine- and cross-direction absorption can be measured from submillimeter wavelength infrared absorption. No other information about the fiber orientation distribution is obtained.

2.6 Laser Beam Diffraction [9]

Analyzing laser beam diffraction based on the familiar 2-D Fourier transform is said to provide fiber orientation information. The distribution of diffraction intensity is obtained and other optical phenomena such as scattering and

refraction are ignored. Another limitation of this technique is that it is only suitable for thin webs.

2.7 Electrical Conductivity [10]

A method was developed to determine the whole fiber orientation distribution in nonwoven webs from measurements of electrical conductivity. The basic concept behind this technique is that electric current is conducted along fibers and greater conductivity will occur in web directions in which a greater number of fibers lie. A restriction of this technique is that it is not adaptable to on-line application.

PART 3

THEORIES

3.1 Two-dimension Fourier Transform

Fibers in a web may exhibit a wide diameter distribution, may be spaced with widely varying distance intervals, may be grouped in widely varying areal densities, and may be aligned in any direction in 2-D space. Although analyzing web structure in the spatial domain by analyzing pixel gray levels is direct, it is rather time consuming. Evaluating web structure by analyzing the 2-D Fourier spectrum in the frequency domain provides a convenient alternative. Unfortunately, the FT spectrum does not allow direct description of web structural features. As this thesis will show, however, webs differing in structure exhibit different FT spectra. Consequently, the perceived value of the tool developed in this thesis is to rapidly detect changes in web structure. This is an important task of web producers.

3.1.1 Discrete Fourier Transform [11]

In the two-variable case, when images are sampled in a square array, the FT pair is given by the equations

$$F(u, v) = \frac{1}{N} \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x, y) \exp[-j2\pi(ux + vy)/N] \quad (3.1)$$

for $u, v = 0, 1, 2, \dots, N-1$, and

$$f(x, y) = \frac{1}{N} \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} F(u, v) \exp[j2\pi(ux + vy)/N] \quad (3.2)$$

for $x, y = 0, 1, 2, \dots, N-1$.

The Fourier transform of a real function, however, is generally complex; that is,

$$F(u, v) = R(u, v) + jI(u, v), \quad (3.3)$$

where $R(u,v)$ and $I(u,v)$ are, respectively, the real and imaginary components of $F(u,v)$. It is often convenient to express Eq.(3.3) in exponential form:

$$F(u,v) = |F(u,v)| \exp[j\phi(u,v)] \quad (3.4)$$

where

$$|F(u,v)| = [R^2(u,v) + I^2(u,v)]^{1/2} \quad (3.5)$$

The magnitude function $|F(u,v)|$ is called the Fourier spectrum of $f(x,y)$, and $\phi(u,v)$ its phase angle.

3.1.2 Some Properties

Several properties of the FT will be discussed to understand the actions of digital image processing applied in this thesis.

3.1.2.1 Translation [11]

The translation properties of the FT pair are given by

$$f(x,y) \exp[j2\pi(u_0x + v_0y)/N] \leftrightarrow F(u-u_0, v-v_0) \quad (3.6)$$

and

$$f(x-x_0, y-y_0) \leftrightarrow F(u,v) \exp[-j2\pi(ux_0 + vy_0)/N]. \quad (3.7)$$

Eq.(3.6) is in a shift of the origin of the frequency plane to the point (u_0, v_0) . Similarly, Eq.(3.7) moves the origin of the spatial plane to (x_0, y_0) . The need of translation for $u_0=v_0=N/2$ is explained in Fig.3.1. To display one full period, all that is necessary is to move the origin of the transform to the point $u=N/2$. So, from Eq.(3.6), it follows that

$$\begin{aligned} \exp[j2\pi(u_0x + v_0y)/N] &= e^{j\pi(x+y)} \\ &= (-1)^{x+y} \end{aligned}$$

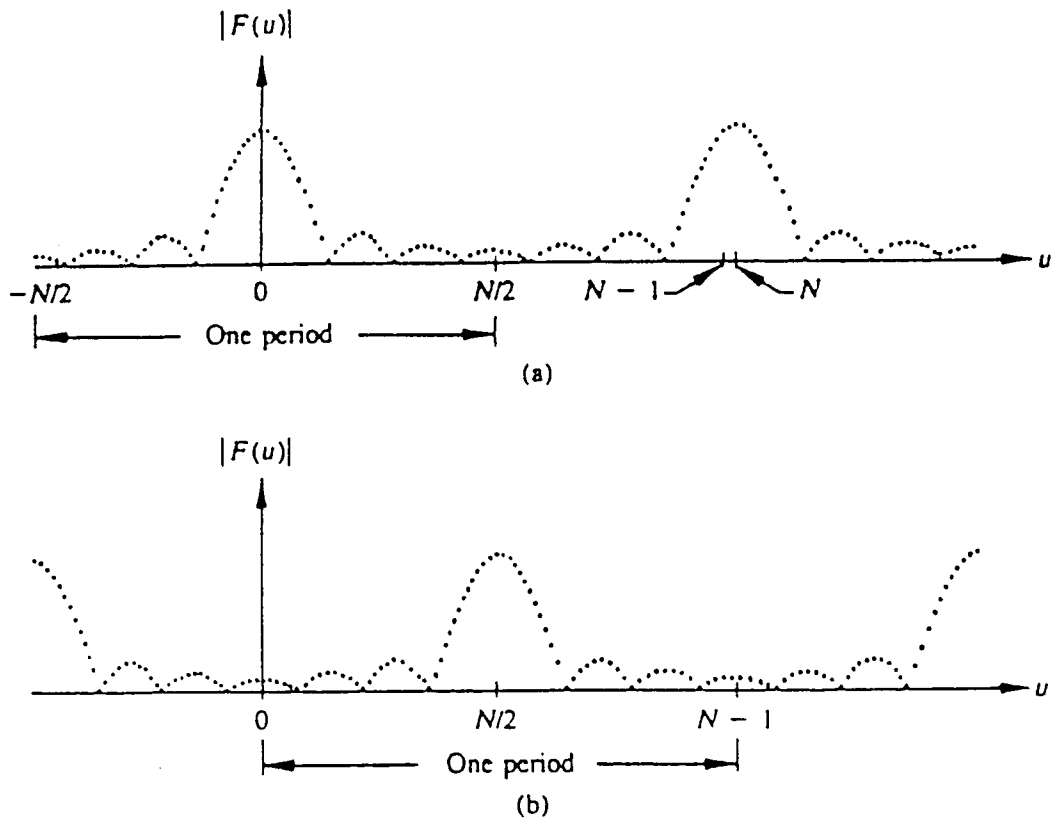


Fig. 3.1 Illustration of the periodicity properties of the Fourier transform. (a) Fourier spectrum showing back-to-back half period in the interval $[0, N-1]$. (b) Shifted spectrum showing a full period in the same interval (From Digital Image Processing [1987], p.78).

and

$$f(x, y) (-1)^{x+y} \leftrightarrow F(u-N/2, v-N/2). \quad (3.8)$$

Thus the origin of the FT of $f(x, y)$ can be moved to the center of its corresponding $N \times N$ frequency square by multiplying $f(x, y)$ by $(-1)^{x+y}$.

It is important to note from Eq.(3.7) that a shift in $f(x, y)$ does not affect the magnitude of its FT since

$$|F(u, v) \exp[-j2\pi(ux_0 + vy_0)/N]| = |F(u, v)|. \quad (3.9)$$

3.1.2.2 Separability [11]

The FT pair given in Eqs.(3.1) and (3.2) can be expressed in the separable forms

$$F(u, v) = \frac{1}{N} \sum_{x=0}^{N-1} \exp[-j2\pi ux/N] \sum_{y=0}^{N-1} f(x, y) \exp[-j2\pi vy/N] \quad (3.10)$$

for $u, v = 0, 1, \dots, N-1$, and

$$f(x, y) = \frac{1}{N} \sum_{u=0}^{N-1} \exp[j2\pi ux/N] \sum_{v=0}^{N-1} F(u, v) \exp[j2\pi vy/N] \quad (3.11)$$

for $x, y = 0, 1, \dots, N-1$.

Furthermore, Eq.(3.10) is expressed in the form

$$F(u, v) = \frac{1}{N} \sum_{x=0}^{N-1} F(x, v) \exp[-j2\pi ux/N], \quad (3.12)$$

where

$$F(x, v) = N \left[\frac{1}{N} \sum_{y=0}^{N-1} f(x, y) \exp[-j2\pi vy/N] \right]. \quad (3.13)$$

Thus the advantage of separability is that $F(u,v)$ or $f(x,y)$ can be obtained in two steps by successive applications of the 1-D FT or its inverse. For Eqs.(3.12) and (3.13), one first takes (row transforms) $\times N$, and then, column transforms.

3.1.2.3 Periodicity and Conjugate Symmetry [11]

The discrete FT and its inverse are periodic with period N , and if $f(x,y)$ is real, the FT also exhibits conjugate symmetry since, in this case,

$$F(u,v) = F^*(-u, -v) \quad (3.14)$$

or,

$$|F(u,v)| = |F(-u, -v)|. \quad (3.15)$$

Also, from Fig.3.1 it is evident that the magnitudes of the transform values from ($[N/2]+1$) to ($N-1$) are images of the values in the half period on the left side of the origin.

3.1.2.4 Displaying [11]

Many FT spectra decrease rather rapidly as a function of increasing frequency and therefore their high-frequency terms have a tendency to become obscured when displayed for visual observation. A useful processing technique that compensates for this difficulty consists of displaying the function

$$D(u,v) = \log(1+|F(u,v)|) \quad (3.16)$$

instead of $|F(u,v)|$. Use of this equation preserves zero values in the frequency plane since $D(u,v) = 0$ when $|F(u,v)| = 0$. It is also noted that $D(u,v)$ is a nonnegative function. Use of Eq.(3.16) before rescaling the values to the same gray scale of the image, greatly facilitates visual interpretation of the 2-D FT display of the spectrum.

3.1.3 Fast Fourier Transform [11]

The number of complex multiplications and additions

required to implement Eq.(3.1) is proportional to N^2 . By a decomposition procedure using the FFT algorithm, this number can be made proportional to $N \log_2 N$. The FFT algorithm offers considerable savings in computational effort compared to direct implementation of the FT, particularly when N is relatively large.

The FFT algorithm developed for this thesis is based on the so-called "successive doubling" method. For convenience, the 1-D FT is illustrated using the FFT algorithm. The 1-D FT is given by the equation

$$F(u) = \frac{1}{N} \sum_{x=0}^{N-1} f(x) \exp[-j2\pi ux/N]. \quad (3.17)$$

If we define $W_M^{ux} = \exp[-j2\pi ux/M]$, then

$$F_{\text{even}}(u) = \frac{1}{M} \sum_{x=0}^{M-1} f(2x) W_M^{ux} \quad (3.18)$$

for $u = 0, 1, 2, \dots, M-1$, and

$$F_{\text{odd}}(u) = \frac{1}{M} \sum_{x=0}^{M-1} f(2x+1) W_M^{ux} \quad (3.19)$$

for $u = 0, 1, 2, \dots, M-1$. Eq.(3.17) then becomes

$$F(u) = \frac{1}{2} \{ F_{\text{even}}(u) + F_{\text{odd}}(u) W_{2M}^u \}. \quad (3.20)$$

Also, since $W_M^{u+M} = W_M^u$ and $W_{2M}^{u+M} = -W_{2M}^u$, it follows from Eqs.(3.18) through (3.20) that

$$F(u+M) = \frac{1}{2} \{ F_{\text{even}}(u) - F_{\text{odd}}(u) W_{2M}^u \}. \quad (3.21)$$

By checking Eqs.(3.20) and (3.21), computation of the first half of $F(u)$ requires the evaluation of the two $(N/2)$ -point transforms given by Eqs.(3.18) and (3.19). The resulting values of $F_{\text{even}}(u)$ and $F_{\text{odd}}(u)$ are then substituted into

Eq.(3.20) to obtain $F(u)$ for $u = 0, 1, 2, \dots, (N/2) - 1$. The other half then follows directly from Eq.(3.21) without additional transform evaluations.

3.2 Interpolation Approximation [14]

The need of interpolation results from the fact that evaluation of the angular distribution of FT energy requires that we deal with pixels nonexistent except for those at 0° , 45° , 90° , 135° and 180° . Thus the use of interpolation is necessary to approximate the gray level of nonexistent pixels from those existent already. The scanning layout is shown in Fig.3.2.

In two dimensions, we are given a matrix of functional values $y_a[j][k]$, where j varies from 1 to m and k varies from 1 to n . We are also given an array $x1a$ of length m , and an array $x2a$ of length n . The relation of these input quantities to an underlying function $y(x_1, x_2)$ is

$$y_a[j][k] = y(x1a[j], x2a[k]). \quad (3.22)$$

An important concept is that of the grid square in which the point (x_1, x_2) falls, that is, the four existent points which surround the desired interior point. More precisely, if

$$\begin{aligned} x1a[j] &\leq x_1 \leq x1a[j+1] \\ x2a[k] &\leq x_2 \leq x2a[k+1], \end{aligned} \quad (3.23)$$

then

$$\begin{aligned} y_1 &= y_a[j][k] \\ y_2 &= y_a[j+1][k] \\ y_3 &= y_a[j+1][k+1] \\ y_4 &= y_a[j][k+1]. \end{aligned} \quad (3.24)$$

Bi-linear interpolation on the grid square as illustrated in Fig.3.3, thus, gives its formulas:

$$\begin{aligned} t &= (x_1 - x1a[j]) / (x1a[j+1] - x1a[j]) \\ u &= (x_2 - x2a[k]) / (x2a[k+1] - x2a[k]) \end{aligned} \quad (3.25)$$

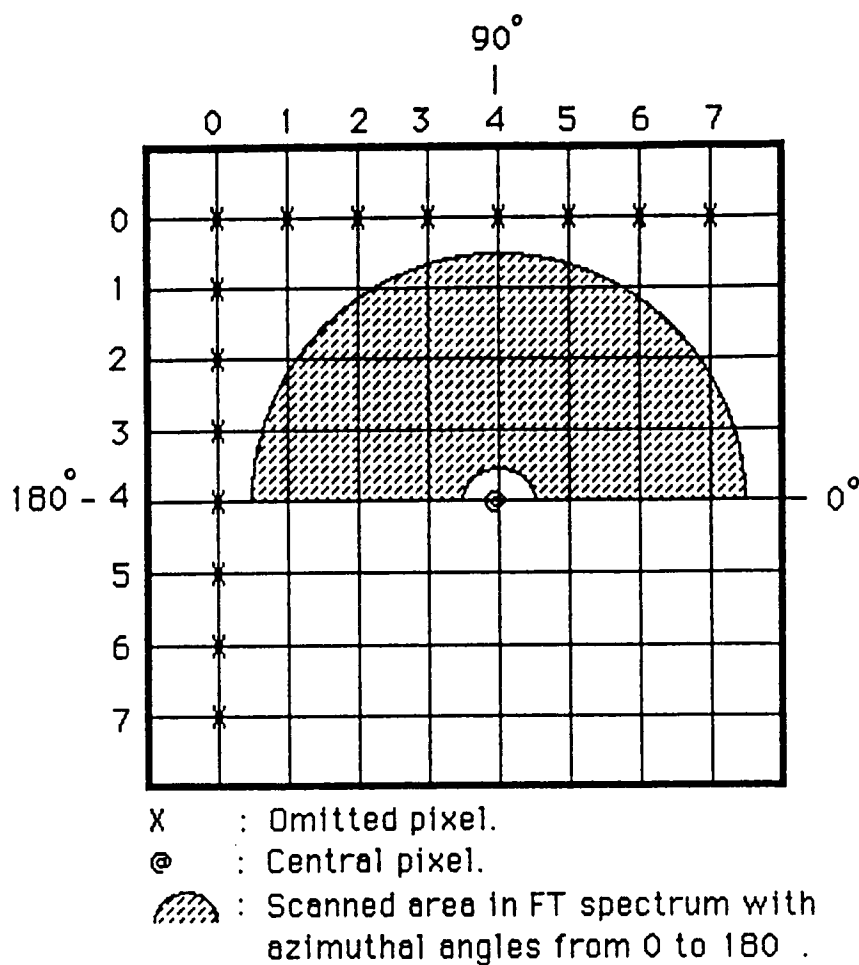


Fig. 3.2 Scanned layout in a FT spectrum, 8 x 8 pixels.

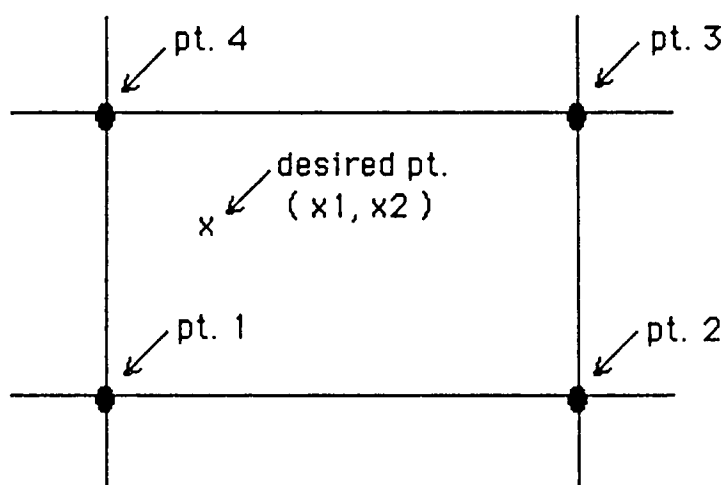


Fig. 3.3 Labeling of points used in 2-D interpolation.

(so that t and u each lie between 0 and 1), and

$$y(x_1, x_2) = (1-t)(1-u)y_1 + t(1-u)y_2 + tuy_3 + (1-t)uy_4. \quad (3.26)$$

3.3 Trainable Pattern Classifiers

Classification of products is a common goal of inspection and quality control activities. Before product classification can be performed, evaluation criteria must be established. These criteria represent typical patterns for each class desired. The method of trainable pattern classifiers is the way to achieve this goal.

3.3.1 Polynomial Decision Functions [15]

A general linear decision function is of the form

$$\begin{aligned} d(x) &= W_1X_1 + W_2X_2 + \dots + W_nX_n + W_{n+1} \\ &= W'_0X + W_{n+1} \end{aligned} \quad (3.27)$$

where $W_0 = (W_1, W_2, \dots, W_n)'$ is called "weight vector".

For convenience, Eq.(3.27) is expressed in the form

$$d(x) = W'X \quad (3.28)$$

where $X = (X_1, X_2, \dots, X_n, 1)'$ and $W = (W_1, W_2, \dots, W_n, W_{n+1})'$.

To apply decision functions with higher degrees, a polynomial decision function of any finite degree is expressed

$$d^2(x) = \left(\sum_{p_1=1}^n \sum_{p_2=p_1}^n \dots \sum_{p_r=p_{r-1}}^n W_{p_1 p_2 \dots p_r} X_{p_1} X_{p_2} \dots X_{p_r} \right) + d^{r-1}(x) \quad (3.29)$$

where r indicates the degree of nonlinearity, and $d^0(x) = W_{n+1}$.

3.3.2 Perceptron Algorithm [15]

Given two training sets belonging to pattern classes C_1 and C_2 , respectively, let $W(1)$ represent the initial weight vector which may be arbitrarily chosen. Then, at the k th

training steps:

If $X(k) \in C_1$, and $W'(k)X(k) \leq 0$, replace $W(k)$ by

$$W(k+1) = W(k) + CX(k) \quad (\text{punishment}) \quad (3.30)$$

where C is a correction increment.

If $X(k) \in C_2$, and $W'(k)X(k) \geq 0$, replace $W(k)$ by

$$W(k+1) = W(k) - CX(k). \quad (\text{punishment}) \quad (3.31)$$

Otherwise, leave $W(k)$ unchanged, that is,

$$W(k+1) = W(k). \quad (\text{reward}) \quad (3.32)$$

Simply stated, the algorithm makes a change in W if and only if the pattern being considered at the k th training step is misclassified by the weight vector at this step. The correction increment C must be positive and is assumed to be constant. Convergence of the algorithm occurs when a weight vector classifies all patterns correctly.

PART 4

EXPERIMENT PROCEDURES

Regardless of the computing platform, most imaging applications require special hardware and software to deal with the image data: frame grabbers and frame buffers to capture, store, and display the images, accelerators to speed up processing, and software to solve the end-user applications. It turns out that the PC bus and the DOS operation system are hosts to the largest selection of commercial imaging hardware and software products. Other instruments, such as a microscope, also may be important hardware components.

4.1 Instruments

The system used in this thesis is illustrated in Figs. 4.1 and 4.2.

- (A) Computer : 386s; 16-Mhz Intel 386sx microprocessor & 1 megabyte of RAM (Compaq Computer Corp.).
- (B) Frame Grabber : PCVISIONplus; stores 2 X 512 X 512 pixel images with 8-bit gray level resolution (Image Technology Inc.).
- (C) Vidicon Camera : 68 Series Quantitative Measurement Camera (Dage-MTI Inc.).
- (D) Video Monitor : PM-127; screen of 480 X 512 pixels (Ikegami Electronics Inc.).
- (E) Microscope : B & L dynazoom; unpolarized trinocular optical microscope.
- (F) 20" Melt Blown Pilot Line : The University of Tennessee.

4.2 Processing Steps

A function can be selected as illustrated in Fig.4.3.

- (1) **ACQUIRE IMAGE**
 - Snap single frame through a vidicon camera.
- (2) **CLEAR IMAGE**
 - Initialize the image with 0.
- (3) **SAVE IMAGE**

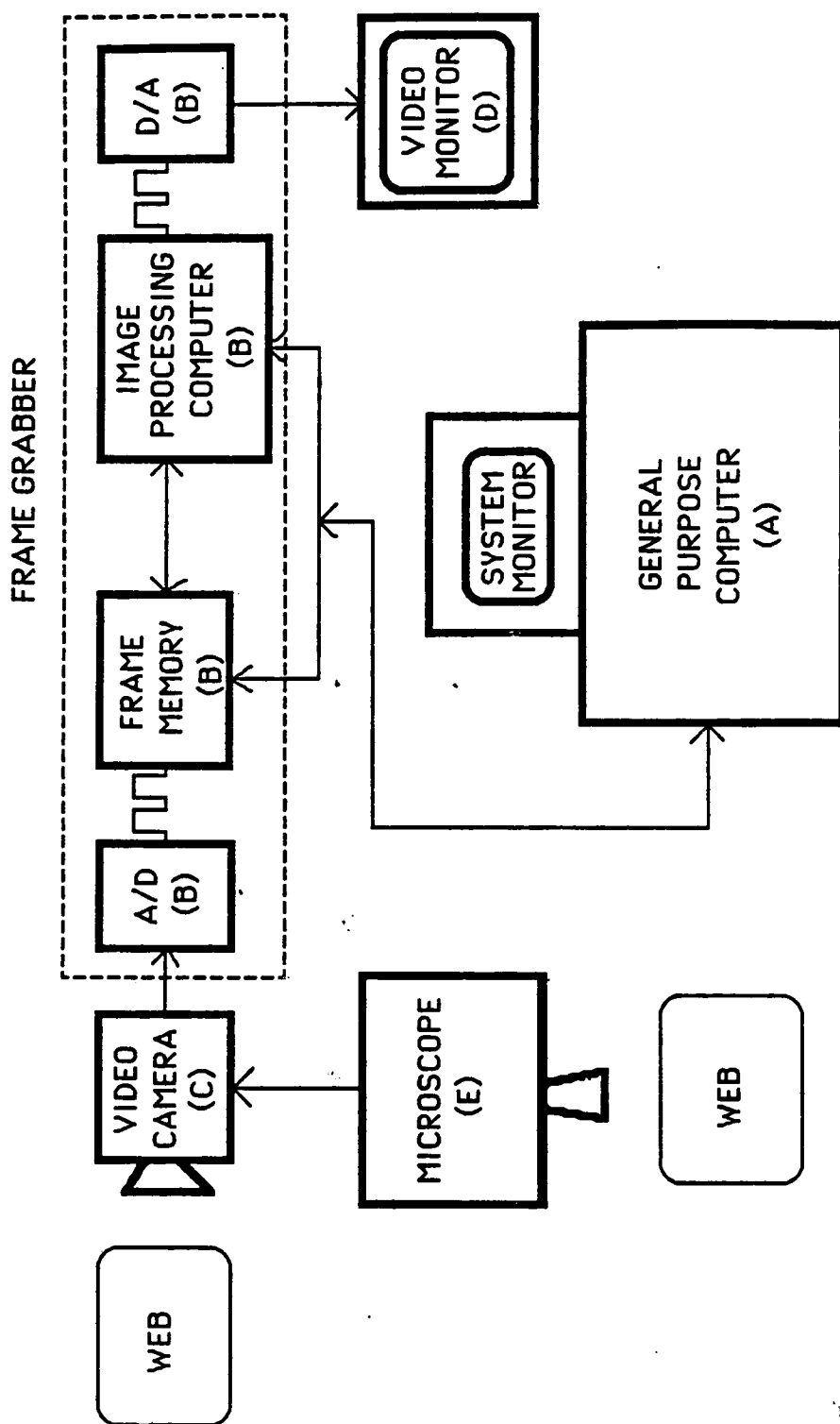


Fig. 4.1 Schematic of the digital image processing system.

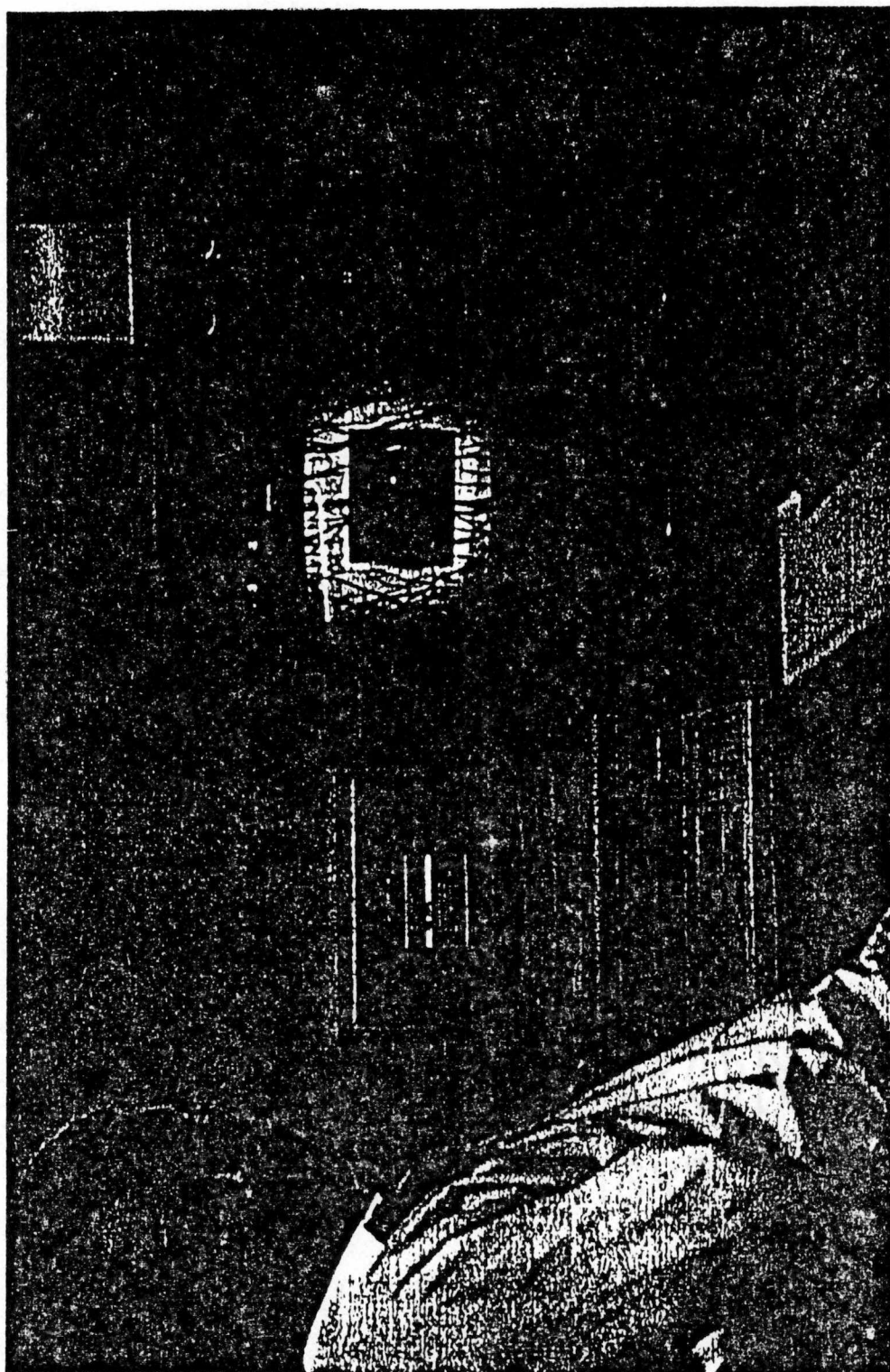


Fig. 4.2 Illustration of the digital image processing system.

WEB STRUCTURE

```
@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@
$      ACQUIRE IMAGE      $
$      CLEAR IMAGE        $
$      SAVE IMAGE         $
$      LOAD IMAGE         $
$      QUADRANTAL IMAGE HISTOGRAM $
$      QUADRANTAL BINARY IMAGE $
$      2-D FOURIER TRANSFORM $
$      3-D PATTERN RECOGNITION $
$      HELP               $
$      EXIT               $
@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@
```

Fig. 4.3 The menu shown on the screen.

- Store each integer gray level with 1 byte.
- (4) **LOAD IMAGE**
 - Load an image which must be saved with step (3).
- (5) **QUADRANTAL IMAGE HISTOGRAM**
 - Display a histogram of gray level vs. pixel %.
- (6) **QUADRANTAL BINARY IMAGE**
 - Apply global threshold.
- (7) **2-D FOURIER TRANSFORM**
 - (a) **TRANSLATION**
 - (b) **COMPLEXATION**
 - (c) **SEPARABILITY**
 - (d) **FFT**
 - (e) **MAGNITUDE**
 - (f) **TAKE LOG & RESCALE**
 - Rescale to a maximum gray level: 255.
 - (g) **DISPLAY SPECTRUM**
 - (h) **SCAN SPECTRAL ENERGY**
 - Apply bi-linear interpolation.
 - Display an energy/angle distribution.
 - Try FT pattern models.
- (8) **3-D PATTERN CLASSIFICATION**
 - (a) **SUPERVISE THE MACHINE**
 - Obtain the decision functions.
 - (b) **CLASSIFY UNKNOWN PATTERNS**
- (9) **HELP**
- (10) **EXIT**

4.3 Image Acquisition

The conditions for snapping images for this thesis were fixed:

- (1) Undyed melt-blown Nylon webs with a sample size 2 in. X 1 in.
- (2) Light intensity switch: 1.
- (3) Adjustor:
 - Gain (auto.) : Nil.
 - Black (auto.) : Nil.

- (4) Objective lens : Nominal magnification = 4.
- (5) Condenser : Lowest position.
- (6) Diaphragm : Fully open.
- (7) Illumination : Brightfield, monochromatic (yellow).
- (8) Resolution : 512 X 512 pixels with a 8-bit gray level.

4.4 Sampling

High, medium, and low oriented melt-blown webs were sampled from three fabric rolls. Their weight were 0.3330 oz/yd², 0.9141 oz/yd², and 1.1653 oz/yd², respectively.

PART 5

RESULTS AND DISCUSSION

5.1 Terminology

- (1) Thin web -- For this project, a thin web was any web whose structure was well revealed in the image examined.
- (2) MD -- Machine direction in spatial domain.
- (3) CD -- Cross direction in spatial domain.
- (4) High frequency -- Large gray-level gradients between the background and fibers.
- (5) Low frequency -- Small gray-level gradients within individual fibers, and entangled fiber groups.
- (6) DC component energy -- A central pixel ($u=0, v=0$) in FT spectra; equals the average value of $f(x,y)$ in the image area.
- (7) Total spectral energy -- Energy is summed for all individual pixels in FT spectrum except the central DC component energy.
- (8) Spectral distribution of energy -- A web containing fibers aligned spatially in one direction produces the greatest gray level variations perpendicular to the alignment direction. When the y-direction in webs corresponds to the MD, MD aligned fibers contribute the most energy in FT spectra to $(0,v)$ frequencies. To facilitate evaluating the distribution of energy among various frequencies in the FT frequency domain, coordinate axes were imposed on spectra with the coordinate system origin placed to coincide with the point $(u=0, v=0)$. An angle of 90° was arbitrarily assigned to $(0,v)$ frequencies. An angle of 0° was arbitrarily assigned to $(u,0)$ frequencies which largely correspond to gray level variations from fibers aligned spatially in the CD. The frequency domain was further partitioned into 1° angular intervals to evaluate other frequencies similarly.
- (9) $\text{Energy}(u,0) / \text{Energy}(0,v)$ -- A ratio of the summed energy at 0° to that at 90° in a FT spectrum.

- (10) Energy CV% -- Energy uniformity from 0° to 179° in the normalized energy distribution expressed as coefficient of variation.
- (11) Average energy -- Energy mean value from 0° to 179° in the normalized energy distribution.
- (12) Energy factor -- Ratio of original energy to energy in the normalized energy distribution.
- (13) Orientation angle -- An angle parallel to lines in web models aligned in only one direction.

5.2 FT Pattern Models

Several groups of simple line patterns were used to model web structure. These models were used to evaluate the effect of web structural features on FT spectra. Conclusions from web models are given in this section. To illustrate the steps used to evaluate each model, the video work area, a model image, its corresponding FT spectrum and parameters derived from its spectral energy distribution are shown in Figs. 5.1 - 5.4. It is probably fair to say that real melt-blown webs are complex combinations of model groups A - G.

Group A (Figs. 5.5 and 5.6):

- Regardless of the gray level of a solid model, energy exists only on the central pixel of the FT spectrum and this energy intensity increases proportionally to the gray level.

Group B (Figs. 5.7 and 5.8):

- Total FT spectral energy and the energy distribution remain constant when gray level differences remain constant but are reversed from line=0 / background=255 to line=255 / background=0. This implies that either brightfield or darkfield illumination could be used to image webs.

Group C (Figs. 5.9 and 5.10):

- Total spectral energy is determined by the gray level difference between background and lines rather than by the

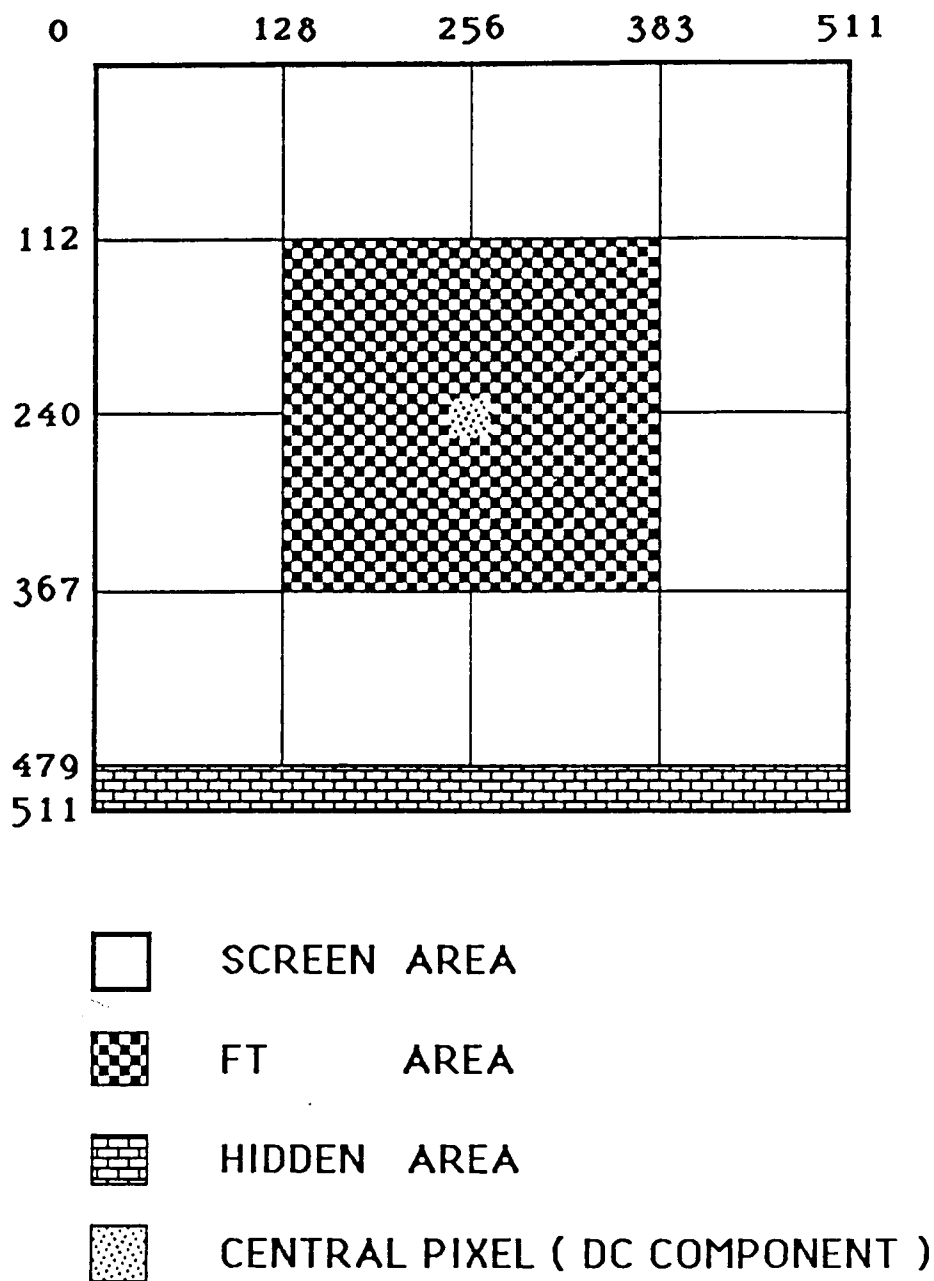


Fig. 5.1 Video function area.

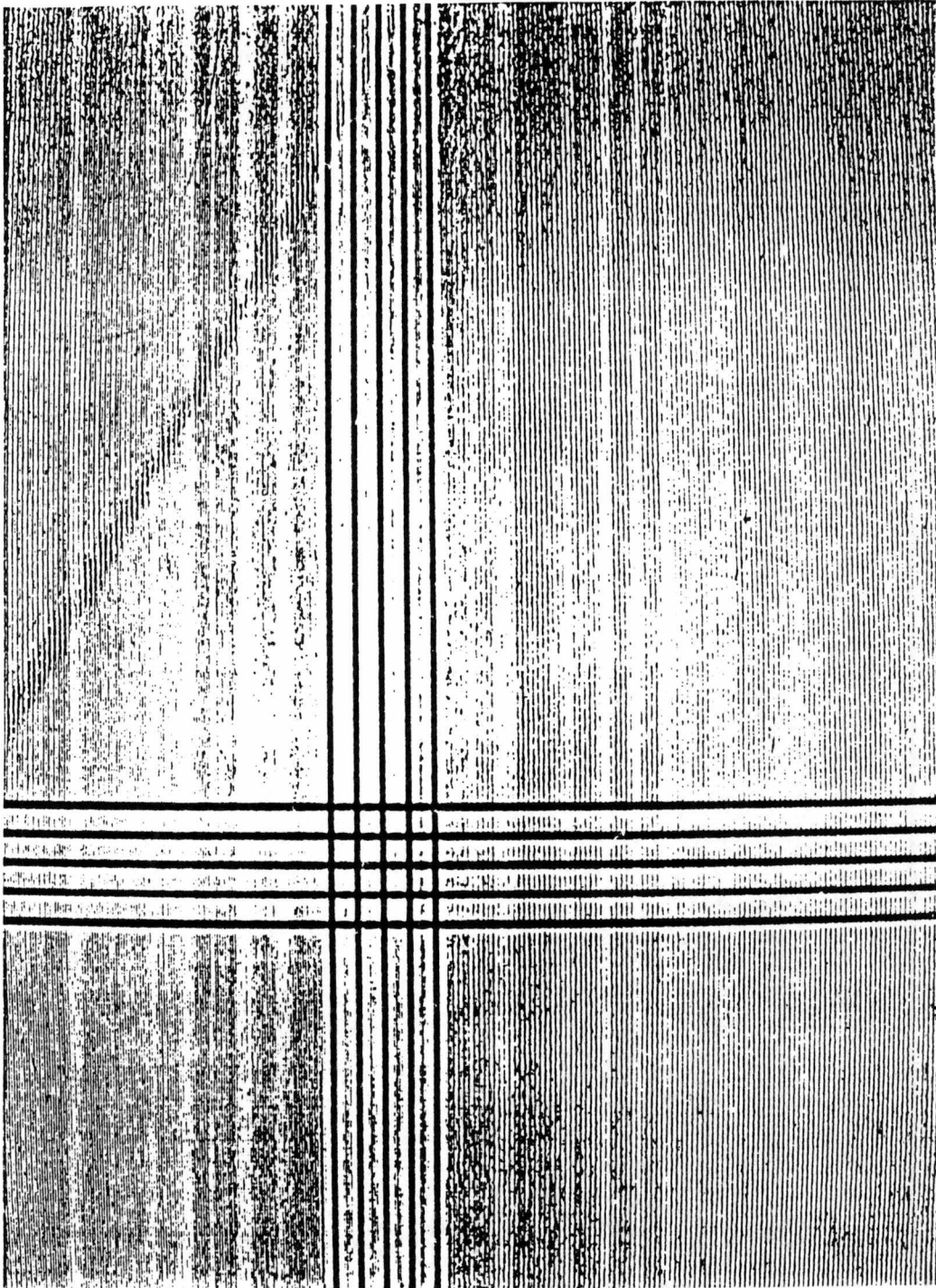


Fig. 5.2 A model image.

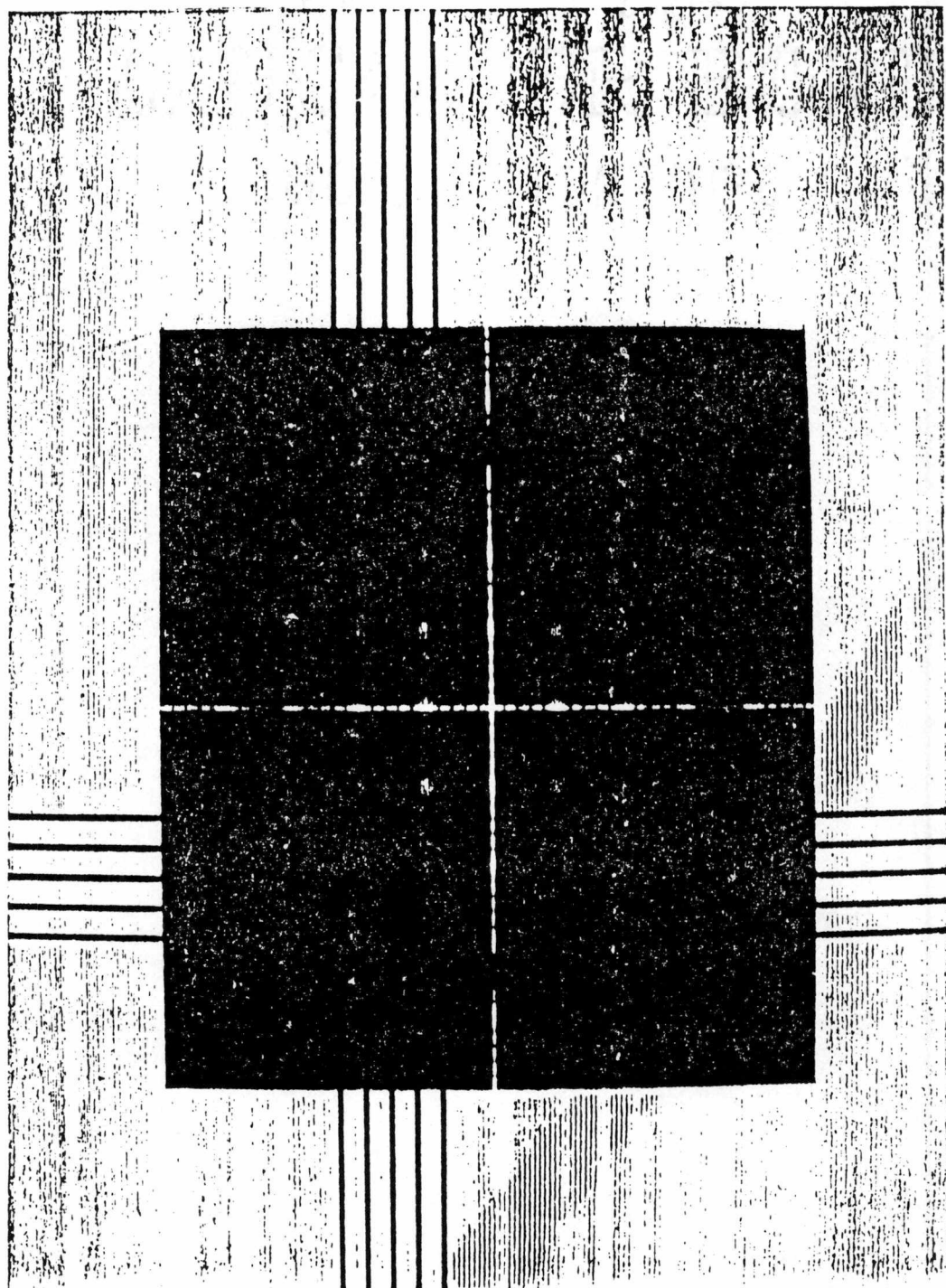


Fig. 5.3 A FT model spectrum.

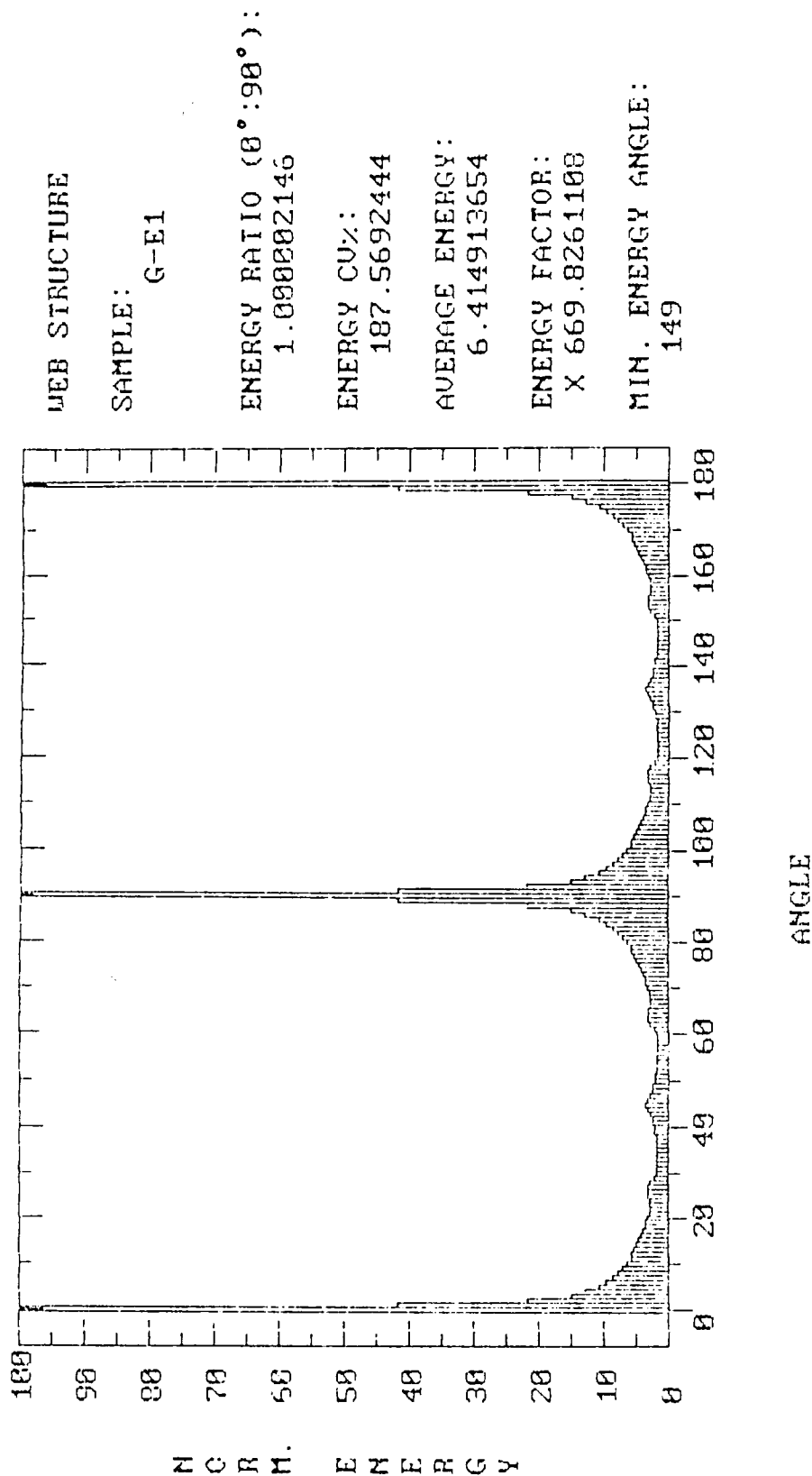


Fig. 5.4 A normalized energy distribution of the FT model spectrum.

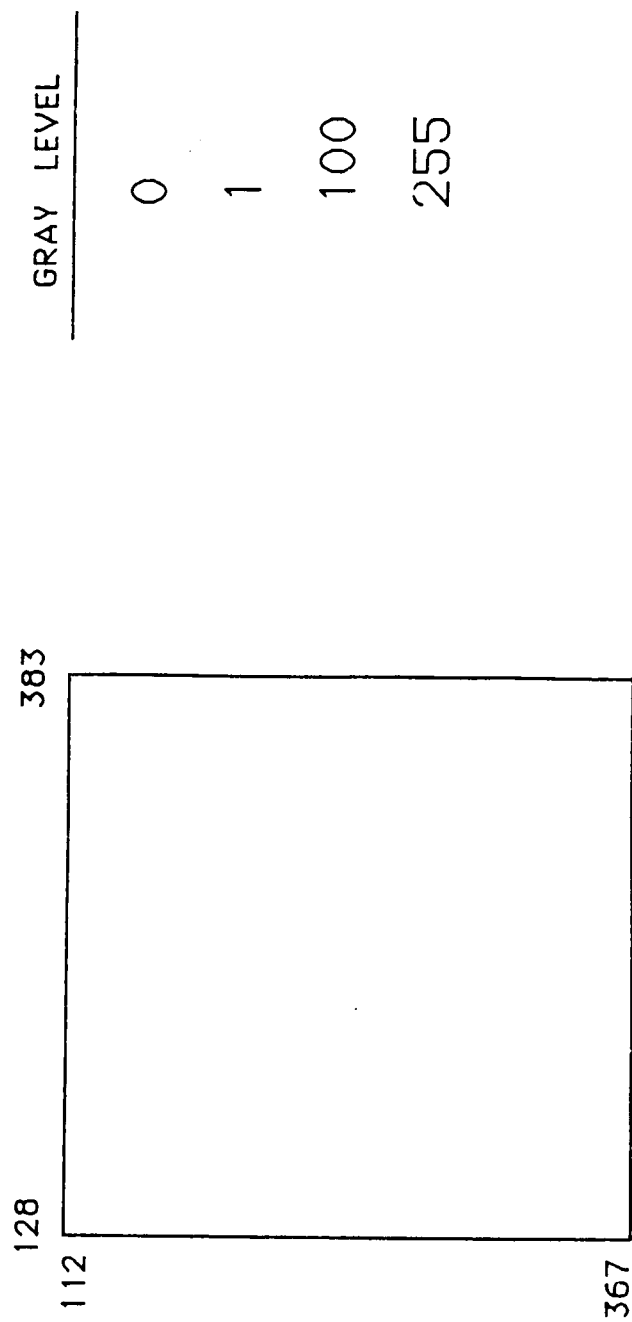


Fig. 5.5 Web model group A.

MODEL: GRAY LEVEL	TOTAL SPECTRAL ENERGY *	NORMALIZED DISTRIBUTION PARAMETERS				
		$\frac{E(U, 0)}{E(0, V)}$	ENERGY CV%	AVG. ENERGY	ENERGY FACTOR	ORIEN. ANGLE
1 : 0	0 (0)	—	—	0	0	—
2 : 1	0 (256.)	—	—	0	0	—
3 : 100	0 (25600.)	—	—	0	0	—
4 : 255	0 (65280.)	—	—	0	0	—

* : Excludes energy of central pixel; energy of central pixel in parenthesis.

Fig. 5.6 Results of web model group A.

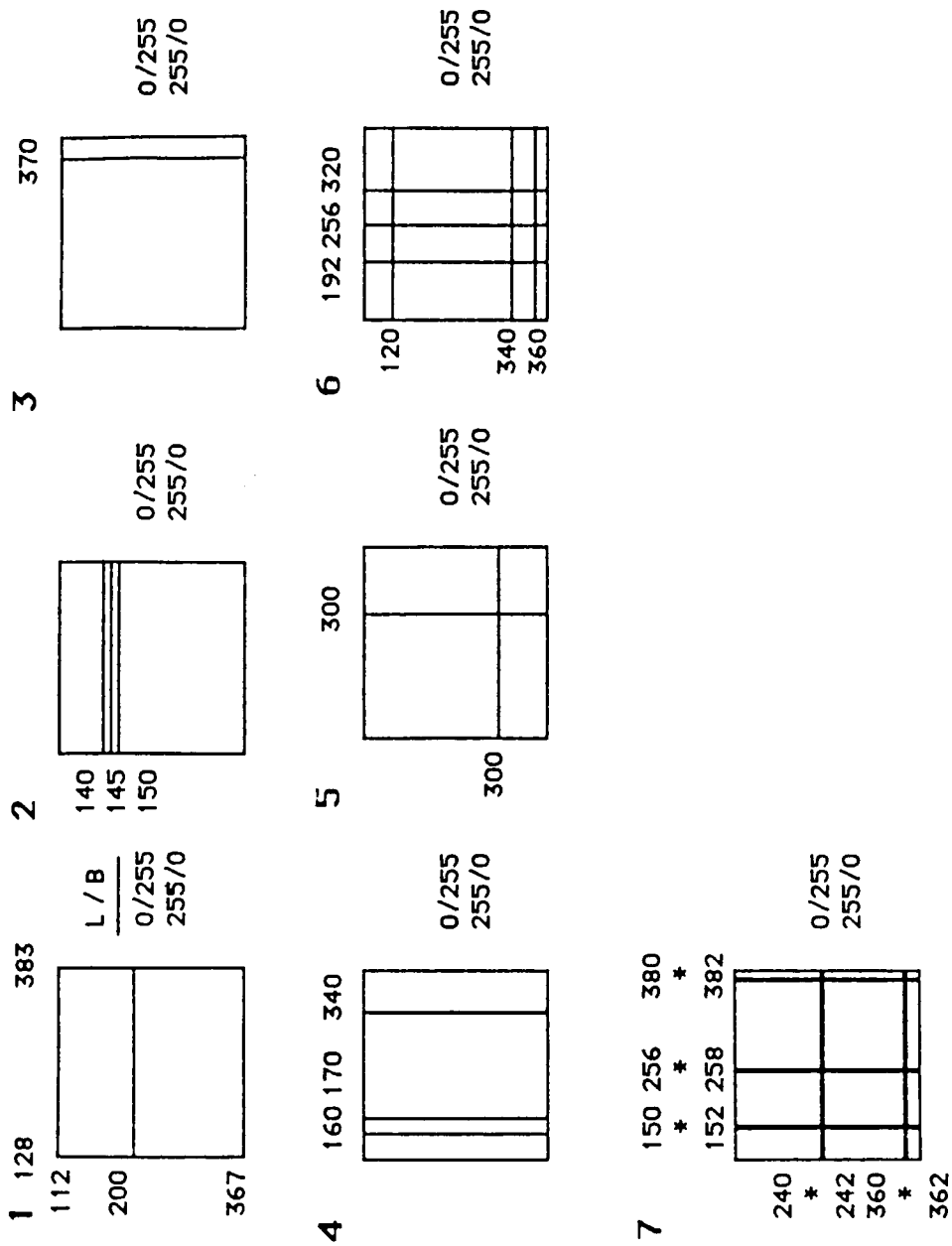
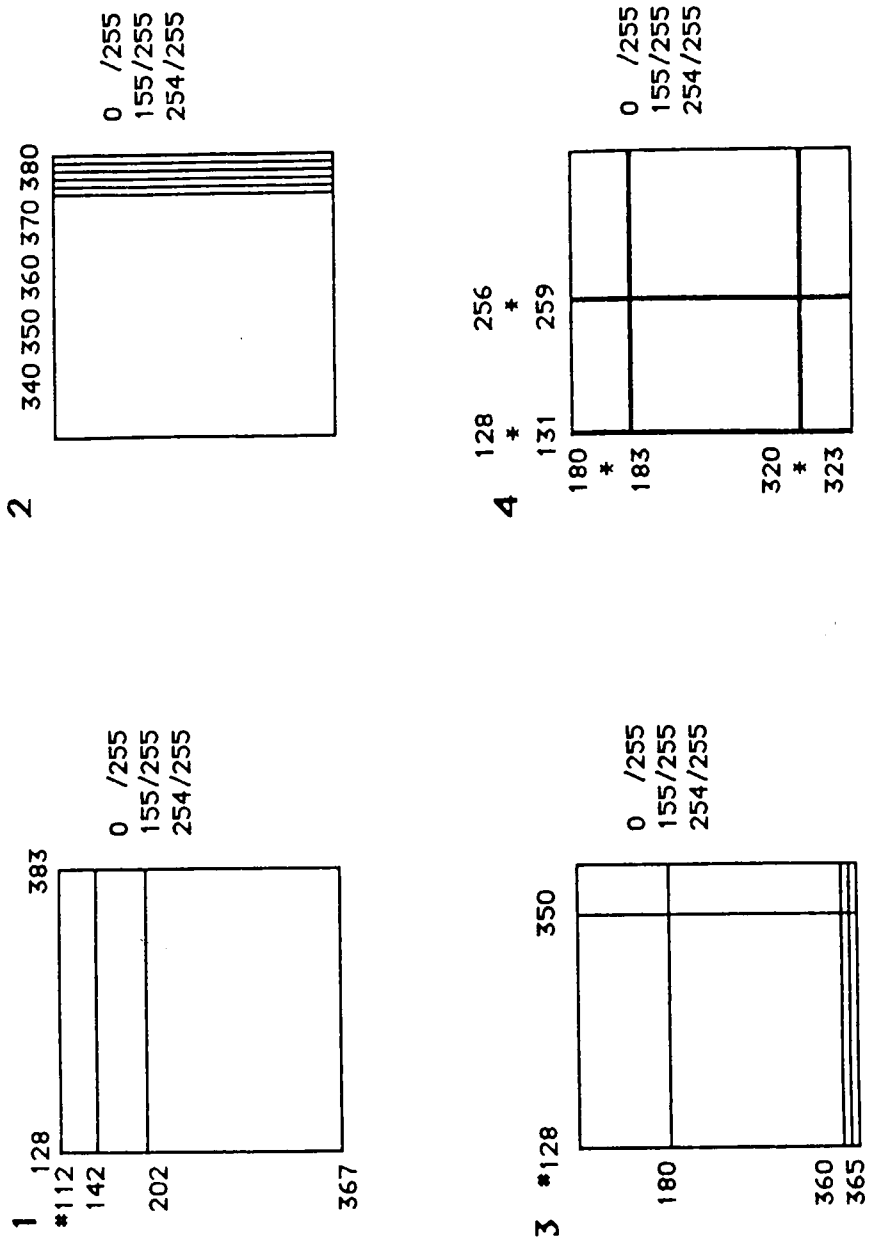


Fig. 5.7 Web model group B.

MODEL: GRAY LEVEL	TOTAL SPECTRAL ENERGY *	NORMALIZED DISTRIBUTION PARAMETERS				
		$\frac{E(U, O)}{E(O, V)}$	ENERGY CV%	AVG. ENERGY	ENERGY FACTOR	ORIEN. ANGLE
1 : 0/255	65024.996094	—	628.792785	1.249615	321.298645	0
1 : 255/0	65024.996094	—	628.792785	1.249615	321.298645	0
2 : 0/255	92977.664063	—	514.194213	1.544419	456.000396	0
2 : 255/0	92977.664063	—	514.194213	1.544419	456.000396	0
3 : 0/255	65025.000000	—	628.794494	1.249611	321.299987	90
3 : 255/0	65025.000000	—	628.794494	1.249611	321.299987	90
4 : 0/255	102043.125000	—	612.861511	1.280281	501.736328	90
4 : 255/0	102043.125000	—	612.861511	1.280281	501.736328	90
5 : 0/255	194433.031250	1.000004	379.199829	2.881573	320.044891	—
5 : 255/0	194433.031250	1.000004	379.199828	2.881573	320.044891	—
6 : 0/255	348845.437500	0.959686	361.623504	2.948076	493.684021	—
6 : 255/0	348845.437500	0.959686	361.623504	2.948076	493.684021	—
7 : 0/255	517629.531250	1.239392	220.664825	5.003359	698.948608	—
7 : 255/0	517629.531250	1.239392	220.664825	5.003359	698.948608	—

* : Excludes energy of central pixel.

Fig. 5.8 Results of web model group B.



* : Line existing on the edge.

Fig. 5.9 Web model group C.

MODEL: GRAY LEVEL	TOTAL SPECTRAL ENERGY	NORMALIZED DISTRIBUTION PARAMETERS				
		$\frac{E(U, 0)}{E(0, V)}$	ENERGY CV%	AVG. ENERGY	ENERGY FACTOR	ORIEN. ANGLE
1 : 0/255	103674.773438	—	660.324523	1.187381	509.786041	0
1 : 155/"	40656.761719	—	660.325256	1.187381	199.916076	0
1 : 254/"	406.567535	—	660.325866	1.187381	1.999160	0
2 : 0/255	105941.859375	—	581.237487	1.340765	511.339386	90
2 : 155/"	41545.824219	—	581.237670	1.340765	200.525238	90
2 : 254/"	415.458191	—	581.235961	1.340766	2.005252	90
3 : 0/255	312186.375000	0.801654	357.600036	2.767804	500.273529	—
3 : 155/"	122426.664063	0.801654	357.600097	2.767804	196.185638	—
3 : 254/"	1224.263672	0.801654	357.600280	2.767802	1.961857	—
4 : 0/255	411960.031250	0.785865	206.365188	5.565734	611.697326	—
4 : 155/"	161552.640625	0.785865	206.365341	5.565729	239.881256	—
4 : 254/"	1615.530029	0.785865	206.365264	5.565732	2.398812	—

Fig. 5.10 Results of web model group C.

line gray level itself. This implies that image contrast is important and must be uniform and constant during web measurement.

- When the line direction distribution remains constant, the total energy proportionally increases when the gray level difference between background and lines increases 100 to 255. This also implies illumination must be uniform and constant.

Group D (Figs. 5.11 and 5.12):

- Total energy increases with increased line density within a fixed area. This implies that the measurement can be used to monitor changes in web "weight" (areal density).

Group E (Figs. 5.13 and 5.14):

- Total energy increases with increased line thickness. This implies that the measurement can be used to monitor changes in fiber diameter.
- The energy ratio, $\text{Energy}(u,0) / \text{Energy}(0,v)$, remains constant when line thickness increases uniformly while all other image parameters remain constant. This implies that this measurement can be used to monitor changes in other structural features when fiber diameter changes.

Group F (Figs. 5.15 and 5.16):

- Total energy is independent of line shifting.
- The energy ratio, $\text{Energy}(u,0) / \text{Energy}(0,v)$ is independent of line shifting.
- The energy CV% is independent of line shifting.
- The average energy is independent of line shifting.
- The energy factor is independent of line shifting.
- The orientation angle is independent of line shifting.

These conclusions imply that image acquisition is independent of web location when the web is uniform.

Group G (Figs. 5.17 and 5.18):

- The energy ratio $\text{Energy}(u,0) / \text{Energy}(0,v)$ is related to the number of lines oriented in these two directions. This implies that the measurement can be used to monitor

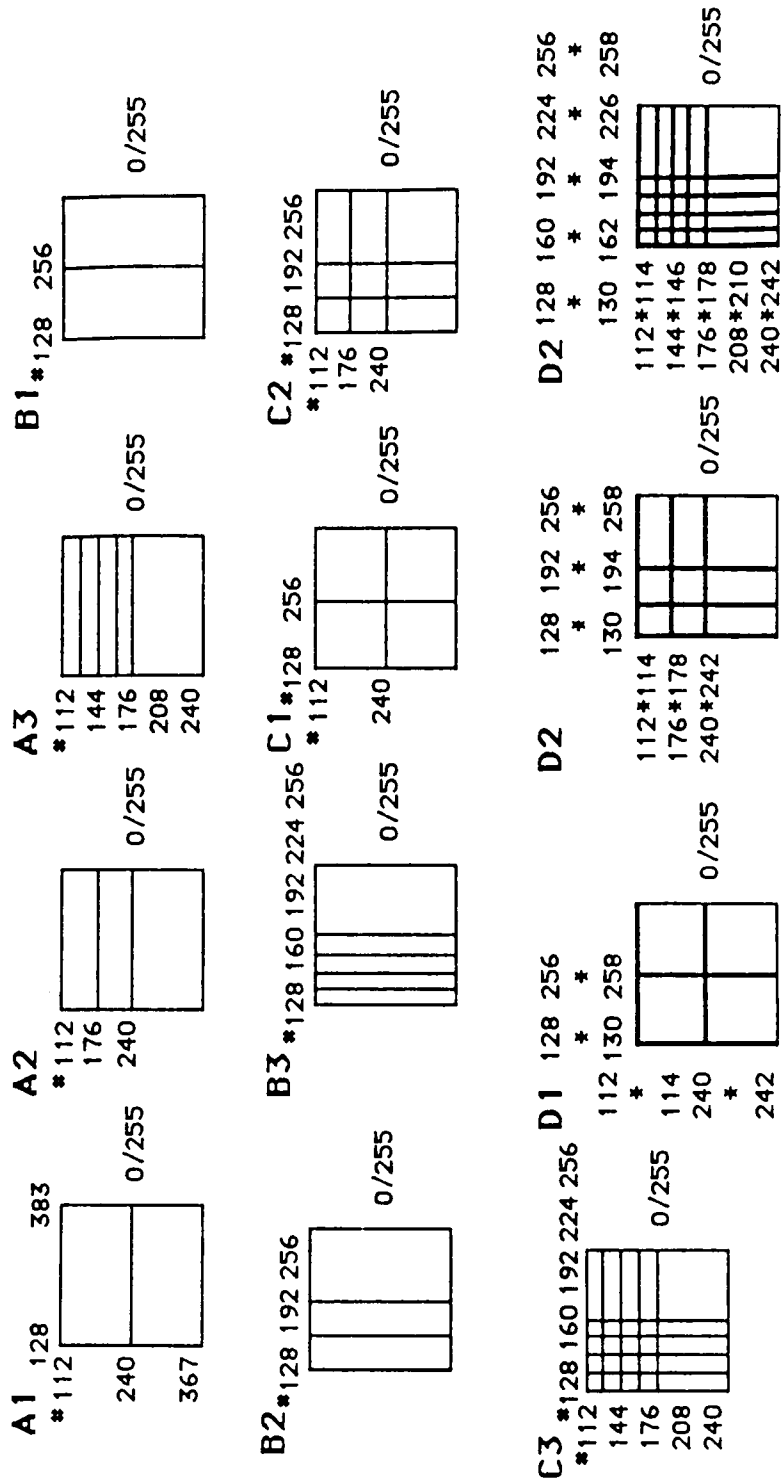


Fig. 5.11 Web model group D.

MODEL: GRAY LEVEL	TOTAL SPECTRAL ENERGY	NORMALIZED DISTRIBUTION PARAMETERS				
		$\frac{E(U, 0)}{E(0, V)}$	ENERGY CV%	AVG. ENERGY	ENERGY FACTOR	ORIEN. ANGLE
A1:0/255	64770.000000	—	597.291626	1.318972	321.299194	0
A2:0/255	97155.000000	—	644.153991	1.219587	479.399322	0
A3:0/255	110164.984375	—	694.970947	1.124864	538.292358	0
B1:0/255	64770.000000	—	597.292480	1.318969	321.299987	90
B2:0/255	97155.000000	—	644.154174	1.219585	479.399993	90
B3:0/255	110164.984375	—	694.971679	1.124862	538.293579	90
C1:0/255	192791.953125	1.000002	362.644989	3.015945	318.789856	—
C2:0/255	336792.531250	1.000001	362.697998	3.006151	473.782043	—
C3:0/255	401918.187500	1.000002	375.518981	2.893193	527.779968	—
D1:0/255	310374.968750	1.000002	233.544570	5.241484	447.784851	—
D2:0/255	560039.625000	1.000002	224.780242	5.391612	656.254272	—
D3:0/255	668320.500000	1.000001	228.833999	5.247013	712.191101	—

Fig. 5.12 Results of web model group D.

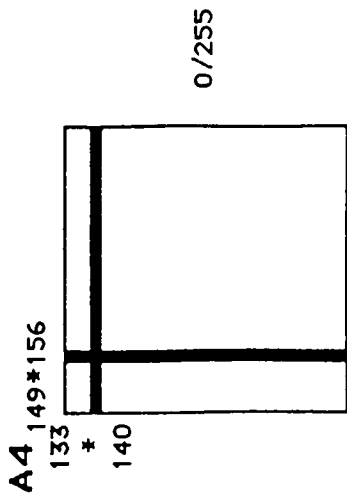
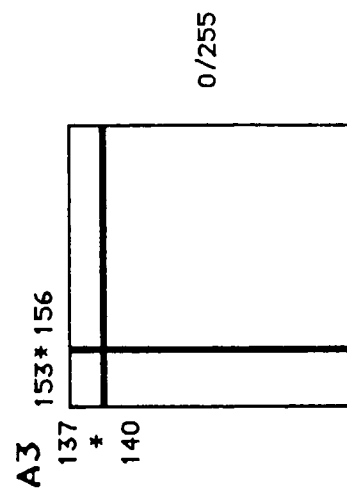
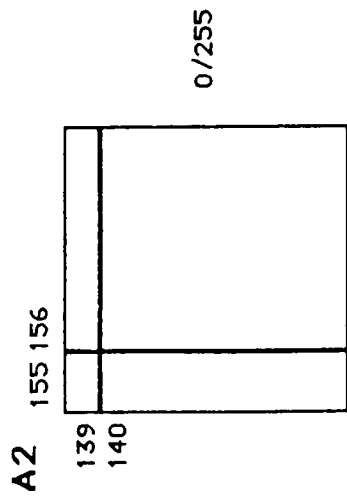
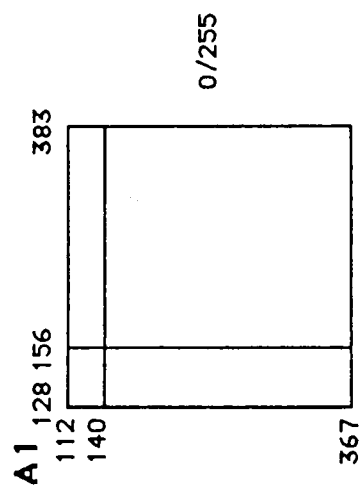
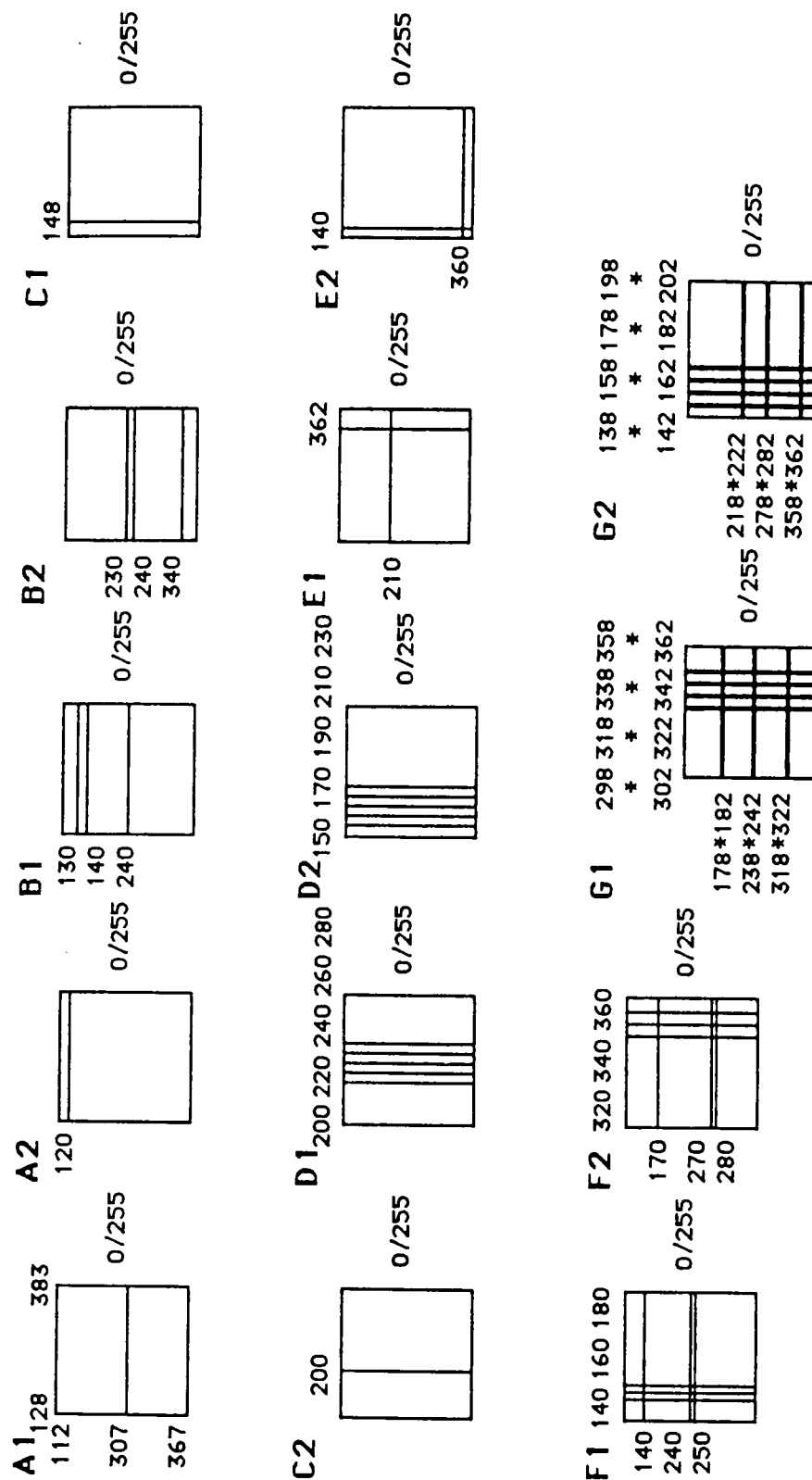


Fig. 5.13 Web model group E.

MODEL: GRAY LEVEL	TOTAL SPECTRAL ENERGY	NORMALIZED DISTRIBUTION PARAMETERS				
		$\frac{E(U, 0)}{E(0, V)}$	ENERGY CV%	AVG. ENERGY	ENERGY FACTOR	ORIEN. ANGLE
A1:0/255	194433.031250	1.000004	379.199829	2.881573	320.044891	—
A2:0/255	268452.812500	1.000002	285.382171	4.046956	404.743286	—
A3:0/255	351509.468750	1.000002	218.550323	5.838835	483.566528	—
A4:0/255	439317.687500	1.000001	166.523956	8.467210	549.560363	—

Fig. 5.14 Results of web model group E.



MODEL: GRAY LEVEL	TOTAL SPECTRAL ENERGY	NORMALIZED DISTRIBUTION PARAMETERS				
		$\frac{E(U, O)}{E(O, V)}$	ENERGY CV%	AVG. ENERGY	ENERGY FACTOR	ORIEN. ANGLE
A1:0/255	65025.000000	—	628.792846	1.249615	321.298706	0
A2:0/255	65025.000000	—	628.792785	1.249615	321.298675	0
B1:0/255	102024.984375	—	590.562744	1.331260	503.087371	0
B2:0/255	102025.000000	—	590.562683	1.331260	503.087463	0
C1:0/255	65025.000000	—	628.794494	1.249611	321.299987	90
C1:0/255	65025.000000	—	628.794494	1.249611	321.299987	90
D1:0/255	105961.945313	—	695.116821	1.120406	513.553649	90
D2:0/255	105961.937500	—	695.116821	1.120406	513.553527	90
E1:0/255	194433.062500	1.000003	379.199859	2.881573	320.044891	—
E2:0/255	194433.046875	1.000004	379.199829	2.881573	320.044891	—
F1:0/255	338072.187500	0.902636	349.015808	2.970847	497.191680	—
F2:0/255	338072.218750	0.902636	349.015838	2.970847	497.191497	—
G1:0/255	708002.000000	0.942456	177.712997	7.122589	750.094055	—
G2:0/255	708001.937500	0.942457	177.712997	7.122591	750.093750	—

Fig. 5.16 Results of web model group F.

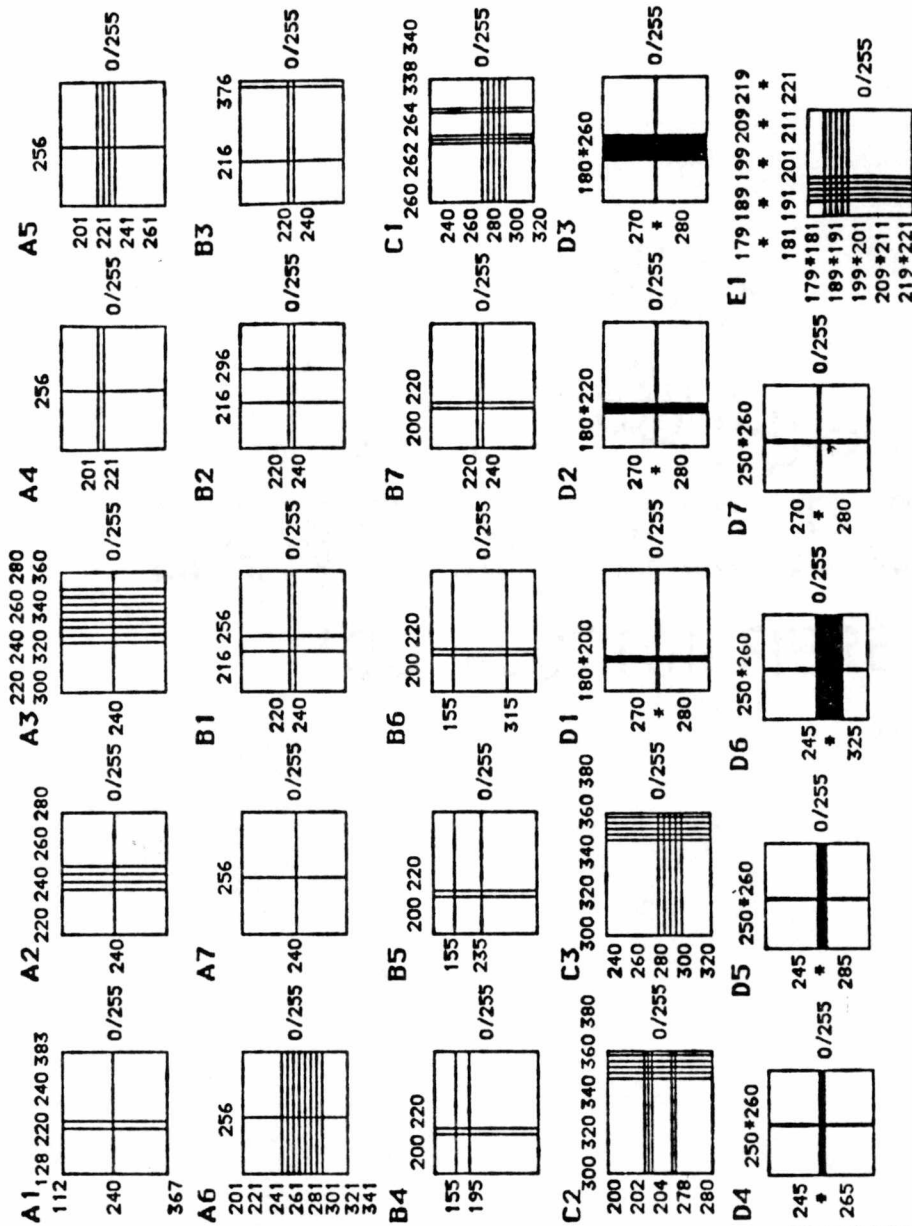


Fig. 5.17 Web model group G.

MODEL: GRAY LEVEL	TOTAL SPECTRAL ENERGY	NORMALIZED DISTRIBUTION PARAMETERS					ORIEN. ANGLE
		$\frac{E(U,V)}{E(O,V)}$	ENERGY CV%	AVG. ENERGY	ENERGY FACTOR		
A1:0/255	229050.781250	1.266891	375.128784	2.619366	403.870910	—	
A2:0/255	263569.562500	1.533807	389.840698	2.356939	485.110626	—	
A3:0/255	295721.781250	1.805698	403.283500	2.179821	562.036757	—	
A4:0/255	229048.765625	0.789338	375.128601	2.619374	403.869598	—	
A5:0/255	263568.656250	0.651976	389.840362	2.356945	485.109283	—	
A6:0/255	295717.625000	0.553805	403.282867	2.179828	562.037170	—	
A7:0/255	194438.015625	1.000003	379.199859	2.881574	320.044921	—	
B1:0/255	268275.500000	1.000494	373.346405	2.917255	402.484527	—	
B2:0/255	267823.812500	1.002127	367.487793	2.962974	403.141723	—	
B3:0/255	265992.187500	0.994391	363.750427	2.988664	402.285827	—	
B4:0/255	268276.625000	0.999512	373.346374	2.917264	402.483245	—	
B5:0/255	267826.843750	0.997883	367.487945	2.962982	403.140380	—	
B6:0/255	265998.062500	1.005646	363.750579	2.988654	402.286956	—	
B7:0/255	268385.218750	1.000002	364.528045	2.986794	402.286956	—	
C1:0/255	414086.156250	1.132431	321.054412	3.290311	570.204345	—	
C2:0/255	414086.406250	0.883059	321.054443	3.290318	570.202880	—	
C3:0/255	379785.593750	1.000002	378.290527	2.866472	503.523315	—	
D1:0/255	517025.718750	1.126099	129.894546	11.209569	617.126342	—	
D2:0/255	543800.937500	1.262033	116.698783	12.313710	632.759826	—	
D3:0/255	546626.437500	1.468283	109.837982	12.323415	599.207824	—	
D4:0/255	517025.687500	0.888023	129.894546	11.209585	617.125610	—	
D5:0/255	543797.062500	0.792373	116.698745	12.313725	632.759094	—	
D6:0/255	546622.125000	0.681068	109.837966	12.323429	599.207153	—	
D7:0/255	480025.250000	1.000001	146.686401	10.038397	571.341857	—	
E1:0/255	632097.062500	1.000002	187.569244	6.414913	669.826110	—	

Fig. 5.18 Results of web model group G.

changes in fiber orientation in webs.

- The energy ratio, $\text{Energy}(u,0) / \text{Energy}(0,v)$ is dependent upon the spacing between 2 lines. This implies that the measure can be used to monitor changes in interfiber spacing when web weight (areal density) is constant.
- The energy ratio, $\text{Energy}(u,0) / \text{Energy}(0,v)$ is dependent upon the spacing between line groups. This implies that the measurement may be used to monitor changes in web uniformity with respect to local fiber laydown.
- The energy ratio, $\text{Energy}(u,0) / \text{Energy}(0,v)$ is directly related to nonuniform changes in the line thickness. This implies that the measurement can be used to monitor nonuniform changes in fiber diameter.

5.3 Training Patterns

The process of classification was applied to three different types of melt-blown webs. The webs differed primarily in fiber orientation and web weight (areal density) although many other structural features also varied among the webs. The goal of classification was not to describe the structure of the webs but rather to objectively identify differences in web structure and then categorize each web into one of several defined classes. A total of 30 web samples were used as the training webs. A typical image from each web class, its corresponding FT spectra and its spectral energy distribution are shown in Figs. 5.19 - 5.27.

Three indices were extracted from FT spectra and energy distributions to formulate the training models: the energy ratio $E(u,0)/E(0,v)$, energy CV%, and energy average. Values of these indices are listed for all training webs in Fig. 5.28. These indices were used because the modeling studies showed that they were sensitive to web structural features.

After evaluation using one, two or three of the indices, these training patterns were well graded as Grade A(C1), Grade B(C2), and Grade C(C3) as shown in Fig. 5.29. The principle of

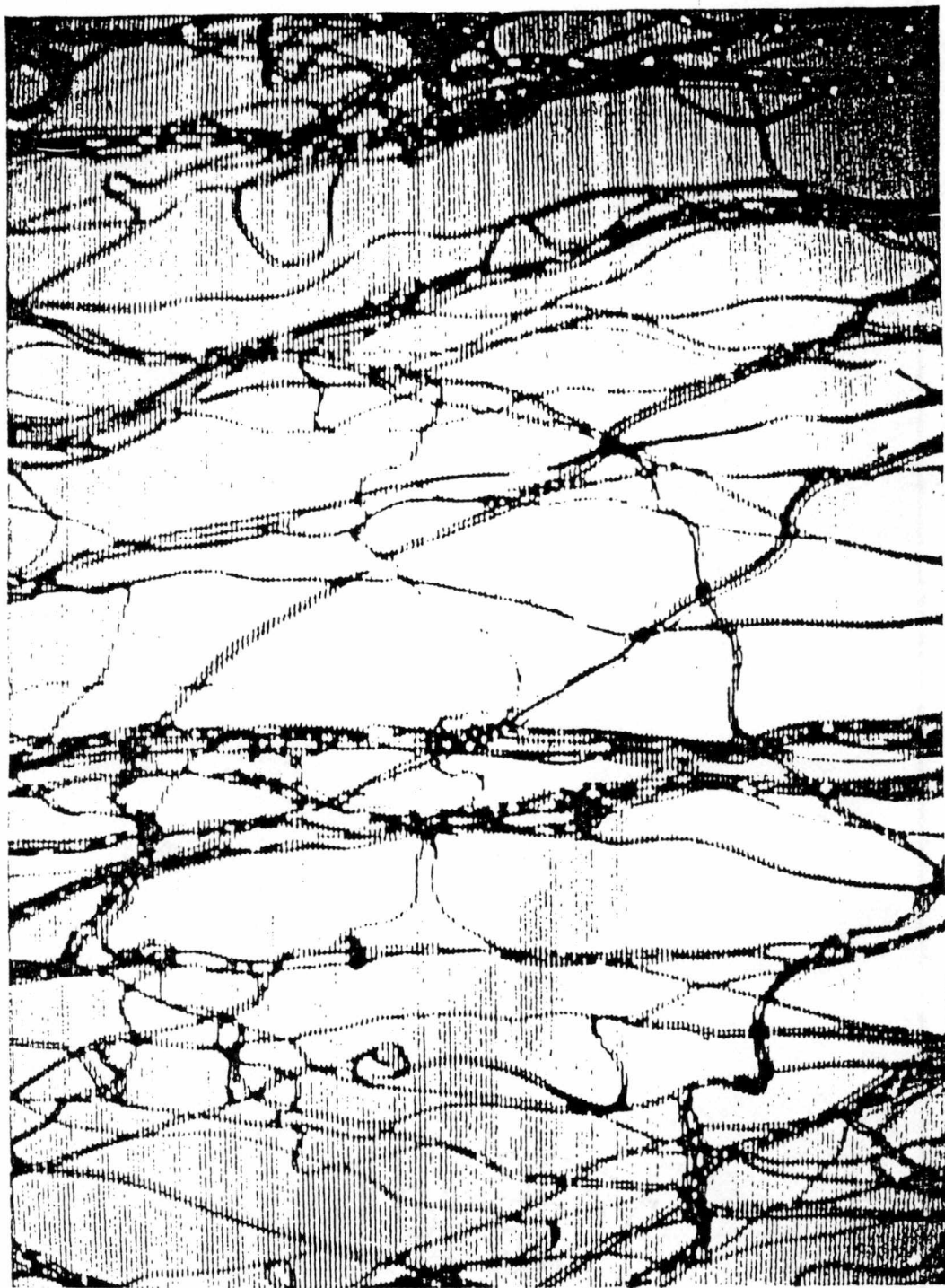


Fig. 5.19 A training image for class C1.

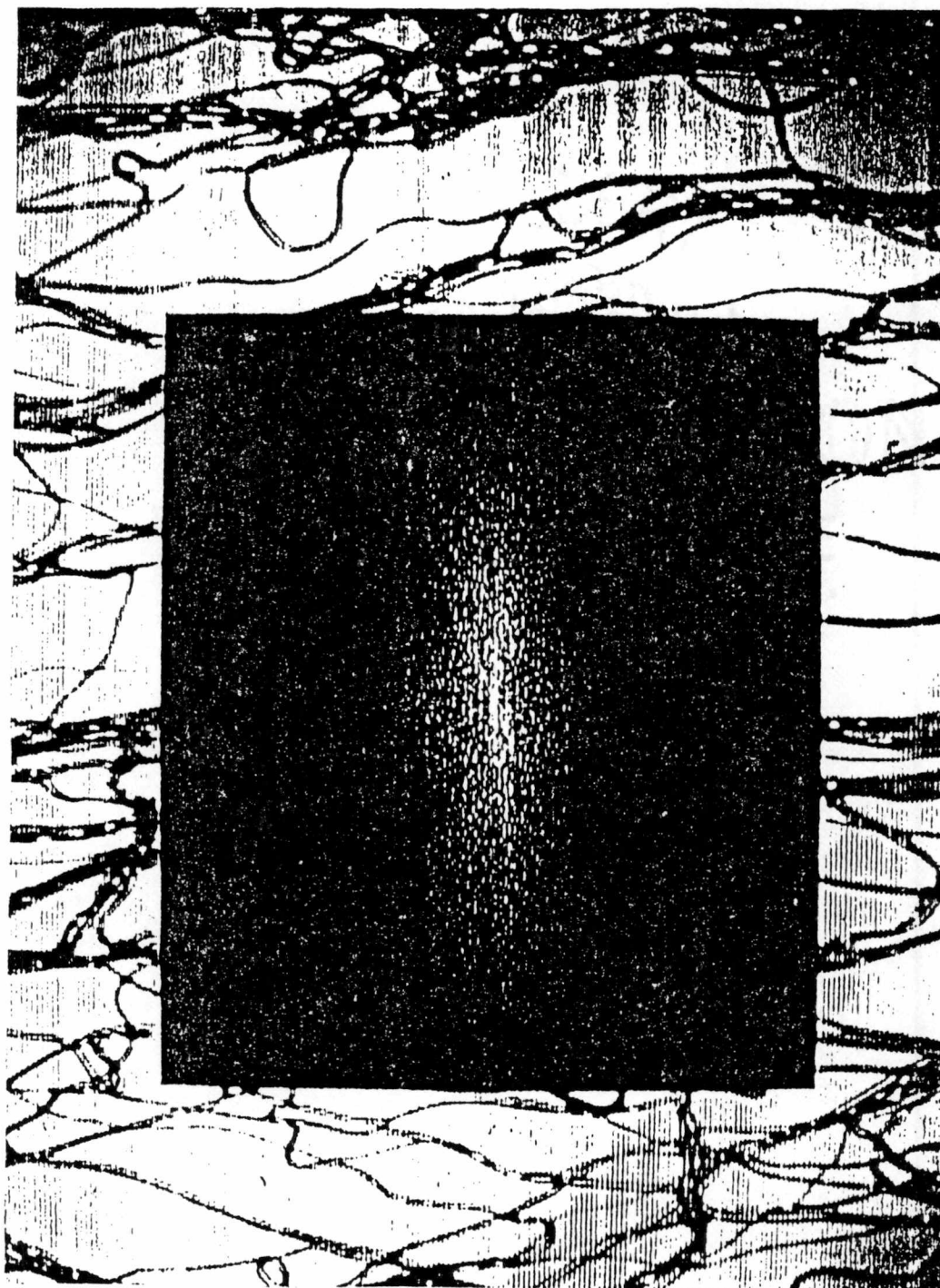


Fig. 5.20 FT spectrum of image shown in Fig. 5.19.

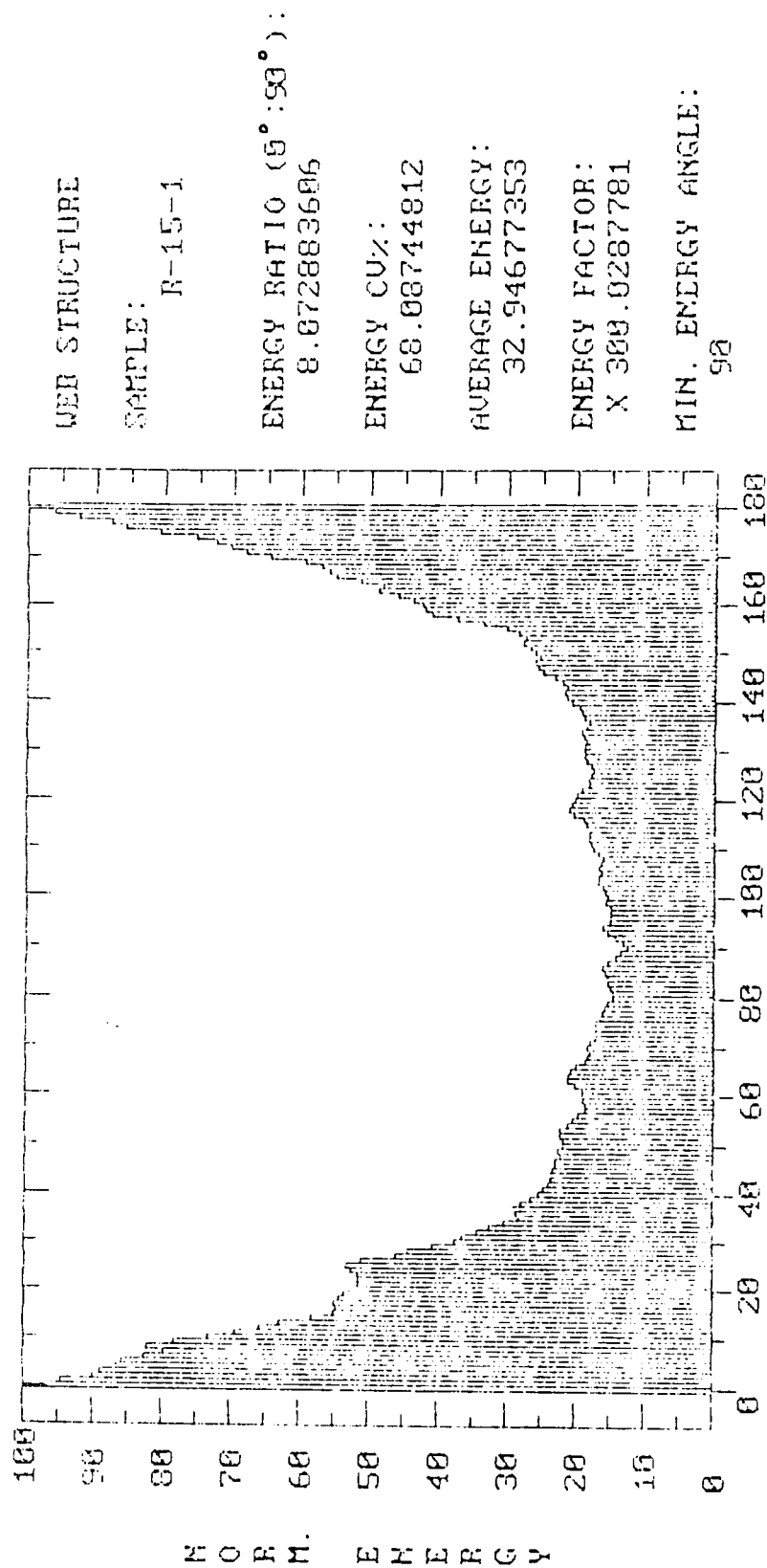


Fig. 5.21 Normalized energy distribution of the FT spectrum shown in Fig. 5.20.



Fig. 5.22 A training image for class C2.

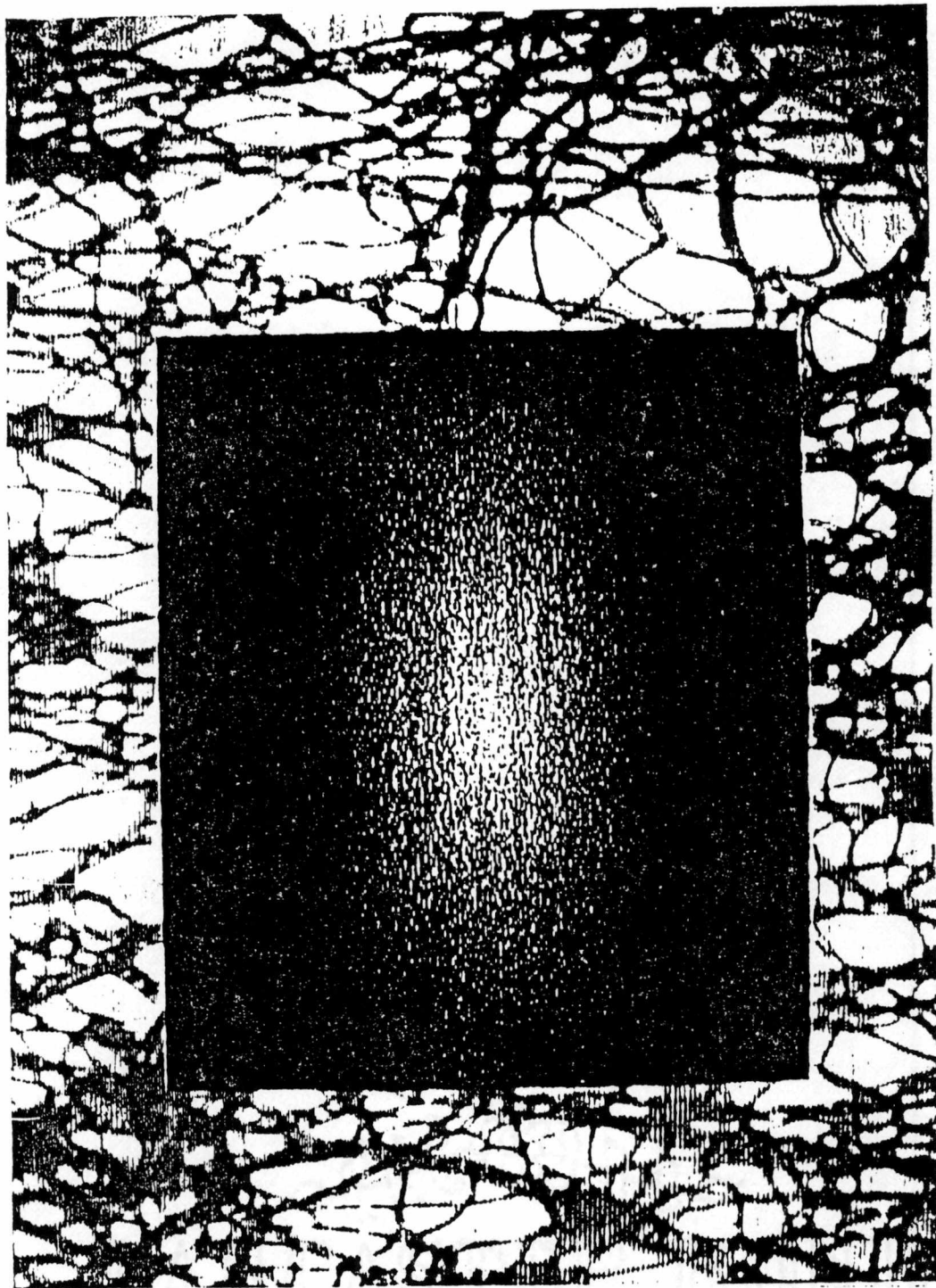
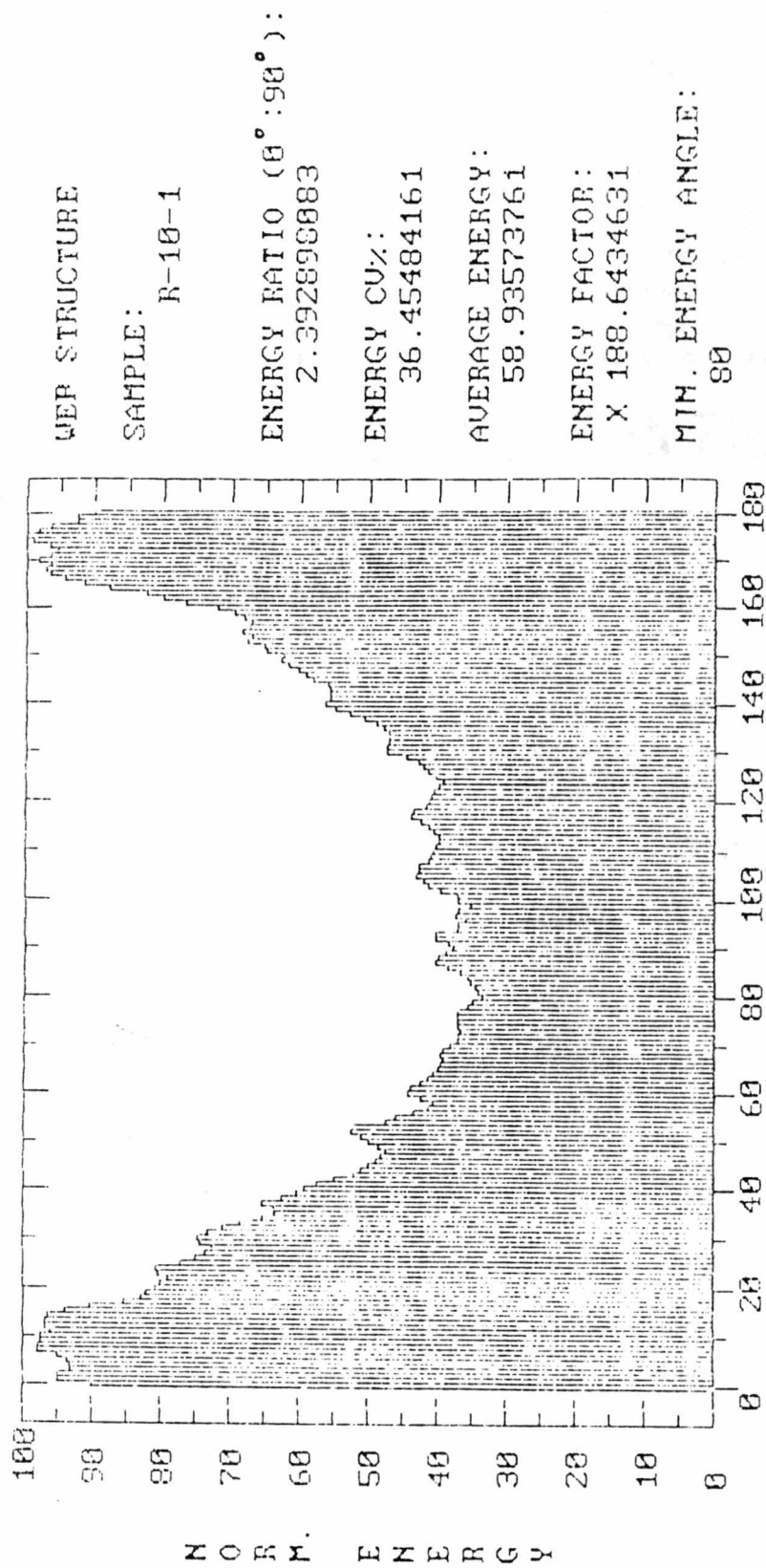


Fig. 5.23 FT spectrum of image shown in Fig. 5.22.



A N G L E

Fig. 5.24 Normalized energy distribution of the FT spectrum shown in Fig. 5.23.



Fig. 5.25 A training image for class C3.

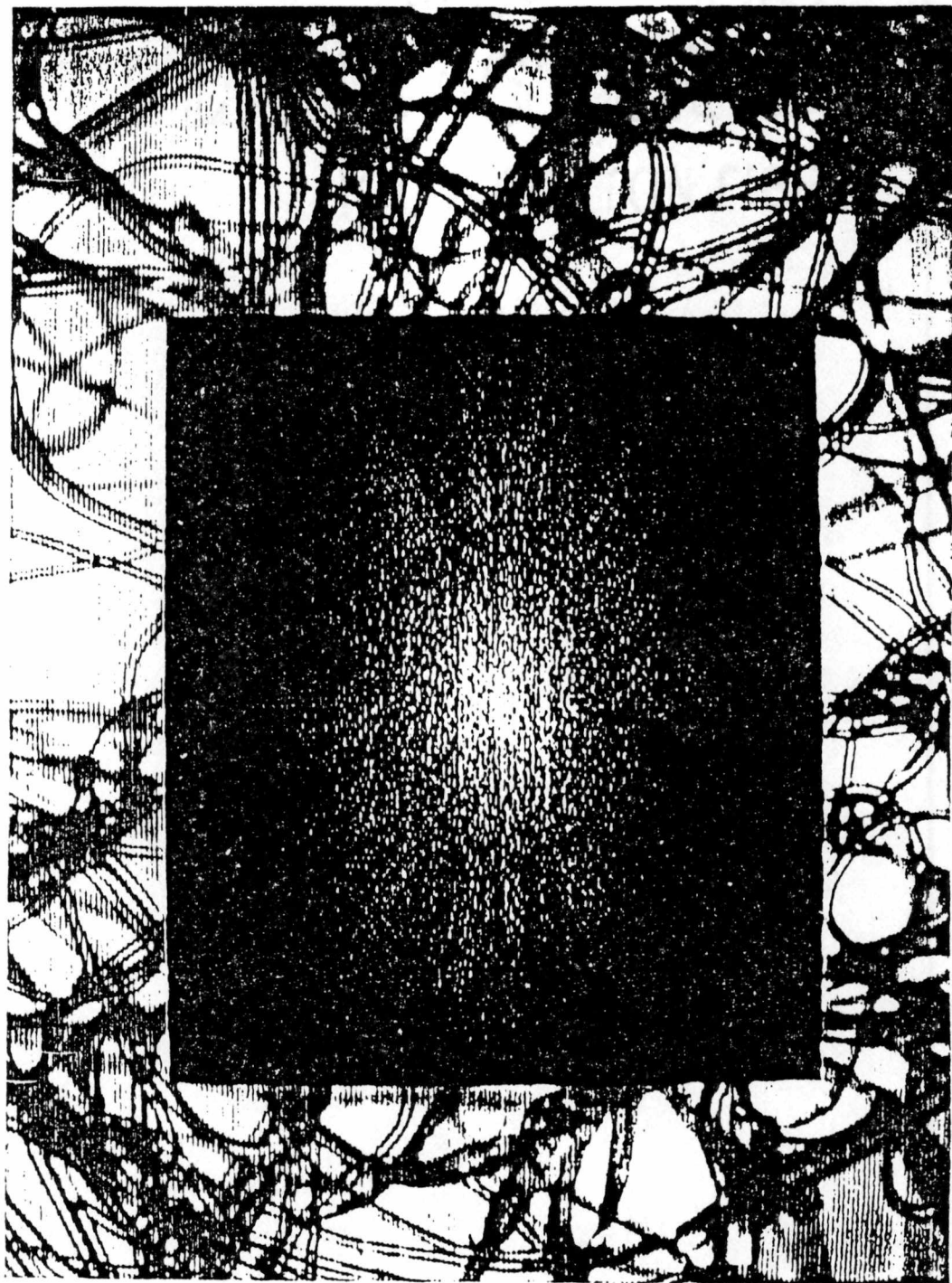
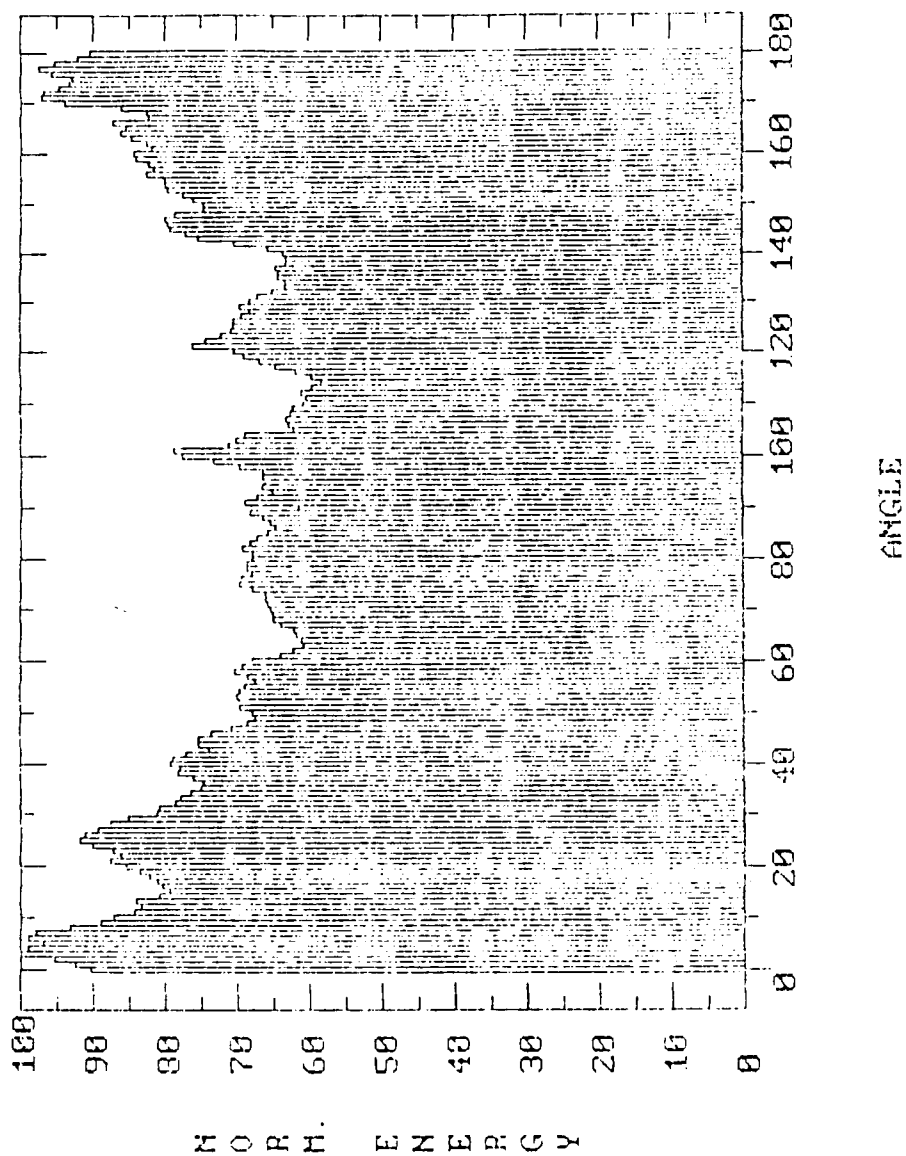


Fig. 5.26 FT spectrum of image shown in Fig. 5.25.



WEB STRUCTURE

SAMPLE:

R-2-1

ENERGY RATIO (0°:90°):

1.473535912

ENERGY CV%:

14.14678574

AVERAGE ENERGY:

74.8786665

ENERGY FACTOR:

X 148.0563049

MIN. ENERGY ANGLE:

114

Fig. 5.27 Normalized energy distribution of the FT spectrum shown in Fig. 5.26.

SAMPLE CLASS	INDEX	$\frac{E(U, 0)}{E(0, V)}$	ENERGY CV%	AVERAGE ENERGY
C 1	1	* 8.072883	68.087448	* 32.946773
	2	5.418816	65.915168	34.415412
	3	* 2.974915	* 71.380844	35.546291
	4	4.519444	* 51.460273	40.006301
	5	5.508247	55.086917	38.251071
	6	4.240467	60.868980	35.979530
	7	3.594335	54.896938	* 44.275451
	8	4.007685	55.495990	36.655925
	9	4.694798	64.394340	36.632518
	10	3.498254	53.283180	40.270530
C 2	1	2.392898	36.454841	58.935737
	2	* 1.968497	* 33.373645	* 60.437496
	3	3.351787	37.667045	46.705173
	4	2.916775	* 44.223045	* 46.563537
	5	2.376683	40.477287	51.531803
	6	2.417894	42.580921	50.706371
	7	2.898231	40.416061	49.695510
	8	3.013874	37.375629	49.817913
	9	2.588012	40.652793	55.977268
	10	* 3.397786	39.899402	51.144939
C 3	1	1.473635	* 14.146785	* 74.870666
	2	1.880857	19.241559	69.650520
	3	1.503088	18.255811	72.718978
	4	1.576774	19.685562	69.830520
	5	1.252173	20.754844	67.661849
	6	* 2.086344	20.442552	66.528259
	7	1.570008	19.739208	61.078086
	8	1.626234	18.524213	73.443260
	9	1.362493	15.742987	69.776046
	10	* 1.185473	* 26.759042	* 60.785232

* : class boundary.

Fig. 5.28 Indices of each training web derived from FT spectra and their energy distributions.

DEGREE CLASS	CAT.	ITERATION NUMBER		GRADE	INDEX & GRADE
		D1(X)	D23(X)		
C1-1*	1	270	360	A	8.072883 = A*
	2	150	340	A	68.087448 = A*
	3	180	320	A	32.946773 = A*
C2-1*	1	270	360	B	2.392898 = B*
	2	150	340	B	36.454841 = B*
	3	180	320	B	58.935737 = B*
C3-1*	1	270	360	C	1.473635 = C*
	2	150	340	C	14.146785 = C*
	3	180	320	C	74.870666 = C*

* : Refer to table 5.8.

Note : D1(X) is a decision function to classify C1 from C2 and C3.

Note : D23(X) is a decision function to classify C2 from C3.

Fig. 5.29 Results of the selection 3-D PATTERN CLASSIFICATION for the training webs.

the decision functions for 3 classes is as follows:

- (1) If $\underline{x} \in C1$, $D1(\underline{x}) > 0$ & $D2(\underline{x}) < 0$;
- (2) If $\underline{x} \in C2$, $D1(\underline{x}) < 0$ & $D2(\underline{x}) > 0$;
- (3) If $\underline{x} \in C3$, $D1(\underline{x}) < 0$ & $D2(\underline{x}) < 0$;

where $\underline{x}$: pattern vector,
C1, C2, C3 : pattern classes,
D1, D2 : decision functions.

Samples were also taken from each of the fabric rolls and their breaking load was measured in the web CD and MD. These were used to compute the MD/CD breaking load ratio as summarized in Fig. 5.30. These results are in qualitative agreement with the spectral energy ratios derived from digital image processing and summarized in Fig. 5.28. Both measuring techniques indicate that fiber orientation in the training webs varied from highly anisotropic, to moderately anisotropic, to slightly anisotropic.

Several unknown webs were classified using the training pattern classes C1, C2, and C3. An example of one unknown melt-blown image, its corresponding FT spectrum and its spectral energy distribution are shown in Figs. 5.31-5.33. Results of classification are shown in Fig. 5.34.

A one-dimensional decision function is sufficient to classify an unknown web when each index falls in only one training grade. It is not necessary to use quadratic and cubic equations for web classification in this case. However, Fig. 5.34 shows that the classification of sample 3 is ambiguous. The classification of this web lies in the buffer zone among classes because energy CV%, falls somewhere between Grade A and B. Therefore, we need a cubic equation to classify this sample more accurately. Fig. 5.34 shows that this web is recognized as Grade A when evaluated with the 3rd degree. The 3rd degree decision is preferred and one would expect the success of web classification to be improved further if a greater number of indices are utilized.

BREAKING DIRECTION CLASS	CD (gram)	MD (gram)	MD : CD
C1	48.33	453.33	9.38
C2	325.83	794.17	2.44
C3	120.83	196.67	1.63
TESTING CONDITIONS* : (1) SAMPLE SIZE 6" X 1" (2) CROSS-HEAD SPEED 5"/MIN. (3) CHART SPEED 5"/MIN. (4) FULL SCALE LOAD 2 KG. (5) GAUGE LENGTH 3"			

* : Refer to ASTM D1682-64.

Fig. 5.30 Breaking load of the training webs.



Fig. 5.31 An unknown web.

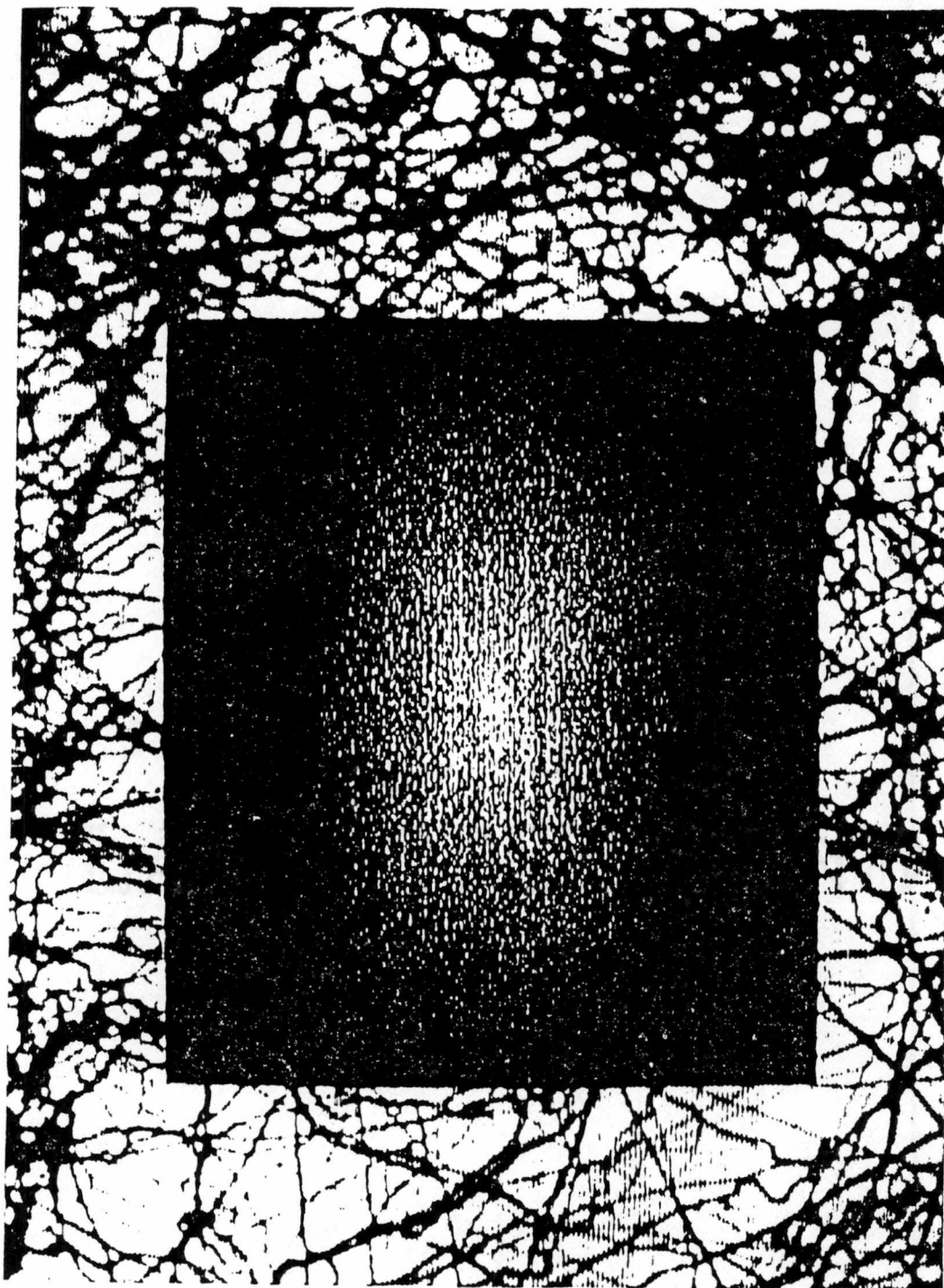


Fig. 5.32 FT spectrum of the web shown in Fig. 5.31.

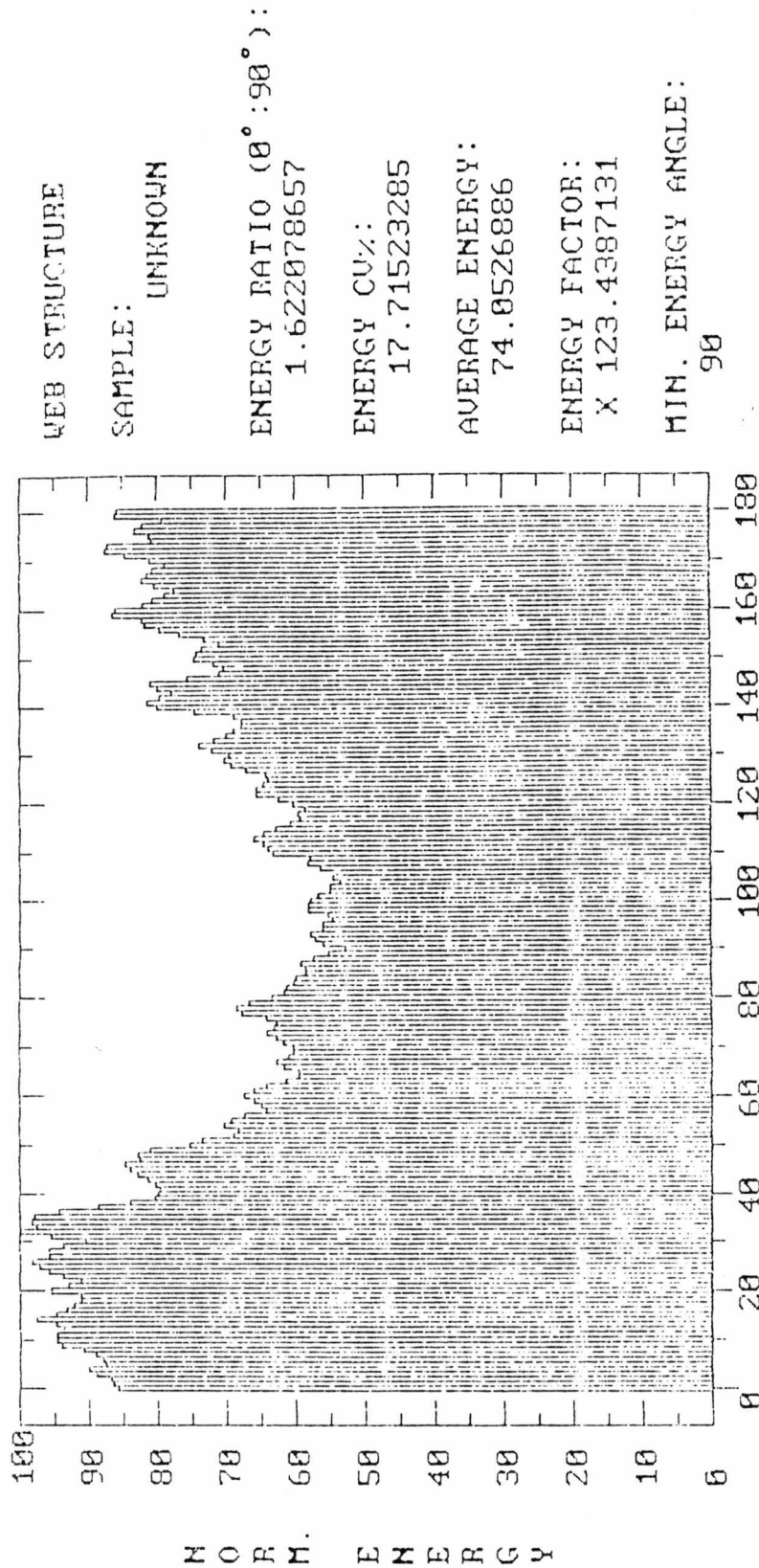


Fig. 5.33 Normalized energy distribution of the FT spectrum shown in Fig. 5.32.

DEGREE SAMPLE	CAT.	ITERATION NUMBER		GRADE	INDEX & GRADE
		D1(X)	D23(X)		
UNKNOWN MELT-BLOWN 1	1	270	360	C	1.568369 = C*
	2	150	340	C	20.847326 = C*
	3	180	320	C	70.975662 = C*
UNKNOWN MELT-BLOWN 2	1	270	360	C	1.371105 = C*
	2	150	340	C	15.478617 = C*
	3	180	320	C	74.789452 = C*
UNKNOWN MELT-BLOWN 3	1	270	360	B	2.698530 = B*
	2	150	340	B	45.325974 = A*-B*
	3	180	320	A	44.128807 = A*
UNKNOWN PRESUMED 4	1	270	360	B	5.000000 = A*
	2	150	340	B	40.000000 = B*
	3	180	320	B	70.000000 = C*

* : Refer to table 5.8.

Note : A presumed sample is described by assigned indices.

Fig. 5.34 Classification of unknown melt-blown webs.

5.4 Further Study

The FT procedure examined in this thesis is a handy tool to monitor changes in web structure and to classify unknown webs. Some suggestion for further studies are provided below:

- (1) Investigate the application of the tool directly on line to determine if changes in web structure at different production intervals can be quickly detected.
- (2) High-grade nonwoven webs exhibit highly uniform distributions of fibers. Investigate with statistical analyses the use of the energy ratio, the energy CV%, and the energy average for evaluating web uniformity.
- (3) Investigate the preparation of a database for various groups of training patterns. Through the database, one can find suitable training patterns for the production conditions desired and then supervise the web forming equipment.

PART 6

CONCLUSION

Fourier transformation of digital web images can be used to monitor structure of thin melt-blown webs. With the use of web image models, structural features contribution to spectral energy were revealed and FT spectral energy was analyzed quantitatively.

With indices extracted from the spectral energy distribution, unknown melt-blown webs were classified successfully. For the classification decision functions, a cubic polynomial form was suggested for practical operation of the tool.

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