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Application of morphological image processing to texture decomposition

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APPLICATION OF MORPHOLOGICAL IMAGE PROCESSING TO TEXTURE DECOMPOSITION

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Abstract

In this thesis, the mathematic morphological operations are reviewed accompanied by the examples to illustrate the concepts. The morphological operations are extended to a more general method that uses the multiple structuring elements combined with other operations, such as logical operations. Two procedures based on the multiple structuring elements morphological processing method have been developed, and these two procedures are implemented to extract the fibers with specific thickness from the fibrous nonwoven material images. The combinations of morphological operations with other set operations and the utilization of multiple structuring elements enhances the performance of morphological-based filters.

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Chapter 1

Introduction

Mathematical morphology, also called morphological filtering, provides an effective tool for image processing and computer vision. Many tasks in image processing and image analysis can be approached or solved through the means of mathematical morphology. This methodology is widely used to decompose images [1], to detect edges [2], and to suppress noise [3]. Mathematical morphology is also used in shape representation [4].

The theory of mathematical morphology is discussed in detail in the book by Serra [5]. The basic morphological operations are defined between two sets, A and B, where A is the set representing an image we want to process and B is called the structuring element. Morphological filters are thus designed by using the shapes of the objects in an image and the goal of the task. This concept of mathematical morphology offers great flexibility to design the structuring elements with different shapes and sizes according to the specific task. The basic morphological operations with binary and gray-scale image are erosion, dilation, opening and closing.

In this thesis, in Chapter 2, the binary morphology and gray scale morphology are reviewed, programs have been written to perform these morphological transforms and the results of those programs are consistent with the examples given in [6] and [4]. Applications such as noise cleaning, smoothing, decomposition and edge detection are discussed for both binary and gray scale cases. The applications are demonstrated by examples. In Chapter 3, the morphological opening operation is used to extract the objects of specific shape from the synthetic images. A synthetic image containing line segments is created to help the analysis of texture image decomposition. Based on the basic morphological operations, multiple structuring elements morphological processing technique is developed combined with logical operations. This multiple structuring elements morphological processing technique has been applied to extract objects of specific orientation or objects of specific size from synthetic images. Two procedures that use the multiple structuring elements technique have been developed and employed to process the web material image, and extract fibers of specific thickness.

This thesis is organized as following. Chapter 2 gives the background of mathematical morphology in both binary and gray scale cases. Chapter 3 applies the multiple structuring elements morphological processing technique to synthetic and web material image. Chapter 4 gives the conclusions.

Chapter 2

Introduction to Mathematical Morphology

Morphological image processing is nonlinear transformation that locally modifies the geometric features of images such as their peaks and valleys. Morphological image processing involves the interaction of the shapes of the objects in an image and compact sets of chosen shape and size, called the structuring elements. The interaction process is done through set operations. To understand the similarities and differences between morphological filtering of binary and gray scale images, the basic manipulations dilation and erosion of both binary images and gray scale images, as well as, the opening and closing based on these manipulations are discussed in this chapter.

2.1 Binary Morphological Transformation

2.1.1 Binary Dilation

First, the binary images are considered. The binary image is represented by a set of pixels which are the objects in the binary image. For example, a three by three square binary object in an image whose origin is located at left top corner may be represented by the set that contains elements:

$$S = \{(0,0),(0,1),(0,2),(1,0),(1,1),(1,2),(2,0),(2,1),(2,2)\}.$$

Let A be the input binary image and B be the binary structuring element. The dilation of A by B, denoted $A \oplus B$, is defined by [4]:

$$A \oplus B = \bigcup_{a \in A} \{b + a \mid b \in B\}.$$

Because addition is commutative, dilation is also commutative, i.e., $A \oplus B = B \oplus A$. Dilation by disk structuring elements corresponds to isotropic swelling or expansion. An the example of dilation is illustrated in Figure 2.2, the resulting image is expanded. Figure 2.1 is the input image.

2.1.2 Binary Erosion

Erosion is the morphological dual of dilation. It is the morphological transformation that combines two sets by using containment as its basis set. The erosion of A by B is denoted by $A \ominus B$ and defined as $A \ominus B = \{x | x + b \in A \ for\ every\ \ b \in B\}$. The erosion of an image A by a structuring element B is the set of all elements x for which B translated to x are contained in A. The image in Figure 2.3 is the

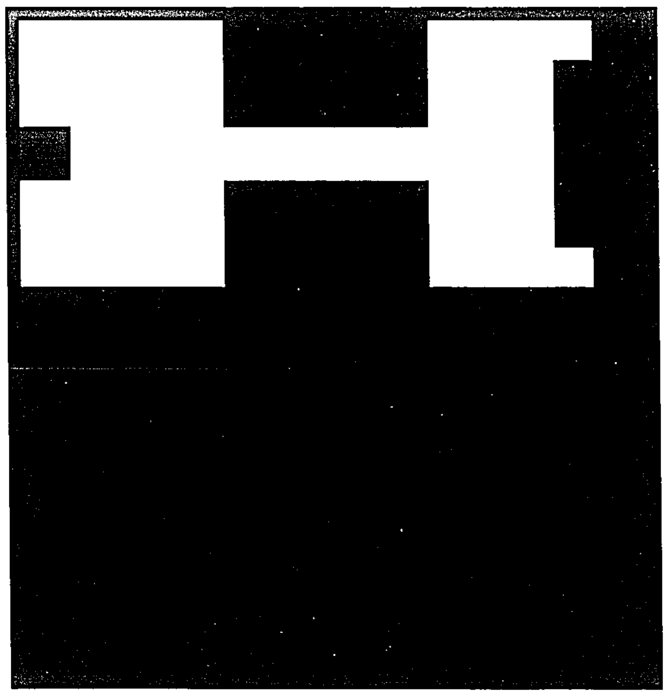


Figure 2.1: The example binary image.

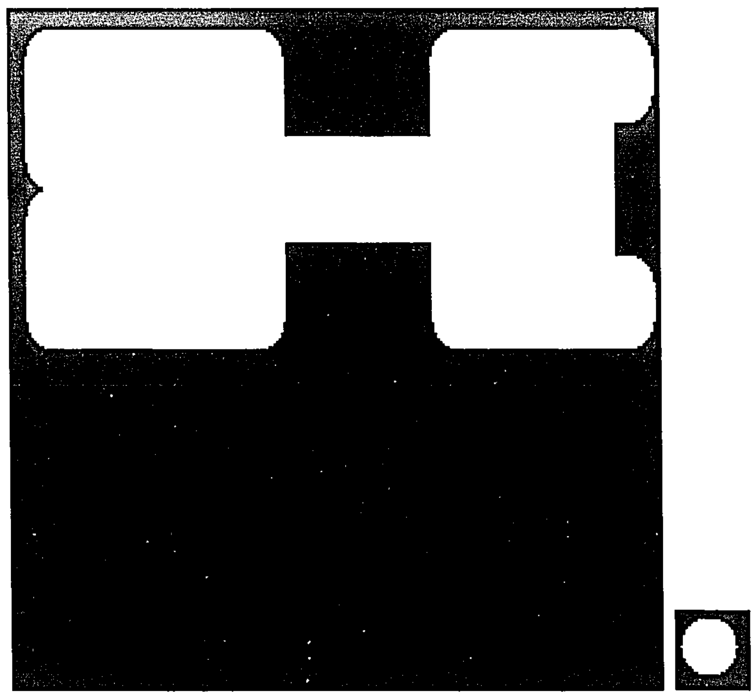


Figure 2.2: Binary dilation. Dilated image and the structuring element which is used to perform the dilation. The input image is shown in the Figure 2.1.

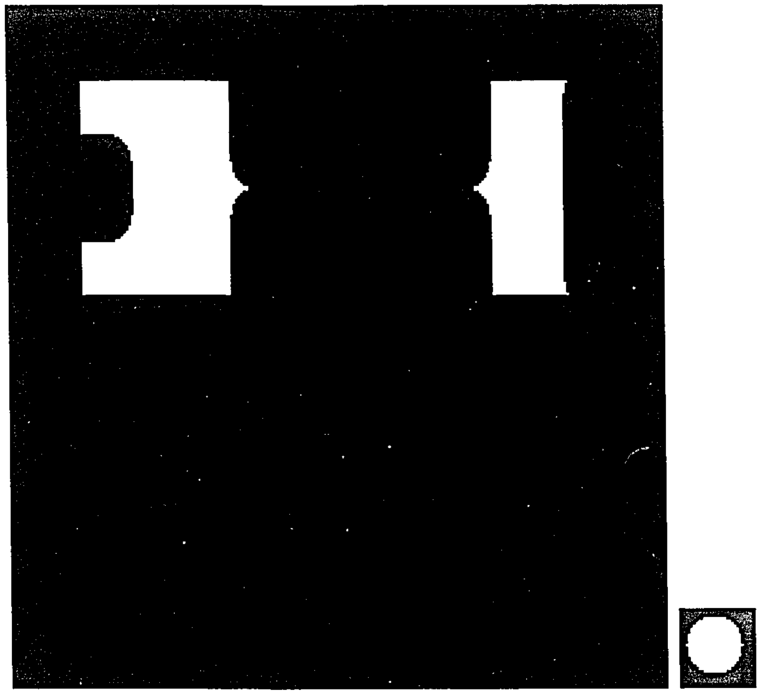


Figure 2.3: Binary erosion. Resulting image and the structuring element which is used in erosion, the input image is shown in the Figure 2.1.

erosion of the image in Figure 2.1, as it is expected that the eroded version is shrunk comparing to the input image, and the link between the ends is broken since the size of the link is smaller than the diameter of the disc.

2.1.3 Binary Opening

The opening of image of A by structuring element B is denoted by $A \circ B$ and defined by

$$A \circ B = (A \ominus B) \oplus B.$$

The opening of A by B selects points of A that match B in the sense that the points can be covered by translation of the structuring element B that itself is entirely contained in A. Opening an image with a disk structuring element smoothes the contours, breaks narrow isthmuses, and eliminates small islands and sharp peaks or capes. As it is illustrated in Figure 2.4 for the input image in Figure 2.1 the link between the two blocks is wiped out, since the structuring elements can not be enclosed entirely inside the link. The corners of the blocks in the image are rounded due to the shape of structuring element.

Several properties of the opening can be established.

1. $(A+x) \circ B = (A \circ B) + x$. This is called translation invariance property. It shows that the opening of an image A which is translated by distance x is equivalent to translating the opening of the image A by the same distance x, alternatively, we also have $A \circ (B+x) = (A \circ B) + x$, it shows that the opening of an image by the translated structuring element is equivalent to translating the opening of the image A by the same distance.

2. $A \circ B < A$. This shows that the opening result is a subset of the input A.

3. $(A \circ B) \circ B = A \circ B$. This is idempotence property. This property shows that the opening result will not be changed by applying the opening operation repeatedly using the same structuring element.

2.1.4 Binary Closing

The closing of image A by structuring element B is denoted by $A \bullet B$ and defined by

$$A \bullet B = (A \oplus B) \ominus B.$$

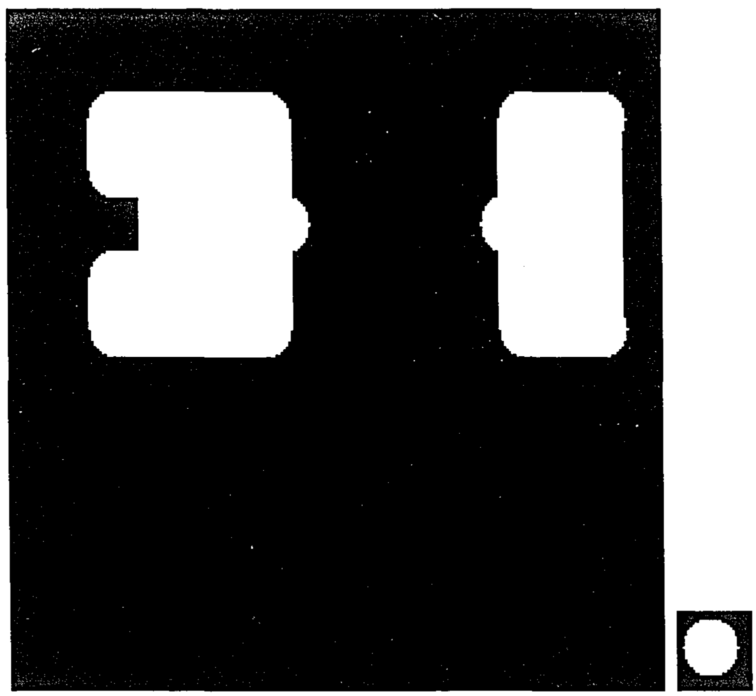


Figure 2.4: Binary opening. Opened image and the structuring element which is involved in opening operation.

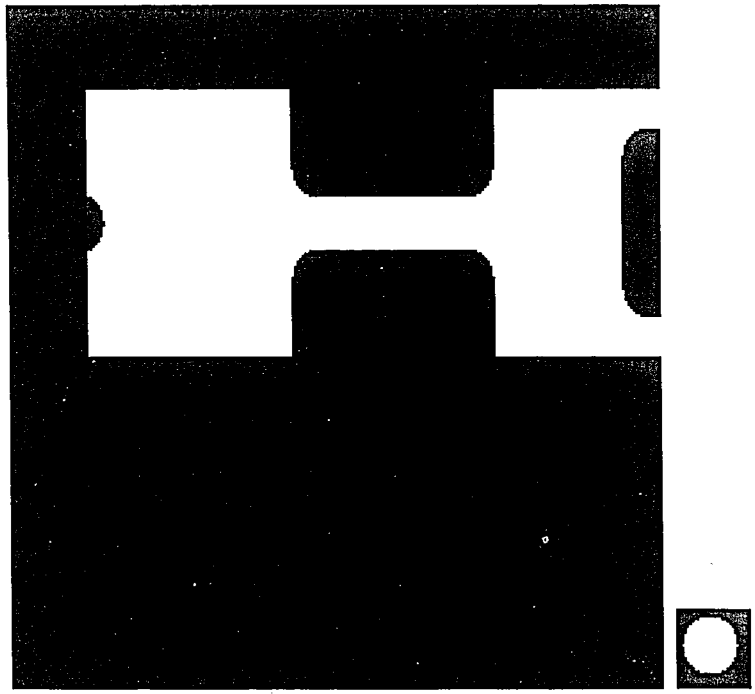


Figure 2.5: Binary closing. Closed image and the structuring element.

Closing an image with a disk structuring element smoothes the contours, fuses narrow breaks and long thin gulfs, eliminates small holes, and fills gaps on the contours. Figure 2.5 is the structuring image and the closed image, the gap at the left end is filled partially due to closing, it could be filled completely if a larger structuring element is used. The input image used for the closing operation is shown in Figure 2.1.

2.1.5 Examples of Applications

Edge Extraction

The edge of an image A, denoted by $\beta(A)$, can be obtained by eroding A by B, and then performing the difference between A and its erosion or by the first dilating A by

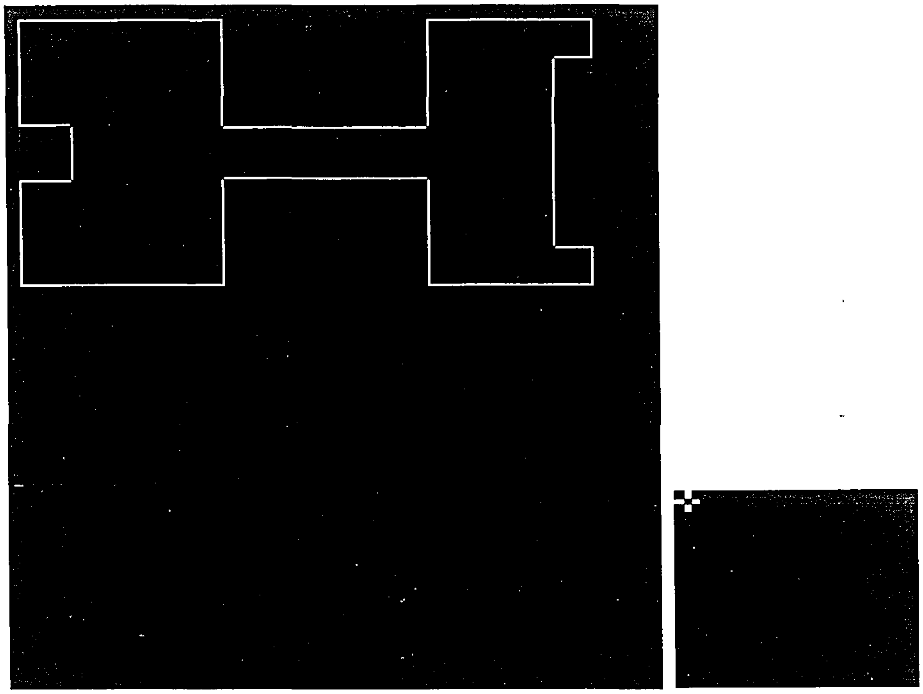


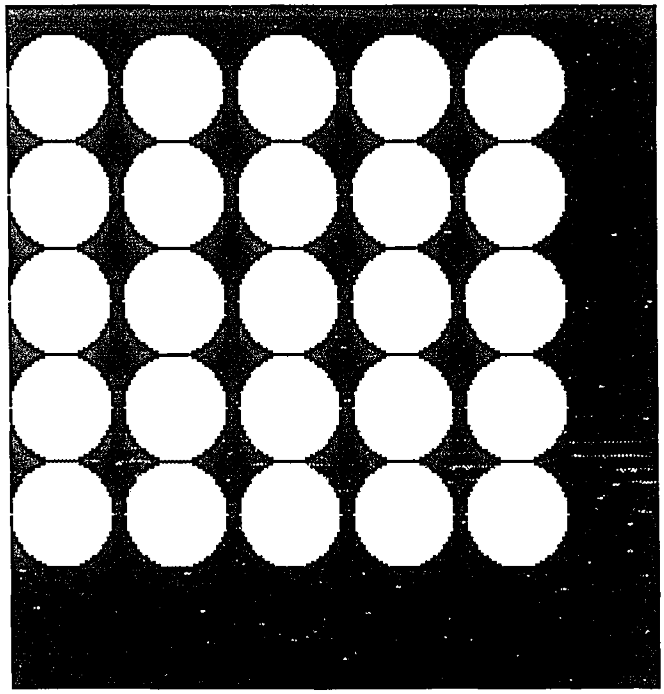
Figure 2.6: Boundary extraction. Boundary of the object shown in the Figure 2.1 and the structuring element used for the boundary extraction.

B, and then subtracting the image A from its dilation [4], i.e., $\beta(A) = A - (A \ominus B)$, or $\beta(A) = (A \oplus B) - A$, where B is a suitable structuring element. The simplest structuring element for this purpose is a binary image containing four foreground points whose coordinates are $(-1,0),(0,-1),(1,0),(0,1)$. This method can produce clear edge which is only one pixel wide for the binary image. The image shown in Figure 2.6 is the edge of the object in Figure 2.1.

Noise Reduction and Shape Decomposition

Morphological operations are very effective in cleaning noisy images. Noise is removed by opening image with a disk structuring element whose radius is less than the objects and larger than the bright dots in the image. Figure 2.7 shows that the noise is removed from the input image by morphological opening operation, and the objects in the image are not deformed after the noise has been cleared.

Morphological opening operation can also be used to decompose objects. Figure 2.8 gives an example of the decomposition by using the opening operation. It shows an object that consists of a big square and a small rectangle as the handle. To decompose this shape into parts, it was opened with a small square structuring element whose size is larger than the handle and smaller than the body. This resulted in extracting the body of the object. The residue of the opening is the handle, as illustrated in Figure 2.8.



Noisy Image

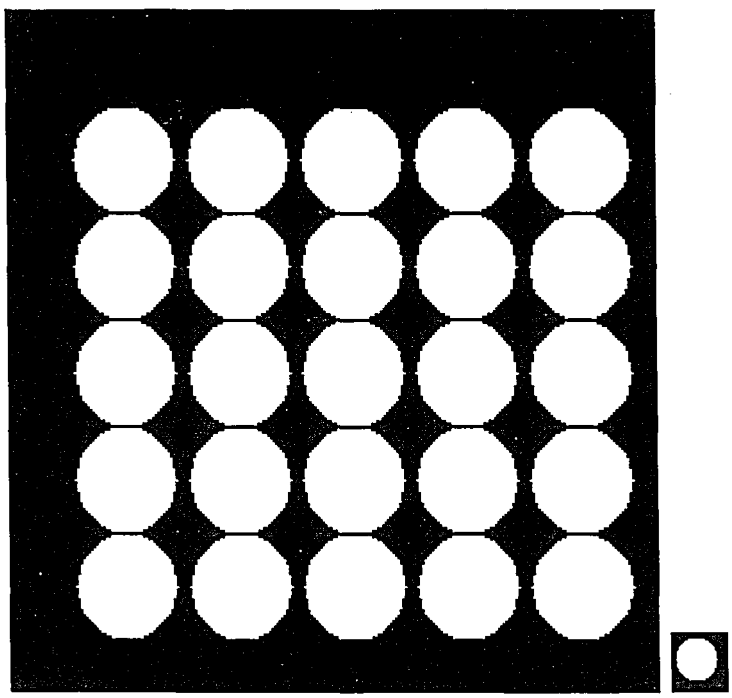
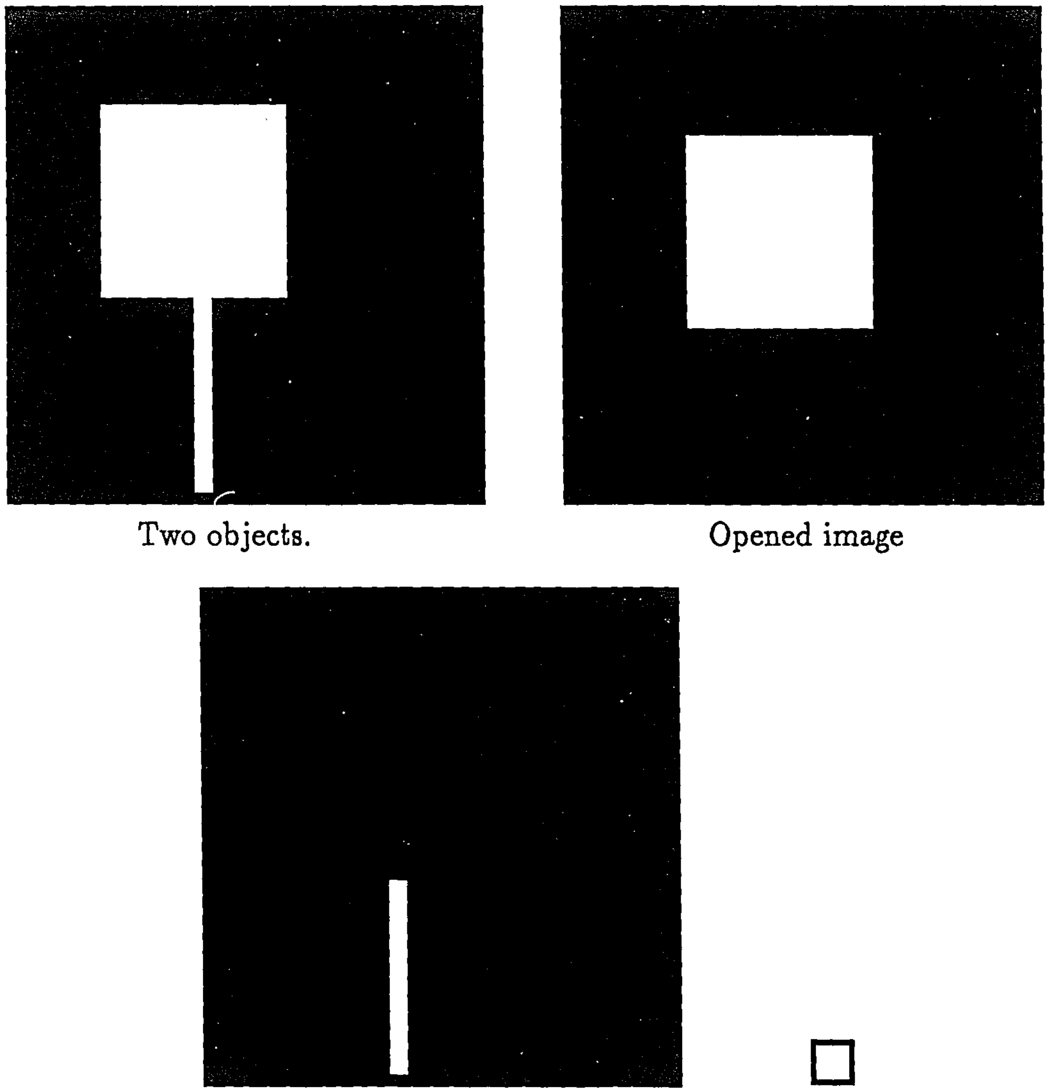


Figure 2.7: Noise reduction. Noise-cleaned image and structuring element.



Two objects.

Opened image

The residue.

Structuring element

Figure 2.8: Object decomposition using the morphological opening.

2.2 Gray Scale Morphological Transformation

2.2.1 Gray Scale Dilation and Erosion

The digital gray scale image can be represented by $f(r,c)$, where r and c are row and column coordinates, respectively, and $f(r,c)$ indicates the gray scale value of the pixel at the location (r,c) in the gray scale image. Similarly to the binary morphology, the gray scale morphology is also defined over two images, $f(r,c)$ and $b(r,c)$, where $f(r,c)$ is the input image and $b(r,c)$ is a structuring element which is a gray scale image as well.

Gray scale dilation of f by b, denoted $f \oplus b$, is defined as [1]

$$(f \oplus b)(s,t) = max\{f(s-x,t-y) + b(x,y) | (s-x),(t-y) \in D_f; (x,y) \in D_b\},$$

where D_f and D_b are the domains of functions f and b, respectively, and the domains $(s-x),(t-y)$ and D_f have to overlap by at least one element. Gray scale dilation is also commutative. The dilation of gray scale image is based on the maximum value of $f+b$ in the neighborhood defined by the shape of the structuring image. The general effect of performing dilation on a gray scale image is to brighten the image, and to reduce or eliminate dark details. The effect of the dilation is dependent on the values of the structuring elements and their shapes.

Gray scale erosion, denoted $f \ominus b$, is defined as

$$(f \ominus b)(s,t) = min\{f(s+x,t+y) + b(x,y) | (s+x),(t+y) \in D_f; (x,y) \in D_b\},$$

where D_f and D_b are the domains of functions f and b, respectively. The sets $(s+x),(t+y)$ should be contained in the domain of f and the structuring element has to be completely enclosed by the set being eroded. As the equation above shows, the erosion is based on selecting the minimum value of $(f - b)$ in a neighborhood defined by the shape of the structuring element. The general effect of performing erosion on a gray scale image is to darken the input image, and to reduce the bright details in the input image. This effect is also decided by the shape and amplitude value of the structuring element.

2.2.2 Opening And Closing

Gray scale opening and closing are defined in an analogous way to opening and closing in binary morphology and have similar properties. The gray scale *opening* of $f(x, y)$ by structuring element $b(x, y)$ is denoted by $f \circ b$ and is defined by

$$f \circ b = (f \ominus b) \oplus b.$$

The gray scale *closing* of $f(x, y)$ by structuring element b is denoted by $f \bullet b$ and is defined by:

$$f \bullet b = (f \oplus b) \ominus b.$$

The interpretation of the gray scale closing of f with b is to take the structuring element b, reflect it left-right, turn it upside-down, and sweep the result above the top of f.

2.2.3 Examples of Applications

Morphological Smoothing

Opening following by closing smoothes the image. The net result of these two operations is to remove or attenuate both bright and dark artifacts or noise. Figure 2.9 shows the comparison of the input image and the smoothed one.

Figure 2.9: Gray scale smoothing.

Morphological Edge Detection

The morphological edge detector introduced by Lee et al. [2] is a good example of edge detection using morphological filtering. Briefly, this algorithm is as follows. The image is blurred by local averaging over a small square region, next, the blurred image $b(i,j)$ is eroded and dilated by using the mathematical morphological operations of erosion (local minimum) and dilation (local maximum) with a square structuring element seperately. For pixel (i,j), the resultant edge strength is the minimum of $(b_{ij} - e_{ij})$ and $(d_{ij} - b_{ij})$ where b_{ij}, d_{ij} and e_{ij} are the gray scale values at pixel (i,j) in the blurred, dilated, and eroded images, respectively. The edge can also be enhanced by using $f - (f \circ b)$, where f is the input image and b is the structuring element. As an example shown in Figure 2.10, the edge of the image is produced by performing $f - (f \circ b)$, the input image is shown in Figure 2.9.

Figure 2.10: Gray scale morphological edge detection.

Morphological Gradient

The morphological gradient, denoted g, is defined as [6]:

$$g = (f \oplus b) - (f \ominus b).$$

Figure 2.11 shows the result of computing the morphological gradient. As expected, the morphological gradient highlights sharp gray-level transitions in the original image.

Object Extraction

The morphological opening operation can be used as a very efficient technique for object extraction. In order to illustrate this, a disc that is close to the center of the image in Figure 2.12 was added intentionally for this illustration. The radius

Figure 2.11: Gray scale morphological gradient.

of the added disc is fifteen pixels. The structuring element used for this purpose is a disc image, the radius of the structuring element for the opening operation is thirteen pixels, the gray scale value of the structuring element is chosen to be a value between the gray scale value of the object and its neighbor in order to achieve best result.

2.2.4 Multiple structuring elements morphological processing techniques

As it has shown in the Sections 2.1.5 and 2.2.3, even a simple task requires several steps of processing. In order to use morphological operators more effectively, combinations of morphological operators with other operations and the use of multiple structuring elements have been introduced [3]. It was shown that the morphological

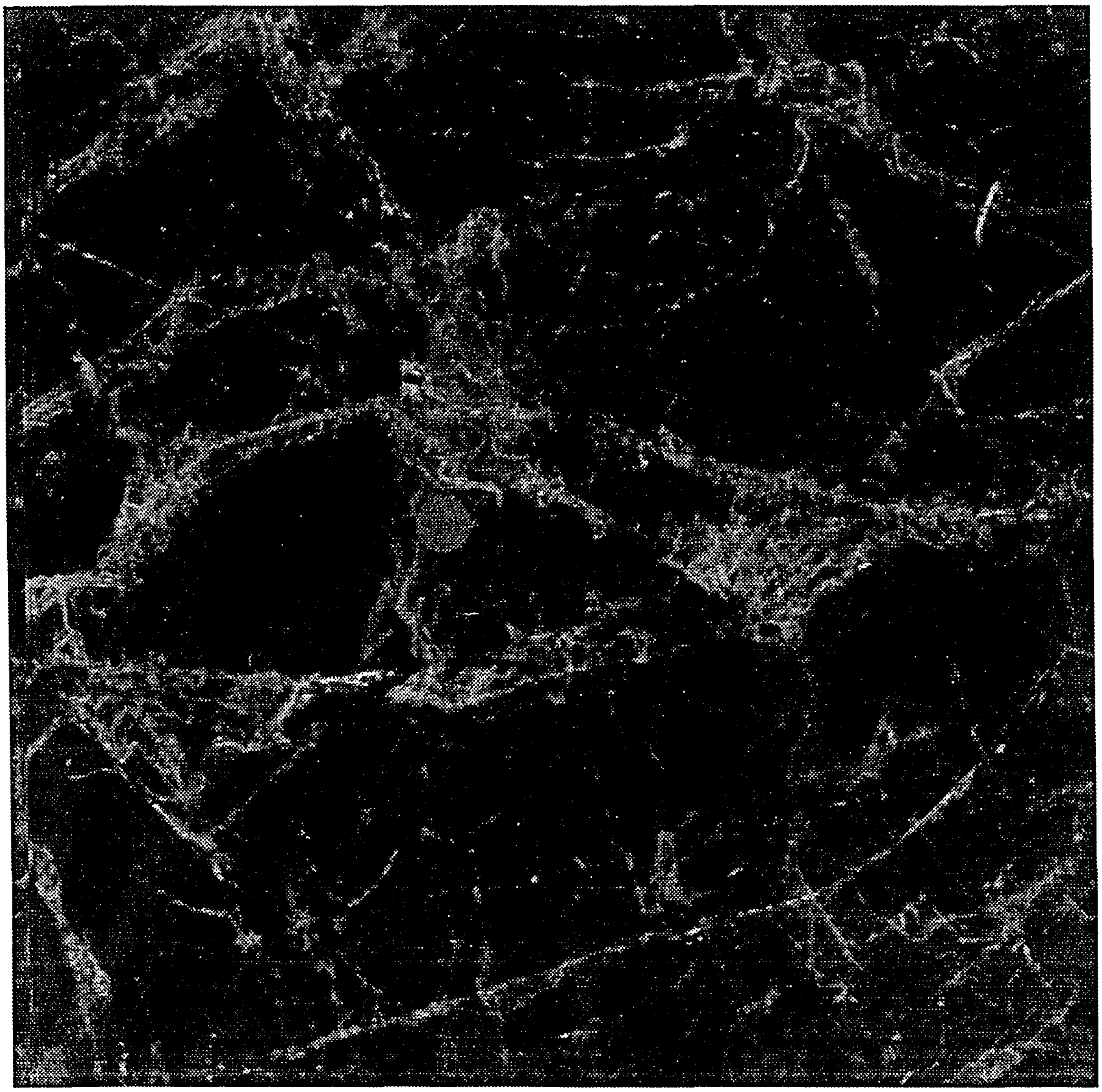


Figure 2.12: The image with a disc near the center.

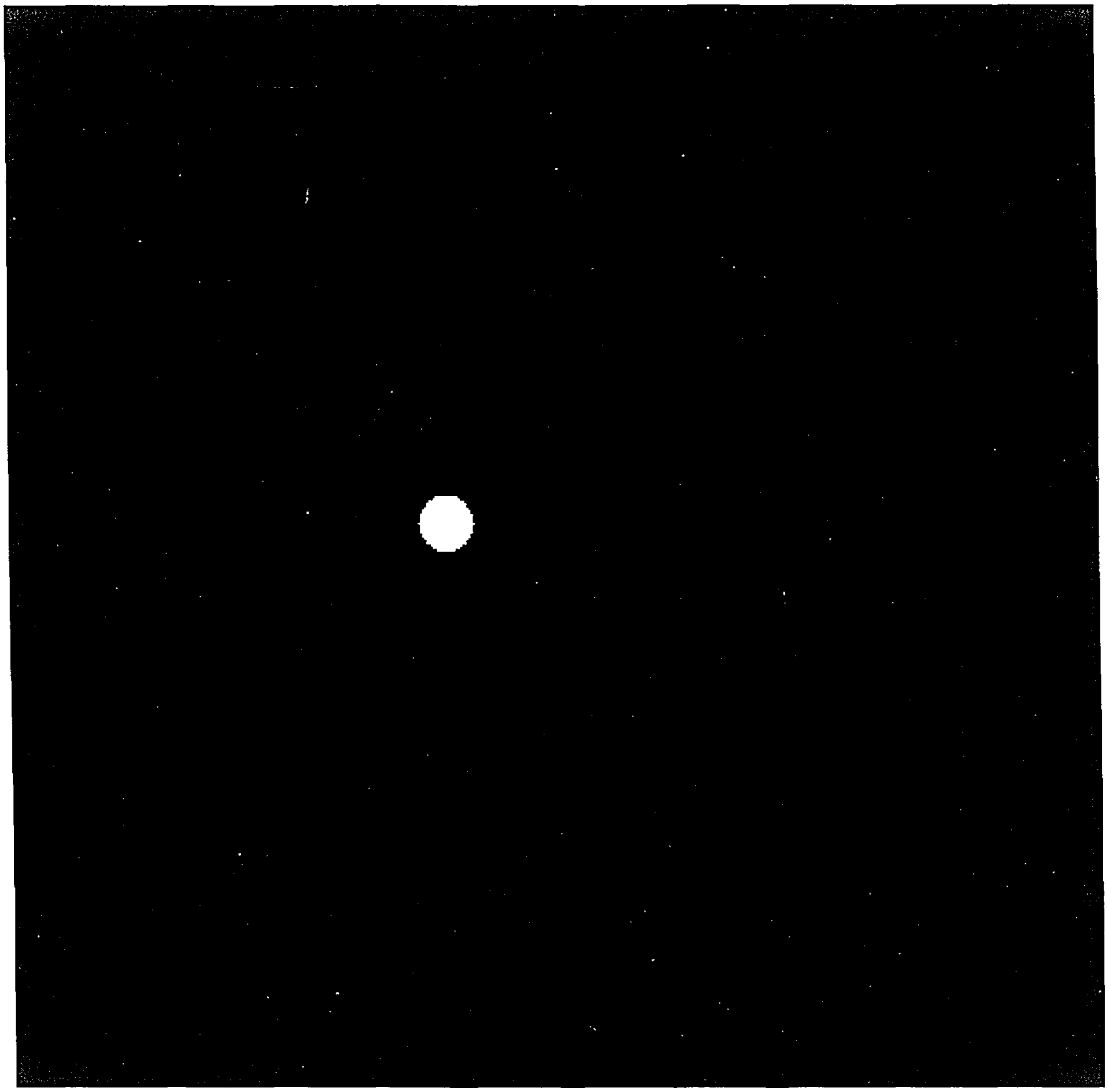


Figure 2.13: Gray scale Object Extraction. The disc is extracted from the image in Figure 2.12.

algorithm can filter the noise in an image without deforming the objects in the original image. A more general approach is therefore based on multiple model concept. In this approach, different geometrical structures are modeled and incorporated into multiple filters which are applied to the input image. The outputs of the filters are combined relative to some predefined criterion. Using this approach, obviously the image is decomposed more precisely by the using several structuring elements and geometrical structure preservation is improved by using more structuring elements. Due to the nature of opening operations of the morphological processing which can remove unmatched structures, or extract matched shapes, increasing the number of structuring elements will help in better object feature extraction, decomposition and geometric feature preservation. For example, performing morphological operations on the set A with different structuring elements B_i, we get a resulting series Y_i. Each specific structuring element B_i filters out a specific kind of information from the original image. By analyzing the resulting set sequence Y_i $(i > 1)$, we can select the specific structuring element to use next. This interaction between set A and structuring elements B_i facilitates image analysis by continuously finding the most suitable structuring element to extract the most useful information at that stage. However, a systematic scheme for designing a general purpose morphological filter using multiple structuring elements is not yet available, current design is based on trial and error.

Chapter 3

Application of the Multiple Elements Morphology Processing

In this chapter, a morphological approach is used to extract objects of specific shape from synthetic images and subsequently in a texture image. A synthetic image containing line segments is created to help analysis the texture decomposition by using the morphological opening operation. Two procedures are implemented based on the multiple structuring elements model introduced in the previous chapter. They are used to decompose the web material image.

The morphological processing method can be applied to extract the objects of specific size or specific orientation in an image. The following two examples are to illustrate this technique on two synthetic images. The first example, shown in Figure 3.1, is an image containing discs whose radii are fifteen and five pixels. The gray-scale opening operation is applied to the image to extract all the larger discs, the structuring element used for this is a disc with radius between the radius of large disc and small disc, the result is shown in Figure 3.2. The second example, shown in Figure 3.3, is also a synthetic image which contains vertical bars and horizontal bars. The gray scale opening is used to extract the vertical bars, the structuring element used for this is a rectangle, its width is less than the width of the vertical bar, and its length is longer than the length of the horizontal bar and less than the length of the vertical bar. The result is shown in Figure 3.4, the horizontal bars are completely wiped out after this operation.

The similar procedure is employed to enhance the fibers in the web material image. As the images in Figure 2.12 shows there are many fine details in the image. Because of uneven distribution of thickness of the web material, some regions appear very fuzzy and some fibers are broken into several segments, and some intersect each other. This image can be modeled by line segments of varying intensity, and therefore this work concentrates on extracting line objects from the image.

3.1 Generation of Synthetic Images

In order to aid the analysis of the decomposition process, the synthetic images are first used. In the synthetic image, the fibers were simulated by line segments in different directions and of different intensity. An image was generated using the following algorithm.

3.1.1 Line Segment Generation

A line segment whose two endpoints are (X_1, Y_1) and (X_2, Y_2) can be represented by the following equation:

$$\frac{X - X_1}{Y - Y_1} = \frac{X_1 - X_2}{Y_1 - Y_2},$$

where X, Y, X_1, Y_1, X_2, Y_2 are real numbers.

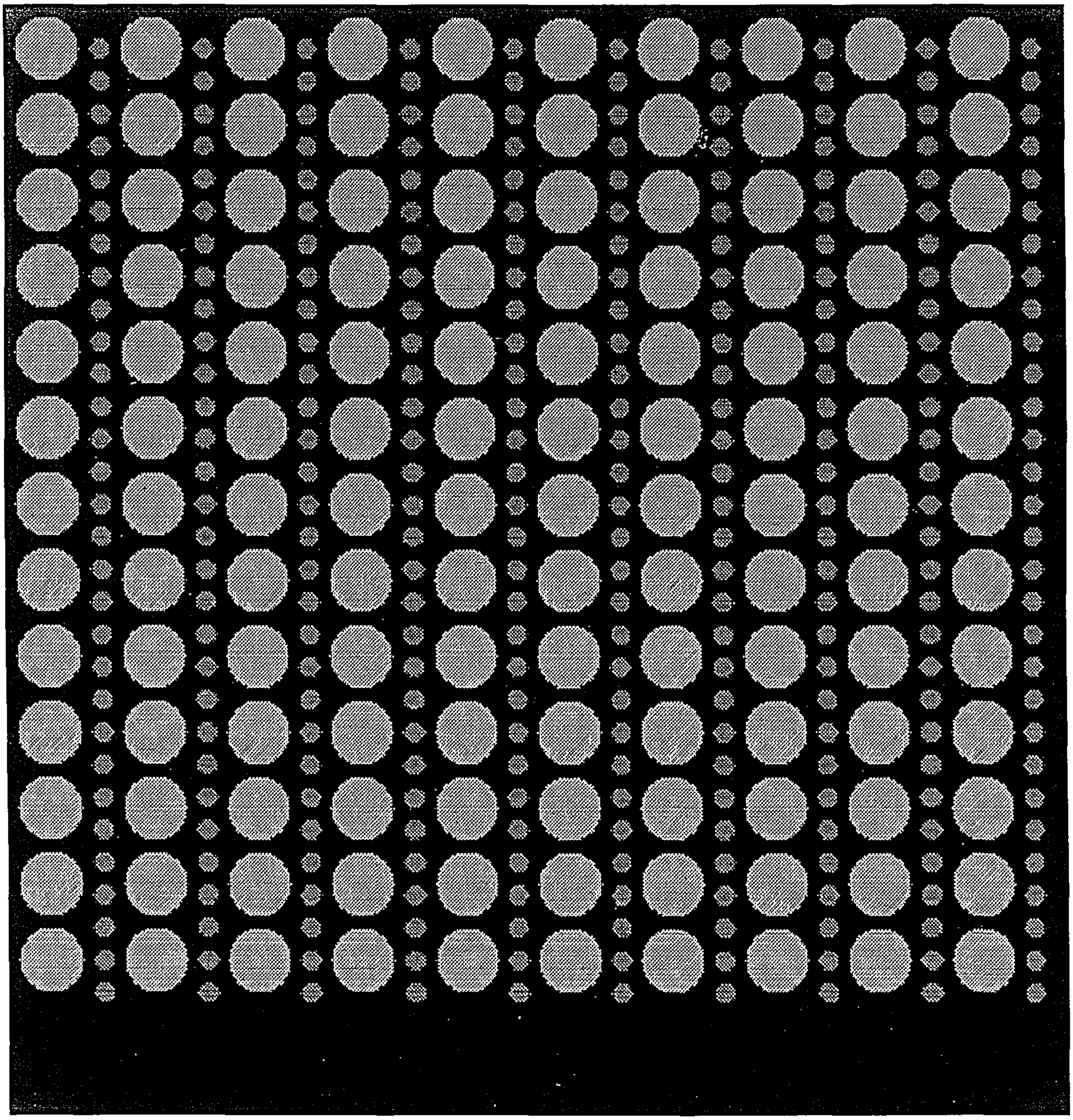


Figure 3.1: A synthetic image containing the discs whose radii are fifteen pixels and five pixels.

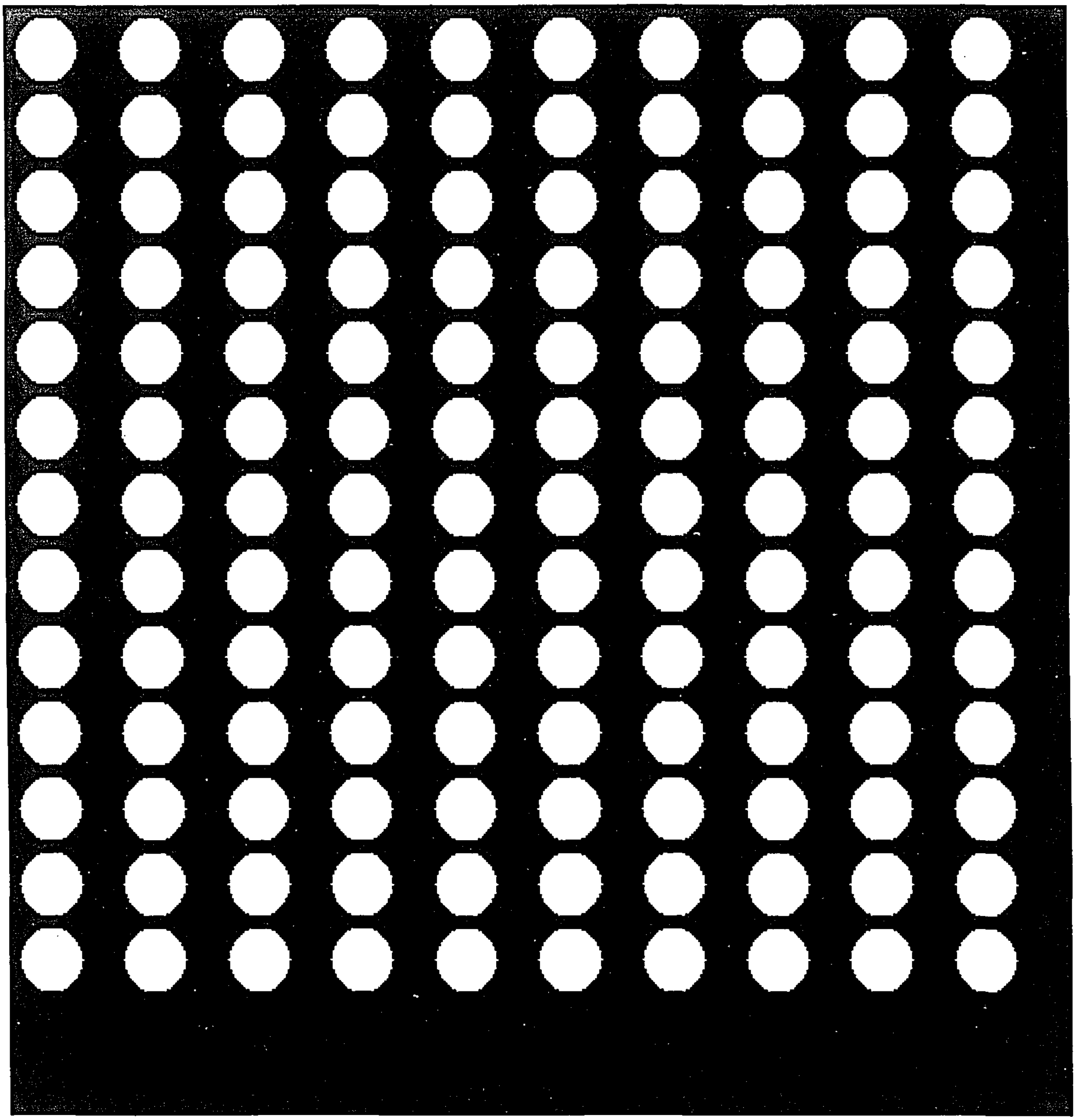


Figure 3.2: Result image after the morphological opening has been applied to the image in Figure 3.1.

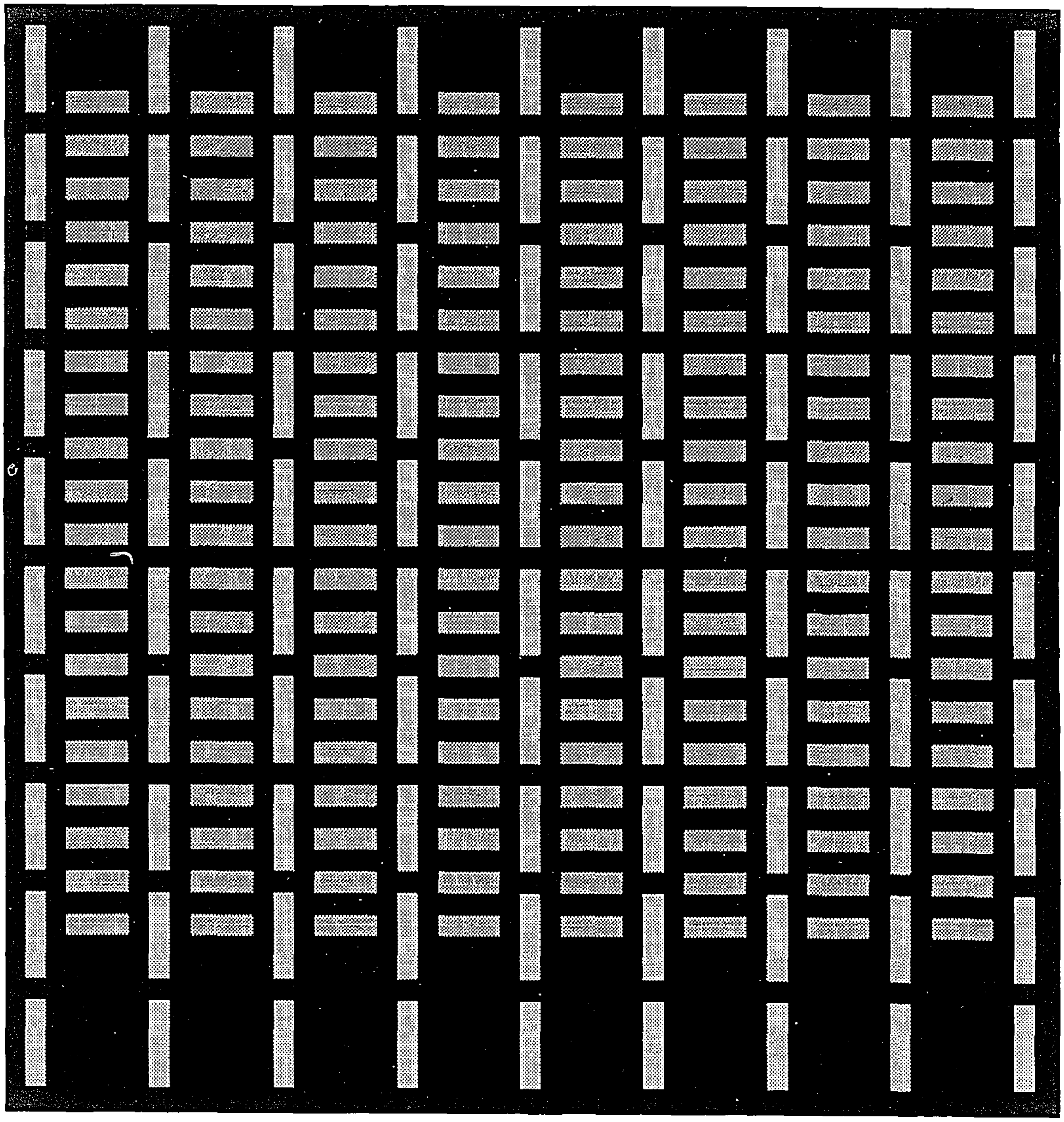


Figure 3.3: A synthetic image containing the vertical bars and horizontal bars.

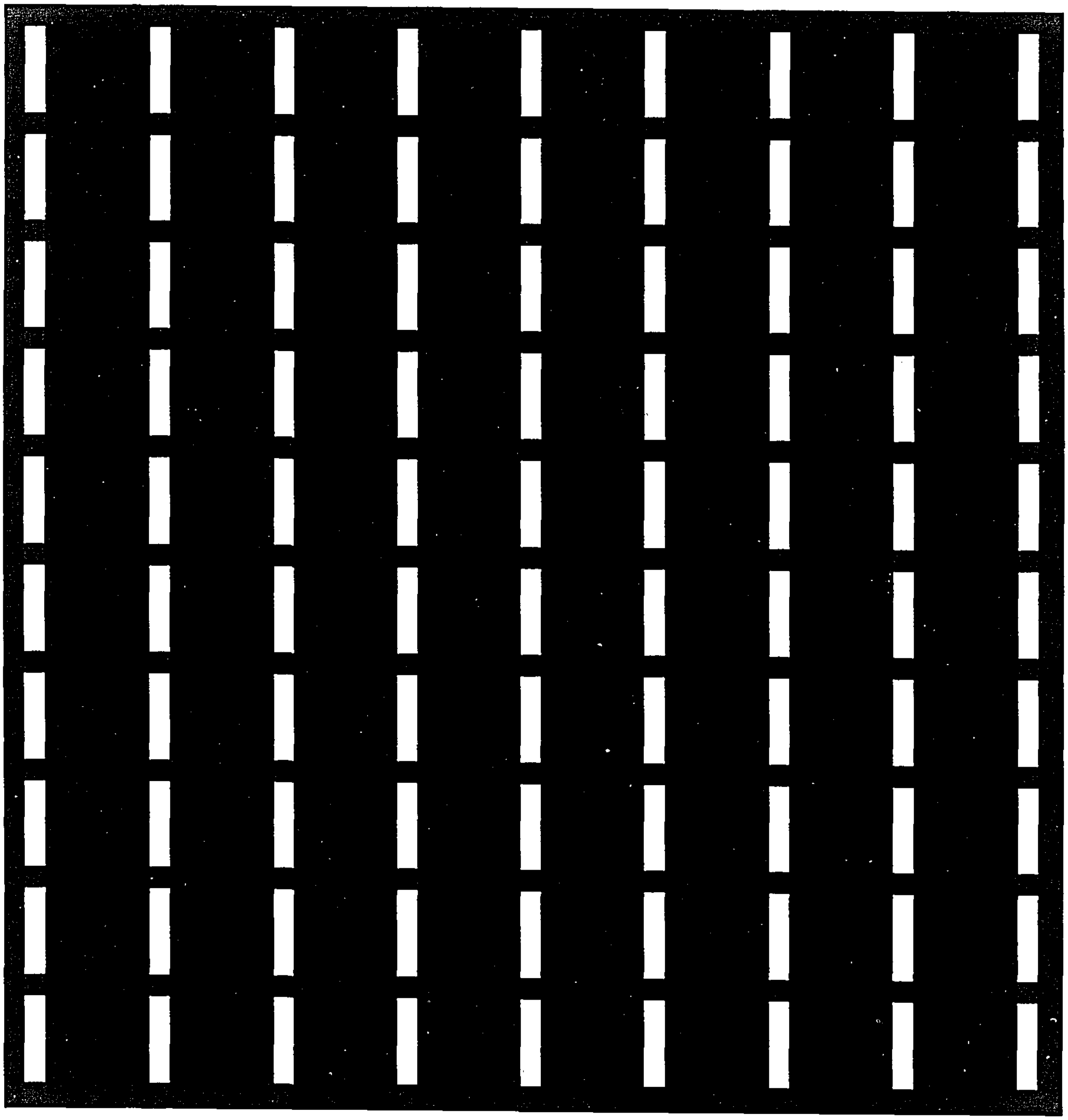


Figure 3.4: Result image after the morphological opening has been applied to the image in Figure 3.3.

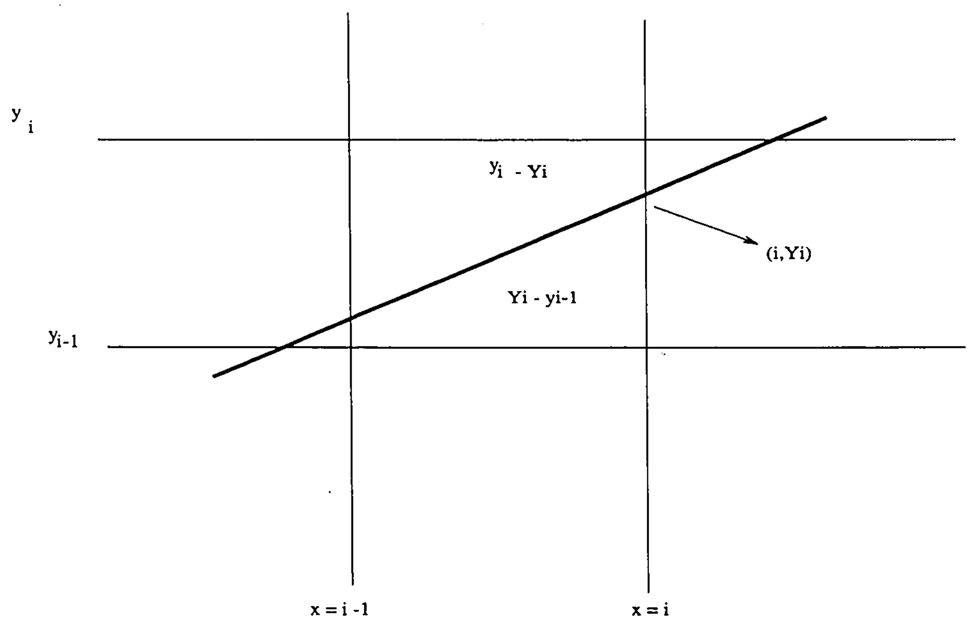


Figure 3.5: Line generation.

The digital form (x_j, y_j) of the exact value, $(X_j,\ Y_j)$ which is a point on a line, has to be rounded off, where x_j, y_j are integers, X_j, Y_j are real numbers, and the positions of the pixels that best represent the line can be located. For example, suppose that at $x = i - 1$ the point $(i - 1, y_{i-1})$ best represents the true position of the line, where y_{i-1} is an integer. Then, at $x = i$, the pixel position chosen should be that which is closest to the true value (i, Y_i), but Y_i is a real number, it has to be rounded off to be an integer. From Figure 3.5, it can be seen that the rule for selection the pixel position $x = i$ should be:

if $(Y_i - y_{i-1}) \geq (y_i - Y_i)$ then the pixel position is (i, y_{i-1})

else the pixel position is (i, y_i),

where Y_i is the true value of the line at $x = i$ which can be a real number, and y_i is its integer form. Based on the above line generation algorithm, the synthetic image was created shown in Figure 3.6.

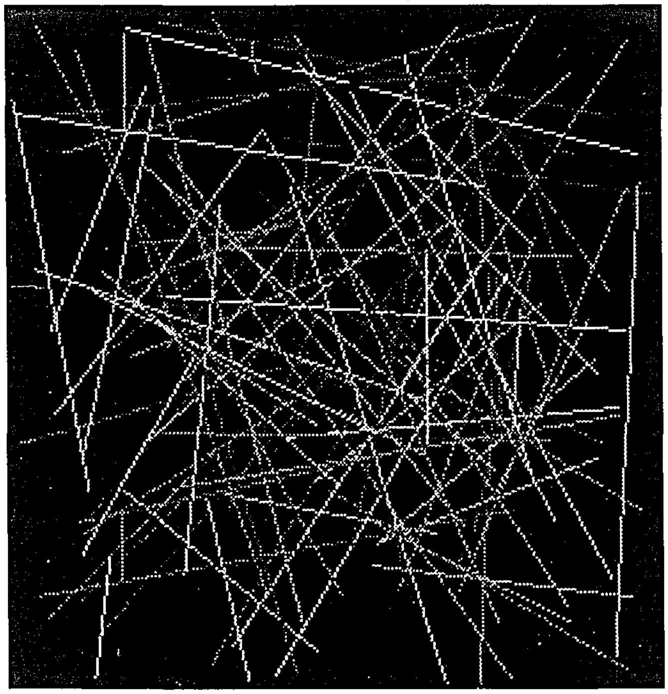
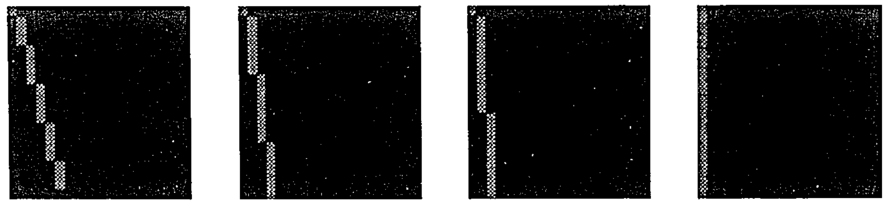


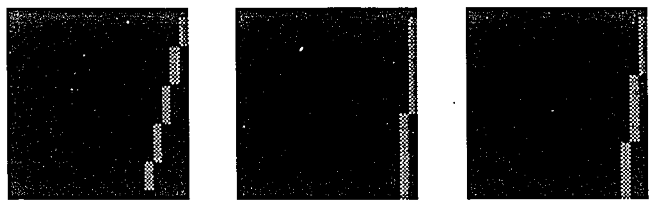
Figure 3.6: Synthesized image.

3.2 Applying the Morphological Approach to Line Segment Extraction

The morphological opening combined with the other operations such as logical operations, was used to detect line segments. To extract line segments with predominantly vertical orientation, the opening operation is used combined with nine structuring elements shown in Figure 3.7, the structuring elements are line segments from 75 degrees to 110 degrees. The length of the line segment is twenty. After the opening operations has been applied, the final result is obtained by taking the maximum of the nine opening results at each pixel location. Figure 3.8 shows the final result, comparing to the original image in Figure 3.5, the line segments of other directions are cleared. But there are some vertical line segments which are missed



75 degrees   80 degrees   85 degrees   90 degrees



95 degrees   100 degrees   105 degrees

Figure 3.7: Structuring elements for line segments extraction (75 to 105 degrees).

as the image shown in Figure 3.8.

To extract lines, the Hough Transform would be another available choice. The key idea of the Hough Transform is to determine specific values of parameters which characterize these patterns. As it is known, the Hough Transform converts a difficult global detection problem in image space into a more easily solved local peak detection problem in a parameter space [7]. However, in the case of web material image, the Hough Transform can hardly be applied to it. The difficulties arise from modeling the fibers to be extracted into the geometric shapes which can be expressed in a relatively simple parameter space. In addition, it is computationally intensive [7]. In the morphological approach, these fibers in the web material image can be extracted by using line segments as structuring elements. Hence it is much easier to implement and it requires less computation time compared to the Hough Transform.

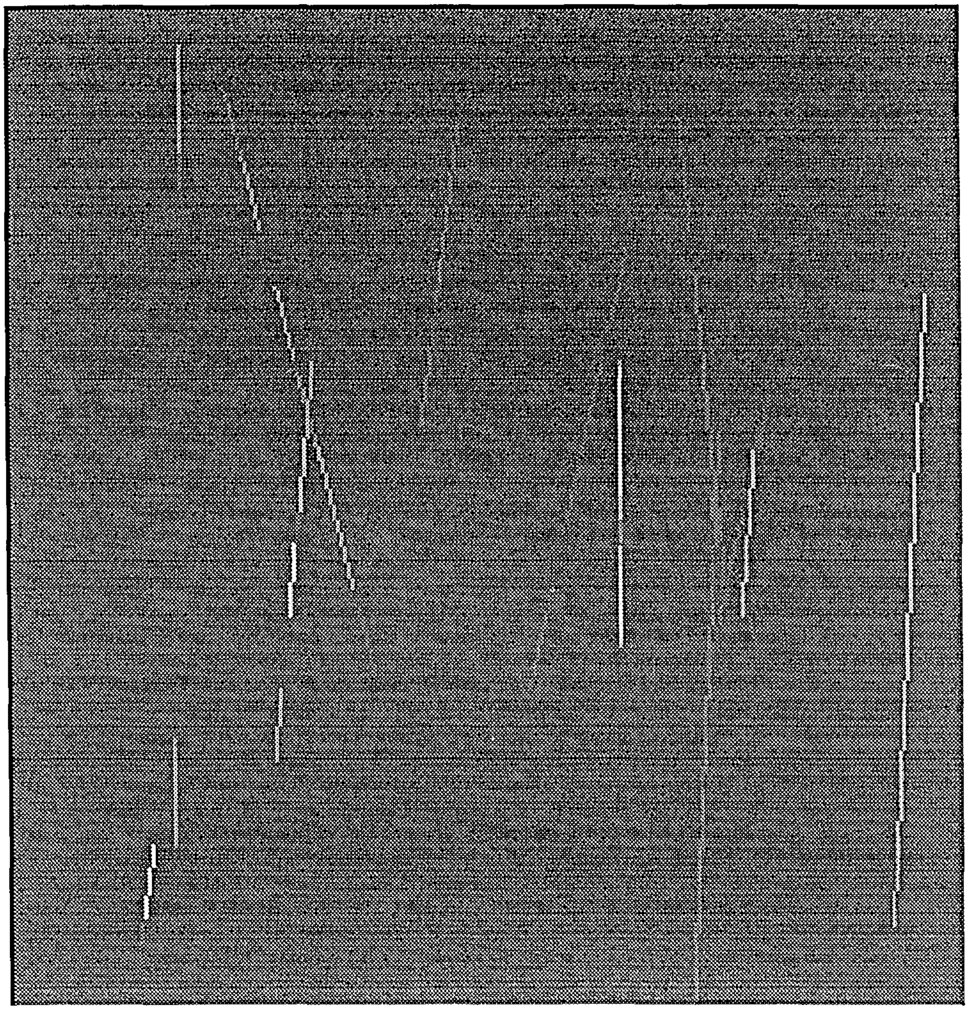


Figure 3.8: Result image of taking the maximum of the eight opening resulting images.

3.3 Using Morphological Method to Decompose Texture Image

3.3.1 Preprocessing – Histogram Equalization

As we have seen in the web material image, there are many fibers of small diameters whose gray-scale intensities are close to the background, thus the morphological operators will fail to distinguish those fine fibers from the background. In order to enhance the details in the web material image to help morphological operations achieve better result, the histogram equalization is utilized as the preprocessing technique.

If the image histogram is considered as a probability distribution, from an information theoretic stand-point, the distribution which conveys the most information is a uniform distribution [8]. Therefore, if the gray levels are redistributed to obtain as a uniform histogram as possible, the image information is maximized, thus the details in the image are enhanced. It has been shown [6] that histogram equalization can be obtained by replacing each normalized gray level with the cumulative distribution from the minimum gray level up to that gray level. For an image with gray scale varying in $[0, L]$, where L is the number of gray levels, the histogram equalization for this image is given by the relation

$$s_k = T(r_k) = \sum_{j=0}^{k} \frac{n_j}{n} \quad 0 \leq s_k \leq 1, \;\; 0 \leq r_k \leq 1 \;\; and \;\; k = 0, 1, \cdots, L-1,$$

where n_j is the number of times of the jth gray-scale intensity appears in the image, and n is the total number of pixels in the image, and $T(r)$ is the transformation function which maps the original gray level $r_i \bullet L$ to the gray level $s_i \bullet L$ in the resulting image. For the web material image, the histogram equalization was employed as a preprocessing technique, as it was expected, after histogram was equalized, it is spread as shown in Figure 3.12, and the contrast of the web material image was increased, the bright dots were eliminated, and each fiber tended to have uniform intensity.

3.3.2 Applying the Morphological Technique to Decomposing Texture Image

Two procedures are developed to enhance the web material image. The two procedures are established on the multiple structuring elements concept combined with logical operation. They are as following.

First procedure:

1. Input image $G(i,j)$.
2. Apply the histogram equalization to the $G(i,j)$, the resulting image is denoted as $G_T(i,j)$.
3. Apply the opening operation to $G_T(i,j)$ by using eleven structuring elements, creating the output images $G_{TO(k)}(i,j)$, where $k = 1, \cdots, 11$.
4. Produce the image $G_M(i,j)$ by taking the maximum of the images $G_{TO(k)}(i,j)$ at each location (i,j).
5. Compare the image $G_M(i,j)$ to the $G_T(i,j)$ at the location (i,j), if $|G_M(i,j) - G_T(i,j)| < t$, where t is a threshold, in this work $t = 20$, then the output image $G_o(i,j) = G_T(i,j)$, otherwise $G_o(i,j) = 0$.

The structuring elements which were used in Step 3 in the above procedure for enhancing the web material image are the line segments in eleven directions: 0, 15,

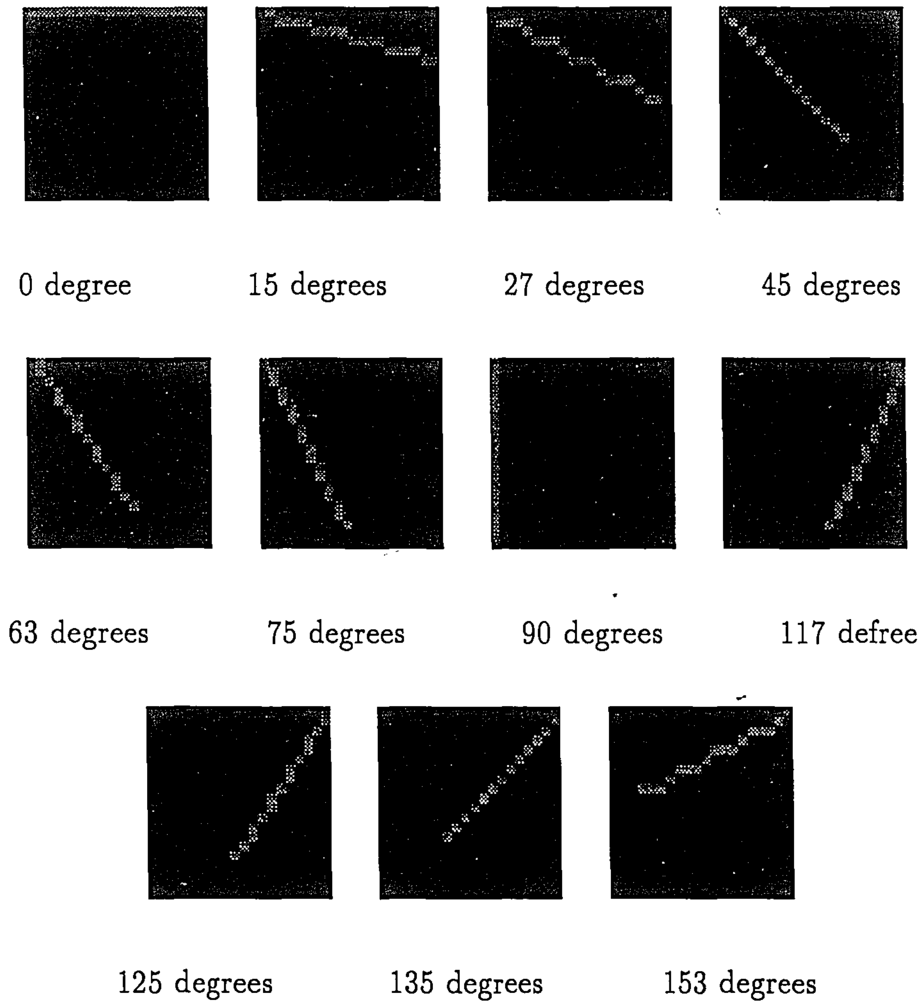


Figure 3.9: Structuring elements used for fiber extraction.

27, 45, 63, 75, 90, 117, 125, 135, 153 (degrees). These structuring elements are shown in Figure 3.9.

For comparison, the result without histogram equalization is also obtained and shown in Figure 3.15. The result with histogram equalization is shown in Figure 3.16. Apparently, the latter image has more details. Both results are produced from the same input example image in 3.10. It is clearly shown in Figure 3.12 that after the histogram equalization has been applied to the original image in Figure 3.10 its

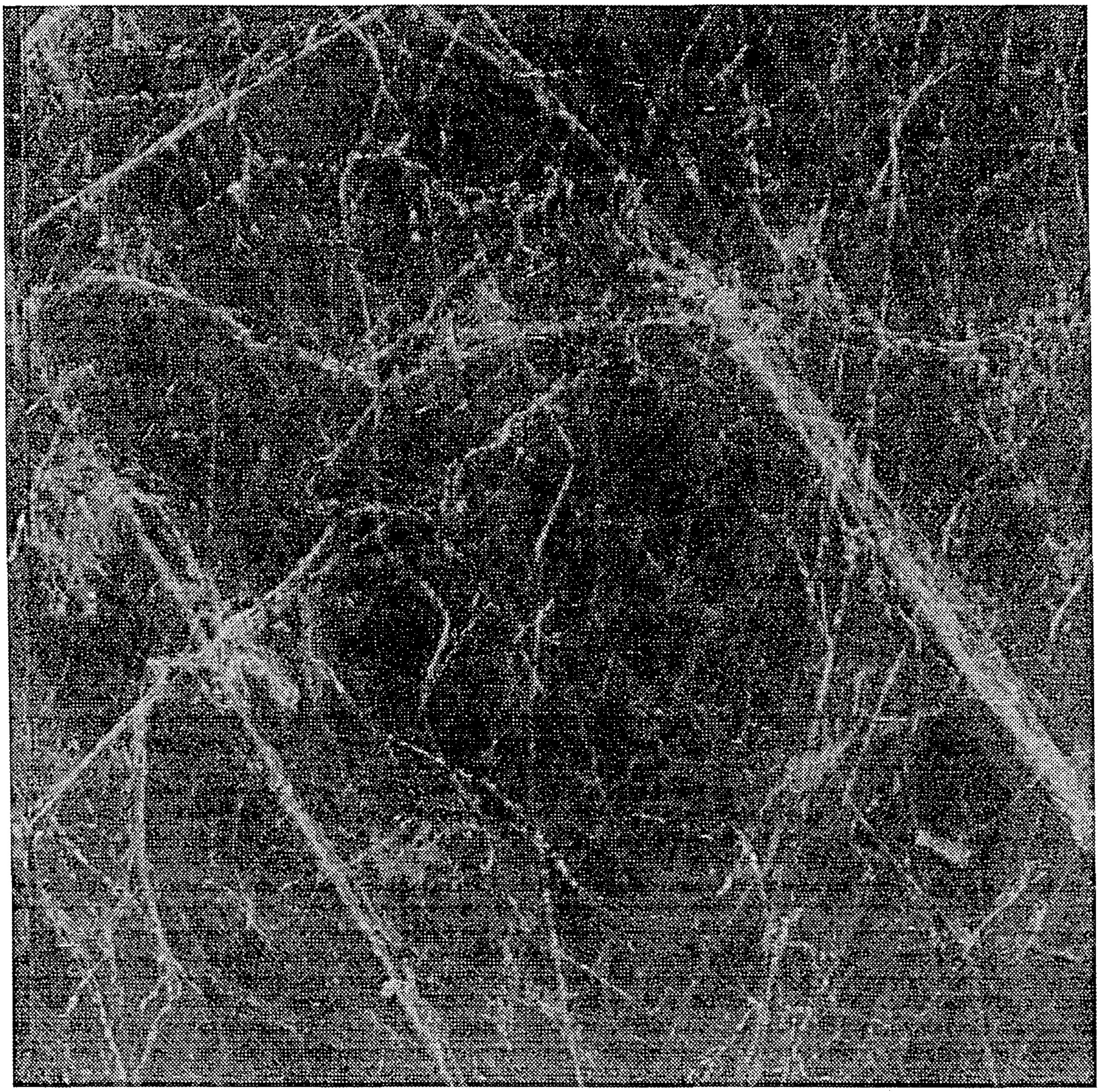


Figure 3.10: The first sample input web material image.

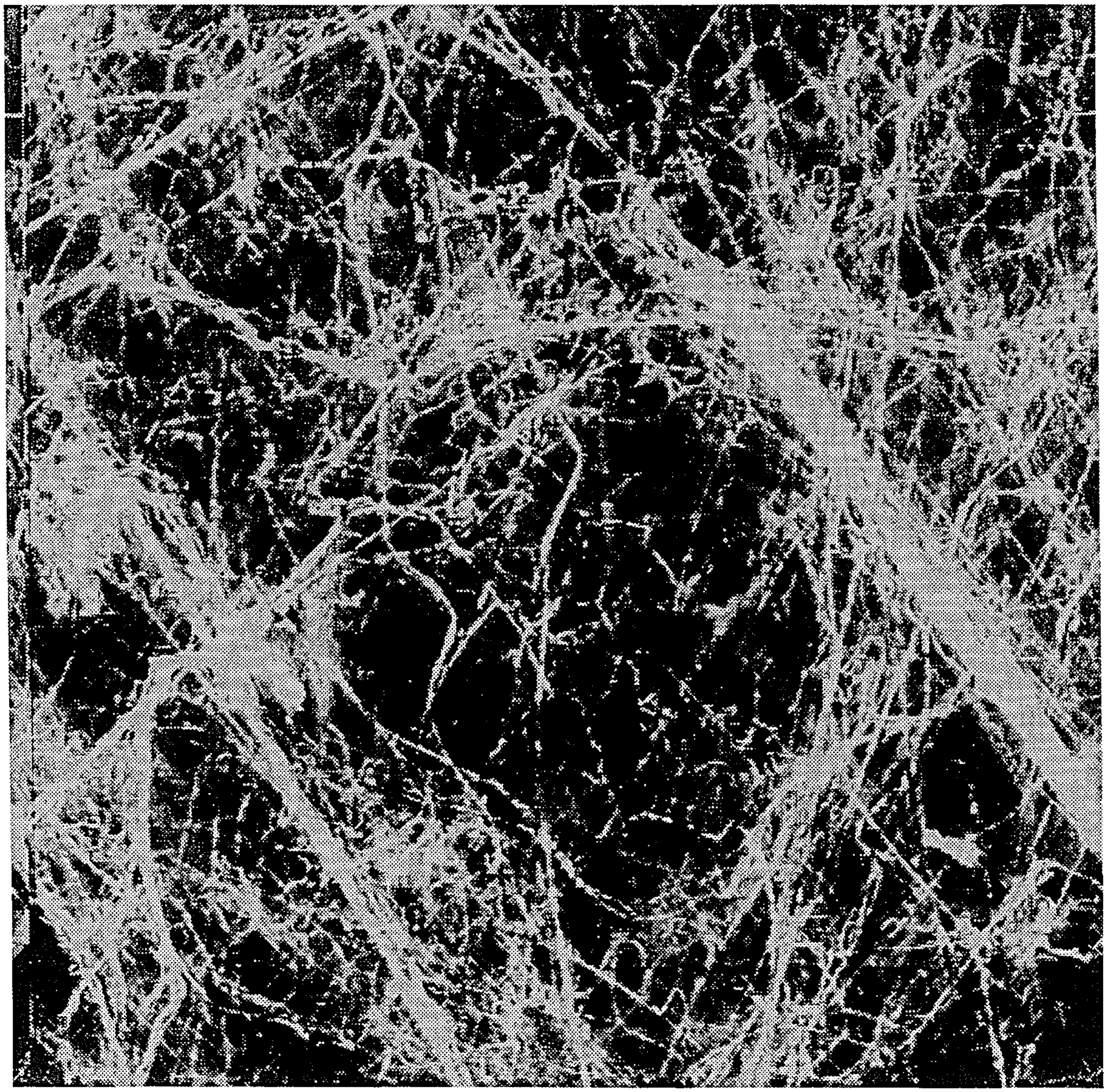
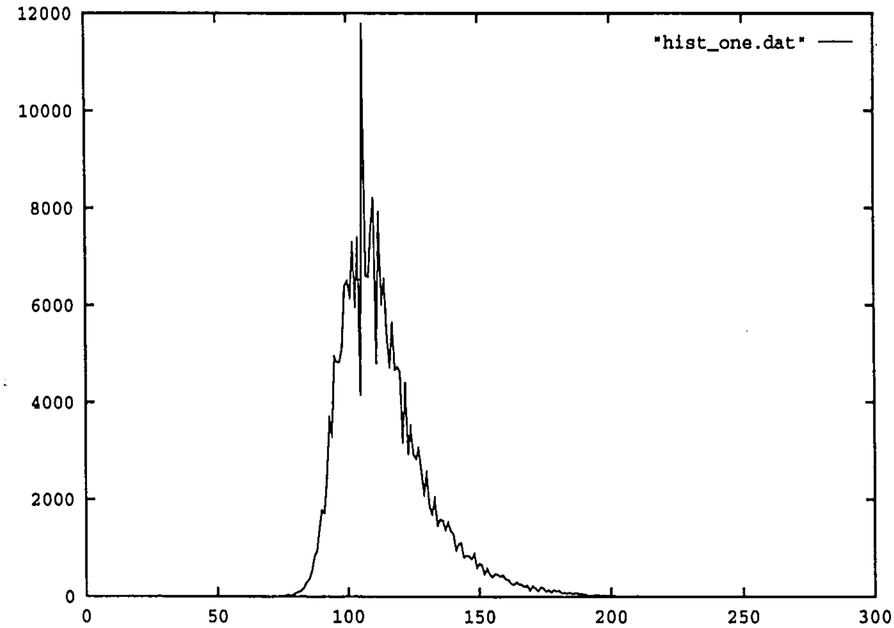
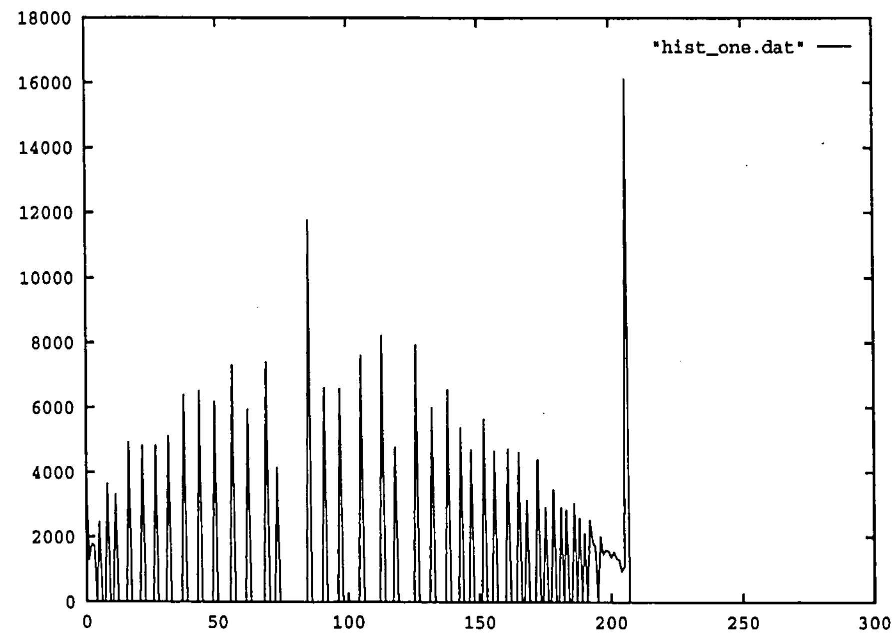


Figure 3.11: After applying the histogram equalization to the image in Figure 3.10.



The histogram of the original input image shown in Figure 3.10.



The histogram of the image shown in Figure 3.11.

Figure 3.12: Histogram comparison.

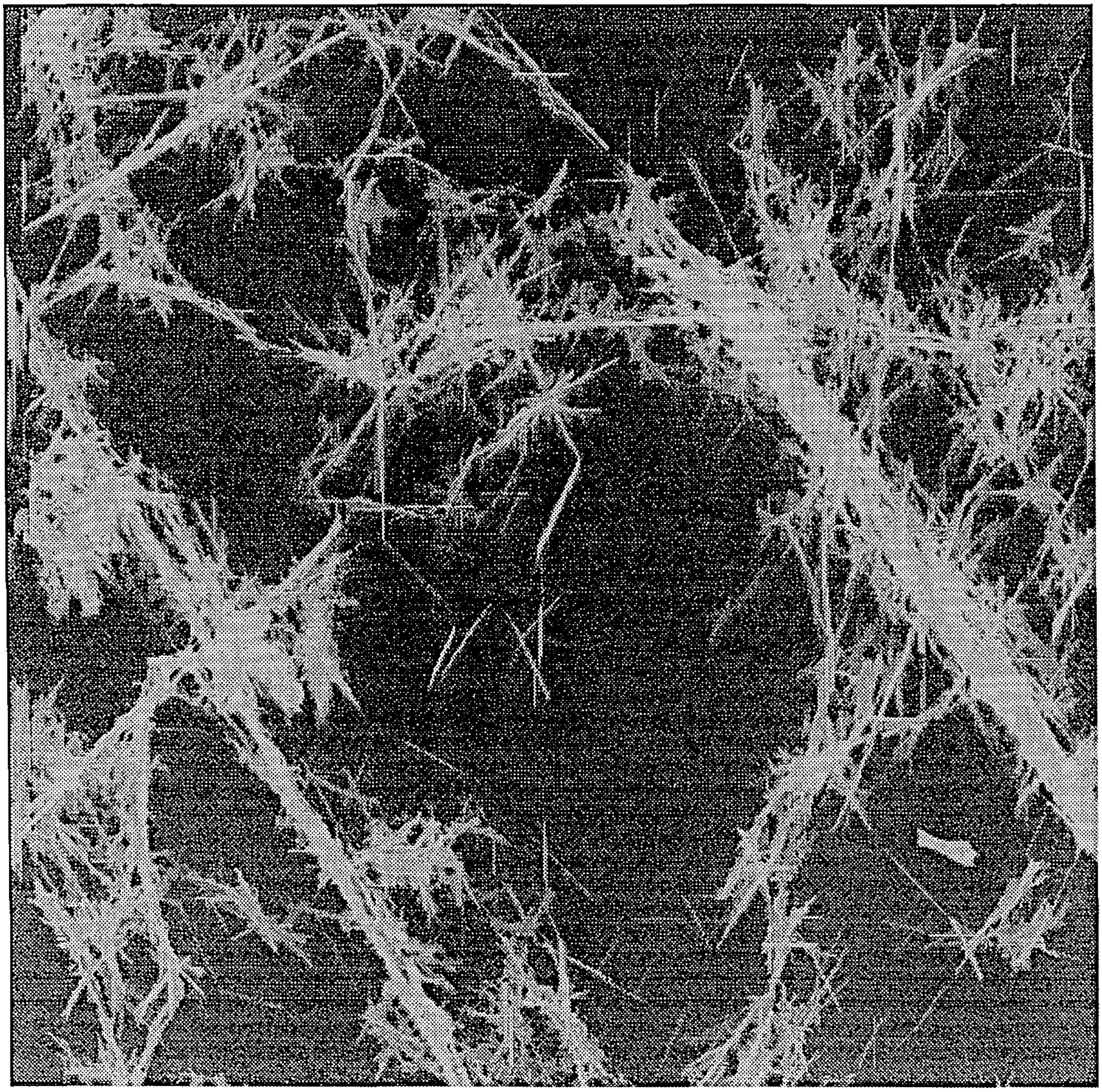


Figure 3.13: Resulting image after opening with eleven structuring elements followed the histogram equalization.

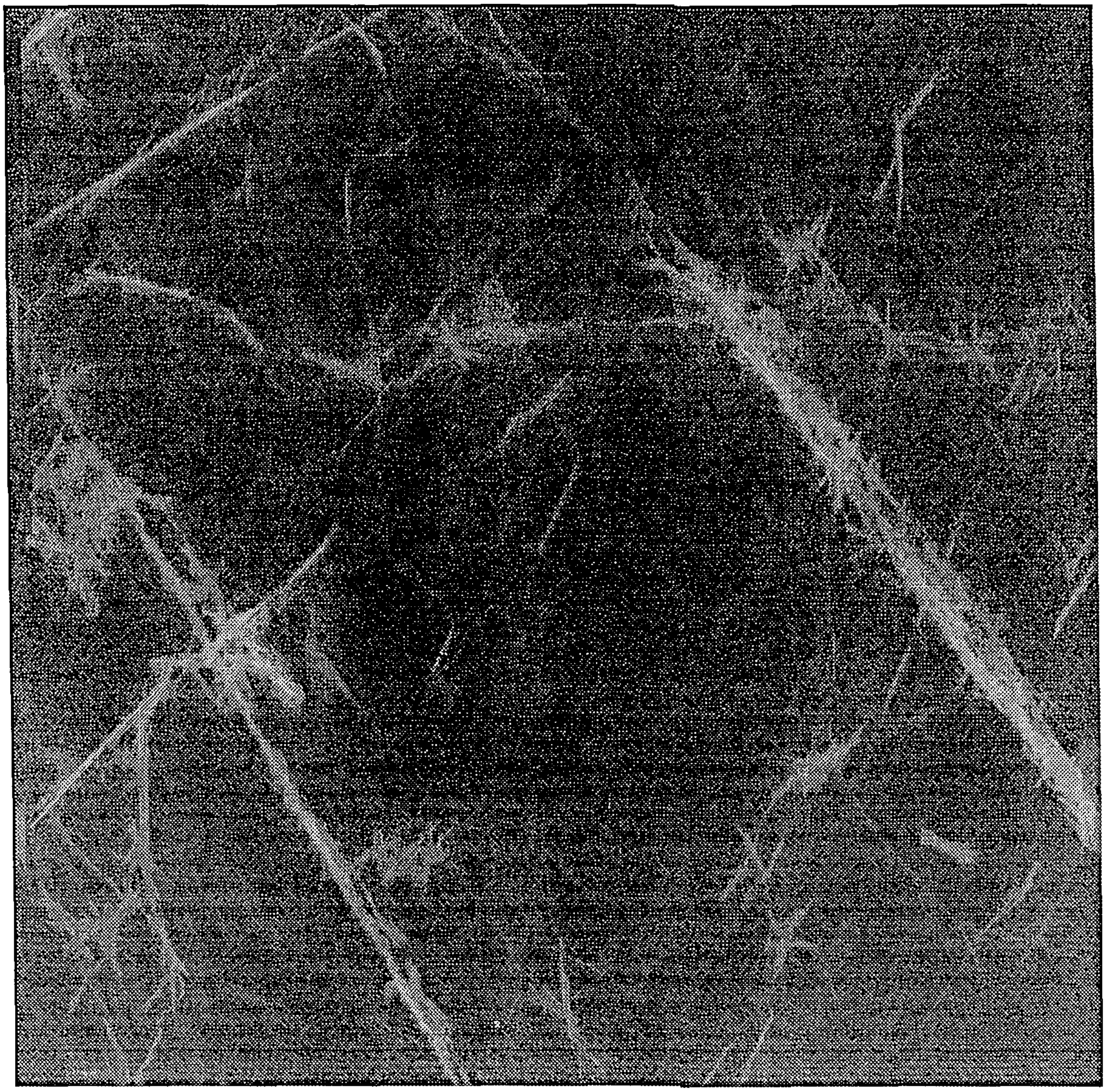


Figure 3.14: Resulting image after opening with eleven structuring elements without the histogram equalization.

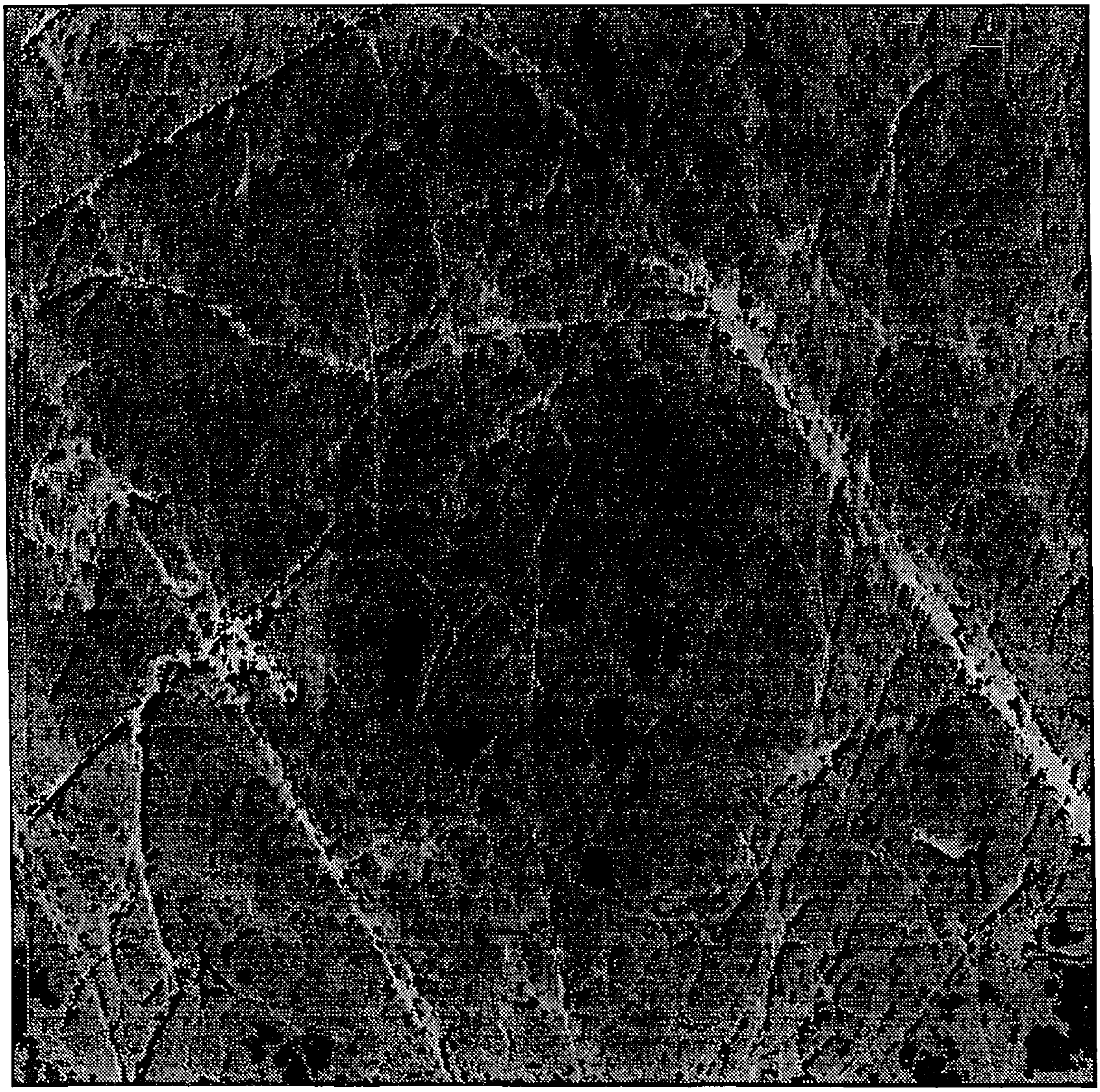


Figure 3.15: The output image without the histogram equalization preprocessing.

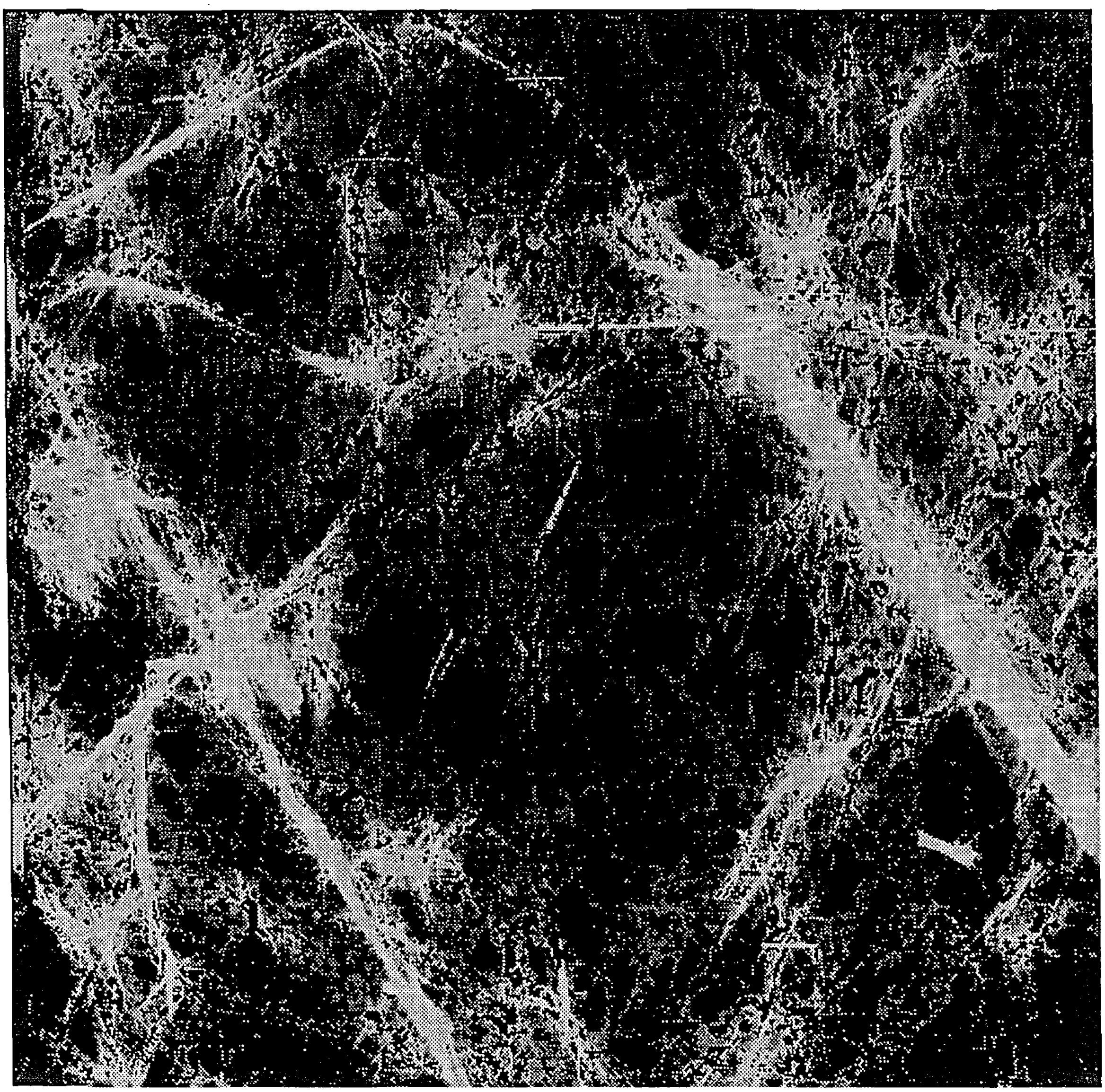


Figure 3.16: The output image with the histogram equalization.

histogram is spread. The histogram equalized image is shown in Figure 3.11.

Second procedure:

1. Input image $G(i,j)$.

2. Apply the histogram equalization to the $G(i,j)$, the resulting image is denoted as $G_T(i,j)$.

3. Apply the opening operation to $G_T(i,j)$ by using eleven structuring elements, creating the output images $G_{TO(k)}(i,j)$, where $k = 1, \cdots, 11$.

4. Produce the image $G_M(i,j)$ by taking the maximum of the images $G_{TO(k)}(i,j)$ at each location (i,j).

5. Compare the image $G_M(i,j)$ to the $G_T(i,j)$ at the location (i,j), if $|G_M(i,j) - G_T(i,j)| < t$, where t is a threshold, in this work $t = 20$, then the output image $G_o'(i,j) = G(i,j)$, otherwise $G_o'(i,j) = 0$.

The only difference in the second procedure from the first one is that the candidate pixel for output image G_o' is taken from the original input image G instead of the histogram equalized version G_T. The resulting image followed by the second procedure is shown in Figure 3.17.

The length of the line segments obviously plays very important role in these approaches, however there is no systematic way to chose the size of the structuring elements. By try and error method, the size of each structuring element is decided in accord with specific features which are desired to extract. In this case, the structuring elements of size ten gave the best results, the output image G_o' followed

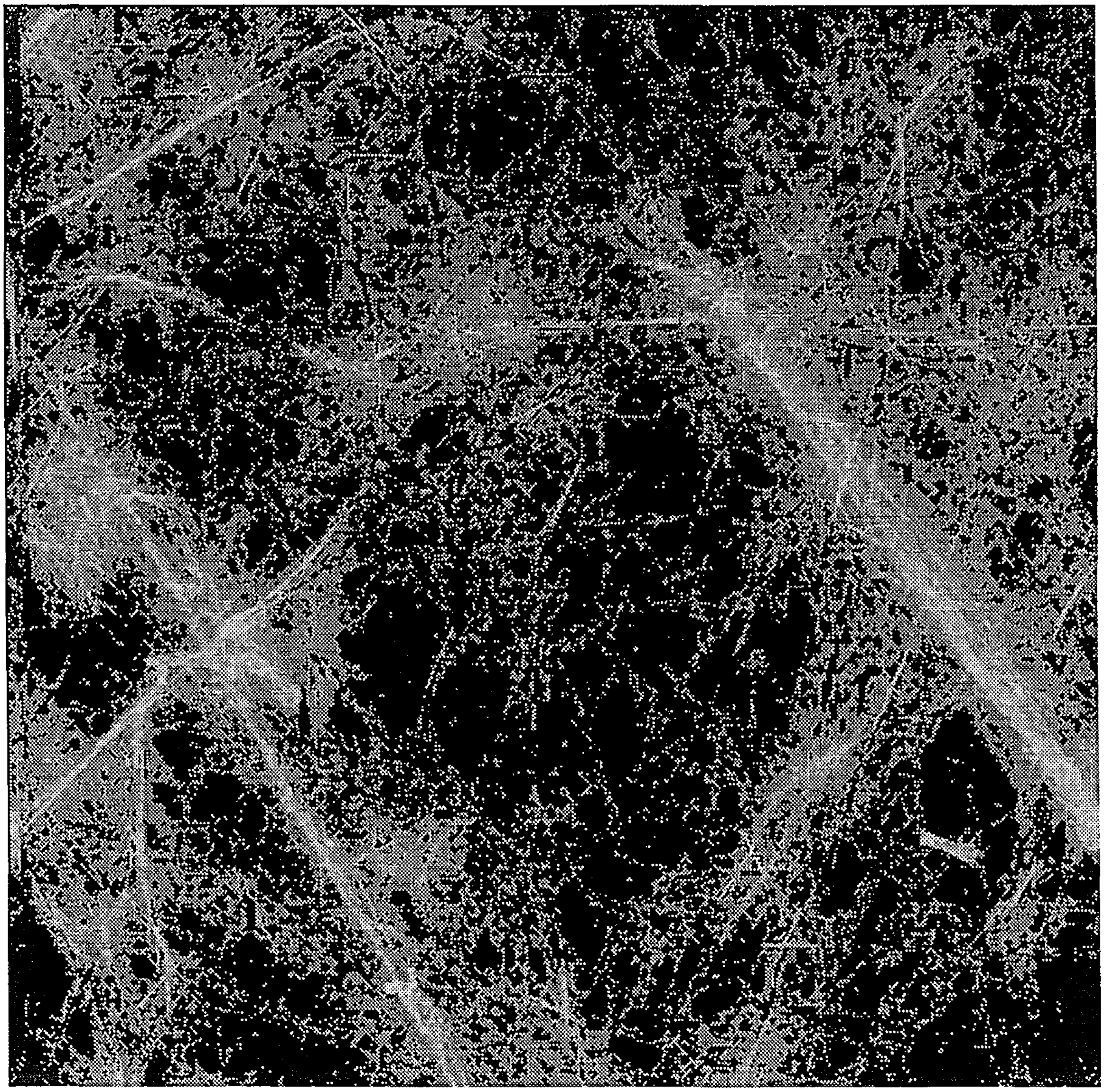


Figure 3.17: The resulting image by using the second procedure.

the second procedure is shown in Figure 3.18, this image contains more fibers than the one shown in Figure 3.16. The intermediate images such as opened images are omitted here.

The fibers of specific orientation in web material image can also be enhanced by the two procedures. The second procedure was applied to enhance the fibers which are vertically oriented. In order to achieve the enhancement, the structuring elements used for the opening operation in Step 3 are chosen to be the line segments at angles { 75,80,85,90,95,100,105 }(degrees), the length of the line segments is ten pixels. The input image is shown in the Figure 3.19, the resulting image, shown in Figure 3.20, contains mainly vertical oriented fibers, fibers of other directions are suppressed.

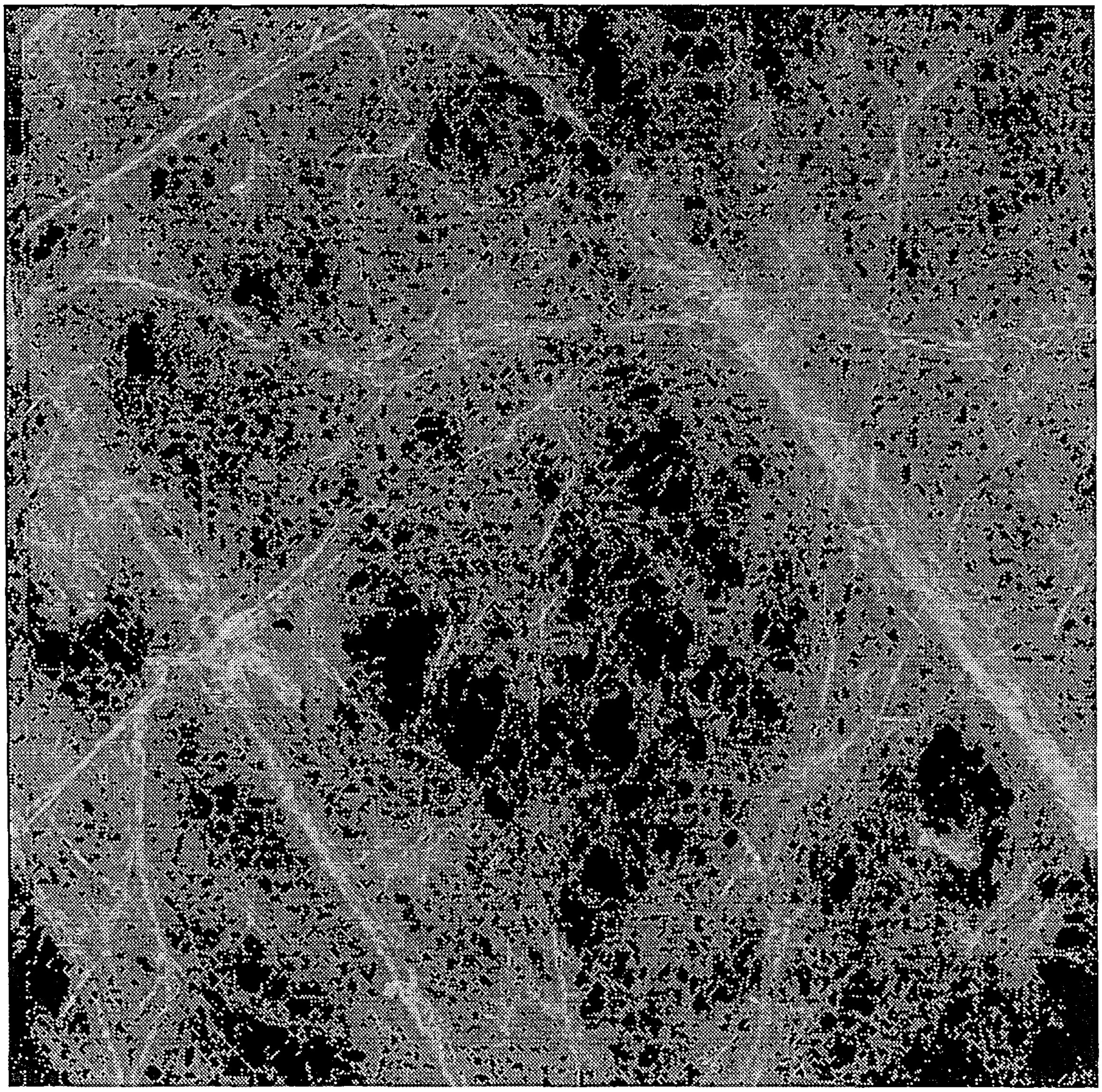


Figure 3.18: Output image applied opening operation with structuring elements of length ten, this result was produced by the second procedure.

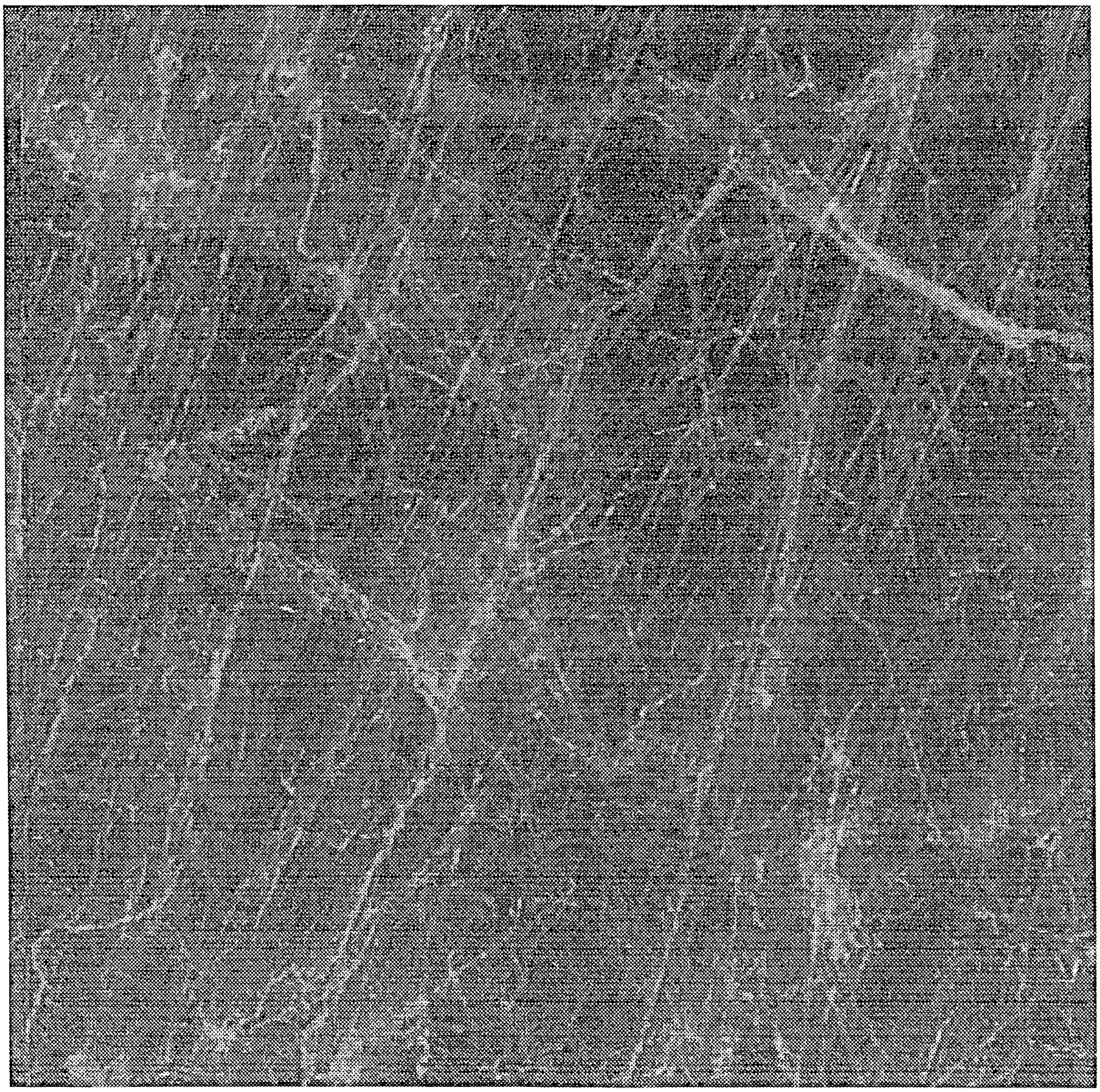


Figure 3.19: The second example input image.

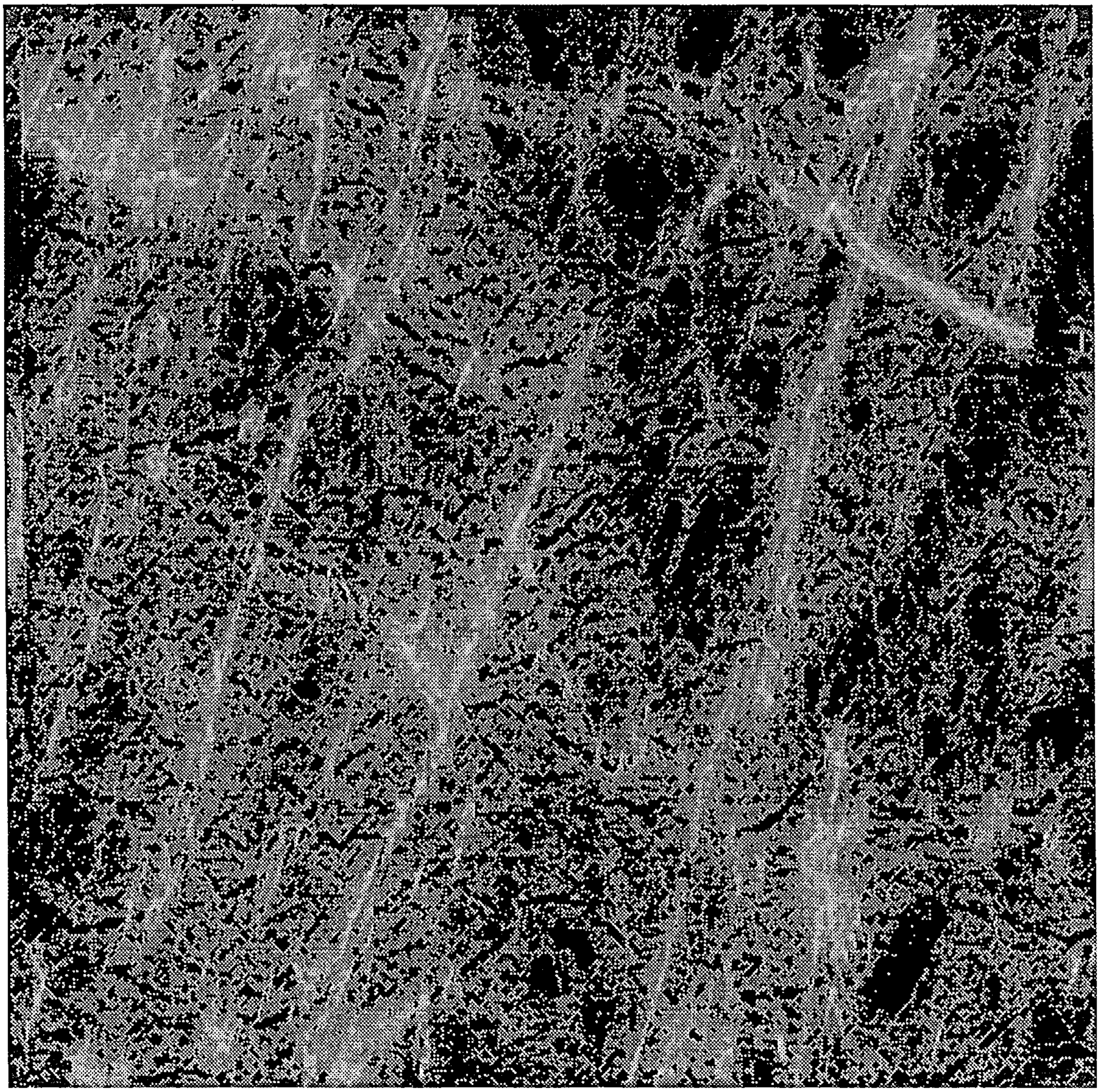


Figure 3.20: The output image resulted from the second procedure with the different opening structuring elements, the original image is shown in Figure 3.19.

Chapter 4

Conclusions

In this thesis, the basic morphology transforms for binary image and gray-scale image are discussed. Applications of these transforms have been provided to illustrate the morphological processing concepts. A multiple structure elements technique is introduced and used for image decomposition. We have further developed two procedures to decompose a texture image based on the multiple morphological processing technique. Those two procedures have been used to extract objects of different sizes from the synthetic images. In order to extract the fine details whose gray scale intensities are close to the background in the image, the histogram equalization is employed as a preprocessing technique. Comparison of the results with histogram equalization and without it shows that much better result is produced if the preprocessing technique is used before the morphological operations are applied. Finally, two procedures are applied to decompose the web material images.

As it has been shown in this thesis, the two procedures are mainly produced by trial and error. For the synthetic image, even though the majority of vertical line segments can be extracted, there are still some vertical line segments that have been overlooked by this method. For web material image, many small fibers have been overlooked. However, the result can be improved by choosing the proper size of the structuring elements. On the other hand, we can see that complex shapes such as fibers can be extracted by using relatively simple structuring elements such as line segments based on the multiple structuring elements model. This can help to design algorithms to decompose the objects from a texture image.

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Vita

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END

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