

SOME ASPECTS OF MULTI-SOURCE SATELLITE IMAGE PROCESSING

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REVISED

Thesis submitted to the Indian Statistical Institute in
partial fulfilment of the requirements for the award of the
degree of DOCTOR OF PHILOSOPHY, 1991

June 1991

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ACKNOWLEDGEMENTS

I am extremely grateful to Prof. D.Dutta Majumder, my supervisor, for his guidance and encouragement to carry out this work.

It is a pleasure to acknowledge the help rendered by several friends, especially, Ms.Swati Chaudhury, Ms.S.Jayasree, Ms.Anusree Sinha, Dr.C.A.Murthy, Dr.B.Chanda, Mr.S.E.Sarma, and Mr.B.Uma Shakar. I am grateful to Mr.M.K.Kundu, Dr.B.B.Chaudhury, Dr.S.K.Pal and Dr.S.K.Parui for their encouragement during the period of this work. I thank Mr.S.Chakravarty, Mr.D.Mitra, and Ms.M.Chatterji for the technical and secretarial support while preparing the thesis.

I am grateful to Chairman, Indian space Research Organisation (ISRO), and Scientific Secretary, ISRO, for granting me leave to carry out this work at I.S.I. I wish to acknowledge the help and constant encouragement provided by all my colleagues at the National Natural Resources Management Systems Office, ISRO, Bangalore; particularly Ms.G.Vijayalakshmi, Ms.R.Parvati, Ms.A.S.Padmavathy, and Mr.Abdul Salam.

I am indebted to Dr.V.R.Rao who introduced the field of remote sensing to me. I thank my parents for their understanding.

CHAPTER 1

1.1 SATELLITE REMOTE SENSING:

The observation of a target by a device placed at some distance from it is called remote sensing as against 'in situ' sensing where the sensor is kept in contact with the target. Usually physical emanations such as the electromagnetic radiation from the target is observed by the sensing device. Sensors mounted on aircraft or satellite platforms measure the amount of energy reflected from or emitted by the earth's surface. Sensors scan the ground below and to either side of the satellite platform and as the platform moves forward, an image of the earth's surface is formed.

A satellite remote sensing system in its simplest form can be conceptualized as in Fig. 1.1. The sun is usually the electromagnetic source and the energy from the sun reaches the target. The radiation by the time it reaches the target is affected by the intervening medium. Some energy gets absorbed; some get reflected and the remaining is allowed to reach the target. Depending on the type of the target, its surface characteristics, some part of this incident radiation is absorbed; some transmitted and the remaining energy is reflected back into the medium. This radiation together with the radiation emitted by the target itself and that emitted by the target neighbourhood reaches the satellite.

sensor after passing through the medium. As before, the medium absorbs a part of the radiation. This process of absorption, transmission and reflection at the target is dependent also on the wavelength of the incident radiation. In principle, all targets at temperatures above 0 deg K radiate electromagnetic energy but the amount of energy radiated and the predominant wavelength bands vary according to nature of the target (Barrett and Curtis, 1982, Curran, 1985).

Although sensing devices could be designed to observe the entire range of electromagnetic wavelengths, attenuation by atmospheric constituents preclude the utility of certain wavelengths. The actual wavelength band to which a sensor is made sensitive depends upon the application to which the data will be put to use and the interaction mechanism between the electromagnetic radiation and targets being observed.

1.2 PROPERTIES OF REMOTE SENSING DATA

It is not possible to directly detect the surface features from satellite images - they have to be inferred from the radiance measurements. Recognition of features from a remote sensing image is based on the principle that every feature has a unique spectral signature. Fig 1.2 shows the idealized spectral reflectance curves for vegetation, soil and water.

It is an idealized curve because it has been obtained under the best conditions, with no atmospheric hindrances and with a spatial resolution approximating a point. Thus vegetation has a low reflection in the visible part of the electromagnetic spectrum and a relatively high reflectance in the near IR part. Non-vegetated surfaces, for e.g., bare soil, water and concrete commonly have similar reflectances at visible and near IR wavelengths. Water has a higher reflectance at shorter wavelengths and virtually no reflectance at wavelengths greater than $0.7 \mu\text{m}$.

Inferences on remote sensing data are aided by the spatial resolution, radiometric resolution, spectral bands and their resolution and temporal resolution of the satellite sensor. Because of the effect of the atmosphere, the entire electromagnetic wavelength bands cannot be used for viewing the earth. There are specific spectral regions called atmospheric windows in which most sensors of the earth resource satellites operate. In Fig 1.3 is shown the percentage of the incident radiation transmitted through the atmosphere (Mather, 1987). The window regions are those with a high transmittance. We observe that the window regions are $0.3-1.3 \mu\text{m}$, $1.5-1.8 \mu\text{m}$, $2.0-2.5 \mu\text{m}$, $3.5-4.1 \mu\text{m}$ and $7.0-15.0 \mu\text{m}$. When it is necessary to study the atmosphere itself using satellite data, sensors can be designed to operate in the region of atmospheric windows. Ideally, we would like to

have a sensor that has narrow spectral bands. However, as the spectral resolution gets more and more finer, the net signal received from the target gets feeblar and the signal to noise ratio gets smaller. This can be compensated to some extent by having a coarse spatial resolution. For certain applications such as in meteorology, coarse spatial resolution may suffice but for applications such as agricultural crop monitoring, a high resolution is a must. Unlike spectral resolution which can be set globally, the spatial resolution has to be decided depending on the field sizes of the study area. Thus for India, where the agricultural field sizes are small, for monitoring even major crops a spatial resolution of the order of 20 m is necessary (Rao and Lalitha, 1981).

The radiometric resolution determines the number of feature classes that can be deciphered in a raw satellite image. Radiometric ranges of 0 to 127 or 0 to 255 are commonly used. The temporal resolution describes how often the satellite views the same area. Landsats 1 to 4 had a repetitivity of 18 days; the present Landsat has a repetitivity of 16 days; the Indian Remote Sensing Satellite (IRS) has a repetitivity of 22 days, the French SPOT has a repetitivity of 26 days. The temporal resolution is very important when dynamic phenomenon are monitored using satellite data. In addition

problems such as non-availability of usable ^{data}/due to the presence of clouds may necessitate high temporal resolution data even when the phenomenon being monitored is not dynamic. (Rao and Lalitha, 1980; Lalitha and Rao, 1980).

Depending on the type of applications envisaged, sensors have been designed and flown onboard satellites since 1960. Currently there are satellites such as Landsat of USA with its thematic mapper (TM), SPOT of France, Indian Remote Sensing Satellite (IRS) of India which are earth resources satellites. The sensors of these satellite operate in the visible, infrared and thermal infrared regions of the electromagnetic spectrum. There are satellites meant for meteorological purposes such as NOAA, INSAT, GOES AND GMS. There are also satellites carrying synthetic aperture radar (SAR) systems. A brief description of some of these satellites is given in Table 1.1. It is seen that while there are some similarities between these satellite sensor systems, there are also a lot of differences. What is not available from one satellite imagery can in fact be supplemented from another.

1.3 NEED FOR MULTI-SOURCE SATELLITE DATA PROCESSING

It is not feasible to have a satellite that will be ideal for all applications; nor can one think of a sensor that will have ideal spectral, and temporal resolutions. With a wide

variety of satellites presently in orbit, however, one has the advantage of being able to integrate data from different satellites to derive maximum information. Some efforts in this direction have been made recently. Using simulated panchromatic and multispectral SPOT data, Cliche et. al. (1985) have shown that it is possible to increase the visual spatial resolution of multispectral data by integrating the two channels. Digital merging of Landsat and SEASAT data (Zobrist et, al. 1980), Landsat TM and SPOT panchromatic data (Welch and Ehlers, 1987) have proved to be useful for providing additional information than if these satellite data were to be used separately. Comparison of spectral information from Landsat TM and SPOT multispectral data (Chavez and Bowell, 1988) revealed that Landsat TM contained more information for the agricultural and geological sites than the multispectral SPOT data. SPOT data, however, was used to sharpen the features. Evaluation of Large Format Camera (LFC), Metric Camera (MC) and Shuttle Imaging Radar-A (SIR-A) data content (Lo, 1988) revealed that LFC photography provides very clear linear features for topographic mapping while the MC data was planimetrically very accurate. SIR-A data on the other hand was a good alternative to both, under bad weather conditions.

The above few studies indicate the advantages of integrating

data from different satellites. Recognizing the importance of such efforts, a CODATA (Committee on Data for Science and Technology) Task group on multi satellite thematic mapping was formed in 1982 for the purpose of establishing a methodology development effort used data from the Landsat, METEOSAT, NOAA AND TIROS-N satellite (CODATA Bulletin, 1986).

1.4 SATELLITE DATA PROCESSING METHODS

Remote sensing data can be interpreted in two ways _ Visual interpretation and Digital interpretation. These two approaches are not necessarily independent. Visual interpretation forms a part of digital interpretation. Generally satellite data is recorded as digital counts which are then converted after suitable processing into image products to enable visual interpretation. Visual interpretation is subjective; as the expertise of the interpreter improves, interpretation accuracy improves as also the amount of information that can be extracted. However, when the number of imagery to be interpreted becomes large, the interpretation task becomes monotonous and time consuming. Often when it is necessary to merge data from multi-satellites to generate a Geographical information system, digital analysis has to be resorted to (Burrough, 1986). Digital processing is fast and objective techniques are available to process the images and to extract information. All techniques make some kind of assumptions

and the accuracy of the information extracted depends on the validity of the assumptions.

Satellite image or any image is full of patterns. Recognition of patterns in a scene is a means to scene understanding. Prior to recognition the pattern must be perceived. For understanding the perceived patterns, the same pattern must have been previously perceived and remembered. This past information must be related with the present perception to recognize the pattern. Statistical pattern recognition techniques achieve this by formulating the problem as a pattern classification problem. Pattern recognition of remotely sensed data involves determining the class or category of each distinct region on the ground using the satellite sensor measurements and thence estimate the error rate for the determined assignments (Haralick, 1983). Broadly the steps involved in this process are

- * Define classes to describe objects to be discriminated
- * Select sensors to make observations on the objects-
Feature extraction
- * Methodology to describe the different classes from the
observations
- * Construct decision rules to assign a measurement as
coming from a particular class
- * Methodology for estimating the error rates.

Statistics and Probability theory play a contributory role in all the above steps (Devijsver and Kittler, 1982). Statistical distributions are used to define the classes. Techniques such as Principal Component analysis are useful for feature extraction. Decision rules are usually restated in the form of statistical hypothesis testing and finally the error rates are measured using a statistical criteria. This approach has certain limitations. If the measurements made by a sensor were to be error free and each class can be accurately modeled as having a well defined probability distribution, then each observation can be uniquely classified into one of several classes. However, in satellite images observations are not point observations, but made over an area which may include more than one class. Often, in order to simplify the mathematical complexities, a Gaussian model is assumed for a class which may not always be valid. Most importantly, the transferring of information from ground measurements to the satellite measurements in order to model a class results in errors that cannot be measured by the error rate (Curran, 1985).

Some of these problems are tackled by a fuzzy set approach. Fuzzy set theory was originally conceptualized by Zadeh (1963). In this approach, fuzzy membership functions are associated with each class and decisions to assign an

observation into a particular class is made based on the membership function values. No attempt is made to force an observation into a particular class.

Recently, syntactic techniques have been developed to handle structural information in a scene. In this approach patterns are described by basic elements called primitives or subpatterns, together with a number of rules called pattern Grammar. The Grammar specifies the way the primitives can be combined together to form a legitimate pattern or class (Fu, 1974). A Grammar is constructed for each class, and patterns are represented by strings of primitives; a language is generated for each pattern from its Grammar. The decision rule then checks to which language a given pattern belongs. This process of decision making is called Syntax analysis or Parsing.

Fundamental to the processing of satellite images is the pre-processing of these images to remove noise. Noise in satellite images could be either spatial or spectral in nature. Spatial errors occur due to satellite and sensor perturbations and require geometric corrections to remove them (Swain and Davis, 1978). These errors are important when a map output from the processed image is desired. For certain applications where the information to be extracted is only a pictorial representation, this step is not essential. Spectral errors are more critical and occur due to

atmospheric effects, varying sun illumination and coarse spatial resolutions. Pre-processing to remove some of these effects is done through radiometric correction, image restoration, image enhancement to improve contrast and feature extraction. Digital image processing techniques encompass the set of algorithms developed to pre-process an image and to process the image for scene understanding. Thus defined, image processing techniques include pattern recognition algorithms be they statistical or syntactic. In Fig 1.4 is shown a block diagram of the elements of an image processing system. Segmentation, we observe forms a part of the processing tasks. Segmentation involves extracting information relevant to specific picture 'segments', such as lines, regions, objects, and their inter-relationships (Offen, 1985). We will discuss about the segmentation process for primitive extraction in subsequent chapters.

1.5 AN APPROACH FOR MULTI-SOURCE SATELLITE DATA PROCESSING

Integration of multi-source satellite data brings forth several problems. At the outset it must be noted that the spatial resolution of the data will not be identical as also the radiometric resolution. The geometry of the sensors will not be identical either. Add to this the dynamic atmospheric conditions that need to be corrected for and we have in hand a very potential data set that requires a lot of pre-

processing prior to information extraction. Integration of the radiometric information poses another problem. It is almost unthinkable to process this variety of data optically or visually.

When the processing of multi-source satellite data is intended a simplistic approach will be to consider the entire data set as a multivariate set and carry a multivariate classification after performing pre-processing operations such as feature selection or principal component transformations. In this case it will be necessary to normalise the various satellite data both spatially and radiometrically. Radiometric normalization process can however, result in the loss of information. Alternatively, the varying spatial resolutions of the data can be exploited using a multistage data analysis approach. Here the problem of integrating the grey values arising from different satellite images remain unsolved.

Syntactic pattern recognition techniques provide a better alternative where in, there will be no need to modify the radiometric values already recorded. After pre-processing, to correct the errors in the image caused by satellite motion and sensor perturbations, the images can be brought to a common scale and a pixel to pixel registration achieved. Rather than carrying out routine analysis, primitives such as

linear features, edges, shapes etc., can be extracted from each of the image set followed by segmentation. These images can then be integrated and interpreted using extraneous information in the form of ground truth or topographic maps.

1.6 SCOPE OF THE THESIS

In this thesis some problems relevant to multi-source satellite data analysis are addressed. We note that one of the prime requirements prior to the analysis of data from different satellite platforms is that all the data sets be brought to the same scale. Image magnification in this context assumes a lot of importance. We discuss the problem in detail. Bilinear and bicubic interpolation techniques are commonly used to magnify an image digitally. Two simple modifications of the bilinear technique are proposed in the thesis that ensure retention of edges and linear features in the magnified image. As at present except for mean square error criterion, no good quantitative measure is available to compare the performance of these techniques, a criterion based on fractal dimensions of an image is proposed in this thesis. A comparison of the performance of the different image magnification technique based on the fractal dimensions suggest up to what scale a particular technique is effective and whether it is always necessary to go in for sophisticated techniques.

Another important problem in processing multi-source satellite images is the extraction of primitives. In this context we will be discussing techniques for linear feature detection. A set of templates that operate on the second order neighbours of a candidate pixel are proposed to detect pixels that form part of a line segment. The templates operate in two stages. Pixels that do not satisfy a pre-set threshold criteria at the first stage are not considered in the second stage. Thus effectively, a pair of templates operate in each stage to detect all types of linear features in an image. The threshold setting is guided by the modes of the image histogram. Once the images are scaled and primitives are extracted, they can be registered using model based registration techniques rather than the traditional control point approach. This aspect is briefly discussed. In this thesis we have not attempted to carry out a full-fledged analysis of multi-source satellite data. Our fundamental objective has been to develop techniques for some specific problems of multi-source satellite data processing.

In chapter 2 we introduce the problem of digital image magnification and the mathematical properties of different surface interpolation techniques.

In Chapter 3 we propose two modified approaches to surface

interpolation techniques. One is a weighted bilinear technique and the other a parametric Bezier interpolation technique. The mathematical properties of these techniques along with a comparative study of the performance of the different technique is also presented in this chapter.

In Chapter 4 we propose an objective criterion based on fractal dimensions to compare the performances of the different image magnification techniques. Experimental results of the utility of the criterion is then discussed.

In Chapter 5 we discuss the problem of linear feature detection and review the different local and global methods of line detection.

In Chapter 6 we propose a new method for linear feature detection based on second order neighbours and illustrate the performance with noise free images as well as Landsat TM subscenes.

Chapter 7 discusses the scope for future work and also illustrates a method of image registration based on linear features.

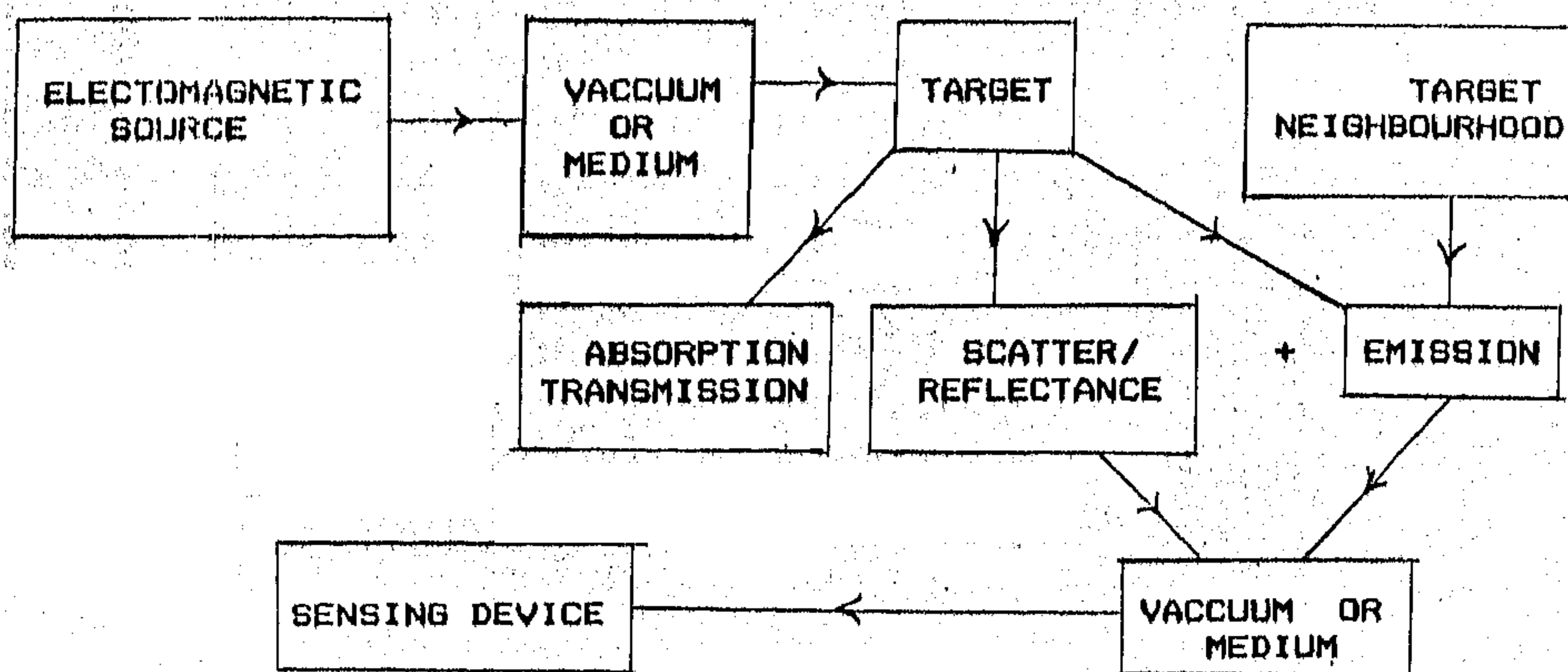


Fig.1.1 A SCHEMATIC OF A REMOTE SENSING SYSTEM

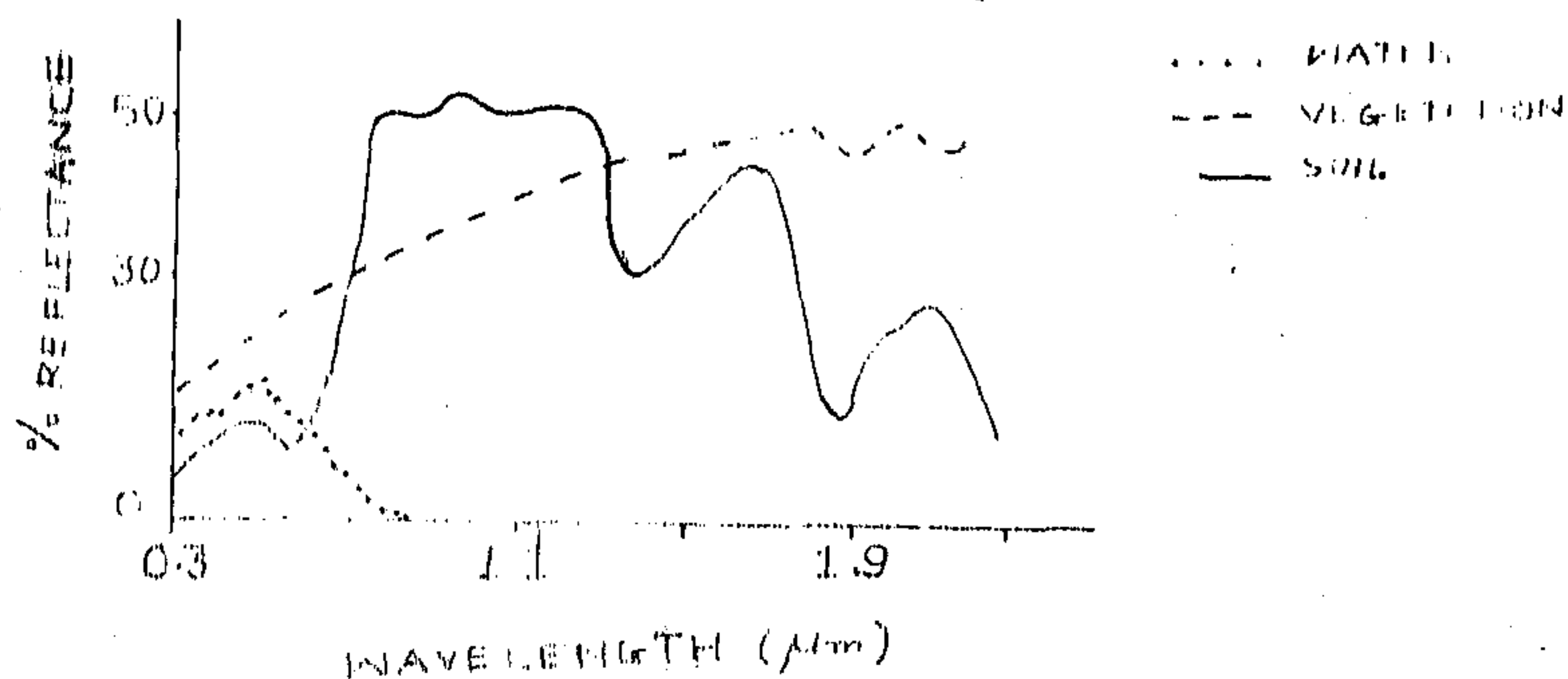


FIG. 1.2 SPECTRAL REFLECTANCE CURVES FOR SOME LAND FEATURES

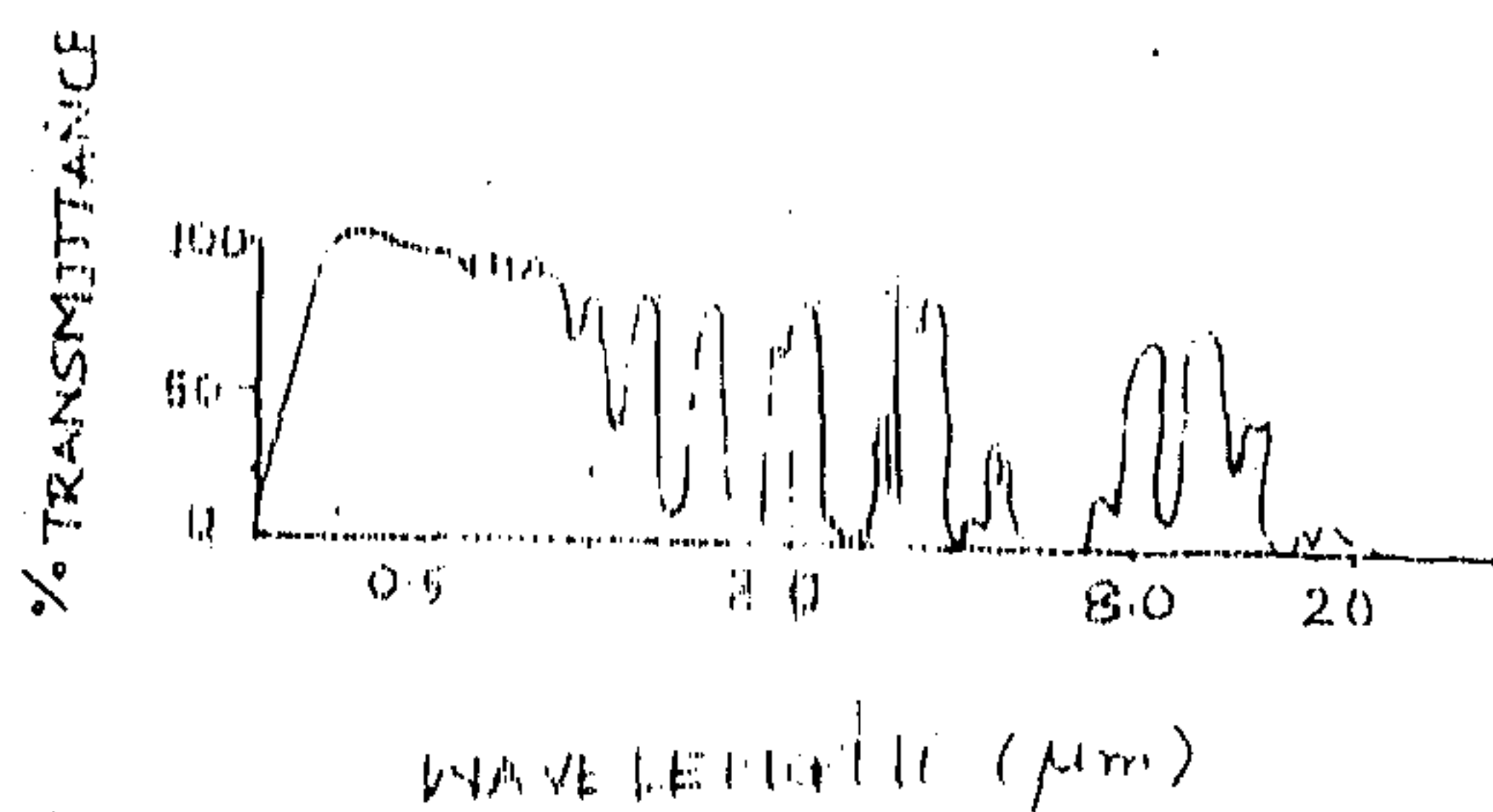


FIG. 1.3 ATMOSPHERIC WINDOWS FOR SATELLITE REMOTE SENSING

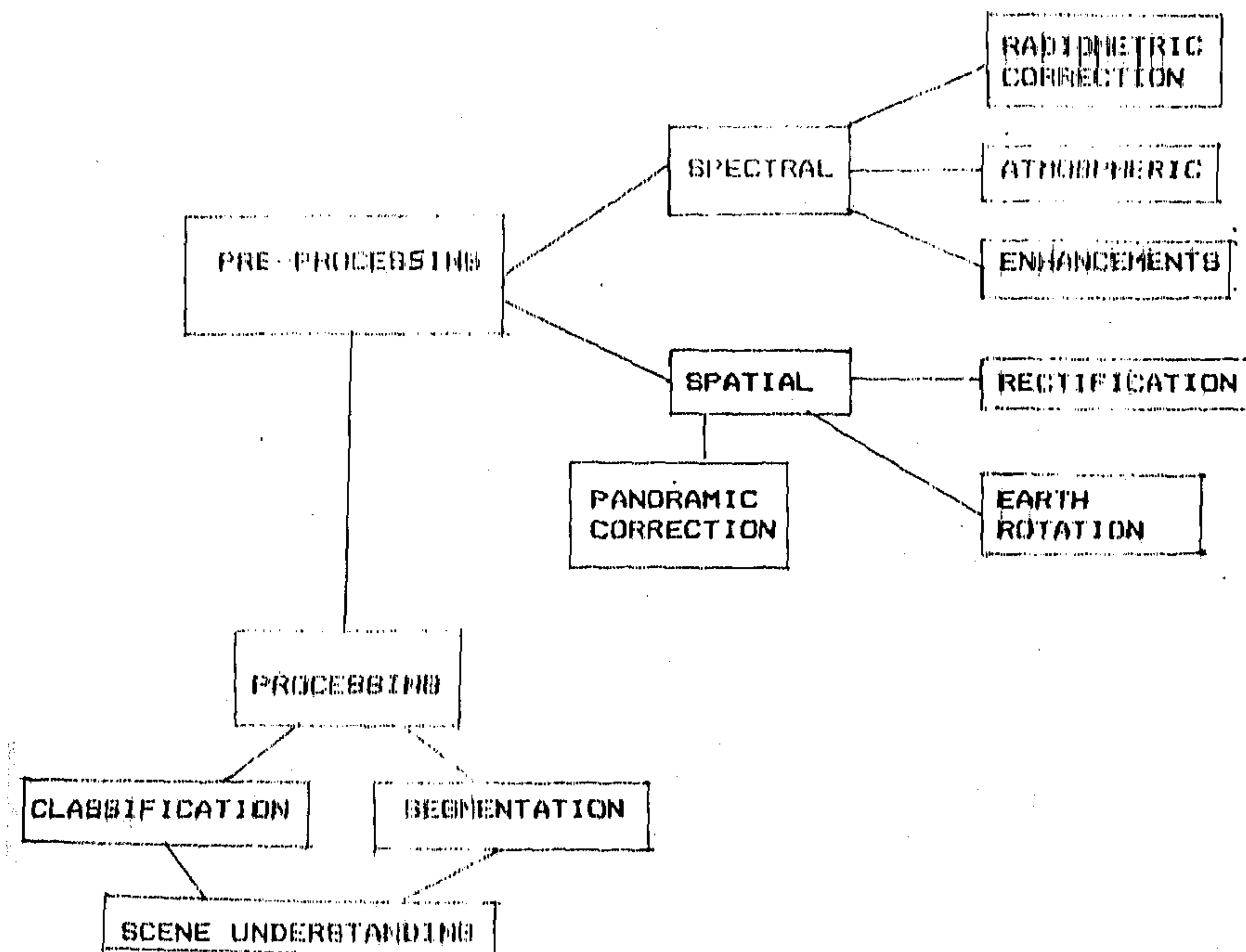


Fig. 1.4 A BLOCK DIAGRAM OF AN IMAGE PROCESSING SYSTEM

TABLE 1.1: CHARACTERISTICS OF SOME SATELLITES

SATELLITE/SENSOR : LANDSAT MSS

ALTITUDE : 905 Km

SWATH : 185 Km

RADIOMETRIC RESOLUTION : 128

SPATIAL RESOLUTION : 80m

REPETITIVITY : 18 DAYS

BANDS	SPECTRAL WAVELENGTH (μm)
1	0.5 - 0.6
2	0.6 - 0.7
3	0.7 - 0.8
4	0.8 - 1.1

SATELLITE/SENSOR : LANDSAT THEMATIC MAPPER (TM)

ALTITUDE : 905 Km

SWATH : 185 Km

RADIOMETRIC RESOLUTION : 256

SPATIAL RESOLUTION : 30m FOR BANDS 1 TO 5, 7 AND 120m FOR BAND 6

REPETITIVITY : 16 DAYS

BANDS	SPECTRAL WAVELENGTH (μm)
1	0.45 - 0.52
2	0.52 - 0.60
3	0.63 - 0.69
4	0.76 - 0.90
5	1.55 - 1.75
6	10.4 - 12.5
7	2.08 - 2.35

SATELLITE/SENSOR : TIROS / NOAA A VERY HIGH RESOLUTION RADIOMETER

ALTITUDE : 833 Km

SWATH : 3000 Km

RADIOMETRIC RESOLUTION : 1024

SPATIAL RESOLUTION : 1.1 Km

REPETITIVITY : 12 Hrs

BANDS SPECTRAL WAVELENGTH (μm)

1 0.58 - 0.68

2 0.725 - 1.10

3 3.55 - 3.93

4 10.3 - 11.3

5 11.5 - 12.5

SATELLITE/SENSOR : INDIAN NATIONAL SATELLITE

ALTITUDE : 36,000 Km

RADIOMETRIC RESOLUTION : 1024/256

SPATIAL RESOLUTION : 2.75 Km FOR BAND 1

11.0 Km FOR BAND 2

REPETITIVITY : 1/2 Hour

BANDS SPECTRAL WAVELENGTH (μm)

1 0.55 - 0.75

2 10.5 - 12.5

SATELLITE/SENSOR : INDIAN REMOTE SENSING SATELLITE

ALTITUDE : 904 Km

SWATH : 148 Km

RADIOMETRIC RESOLUTION : 128

SPATIAL RESOLUTION : 72.5m FOR LISS I, 36.25m FOR LISS II

REPETITIVITY : 22 DAYS

BANDS	SPECTRAL WAVELENGTH (μm)
1	0.45 - 0.52
2	0.52 - 0.59
3	0.62 - 0.68
4	0.77 - 0.86

SATELLITE/SENSOR : SPOT

ALTITUDE : 832 Km

SWATH : 108 Km

RADIOMETRIC RESOLUTION : 256

SPATIAL RESOLUTION : 20m FOR MULTI SPECTRAL MODE
10m FOR PANCHROMATIC MODE

REPETITIVITY : 26 DAYS

BANDS	SPECTRAL WAVELENGTH (μm)
1	0.50 - 0.59
2	0.61 - 0.68
3	0.71 - 0.89
PANCHROMATIC BAND	0.51 - 0.73

CHAPTER 2

DIGITAL IMAGE MAGNIFICATION

2.1 INTRODUCTION

Suppose that we are viewing a scene from a distance 'd' with our naked eye. Let us say that the scene comprises of a group of trees. Now if 'd' was very large, what we see with our eye will be just a crown of greenery and we will not be able to discern the individual trees. As 'd' gets smaller which is the same as moving closer to the scene, we will be able to see the individual trees and even the leaves. Note that the optical system has remained as such in the process. Therefore subject to our optical system capability, once we are at a distance of about 2.4m we will be able to see all that our eyes are capable of. As such we will not be able to see the cell structure within a leaf or any microdetails since the optical characteristics of our eyes do not permit this. Suppose that we have an external aid in the form of magnifying lens and we observe a single leaf, many more microdetails become visible. Using better and better lens systems we can in principle get a magnified image of the scene that enables us to see more and more details. Electron microscopes are amongst the best magnifiers. Essentially the optical system used to view an object decides the extent of detail that can be seen. Using better and better optical aids micro details of the objects can be deciphered. The extent of

details is limited only by the availability of appropriate optics. On the other hand in image magnification, the optics used to obtain the image decides primarily the extent of details that can be had by magnification. Beyond a limiting factor, there is no point in magnifying an image.

In this chapter, the problem of magnifying an image by digital methods will be posed. Standard techniques of magnification are described together with two important mathematical properties. This is mainly to point out the need for a criterion to decide which of the different techniques is the most appropriate for satellite image magnification.

2.11 WHAT IS AN IMAGE

There are a variety of definitions or connotations when we speak of the term image. One of them is that of an appearance or optical counterpart of an object; such as produced by reflection from a mirror. An image can also be considered as a projection of a three dimensional object on to a two dimensional plane.

A satellite imaging sensor receives a signal $f(x,y)$ from an area of size equivalent to the instantaneous field of view, whose location is identified by two real values (x,y) . This value $f(x,y)$ is referred to as grey value and is a continuous function. However, it is not practically feasible to record

the received signal as such on a photographic film. Therefore, the received signal is sampled or digitized to lie between a prespecified interval $[0, k-1]$ and we call k the radiometric resolution. The digitized values or grey values as they are called take integral values in this interval.

A satellite image signal undergoes two types of digitization. The obvious one is the digitization of the received signal values. The other less obvious one is in the spatial domain. In principle, we receive continuous signals from every point of the object surface. However, the sensor records the integrated signal received over an area equivalent to the spatial resolution of the sensor. Thus we can imagine our object surface to be composed of two dimensional grids, where the size of the grid is the same as the spatial resolution or ground resolution of the imaging sensor. The sensor records the signals received from each cell of the grid. A single grey value $f(x,y)$ is assigned to the cell corresponding to (x,y) . For digital images, the variable (x,y) is integer valued. Therefore, the normal notion of the derivatives of a function are no longer valid.

A digital image can therefore be considered as a function from some finite non-empty subset D in $Z \times Z$, the integral lattice, into the set of real numbers R . Although an image can be considered as a surface, the integral values assumed

by $f(x,y)$ prevents mathematical manipulation of the digital image. A parametric representation for the image surface is very useful for mathematical manipulation of a digital image.

DEFINITION A parametrized surface is a function $F:D \subset \mathbb{R}^2 \rightarrow \mathbb{R}^3$ where D is some domain in $\mathbb{R}^2$. The surface corresponding to the function F is its image $S = F(D)$. We can write

$$S(u,v) = [x(u,v) \ y(u,v) \ z(u,v)]$$

Normally while dealing with images we can choose D as $[0,1] \times [0,1]$. This representation of an image allows us to deal with the smoothness property of images in terms of the tangent planes, normal planes and orders of continuity. We can also study the properties of a sub image by considering the image to be made up of surface patches of different sizes. A group of $n \times k$ pixels can be considered as a surface patch. We can then investigate the conditions required to maintain continuity between surface patches that ensures smoothness. This is important particularly when we try to digitally magnify an image, where we build up the magnified image by compositing a number of surface patches.

2.2 DIGITAL MAGNIFICATION - THE PROBLEM

The basic urge in digital magnification of remote sensing images has been to attain the ease and perfection of optical

magnification techniques. Just as elaborate procedures are necessary to build a near perfect optical instrument for magnification, elaborate techniques have been developed for digitally magnifying images. Yet optical magnification techniques are not error free, the errors occurring mainly due to lens size, lens aberrations, film size, among others.

A digital image magnification problem can be posed as an image reconstruction problem where the coordinates of the magnified image have to be defined first. The grey values at the new coordinates are then determined using piecewise interpolation or approximation techniques. The size of the surface patch used to interpolate may vary from 2×2 pixels to any convenient size.

2.21 COORDINATE DEFINITION

There are two ways of defining the coordinates of the magnified image (Lalitha and Dutta Majumder, 1989). In the first method the coordinate definition depends on the size of the surface patch to be used in the interpolation technique in addition to the magnification factor. Suppose that the surface patch to be used is of size $s \times s$ and k is the magnification factor, then the coordinates are defined to ensure that each surface patch is magnified k times. To illustrate, consider an input image of size 4×4 which is to be magnified 2 times with surface patches of size 2×2 . Then

the new coordinates are defined as shown in Fig.2.1. Here every surface patch of size 2×2 in the input image is magnified into a 4×4 surface patch such that the corner coordinates of the input surface patch are retained as the corner coordinates of the output surface patch. The output image in this case has 10×10 pixels resulting in a magnification factor of $10/4 = 2.5$ and not as 2 originally intended. If the surface patch to be used is 3×3 , this method of defining the coordinates will result in a magnification factor of 2.2 when a factor of 2 was intended. It is readily seen that as the size of the original image gets larger and larger, this process of coordinate specification will result in a magnification factor of 3 for a surface patch of size 2×2 . The second approach ensures that the required magnification factor is achieved. In this case given the original input image size $(n \times n)$ and the resultant magnified image size $(kn \times kn)$, the coordinates are defined with a spacing of $(n-1)/(kn-1)$ for a magnification factor of k . This definition of coordinates is independent of the size of the surface patch to be used in the image reconstruction process. To illustrate, for an input image of size 4×4 to be magnified by a factor of 2, the coordinates of the output image will be as in Fig.2.2. In order to have a properly scaled image, it is necessary to define the coordinates of the output image correctly. This is achieved

by the second method of defining the coordinates.

2.22 SURFACE INTERPOLATION

Once the pixel coordinates of the magnified image are specified, grey values are to be assigned to each pixel. This is done through the surface interpolation techniques. Given a surface patch of size $m \times n$ pixel, the surface can be mathematically described by the following expression (Pratt, 1987)

$$s(u, v) = \sum_{j=0}^{n-1} \sum_{i=0}^{m-1} F_{ij} I_i(u) I_j(v) \quad 0 < u, v < 1 \quad (2.1)$$

where,

$$s(u, v) = \begin{pmatrix} x(u, v) \\ y(u, v) \\ z(u, v) \end{pmatrix}$$

$$F_{ij} = \begin{pmatrix} x(i, j) \\ y(i, j) \\ z(i, j) \end{pmatrix}$$

$s(u, v)$ is a parametric representation of the surface patch. F_{ij} is the vector of the original values assumed by the function at pixel (i, j) . $I(.)$ is called the interpolating function or the kernel function or the weighting function.

By using different interpolating functions $I(.)$ in (2.1) above and using different values for m and n , a variety of approximation for the surface patch can be obtained. The

above equation expresses the grey value at any pixel in terms of the grey values of the neighbouring pixels. The region of influence is set by the values of m and n . This expression for surface patches is very useful in image reconstruction such as in image magnification. The surface of $I(.)$ determines the continuity between adjacent surface patches.

In the parametric representation of a surface the kernel function is expressed as a product of two kernel functions corresponding to the parameters u and v . This allows the nature of interpolating function in the one dimensional case to be extended for a surface. This is particularly useful while discussing the convergence of different interpolating functions.

As already mentioned the interpolating functions can be varied to obtain a variety of approximations for a surface patch. Some of the standard interpolating functions include Bilinear or Bezier functions, cubic splines, cubic convolution, nearest neighbour; used specially for digital image magnification purpose. In the following section we will discuss the mathematical properties of Bezier and cubic interpolation functions.

2.3 ORDER OF CONVERGENCE

Let $(x_0, f(x_0)), (x_1, f(x_1)), \dots, (x_n, f(x_n))$ be a set of

sample observations on a function $f(x)$, where the spacing between successive observations is a constant h . the interpolation function with this set of observations can be written in the form,

$$g(x) = \sum_K c_k I\left(\frac{x-x_k}{h}\right)$$

where,

x_k are the interpolation nodes or the guiding points

$I(.)$ is the interpolation kernel

g is the interpolation function

c_k 's are parameters which depend upon $f(x_k)$'s

The order of convergence or the convergence rate of an interpolating function is a measure of how fast the approximation or interpolation error goes to zero as the sampling interval decreases (Conte and de Boor, 1981). When $I(.)$ is defined to be zero everywhere except in the interval $(-m, m)$; we can expand $g(x)$ as,

$$g(x) = c_{j-m+1} I(u+m-1) + c_{j-m+2} I(u+m-2) + \dots \\ + c_{j+m} I(u-m) \quad \dots (2.2)$$

where $u = (x - x_j) / h$ and $0 < u < 1$

Usually we choose,

$$c_{j-m+1} = f(x_{j-m+1})$$

... ..

... ..

$$c_{j+m} = f(x_{j+m})$$

Assuming that $f(\cdot)$ has at least three continuous derivatives in the interval $[x_j, x_{j+1}]$, we can expand $f(x_{j-m}), \dots, f(x_{j+m+1})$ as a Taylor's series about x_j and since $uh = x - x_j$, we can expand $f(x)$ about x . Thus ,

$$f(x) = f(x_j) + uh f'(x_j) + (u^2 h^2) f''(x_j) + O(h^3) \quad (2.3)$$

$$\begin{aligned} g(x) = & [f(x_j) - (m-1)h f'(x_j) + (m-1)^2 \frac{h^2}{2} f''(x_j)] I(u+m-1) \\ & + \dots + [(f(x_j) + mh f'(x_j) + m^2 \frac{h^2}{2} f''(x_j))] I(u-m) + \\ & O(h^3) \end{aligned} \quad (2.4)$$

The approximation error is then given by $f(x) - g(x)$. For different interpolation kernels the nature of approximation error and the rate at which it goes to zero can be investigated by substituting for m and $I(\cdot)$ in (2.3) and (2.4). We will now investigate the orders of convergence for Bezier and cubic interpolating functions.

2.31 BEZIER FUNCTIONS

The Bezier kernel function can be defined for any integral value $m < n$ (Bohm et al., 1984). Bilinear interpolation

technique used commonly for digital image magnification is a particular case of Bezier function with $m = 1$. In this case,

$$I(u) = 1-u \quad \dots\dots\dots(2.5)$$

$$I(u - 1) = u$$

The interpolating function in this case can be expressed as,

$$g(x) = f(x_{j-1}) (1-u) + f(x_j)u$$

The approximation error is then

$$f(x) - g(x) = hf'(x_j) + 1/2 h^2 f''(x_j) (u^2 + u - 1) + o(h^3) \quad \dots\dots(2.6)$$

The approximation error then goes to zero at the same rate as $o(h)$, so that the interpolation function has a first order convergence. Further for small magnification factors the approximation error will have a second order convergence.

2.32 CUBIC INTERPOLATION FUNCTION

The kernel function in this case can be written as,

$$\begin{aligned} &(\alpha + 2) u^3 - (\alpha + 3) u^2 + 1, \quad 0 < u < 1 \\ I(u) &= \alpha |u|^3 - 5\alpha |u|^2 + 8\alpha |u| - 4, \quad 1 < u < 2 \\ &0 \end{aligned}$$

For a standard cubic function $\alpha = -1$. For $m = 2$ and $0 < u < 1$, we will have

$$\begin{aligned} I(u+1) &= -u^3 + 2u^2 - u \\ I(u) &= u^3 - 2u^2 + 1 \end{aligned} \quad \dots\dots(2.8)$$

$$I(u-1) = -u^3 + u^2 + u$$

$$I(u-2) = u^3 - u^2$$

Expanding $f(x)$ and $g(x)$ in Taylor's series, the approximation error will be

$$f(x) - g(x) = hf'(x_j) [-2u^3 + 3u^2 - u] + h^2f''(x_j) [u^2 - u^3] + O(h^3) \dots\dots\dots(2.9)$$

For $0 < u < 1$, the behaviour of the coefficients of $hf'(x_j)$ and $h^2f''(x_j)$ is as shown in Fig.2.3. From (2.9) it is observed that the approximation error has a first order convergence. When the magnification factor is small, a third order convergence is possible. Keys(1981) has shown that if $\alpha = -1/2$ in the expression (2.7) the resulting interpolating function will have an exact third order convergence.

The above convergence rates obtained for a one dimensional function can be extended to the case of two dimensional function. In fact the observations made for the one dimensional case will hold good for the two dimensional case also. While the order of convergence investigates the behaviour of interpolating function within the surface patch, another property namely the order of continuity considers how well the interpolating function blends two adjacent surface patches.

2.4 ORDER OF CONTINUITY

In this section we will discuss what should be the nature of

grey value distribution of the original image in order that the continuity is ensured between two adjacent surface patches. The requirements will depend on the nature of the interpolating kernel.

Given two adjacent surface patches $S_1(u,v)$ and $S_2(u,v)$, we say that a zero order continuity or C^0 continuity is ensured if the grey values of the pixels along the boundaries of the two patches are identical. A first order continuity or C^1 continuity is assured if in addition the partial derivatives at points common to the two patches are collinear (Farin, 1982). This is equivalent to demanding that the tangent planes at every point along the common boundary of S_1 and S_2 coincide. For second order continuity the indicators of curvature of S_1 and S_2 must be identical at every point of the boundary curve (Veron et al. 1976).

Let $S_1(u,v)$ and $S_2(u,v)$ be two adjacent surface patches with $0 < u,v < 1$. As such in the case of images that we will be considering, the surface patches will be rectangular. Each surface patch will therefore have four adjacent surface patches. Common boundary between the two patches S_1 and S_2 is obtained by putting $u = 0$ (say) in the parametric representation for $S_1(u,v)$ and $S_2(u,v)$. Then a first order continuity between the two patches is ensured if

$$\gamma(v) S_{2u} = \alpha(v) S_{1u} + \beta(v) S_{1v} \quad \dots\dots (2.10)$$

$$S_{2u} = \left. \frac{\partial S_2(u,v)}{\partial u} \right|_{u=0}$$

$$S_{1u} = \left. \frac{\partial S_1(u,v)}{\partial u} \right|_{u=0}$$

$$S_{1v} = \left. \frac{\partial S_1(u,v)}{\partial v} \right|_{v=0}$$

(2.10) is true for all v on the boundary curve. $\beta(v)$ is a linear function of v . $\alpha(v)$, $\gamma(v)$ could be constants. When we consider the parametric representation of a surface, we must ensure that the conditions specified by (2.10) are satisfied for $x_1(u,v)$, $y_1(u,v)$, $z_1(u,v)$ in the case of $S_1(u,v)$ and for $x_2(u,v)$, $y_2(u,v)$, $z_2(u,v)$ in the case of $S_2(u,v)$. In the case of image magnification, since the input image coordinates are equispaced, the first order continuity conditions will be satisfied for the x and y coordinates. In fact this enables us to determine the values of $\alpha(v)$, $\beta(v)$, $\gamma(v)$, in (2.10) from which conditions for the first order continuity of $z(u,v)$ can be derived.

2.41 ORDER OF CONTINUITY FOR BEZIER INTERPOLATION FUNCTION

The surface patches $s_1(u,v)$ and $s_2(u,v)$ can be parametrically represented in the matrix form as

$$S_1(u,v) = U A P A^t V \quad (2.11)$$

$$S_2(u,v) = U A Q A^t V$$

where $U = [1 \ U \ U^2 \ \dots \ U^m]$

$$v^t = [1 \ v \ v^2 \ \dots\dots\dots v^m]$$

For $m = 4$

$$Q = \begin{pmatrix} b_{30} & b_{31} & b_{32} & b_{33} \\ b_{20} & b_{21} & b_{22} & b_{23} \\ b_{10} & b_{11} & b_{12} & b_{13} \\ b_{00} & b_{01} & b_{02} & b_{03} \end{pmatrix}$$

$$P = \begin{pmatrix} a_{00} & a_{01} & a_{02} & a_{03} \\ a_{10} & a_{11} & a_{12} & a_{13} \\ a_{20} & a_{21} & a_{22} & a_{23} \\ a_{30} & a_{31} & a_{32} & a_{33} \end{pmatrix}$$

The P & Q matrices describe the spatial distribution of the pixels in the input image together with the grey values at each pixel. Actually, $a_{00} = [x_1(0,0) \ y_1(0,0) \ z_1(0,0)]$ is the vector that defines the (x,y,z) co-ordinates in the parametrized form.

The two surfaces S_1 and S_2 can be visualized as follows -

$b_{03} \ b_{13} \ b_{23} \ b_{33}$	$a_{03} \ a_{13} \ a_{23} \ a_{33}$
$b_{02} \ b_{12} \ b_{22} \ b_{32}$	$a_{02} \ a_{12} \ a_{22} \ a_{32}$
$b_{01} \ b_{11} \ b_{21} \ b_{31}$	$a_{01} \ a_{11} \ a_{21} \ a_{31}$
$b_{00} \ b_{10} \ b_{20} \ b_{30}$	$a_{00} \ a_{10} \ a_{20} \ a_{30}$
$S_2(u,v)$	$S_1(u,v)$

The matrix A is the matrix that characterizes the interpolating function whose elements are the coefficients of the kernel function.

The Bezier function can be defined for any $m < N$ where N is the number of observations. The bilinear interpolating function used commonly in digital image magnification is a particular case of Bezier interpolating function with $m = 1$. In this case,

$$\begin{aligned}
 U &= [1 \quad u] & v^t &= [1 \quad v] \\
 Q &= \begin{pmatrix} b_{10} & b_{11} \\ b_{00} & b_{01} \end{pmatrix} & P &= \begin{pmatrix} a_{00} & a_{01} \\ a_{10} & a_{11} \end{pmatrix} \dots (2.12) \\
 A &= \begin{pmatrix} 1 & 0 \\ -1 & 1 \end{pmatrix}
 \end{aligned}$$

Adjacency between S_1 and S_2 requires

$$\begin{aligned}
 a_{01} &= b_{11} \\
 a_{00} &= b_{10}
 \end{aligned}
 \dots (2.13)$$

The conditions for first order continuity expressed in (2.10) works out as

$$\begin{aligned}
 \gamma(v) [(b_{00} - b_{10}) - v(b_{00} - b_{10}) + v(b_{01} - b_{11})] \\
 = \alpha(v) [(a_{10} - b_{10}) - v(a_{10} - b_{10}) + \\
 v(a_{11} - b_{11})] + \beta(v) [(b_{11} - b_{10})] \\
 \dots (2.14)
 \end{aligned}$$

$$\text{Let } \gamma(v) = \gamma, \quad \alpha(v) = \alpha, \quad \beta = r + sv$$

Equating the constant terms and the coefficients of v on both sides of (2.14), together with the information that the pixels are equispaced in both the surface patches, we can obtain values for $\sqrt{\gamma}, \alpha, r, s$. It turns out that $\beta = 0, \sqrt{\gamma} = -\alpha$, which implies that for $\alpha = 1$,

$$a_{10}(z) - b_{10}(z) = b_{10}(z) - b_{00}(z) \dots\dots(2.15)$$

$$a_{11}(z) - b_{11}(z) = b_{11}(z) - b_{01}(z)$$

Equations (2.13) and (2.15) together provide the condition on the distribution of grey values so that a first order continuity is maintained between adjacent patches. Equation (2.15) demands that the gradient on either side of the common boundary between the two surface patches be identical. In other words, as long as the grey values do not change abruptly in an image, bilinear interpolation will ensure a first order continuity while reconstructing the output image.

2.42 ORDER OF CONTINUITY OF BICUBIC INTERPOLATION FUNCTION

The characteristic matrix A in this case is

$$A = \begin{pmatrix} 0 & 1 & 0 & 0 \\ -1 & 0 & 1 & 0 \\ 2 & -2 & 1 & -1 \\ -1 & 1 & -1 & 1 \end{pmatrix} \quad (2.16)$$

In defining composite patches using bicubic interpolating

functions, we first of all ensure adjacency between the two patches in the following manner

$$\begin{aligned} b_{23} &= a_{03} & b_{33} &= a_{13} \\ b_{22} &= a_{02} & b_{32} &= a_{12} \\ b_{21} &= a_{01} & b_{31} &= a_{11} \\ b_{20} &= a_{00} & b_{30} &= a_{10} \end{aligned}$$

As a result

$$Q = \begin{pmatrix} b_{30} & b_{31} & b_{32} & b_{33} \\ b_{20} & b_{21} & b_{22} & b_{23} \\ b_{10} & b_{11} & b_{12} & b_{13} \\ b_{00} & b_{01} & b_{02} & b_{03} \end{pmatrix}$$

$$P = \begin{pmatrix} b_{20} & b_{21} & b_{22} & b_{23} \\ b_{30} & b_{31} & b_{32} & b_{33} \\ a_{20} & a_{21} & a_{22} & a_{23} \\ a_{30} & a_{31} & a_{32} & a_{33} \end{pmatrix}$$

Choosing $\gamma(v) = \gamma$, $\alpha(v) = \alpha$ and $\beta(v) = r + sv$ as before and equating the coefficients of v^0 , v^1 , v^2 , and v^3 in

$$\gamma S_{2u} = \alpha S_{1u} + (r + sv) S_{1v}$$

where S_{1u} , S_{2u} , and S_{1v} are as defined in (2.10), we will get

$$\gamma(b_{11} - b_{21}) = \alpha(a_{21} - b_{21}) + r(-b_{30} + b_{32}) \dots\dots\dots(2.17)$$

$$\gamma[-(b_{10} - b_{30}) + (b_{12} - b_{32})] = \alpha[-(a_{20} - b_{20}) +$$

$$(a_{22} - b_{22})] + r [4(b_{30} - b_{31}) + 2(b_{32} - b_{33})] + s[(b_{32} - b_{30})] \dots\dots(2.18)$$

$$\begin{aligned} \sqrt{[2(b_{10} - b_{30}) - 2(b_{11} - b_{31}) + (b_{12} - b_{32}) - (b_{13} - b_{33})]} &= \alpha[2(a_{20} - b_{20}) - 2(a_{21} - b_{21}) \\ &\quad + (a_{22} - b_{22}) - (a_{23} - b_{23}) + \\ &\quad r [-3(b_{30} - b_{31}) + 3(b_{33} - b_{32})] + s[4(b_{30} - b_{31}) \\ &\quad - 2(b_{33} - b_{32})] \dots\dots(2.19) \end{aligned}$$

$$\begin{aligned} \sqrt{[-b_{10} - b_{30}) + (b_{11} - b_{31}) - (b_{12} - b_{32}) + (b_{13} - b_{33})]} \\ = \alpha[-(a_{20} - b_{20}) + (a_{21} - b_{21}) - (a_{22} - b_{22}) + (a_{23} - b_{23})] \\ + s[-3(b_{30} - b_{31}) + 3(b_{33} - b_{32})] \dots\dots(2.20) \end{aligned}$$

Since we know that a_{ij} 's and b_{ij} 's are equidistant along the X and Y direction, we can determine α , $\sqrt{}$, r , s from the above set of equations to get $\sqrt{} = -\alpha$, $r = s = 0$. Choosing $\alpha = 1$, the condition on the grey values can be written as

$$\begin{aligned} a_{20}(z) - b_{30}(z) &= b_{20}(z) - b_{10}(z) \\ a_{21}(z) - b_{31}(z) &= b_{21}(z) - b_{11}(z) \dots\dots(2.21) \\ a_{22}(z) - b_{32}(z) &= b_{22}(z) - b_{12}(z) \\ a_{23}(z) - b_{33}(z) &= b_{23}(z) - b_{13}(z) \end{aligned}$$

These conditions are similar to what was obtained for Bezier interpolating functions. However, since the surface patch size is larger the conditions appear more stringent and will be satisfied so long as no edge or linear feature occur along the boundary between two surface patches.

These conditions can be generalized for any two adjacent surface patches. When we consider all the four adjacent patches of a given surface patch, the first order continuity conditions can be expected to hold only for images that do not have abrupt variations in grey values when using bilinear interpolation. In the case of bicubic interpolation, homogeneity within a pixel window of size 4 X 4 must be ensured.

2.5 IMPLEMENTATION ALGORITHMS

For the purpose of digital magnification, the interpolation can be carried out first along the rows and then along the columns - in effect a one dimensional interpolation algorithm can be implemented. Let $x_0, x_1, x_2, \dots, x_n$ be the input pixel coordinates in the i^{th} row(say) of the image with grey values $z_0, z_1, \dots, z_n$. Suppose that the surface patch size is 2 X 2 and we need to determine the grey value at a pixel $x_j, x_0 \leq x_j < x_1$. We will be using interpolation techniques not to build up the entire surface but to estimate the grey values at discrete locations. In the one dimensional case the interpolation function can be expressed as

$$S(u) = UAP, \text{ where } S(u) = \begin{pmatrix} x(u) \\ z(u) \end{pmatrix} \dots (2.22)$$

$$U = [1 \ u] \quad P = \begin{pmatrix} x_0 & z_0 \\ x_1 & z_1 \end{pmatrix}$$

A is the matrix that characterizes the interpolating kernel. The following steps then have to be carried out to obtain the output magnified image.

1. Determine the two pixels closest to x_j in the input image.
2. Solve (2.22) for u with the information that $x(u) = x_j$.
3. For this value of u , calculate $z(u)$, from (2.22) which is the interpolated value.
4. Repeat steps (1) to (3) for all pixels in the i th row of the output image. Since the pixels in the output image are uniformly spaced in every row, the calculation of u needs to be done only for the first row. The above steps have to be repeated along the columns treating the image obtained after row operation as the input image.

The differences in the computational efforts required for different interpolation techniques arises due to the dimensions of the matrices U , A and P . As the dimensions increases the computations also increase. It can be readily seen that if the surface patch size is n , then the number of operations to be performed in the estimation of the grey value of one pixel is $2n^2 + 3n - 2$. As the input image size gets larger, as also the magnification factor, the number of operations will be enormous for large n .

2.6 CONCLUSION

In this chapter, we introduced the problem of digital image magnification and investigated the mathematical properties of standard techniques such as bezier and bicubic interpolating functions. The definitions of the image coordinates of the magnified image is an important problem and care has to be taken to ensure that it is done by the method proposed. The bicubic interpolating function has approximately a third order convergence rate while the bilinear function has a first order convergence rate.

The conditions for a first order continuity between adjacent patches is derived. It is shown that if the grey values do not change abruptly across the common boundary of the surface patches then a first order continuity will be ensured. Computationally bicubic interpolation is more intensive than bilinear interpolation. In the following chapter we will discuss two modifications for bilinear interpolation and a need for a more objective criterion to compare the performances of the different interpolation techniques for image magnification purposes.

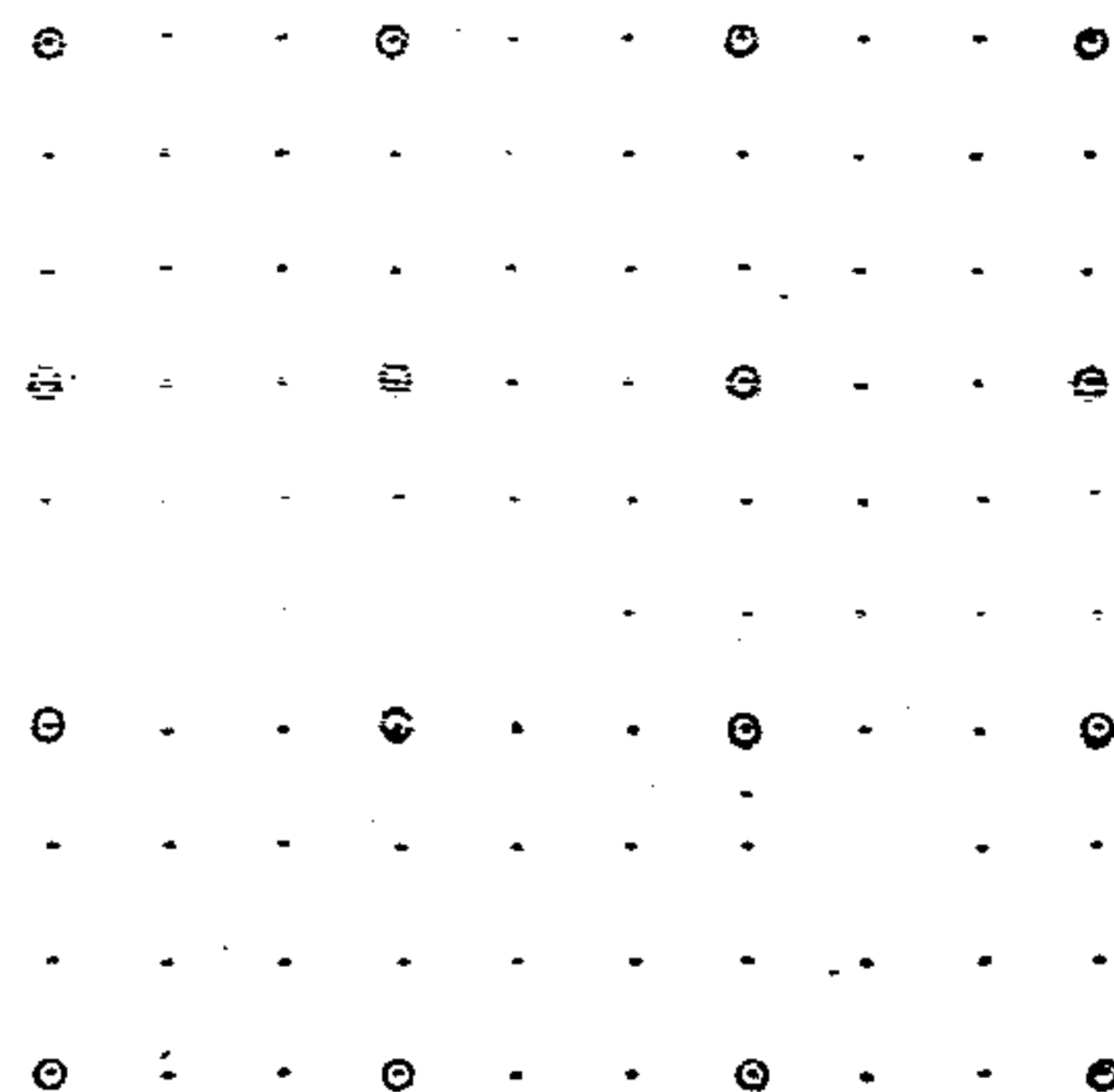


FIG.2.1 METHOD 1

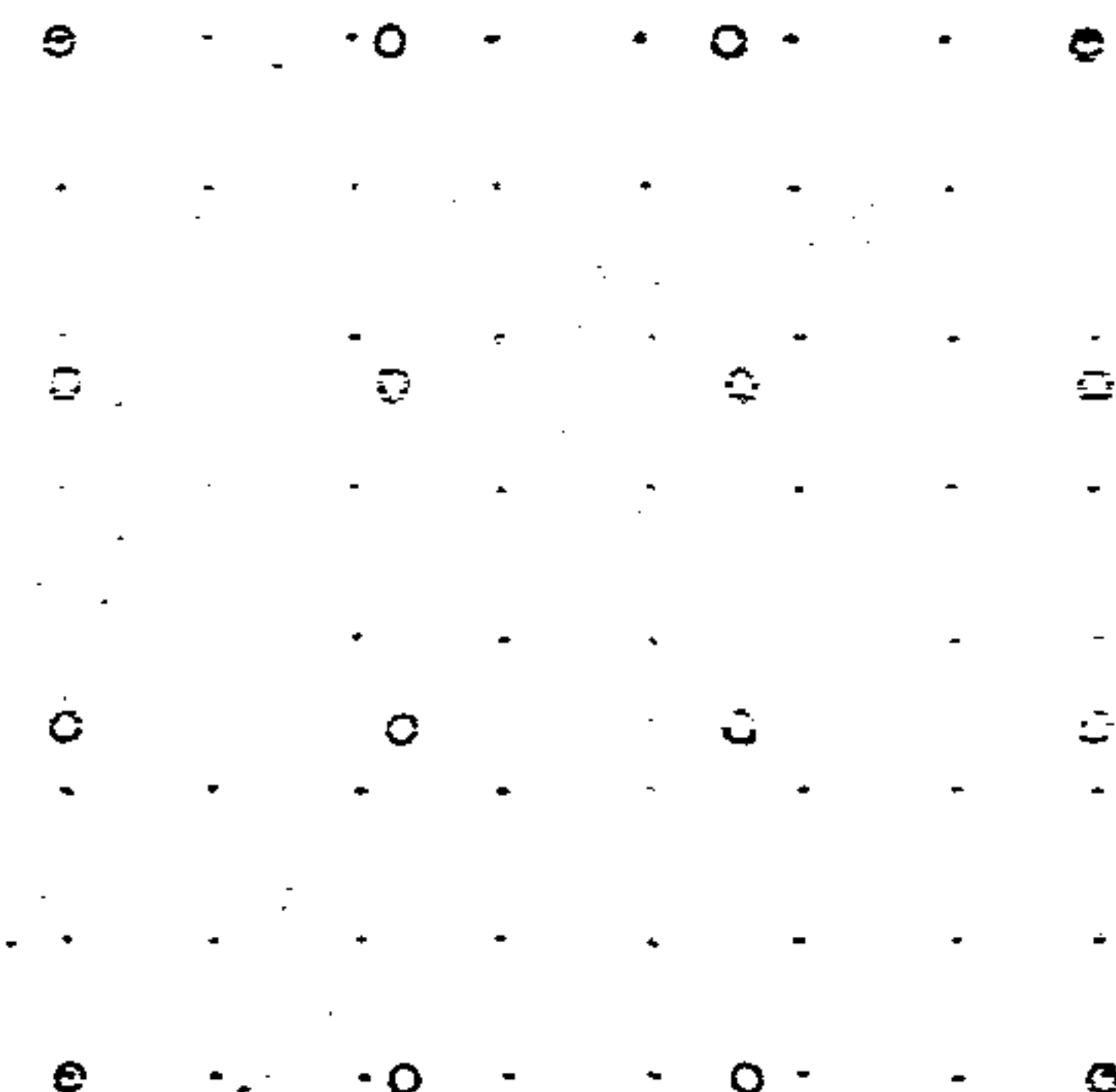


FIG.2.2 METHOD 2

CO-ORDINATES OF A MAGNIFIED IMAGE

⊙ INPUT IMAGE COORDINATES

. OUTPUT IMAGE COORDINATES

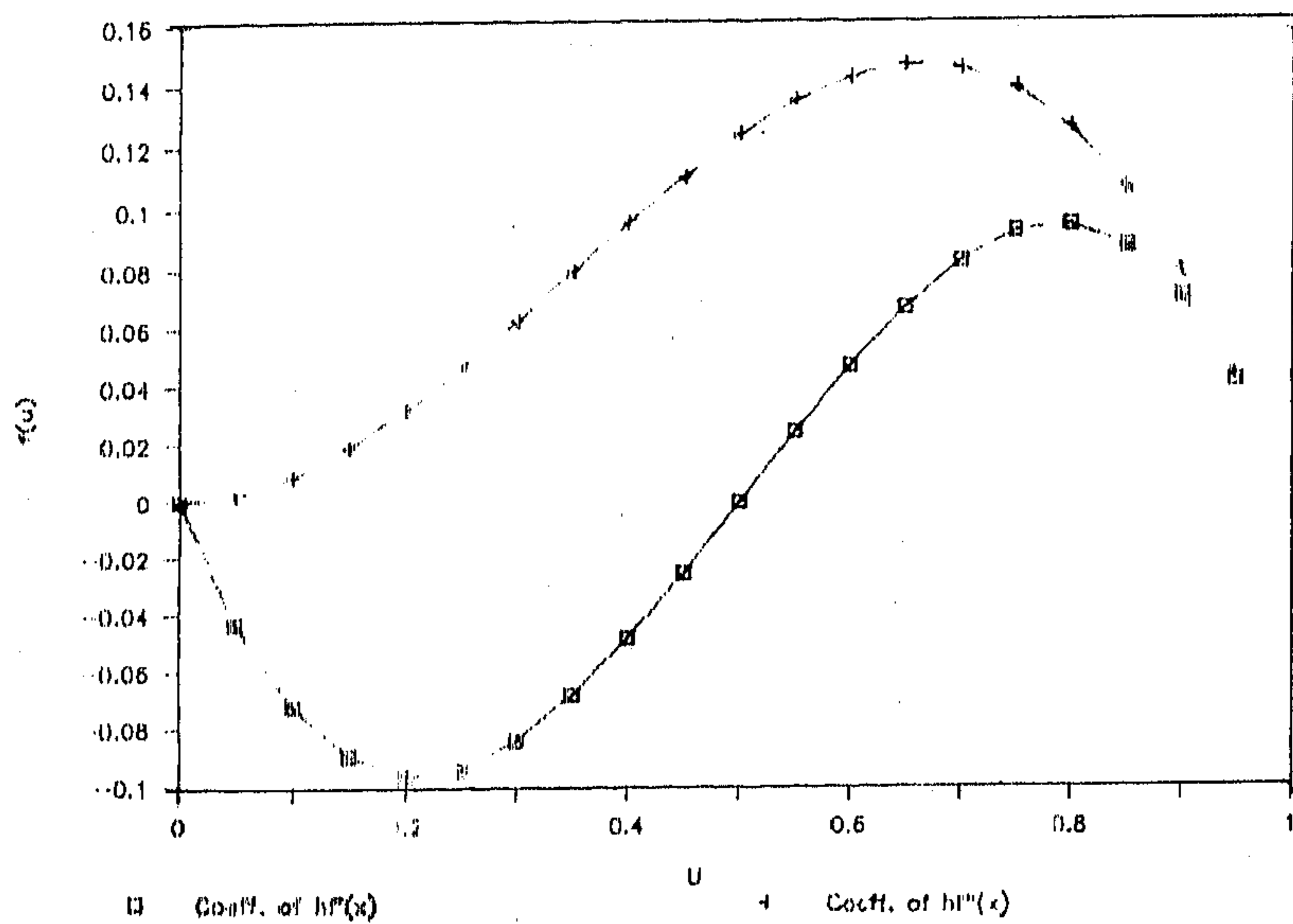


FIG. 2.3 APPROXIMATION ERROR -- CUBIC CONVOLUTION TECHNIQUE

CHAPTER 3

NEW TECHNIQUES FOR SURFACE INTERPOLATION

3.1 INTRODUCTION

We noted in Chapter 2 that as the surface patch size increases, the computational requirements become quite enormous. Both bilinear and bicubic techniques ensure first order continuity as long as there are no abrupt changes in the grey values across the common boundary between the adjacent surface patches. This condition is more stringent for bicubic interpolation where the surface patch size is 4×4 as against a 2×2 patch used in bilinear interpolation. In the following section we propose a modification of the bilinear technique, that takes into account the gradient at every pixel to ensure that no edge or linear feature gets suppressed in the output magnified image. yet another modification is suggested which is an extension of a technique proposed for curve approximation (Chaudhury and Datta, 1986) to surface interpolation. In this technique the smoothness in curve approximation was achieved without increasing the surface patch size but by incorporating two additional parameters.

In this chapter we will look at the conditions required for first order continuity of these two techniques. The computational requirements in using these techniques for

digital magnification is also discussed. A visual comparison of the different techniques discussed so far is then made.

3.2 WEIGHTED BILINEAR TECHNIQUE

Bilinear interpolation considers only the nearness of the reference pixel to the neighbourhood pixels. It does not consider the grey value distribution of the neighbourhood pixels. Hence whenever an edge passes through the pixel to be interpolated, the grey value assigned to it does not correspond to the edge grey value, but an average of the grey values of the neighbourhood pixels is taken. To compensate for this, a measure of the gradient taken at every pixel of the surface patch can be taken as an additional weighting factor while reconstructing a magnified image.

Using the same notation for a surface patch as used in Ch.2, the weighted bilinear function has the form

$$S(u,v) = (1/w) [U A P A^t V]$$

$$\text{where, } U = [1 \ u \]$$

$$V = [\ 1 \ v \]^t$$

$$P = \begin{pmatrix} w_{00} & a_{00} & w_{01} & a_{01} \\ w_{10} & a_{10} & w_{11} & a_{11} \end{pmatrix} \quad A = \begin{pmatrix} 1 & 0 \\ -1 & 1 \end{pmatrix}$$

The w_{ij} 's are the gradient at pixel a_{ij} defined as follows.

Suppose that a_{ij} are distributed as shown in Fig.3.1, then the gradient at the center pixel a_{11} is

$$\text{grad} = w_{11} = \frac{|a_{02} - a_{11}| + |a_{20} - a_{11}|}{|a_{22} - a_{11}| - |a_{00} - a_{11}|}$$

$W = w_{00} (1-u)(1-v) + w_{10} u(1-v) + w_{01} (1-u)v + w_{11}vu$ is a scalar. It will be seen that whenever w_{ij} 's are equal for all the four pixels in a surface patch, meaning homogeneity, the weighted bilinear will be identical to the standard bilinear interpolating function.

3.3 PARAMETRIC BEZIER TECHNIQUE

Bezier interpolation techniques perform better at higher orders, that is, when the surface patch size is larger (Pavlidis, 1982). However, the computational efforts involved increases with larger surface patch size. To overcome this problem for curve approximation, a parametric Bezier interpolation was proposed by Chaudhury and Datta, (1986). In this method, given a set of guiding points $P_0, P_1, \dots, P_n$ additional points $P'_0, P'_1, \dots, P'_{N-1}$ are defined such that $P'_1 = (1-C) P_1 + CP_{1+1}$, $0 \leq C \leq 1$ where C is a parameter to be defined. The curve approximation is then carried out using the point P_i, P'_i, P_{i+1} . We will now extend this to surface interpolation.

For the case of surface interpolation, two parameters c and d

are defined. We then define a point inside every 2×2 surface

patch size at $u = c$, $v = d$ by

$$S(u,v) = U A P A^t V$$

$$\text{where } U = [1 \ u] \quad , \quad V^t = [1 \ v]$$

$$A = \begin{pmatrix} 1 & 0 \\ -1 & 1 \end{pmatrix} \quad P = \begin{pmatrix} a_{00} & a_{01} \\ a_{10} & a_{11} \end{pmatrix}$$

The input image can be schematically represented as shown in Fig. 3.2.

The magnified image is then reconstructed by Bezier interpolation with a non-rectangular surface patch. Thus the technique can be treated as a two-stage Bezier interpolation. We need to specify the parameter c and d so that some desirable properties are satisfied. We will show in the following section that the specification of these parameters is guided by the order of continuity property (Lalitha and Dutta Majumder).

3.4 ORDER OF CONTINUITY

For the weighted bilinear technique, as before, let $S_1(u,v)$

$$\text{and } S_1(u,v) = \frac{1}{w} [U A P A^t]$$

$$S_2(u,v) = \frac{1}{w} [U A Q A^t]$$

$$Q = \begin{pmatrix} w_{10}' & b_{10} & w_{01}' & a_{01} \\ w_{00}' & b_{00} & w_{01}' & b_{01} \end{pmatrix}$$

$$P = \begin{pmatrix} w_{00} & a_{00} & w_{01} & a_{01} \\ w_{10} & a_{10} & w_{11} & a_{11} \end{pmatrix}$$

First order continuity demands

$$\sqrt{S_{2u}} = \alpha S_{1u} + (r + sv) S_{1v}, \text{ with } \alpha \neq 0$$

For the x and y co-ordinates, it is obvious that

$$w_{00} = w_{01} = w_{10} = w_{11} = w_{00}' = w_{01}' = w_{10}' = w_{11}'$$

$$\sqrt{r} = -\alpha, \quad \sqrt{s} = 0$$

By adjacency of the two surface patches it follows that

$$w_{11}'(z) = w_{01}(z), \quad w_{10}'(z) = w_{00}(z)$$

As a result, the first order continuity conditions on the grey values simplify as

$$\frac{w_{10}(z) a_{10}(z)}{w(z)} - \frac{w_{10}'(z) b_{10}(z)}{w'(z)} = \frac{w_{10}'(z) b_{10}(z)}{w'(z)} - \frac{w_{00}'(z) b_{00}(z)}{w'(z)} \dots\dots\dots (3.1)$$

$$\frac{w_{11}(z) a_{11}(z)}{W(z)} - \frac{w_{11}'(z) b_{11}(z)}{W'(z)} = \frac{w_{11}'(z) b_{11}(z)}{W'(z)} \dots (3.1)$$

$$- \frac{w_{01}'(z) b_{01}(z)}{W'(z)}$$

(3.1) implies that the weighted grey values must be distributed in such a way to ensure that the gradient across the boundary of the surface patch is identical.

In the case of parametric bezier we consider a non - rectangular surface patch where S_1 and S_2 are as schematically shown in Fig.3.3. Then a first order continuity between two adjacent patches will require,

$$\gamma(b_{00} - b_{10}) = \alpha(a_{10} - b_{10}) + r(b_{11} - b_{10})$$

$$\gamma[(b_{10} - b_{00}) + (b_{01} - b_{11})] = \alpha[(b_{10} - a_{10}) + (a_{11} - b_{11}) + s(b_{11} - b_{10})] \dots (3.2)$$

For the x and y variable we will get

$$\gamma(c-1) = \alpha c + r(c-1) \dots (3.3)$$

$$\gamma(1-2c) = \alpha(1-2c) + s(c-1) \dots (3.4)$$

$$\gamma d = \alpha(d-1) + r(d-1) \dots (3.5)$$

$$\gamma(1-2d) = \alpha(1-2d) + s(d-1) \dots (3.6)$$

Suppose that $\gamma = -$, $r = s = 0$, then $c = d = 1/2$.

In this case the grey values must satisfy conditions specified by equations (3.7) in order that the first order continuity conditions are met.

$$\begin{aligned} a_{10}(z) - b_{10}(z) &= b_{10}(z) - b_{00}(z) \\ a_{11}(z) - b_{11}(z) &= b_{11}(z) - b_{01}(z) \end{aligned} \dots\dots (3.7)$$

These expressions are similar to those derived for standard bilinear and bicubic interpolation techniques. For the case when α, γ, r, s are different the equations (3.3) to (3.6) have to be solved. These equations can be represented in matrix notation as

$$\begin{bmatrix} c-1 & -c & -(c-1) & 0 \\ 1-2c & -(1-2c) & 0 & -(c-1) \\ d & -(d-1) & -(d-1) & 0 \\ 1-2d & -(1-2d) & 0 & -(d-1) \end{bmatrix} \begin{bmatrix} \gamma \\ \alpha \\ r \\ s \end{bmatrix} = 0$$

The solution for γ, α, r, s will exist, provided that the determinant of the coefficient matrix is 0 in which case three of the quantities can be expressed in terms of the fourth quantity uniquely. This simplifies to

$$d = 3c - 2 \dots\dots\dots (3.8)$$

$$d = 1 + (c-1)/(2c-1) \dots\dots\dots (3.9)$$

From (3.8) it follows that $c > 2/3$. Thus for $c > 2/3$ and d obtained from (3.9), first order continuity will be ensured. Thus, the guideline is obtained to set the parameter values c

and d. Fig. 3.4 gives a c-d graph from which c-d values can be chosen. This technique thus ensures a first order continuity irrespective of the grey value distribution in the input image by a suitable selection of the parameters c and d. (Lalitha and Dutta Majumder)

3.5 COMPUTATIONAL REQUIREMENTS

In addition to the number of operations required for bilinear interpolation, twelve more operations need to be performed in the case of both weighted bilinear and parametric Bezier techniques. In other words, the total number of operations for these techniques is twice that necessary for bilinear techniques. Still, this is half the number of operations required for bicubic interpolation technique.

The advantage of Parametric Bezier technique lies in its ability to improve the magnified image by modifying the parameters c and d interactively. The setting of the parameters is aided by the c and d graph. Consider Fig. 3.5(a) where an input image of size 32 X 32 pixels is shown. The image is part of a satellite scene showing a water body (The dark object). The image is magnified 2X times for different values of c and d and the resultant images are shown in Fig. 3.5(b) - 3.5(g). It is observed that the edges of the water body are blurred for most values of c and d.

This is particularly noticeable on the lower edges of the water body. For $c=0.7$ and $d=0.1$ however, the edges are sharp and thus turns out to be the best in visual clarity. The parametric Bezier technique essentially gives additional weights to some of the interpolating pixels. The c and d values decide which pixel gets more weight. For instance when $c = 0.7$ and $d = 0.1$ the pixel on the top right is given the maximum weight. In any given image it is not possible to set the c and d values before magnification. However, as already pointed out the advantage of this technique is the ability to change the values of c and d interactively and decide on the best value depending on the visual clarity. Fig.3.6 shows the magnified outputs using standard techniques. The nearest neighbour technique provides the simplest approach to digital image magnification. Here the grey value of a pixel is repeated K times along the row and column in order to obtain an image magnified by a factor K . It is observed that the image magnified using nearest neighbour technique has a prominent block like structure and lacks smoothness. In the bilinear magnified image the edges around the water body are blurred. fig.3.7 shows a subscene of 256×256 pixels from the Indian Remote sensing satellite. From this subscene a portion (64×64) of the image was magnified 4 times using bilinear, bicubic and parametric bezier techniques. It was noted that the image magnified using bicubic technique when

displayed on a COMTAL display device produced relatively sharper image. In the region marked (1) note that a few additional features are seen in the bicubic image in comparison with the bilinear image which has a tendency to smoothen the image (Fig.3.8(a), Fig.3.8(b)). A similar thing is noted in the region marked (4). The image magnified using parametric bezier technique for different values of c and d are shown in Fig.3.8(c) - (f). In Fig.3.8(d) - (f) the edges have a blocky appearance. The image magnified using $c = 0.7$, $d = 0.1$, however resulted in a visually appealing image. Compared to the bicubic magnified image this was not a very sharp image. In the area marked (2), observe that bicubic and parametric bezier technique produced identical results but the bilinear magnified image missed out a few features. In the area marked (3) the parametric bezier image has a diffused appearance. In any case it is difficult to decide based on visual clarity alone which of the several techniques is the best. In addition if the final output is the main consideration the quality of the output generator has also to be considered. If the output generator is incapable of showing as many grey levels as the display monitor, then even the image generated using the most sophisticated technique will lose its significance.

3.6 DISCUSSION

Leberl(1978) points out that any criterion used for comparing the performances of different interpolation techniques must be data structure dependent when they are applied to image magnification problems.

The mean square radiometric error is one such measure that has been used to compare the performances of the digital image magnification techniques (Simon,1975; Schlien,1979; Park and Schowengerdt,1982). It has been shown empirically by the above authors that the mean squared resampling error in nearest neighbour resampled images is about 4 times that of the bilinear resampled images which is 3 times that of the standard bicubic resampled images.

A visual comparison of the performances of the nearest neighbour, bilinear and bicubic techniques by Schowengerdt(1983) shows the superiority of the bilinear and bicubic techniques over the nearest neighbour technique. The standard bicubic interpolators apparently produce some grey level overshoot on either side of sharp edges resulting in considerable sharpness in the magnified image. Although this has a pleasing visual effect, it results in undesirable artifacts in the grey values of the output image and contributes to classification errors in subsequent image processing operations (Schowengerdt, 1983). It has been shown

theoretically (Keys, 1981) and tested on a few images (Park and Schowengerdt, 1983) that a cubic interpolating function with $\alpha = -0.5$ in equation (2.7) performs better than the standard cubic functions in the sense that the former result in a lower root mean square error than the latter. Often image magnification is required as an intermediate step in image processing task. We have to then ensure that the original radiometric values of the image are not tampered with to the extent that artifacts are introduced in the output image.

A point that needs to be investigated is, does a technique perform equally well at all scales of magnification? In other words, is there a limiting scale up to which a technique is as good as any other? Is there a quantitative measure of the image data structure by means of which one can decide to use a particular technique to magnify an image. These points are important because at lower scales of magnification, a simple computationally less intensive technique may perform as well as a more sophisticated, computationally intensive technique.

In the following chapter we will introduce a new criterion based on the fractal dimensions of an image to compare the performances of the different interpolation techniques. Fractal dimensions apart from being a measure of the image surface roughness is also invariant to scale changes of the

original data (Pentland,1984). Thus the scale at which the fractal dimensions of the magnified image differs from that of the original image can be ascertained to determine the limiting scale for any magnification technique.

a_{20}	a_{21}	a_{22}
a_{10}	a_{11}	a_{12}
a_{00}	a_{01}	a_{02}

Fig 3.1 NEIGHBOURHOOD OF A PIXEL

x	x	x	x	x
	x	x	x	
x	x	x	x	x
	x	x	x	
x	x	x	x	x

Fig 3.2 A SCHEMATIC OF INPUT IMAGE COORDINATES FOR PARAMETRIC BEZIER

		a_{11}	
	a_{01}		a_{10}
b_{01}		b_{10}	
	b_{00}		

Fig 3.3 SURFACE PATCHES FOR PARAMETRIC BEZIER INTERPOLATION

c--d GRAPH

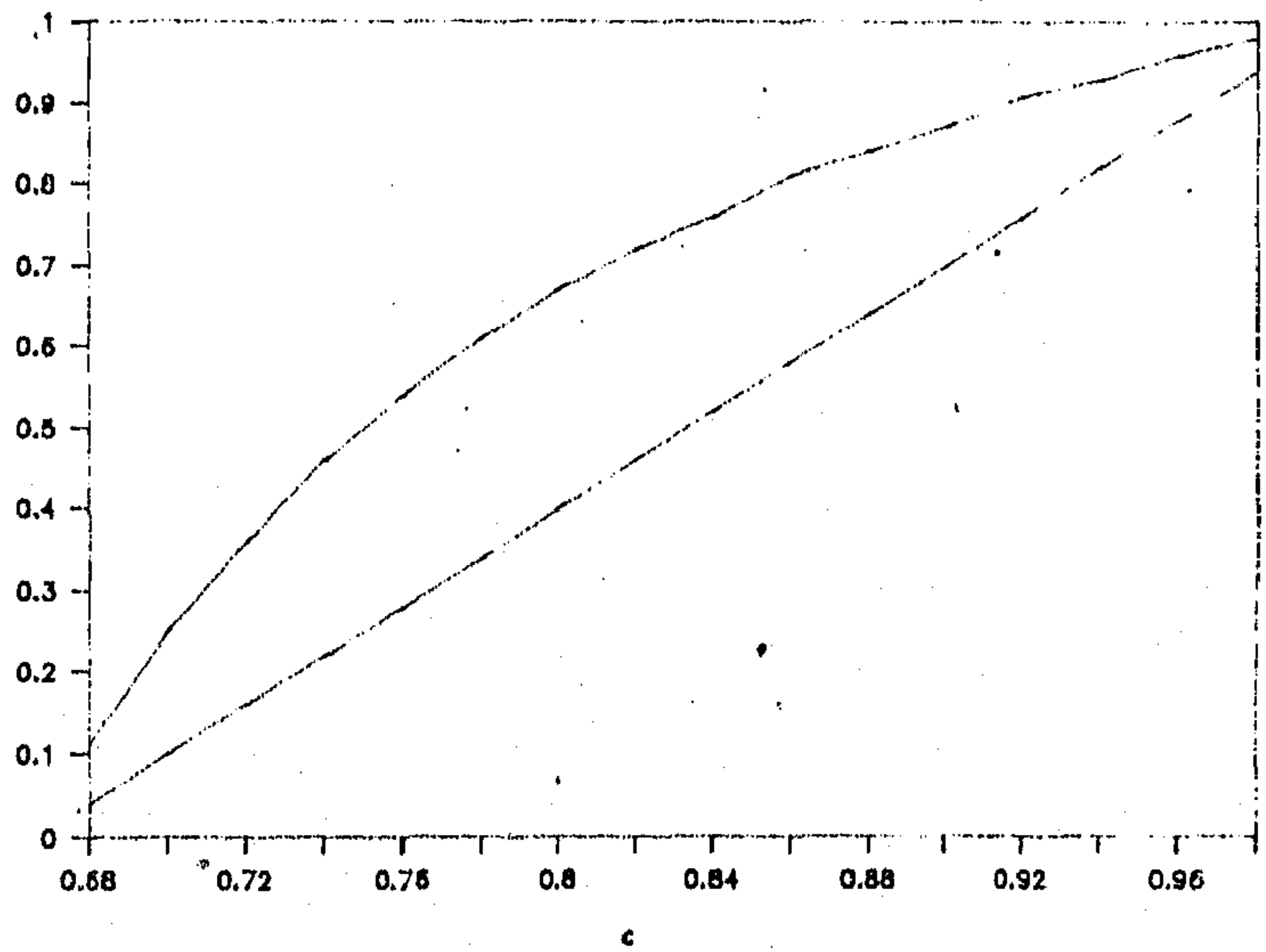


FIG.3.4 c - d GRAPH

[illegible]

3.5(a) INPUT IMAGE

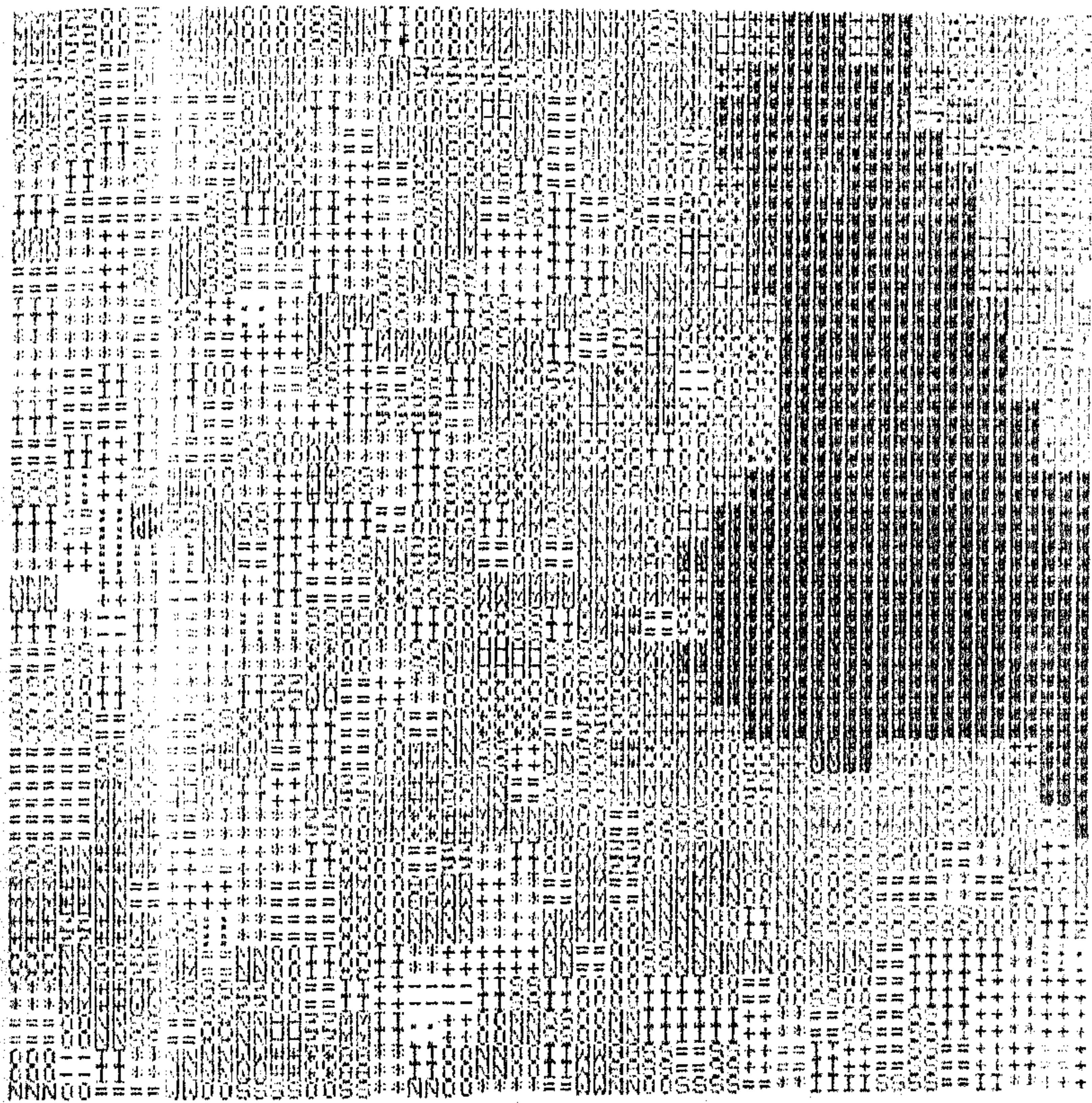
3.5(d) 2X MAGNIFIED IMAGE USING PARAMETRIC BEZIER
TECHNIQUE C = 0.9 D= 0.7

2X MAGNIFIED IMAGE USI
TECHNIQUE C = 0.9 D= 0.7

[The page contains dense, illegible vertical markings resembling noise or corrupted data.]

3.5(f) 2X MAGNIFIED IMAGE USING PARAMETRIC BEZIER
TECHNIQUE C = 0.8 D = 0.67

3.5(g) 2X MAGNIFIED IMAGE USING PARAMETRIC BEZIER
TECHNIQUE C = 0.9 D= 0.87

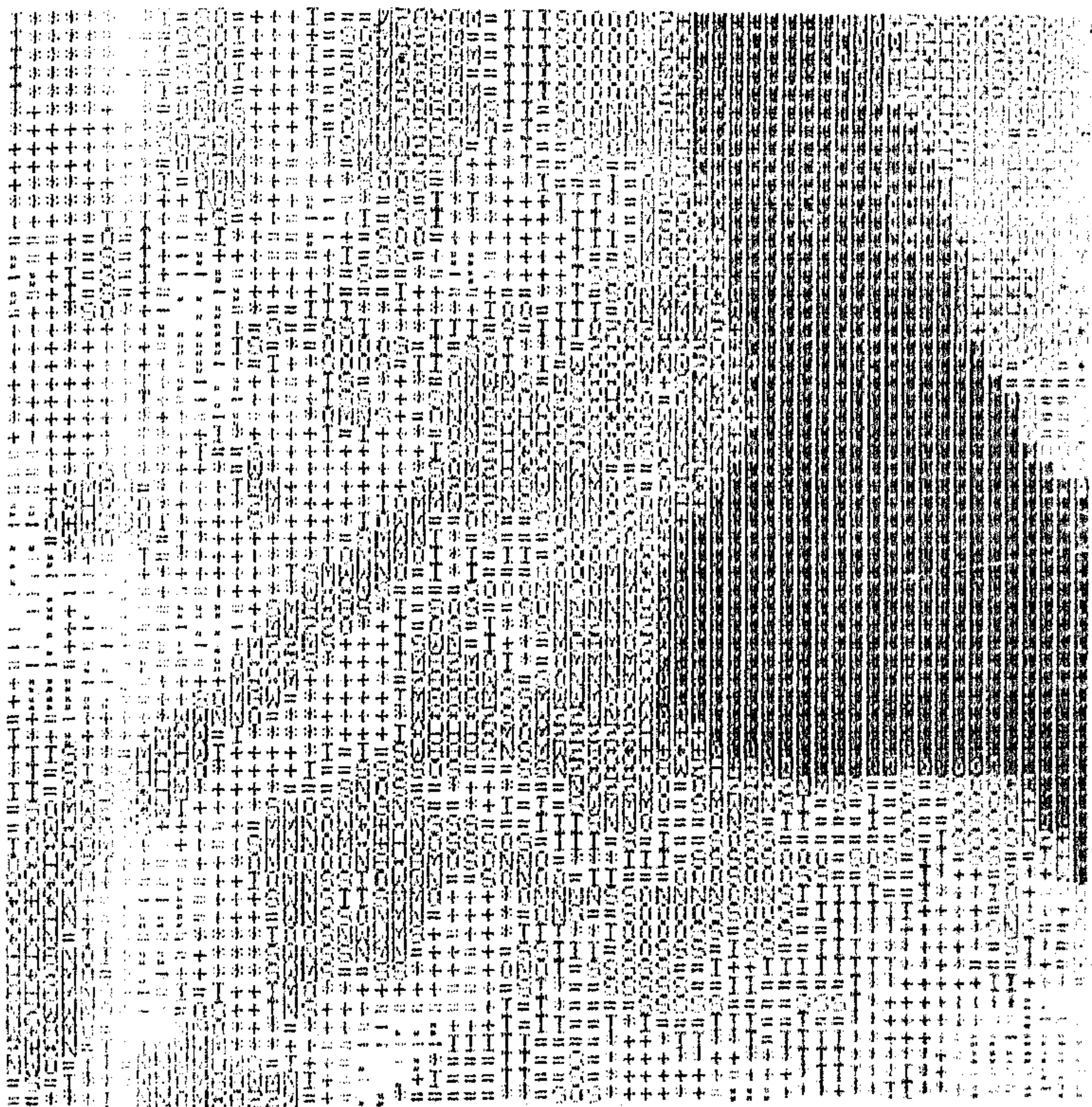


3.5(h) 2X MAGNIFIED IMAGE USING NEAREST NEIGHBOUR
TECHNIQUE

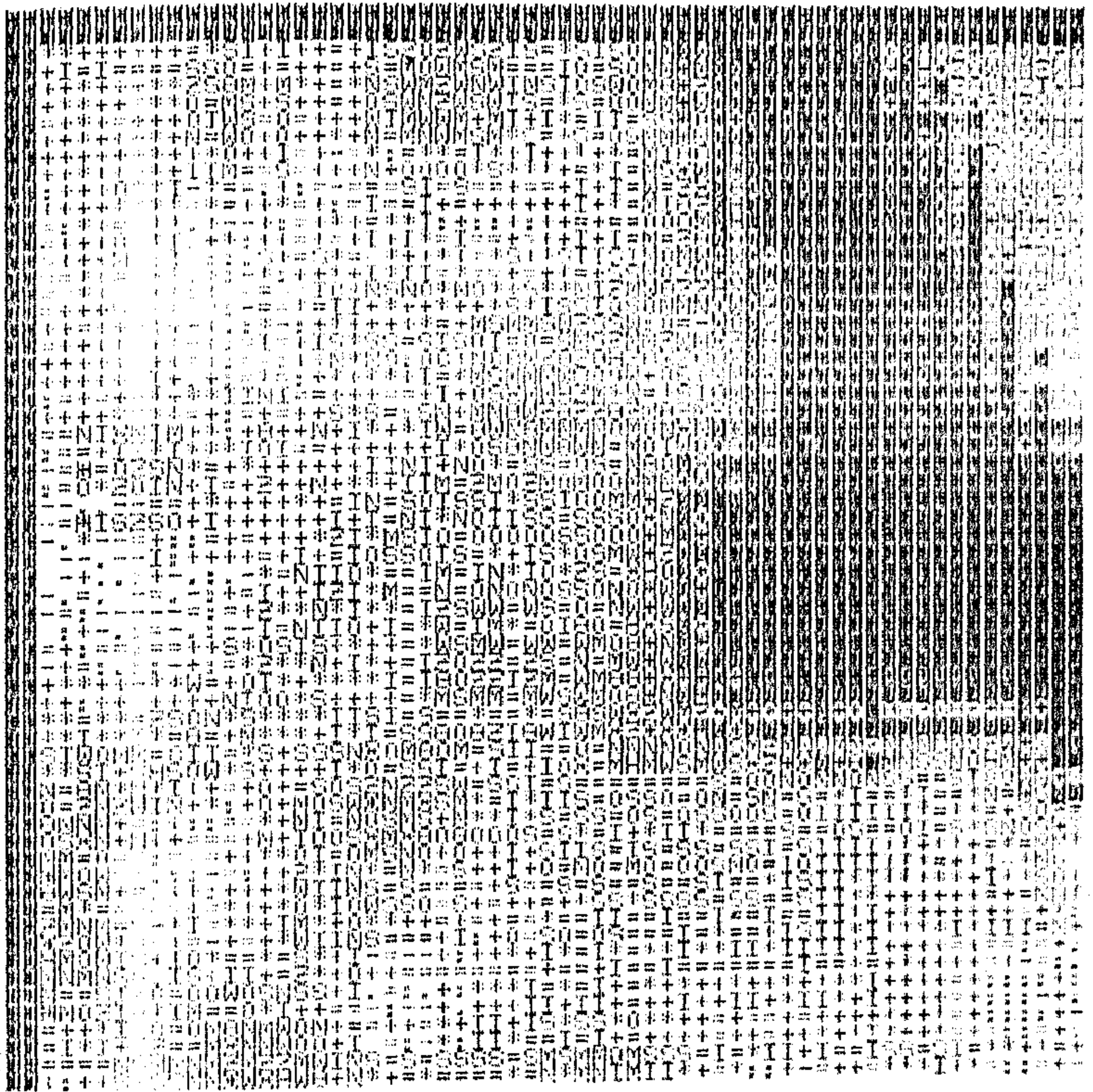


3.5(i)

2X MAGNIFIED IMAGE USING BILINEAR TECHNIQUE

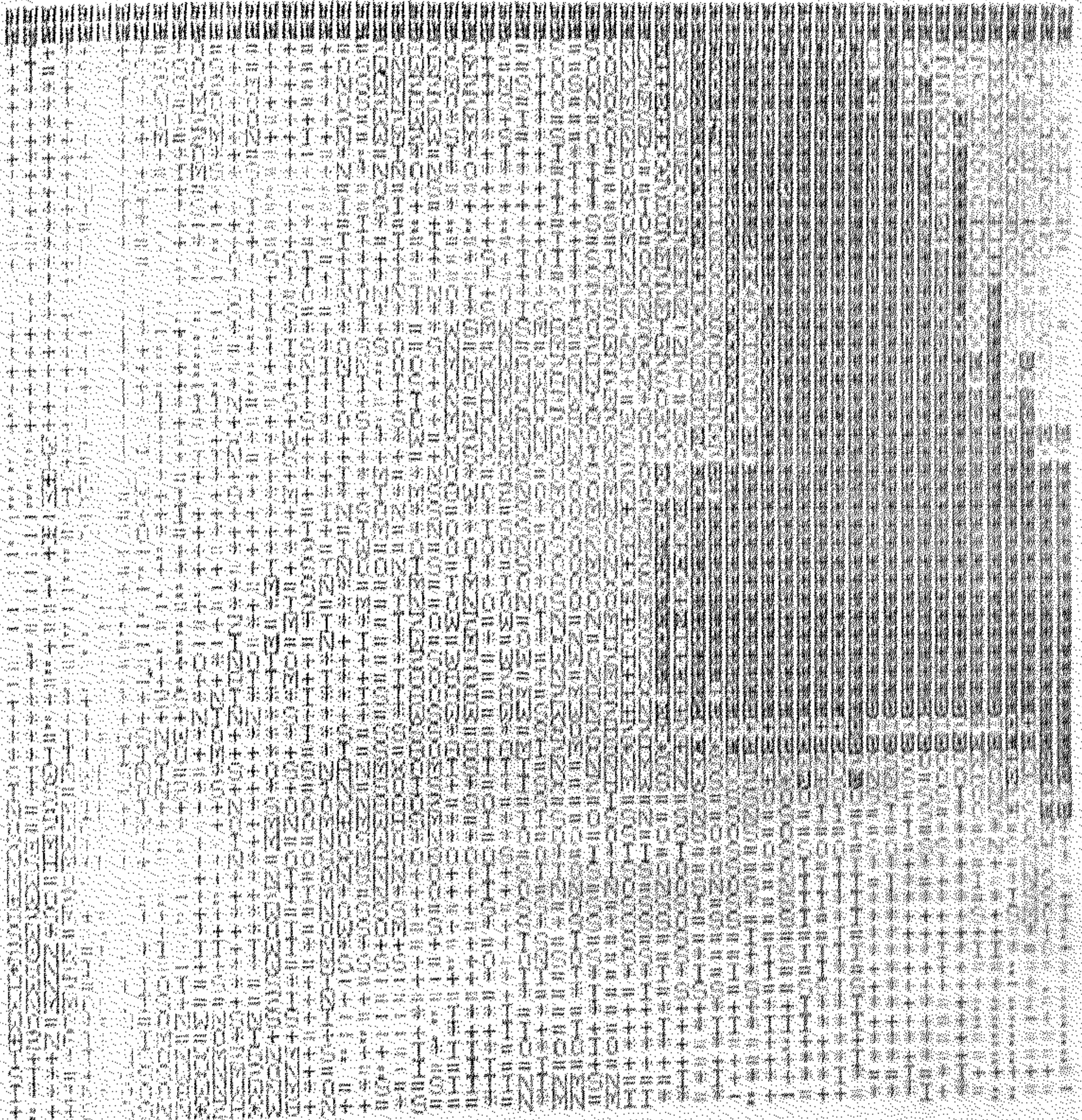


3.5(j) 2X MAGNIFIED IMAGE USING WEIGHTED BILINEAR
TECHNIQUE



3.5(k)

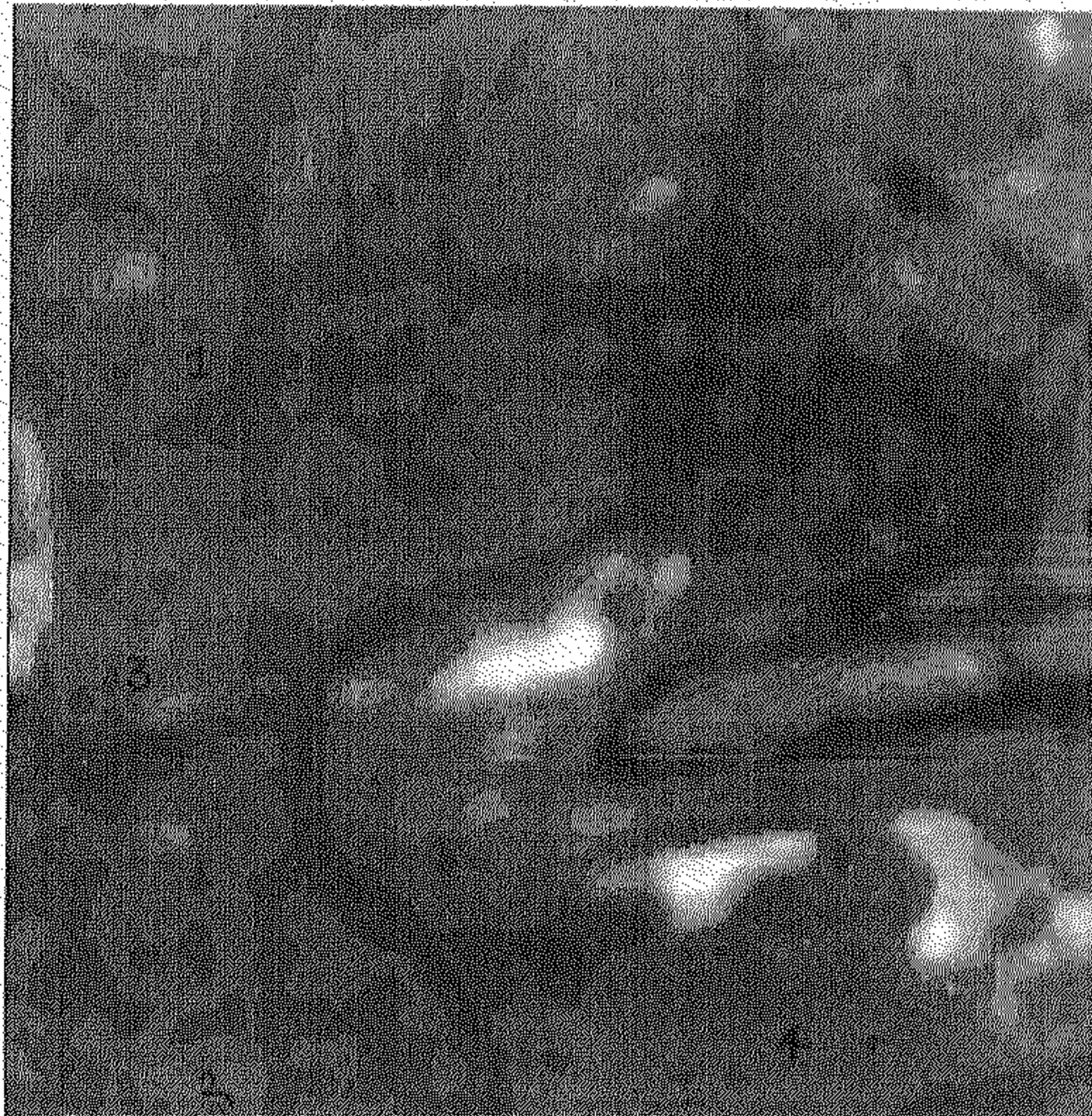
2X MAGNIFIED IMAGE USING BICUBIC TECHNIQUE



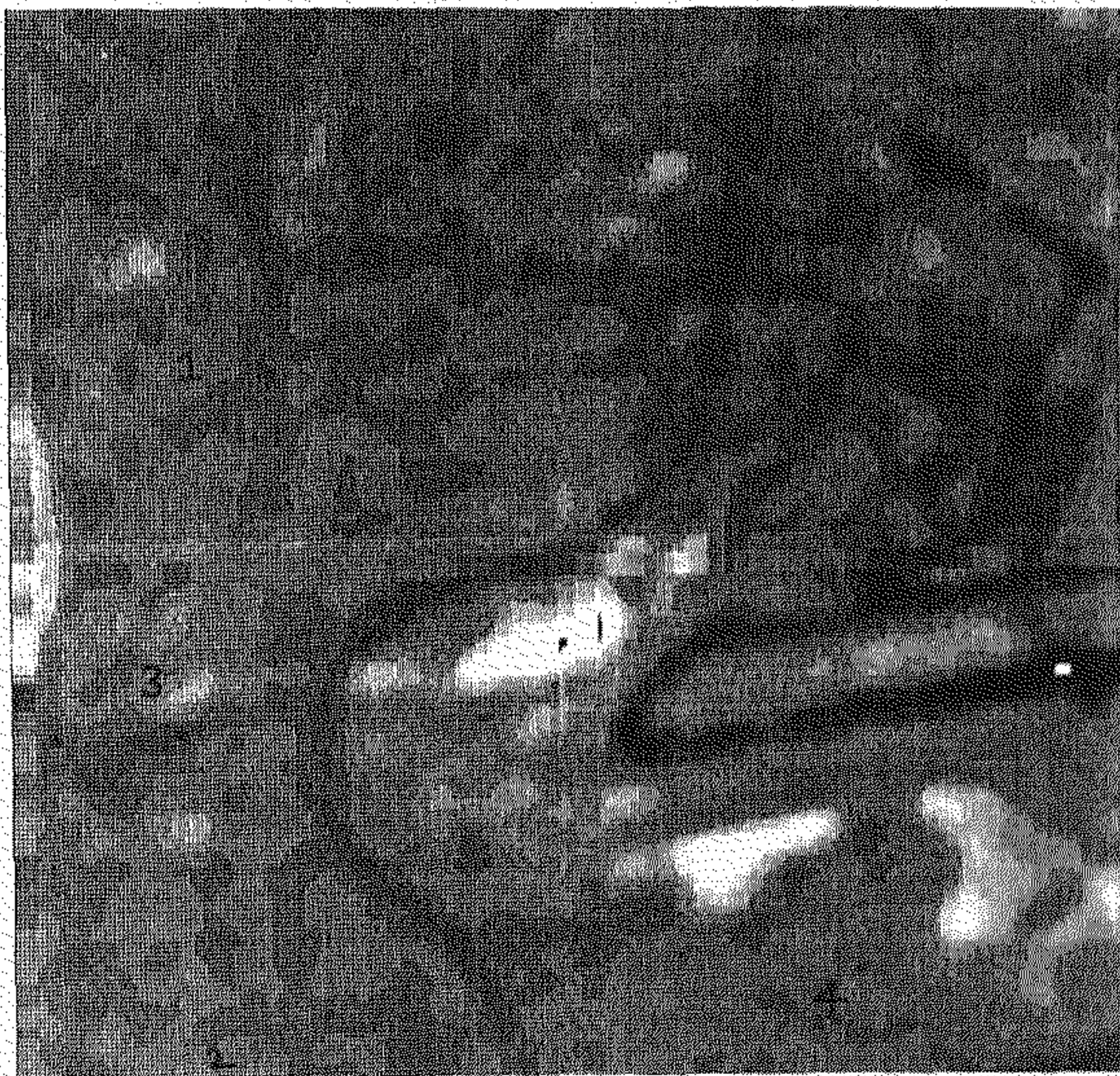
3.5(1) 2X MAGNIFIED IMAGE USING PARAMETRIC BICUBIC
TECHNIQUE



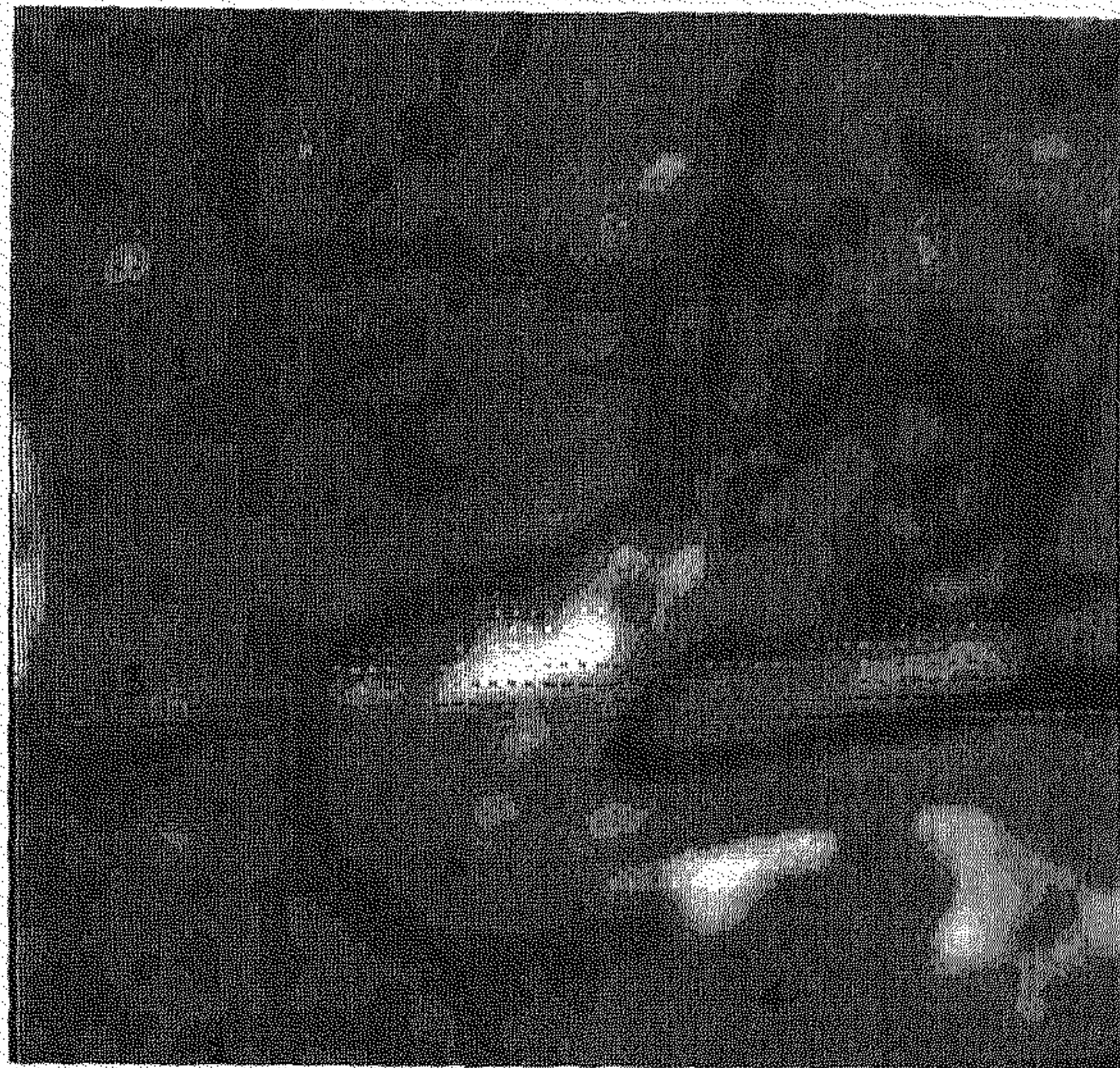
3.6(a) ORIGINAL IMAGE FROM IRS



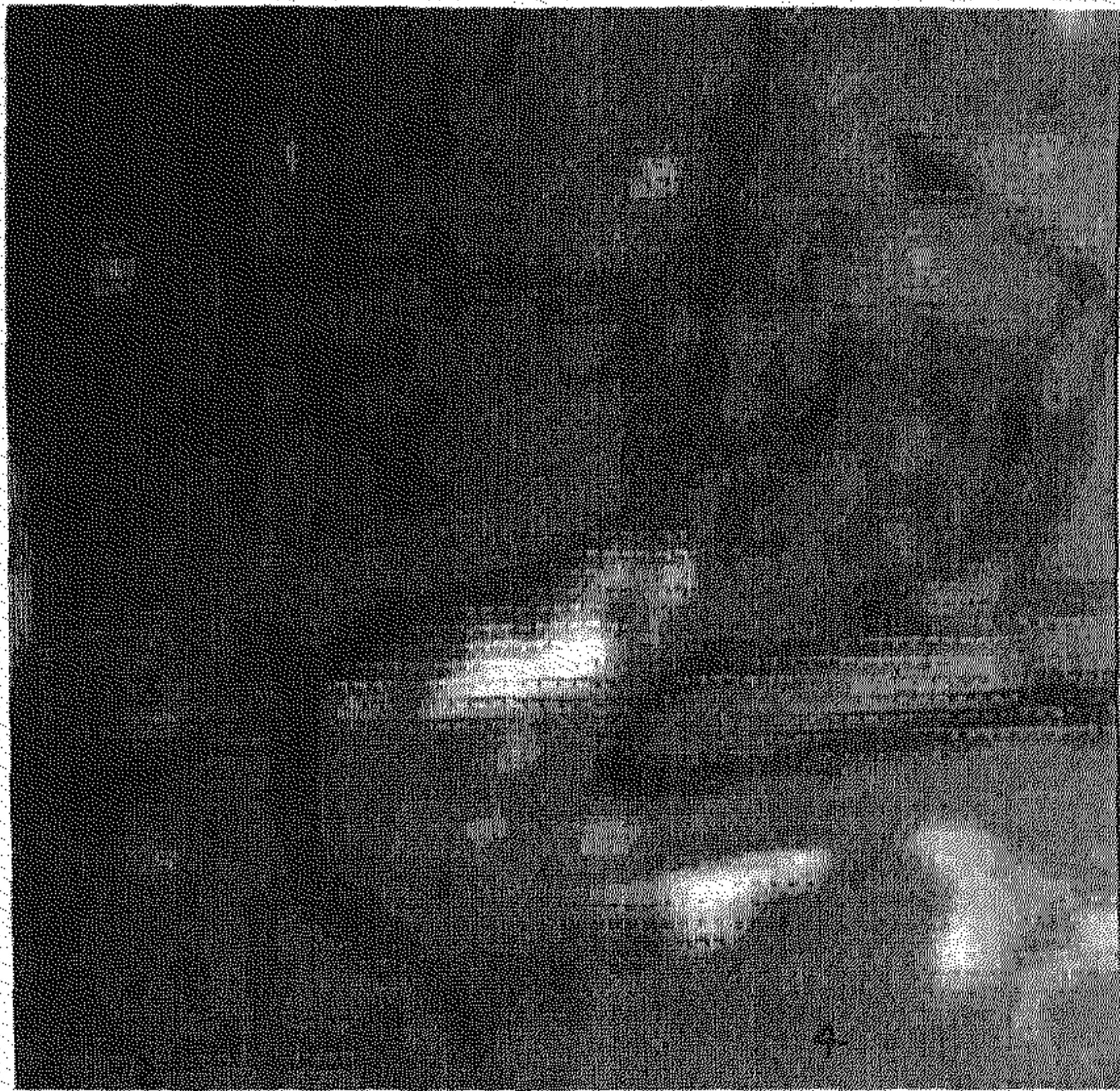
3.0(b) 4X MAGNIFIED IMAGE - BILLINER



1.6(C) 4 MAGNIFIED IMAGE - BICUBIC



3.6 (d) 4x MAGNIFIED IMAGE - PARAMETRIC FILTER
 $C=0.7$ $D=0.1$



3.6(e) 4X MAGNIFIED IMAGE - PARAMETRIC BEZIER
C=0.8 D=0.4



3.6(f) 4X MAGNIFIED IMAGE - PARAMETRIC BEZIER
 $C=0.7$ $D=0.25$



3.6(g) 4X MAGNIFIED IMAGE - PARAMETRIC FEZIED

C=0.9 D=0.88

CHAPTER 4

COMPARISON OF IMAGE MAGNIFICATION TECHNIQUES USING FRACTAL DIMENSIONS

4.1 WHAT ARE FRACTALS

For most naturally occurring phenomenon, as the map scale is increased, more and more variations come into the foreground; there is really no increase in the resolution. This observation noted by Mandelbrot while measuring the length of Britain's coastline length led to the discovery of fractals. Mandelbrot found that as the scale of measurement improved the coastline length kept increasing; it was not possible to give a measure of the length!. It also appeared that the length depended on the nature of the measuring unit. Normally, a line is characterized by its length, a plane by its area, a cube by its volume and associated with these are their dimensions 1, 2 and 3. Thus in order to measure length of any one-dimension figure, we use a measuring unit of size say λ and determine how many such units are covered by the figure. If it is n , then we say that the length of the figure is $n\lambda^1$. Similarly, if we were to measure the area of a two-dimensional figure, we use a square of side $\lambda \times \lambda$ as a measuring unit and count the number of such squares covered by the figure. If this is n , we say that the area of the figure is $n\lambda^2$. In general we have measures given by $n\lambda^D$ for

a D-dimensional shape. Normally we take D to be an integer. Mandelbrot (1977) pointed out that the inconsistency in measuring the length of coastlines arises because of this assumption that D is an integer. He pointed out that the coastline with all its bays and estuaries cannot have a dimension 1 but something between 1 and 2, a fractional dimension. He called sets that do not have an integral dimension as fractal sets.

A fractal curve can be meddled using an initiator _ a straight line _ and a generator which introduces an irregularity into the line (Batty, 1985). This is illustrated in Fig. 4.1. The resulting fractal curve can be described as follows (Burrough, 1986). The length AB in Fig. 4.1 (b) is 4x units when measured with a scale of length x. Suppose that the scale is increased by a factor r=3, additional details will be noted as in fig. 4.1 (c). The length AC will measure 4y units where y is the length of the new scale and the total length AB measured in this new scale will be longer than 4x measured earlier. As r is increased, it will be noted that the length AB increases and yet the nature of variation noted at all scales will be similar. The level of variation present at all scales can be described by a single parameter, the fractal dimension defined as

$$D = \text{Log } N / \text{Log } r$$

where N is the number of steps used to measure a pattern unit length and r is the scale ratio.

This type of modelling can be used in a variety of ways to generate fractal sets of varied forms. However, once we are given a fractal set it will be difficult to resolve it in terms of its generator and initiator. This is necessary to obtain the fractal dimension by the above formula.

4.2 HAUSDORFF- BESICOVITCH DIMENSION (Mandelbrot, 1983)

A fractal set is by definition (Mandelbrot, 1983) a set for which the Hausdorff- Besicovitch dimension (H-B dimension) D strictly exceeds the topological dimension D_T . D is called the fractal dimension of the set.

Rather than use squares for approximating the area of a planar shape S , Caratheodory, suggested the use of discs to extend the ideas of length and area to some non-standard shapes. In general, for a d -dimensional standard shape a summation of terms of the form $h(\rho) = \gamma(d) \rho^d$ gives the measure of the contents of the shape. Here ρ is the radius of the ball used to cover the shape,

$$\gamma(d) = \frac{[\sqrt{(1/2)}]^d}{[1 + d/2]}$$

is the contents of a ball of unit radius.

Hausdorff extended this concept to include fractional values of d to provide a measure for non-standard shapes. Given a test function $h(\delta)$ a finite covering of the set S by balls of radii δ can be said to have the measure $\sum h(\delta_m)$. Here, the function $h(\delta_m)$ is any positive function that tends to 0 with δ_m . The h -measure of a set S is then defined as,

$$\lim_{\delta \rightarrow 0} \inf_{\delta_m < \delta} \sum h(\delta_m)$$

This limit may be either finite and positive, or infinite, or zero. When $h(\delta) = r(d) \delta^d$, the h -measure is called the normalized d -dimensional measure. Besicovitch showed that for every set S there exists a real value D such that the d -measure is infinite for $d < D$ and vanishes for $d > D$. This D is called the Hausdorff-Besicovitch dimension of S .

A fractal dimension D is a single non-integer parameter that intuitively corresponds to an object's degree of roughness or regularity. Linear fractal functions would have D between 1.0 and 2.0. For fractal surfaces D would lie between 2.0 (absolutely smooth) and 3.0 (infinitely crumpled). Fractals have been shown to be a good model of natural surface textures (Pentland, 1985, Kube and Pentland, 1983). It has also been suggested that the fractal dimension can be estimated from a digitized aerial photograph (Loehle, 1983; MacLennan and Howarth, 1987).

4.3 IMAGES AS FRACTAL SETS

Most natural phenomenon can be modelled as fractal Brownian motions (Mandelbrot and Van Ness, 1968). Given a random function $I(x)$, we call it a fractal Brownian function $B_H(x)$ if for all x and Δx ,

$$\Pr \left(\frac{|I(x + \Delta x) - I(x)|}{|\Delta x|^H} < Y \right) = F(Y) \quad (4.1)$$

Where $F(Y)$ is a cumulative distribution function. The quantity H is related to the fractal dimension D of the graph defined by $I(x)$; $D = 2-H$ whenever $I(x)$ is a scalar. For the classical Brownian function $H=1/2$ and $F(Y)$ is a zero-mean Gaussian with unit variance. The above definition can be extended to define a fractal Brownian surface by considering x as a two-dimensional vector. Pentland (1984) has shown that the image of a spatially isotropic fractal Brownian surface is itself a fractal Brownian provided, it is a result of a Lambertian surface reflectance function under constant illumination and albedo. The converse of the above statement is true. Thus, satellite and aerial images can be considered to be fractal Brownian functions and can be used to infer about the nature of the topographic surface whose image it is.

The fractal dimension of a fractal Brownian function is invariant with respect to linear transformations of the data and to transformations of scale. It is this latter feature of fractal dimensions that suggests their suitability as a criterion for comparing the performances of different interpolation techniques for image magnification. In addition, fractal Brownian functions satisfy what is called a T^H law. (Keller et al., 1987). According to this law the standard deviations of increments of a fractal Brownian motion $B_H(t)$ is proportional to T^H where T is the lag between two points. Mathematically,

$$\sigma [B_H (t + T) - B_H (t)] = C_H T^H$$

$$\text{Or } \{ E [I (t) - I (t + T)]^2 \}^{1/2} = C_H T^H \text{ ----4.2}$$

Where, C_H is constant.

The interesting aspect of the above law is its relation to the semivariogram which is defined as,

$$2 = E [I (t) - I (t + T)]^2 \text{ -----4.3}$$

From (4.2) we get, $2 \sqrt{\gamma} \propto T^{2H}$

For a fractal Brownian function then if we plot $\log T$ against $\log \gamma$, we will get a straight line. Curran (1988) has obtained the semivariograms for different surfaces from their aerial images showing that the relation is linear up to a lag of 15m. This indicates the suitability of the fractal

model for these images.

4.4 CRITERION BASED ON FRACTAL DIMENSION

The fractal dimension of an image is an indicator of surface roughness. The closer the fractal dimension of an image is to its topological dimension, the smoother the surface. The fact that the fractal dimension is invariant to scale changes, suggests that the fractal dimension, of a magnified image must be no different from that of the original image (Dutta Majumder and Lalitha). This implies that a technique used for digitally magnifying an image should leave the fractal dimension of the original image intact. This provides a basis for comparing the performances of different image magnification techniques-this approach is particularly attractive since the fractal dimension of an image is data structure dependent. The efficacy of a technique can be studied by noting up to what scale of magnification, the technique preserves the fractal dimension of the original image. Many approaches for estimating the fractal dimension of an image have been suggested and we describe the technique based on the power spectrum of an image. Dubuc et al (1989) have compared the various algorithms for the estimation of fractal dimension and point out that although all the techniques are equivalent in continuous domain, they differ substantially when applied to digitized data.

4.5 ESTIMATION OF FRACTAL DIMENSION

The T^H law provides a method for estimating the fractal dimension D of an image. By estimating the semivariograms for different lags T and regressing $\log T$ on $\log H$, H can be estimated and then D . The semivariogram can be obtained at different orientations for various lags.

Pentland (1984) suggests a frequency approach for estimating the fractal dimension. The spectral density $p(f)$ of a fractal Brownian function is proportional to $f^{-2(2-D)-1}$, where D is the fractal dimension. By regressing $p(f)$, the parameter D can be estimated. Rather than considering the entire image, the fractal dimension can be estimated for every 8×8 block considering it as a scalar. We will thus get a distribution of fractal dimensions for an image.

In using the fractal dimension as a criterion to compare different interpolation techniques, we shall be obtaining the frequency distribution of fractal dimensions of the original image and the magnified images. The equality of this frequency distribution of the original image and the magnified image is tested by Kolmogorov-Smirnov two sample test (Rohatgi, 1985). The magnification factor for which the test is rejected is then recorded for different techniques. Results of applying this method to two sets of subscenes from

satellite images are discussed in the following section (Lalitha and Dutta Majumder, 1989).

4.6 EXPERIMENTAL RESULTS

Two subscenes of Landsat TM image (Fig 4.2, 4.3) of size 32 X 32 are magnified using nearest neighbour, bilinear, bicubic interpolation, weighted bilinear and parametric Bezier techniques up to eight times the original size. The fractal dimension of every 8 X 8 blocks was obtained in all the images. The mean fractal dimension of the images at different scales of magnification are shown in Fig 4.4. It is seen that the mean fractal dimension of the images magnified by bicubic interpolation is outside the $\pm 1\sigma$ limits of the fractal dimension of the original image. The mean fractal dimension of the image magnified by other techniques are within $\pm 1\sigma$ limit up to 4X magnification. In Fig 4.5 and 4.6 are shown the frequency distribution of the fractal dimensions typically at scales 2X and 8X obtained from images magnified using different techniques.

The results of applying the Kolmogorov - Smirnov test to the frequency distributions are summarized in Table 4.1. In Image 1, the nearest neighbour and bilinear interpolation techniques perform identically. In fact there is no evidence to reject the hypothesis of equal frequency distributions up

to 4X magnification factor with any of the techniques except the Parametric Bezier. In the case of Image 2, bilinear and weighted bilinear are adequate up to 8X magnification; nearest neighbour is suitable up to 6X magnification factor. Image 2 is more interesting in that it has some distinct regions and it is important that these regions are retained after magnification. The frequency distribution of fractal dimensions of images magnified by standard bicubic interpolation is significantly different from that of the original image even at 2X magnification. This is probably because the bicubic interpolation modifies the original radiometric values much more than the other techniques. To ascertain the performance at individual blocks, the fractal dimensions were investigated for blocks 3 and 8 in image 2. The fractal dimensions of the two blocks were 1.37 and 1.5 respectively. It was noted that for block 8 all the techniques performed equally well. For block 3, only bilinear technique preserved the original fractal dimension of the block even at 8X magnification factor. All other techniques preserved it only up to 4X magnification.

4.7 CONCLUSION

In this chapter a criterion based on the fractal dimension of an image is proposed for comparing the performances of different magnification techniques. The scale invariant

property of fractal dimension enables us to test up to what scale of magnification a technique preserves the fractal dimension of the original image in the magnified image. Results of applying this criterion on subscenes of Landsat image showed that the fractal dimensions of the magnified images using bicubic interpolation are quite different from those magnified by other techniques. Simple techniques such as nearest neighbour and bilinear interpolations preserve the fractal dimension of an image up to 8X magnification factor. This suggests that these techniques do not generally modify the grey values of the original image even at large magnifications. However, it is well known that a nearest neighbour magnified image is not visually appealing for large scaling factors. If image magnification is being carried out to produce a final product, then the visual clarity of the output image will be important. In this case bicubic interpolation technique as well as the parametric bezier interpolation could be used. If image magnification is carried out as a pre-processing task, then it is important to ensure that grey values are not modified too much; the simpler techniques will then be a better choice.

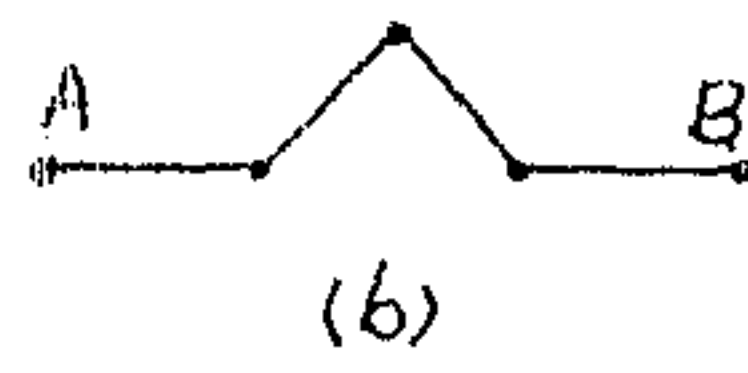
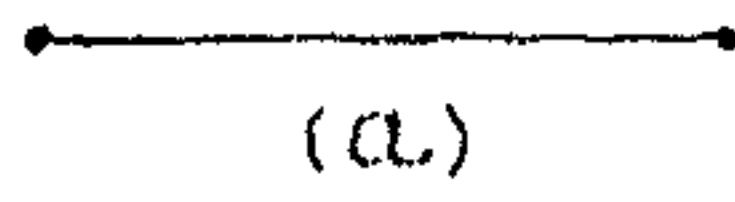
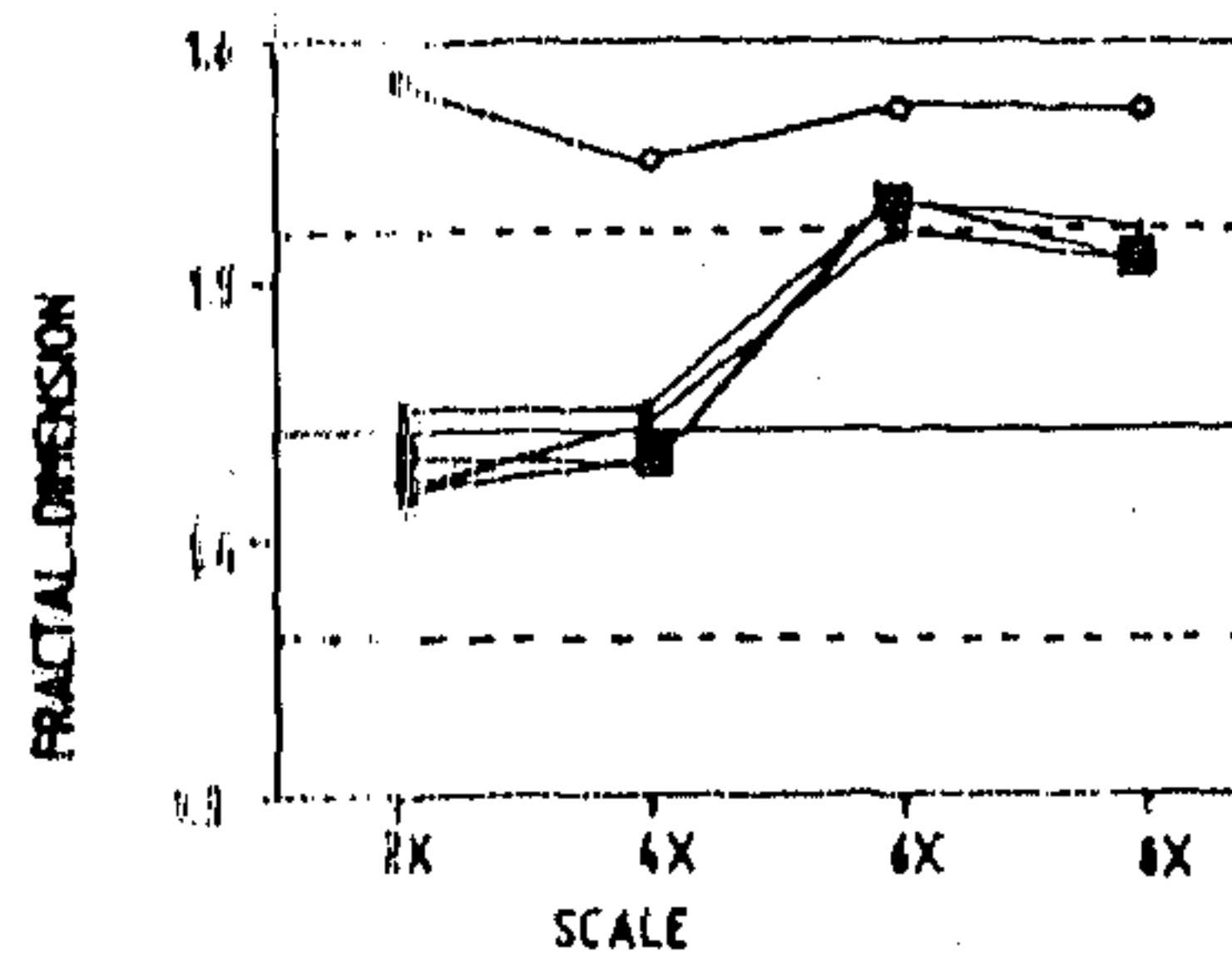
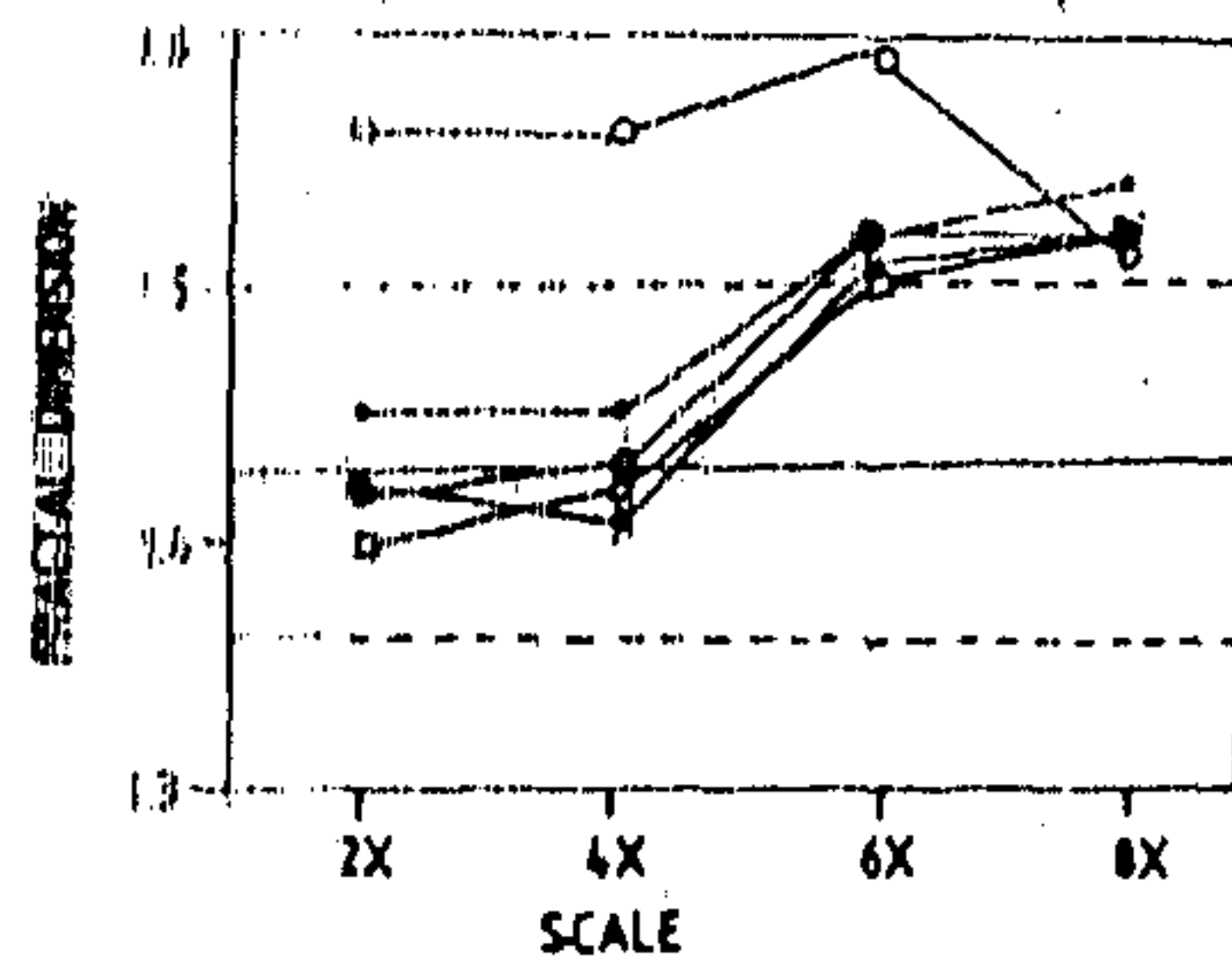


FIG.4.1 A MODEL OF A FRACTAL CURVE



(a) IMAGE 1



(b) IMAGE 2

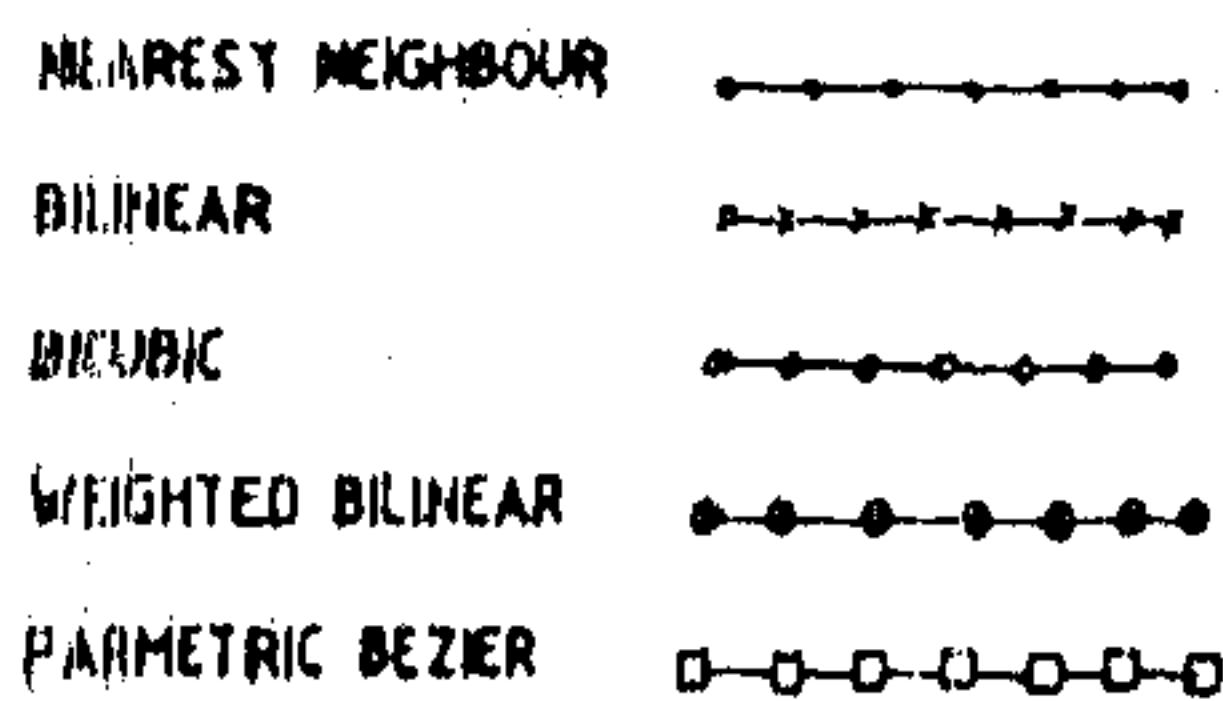


FIG.4.4 MEAN FRACTAL DIMENSION AFTER MAGNIFICATION

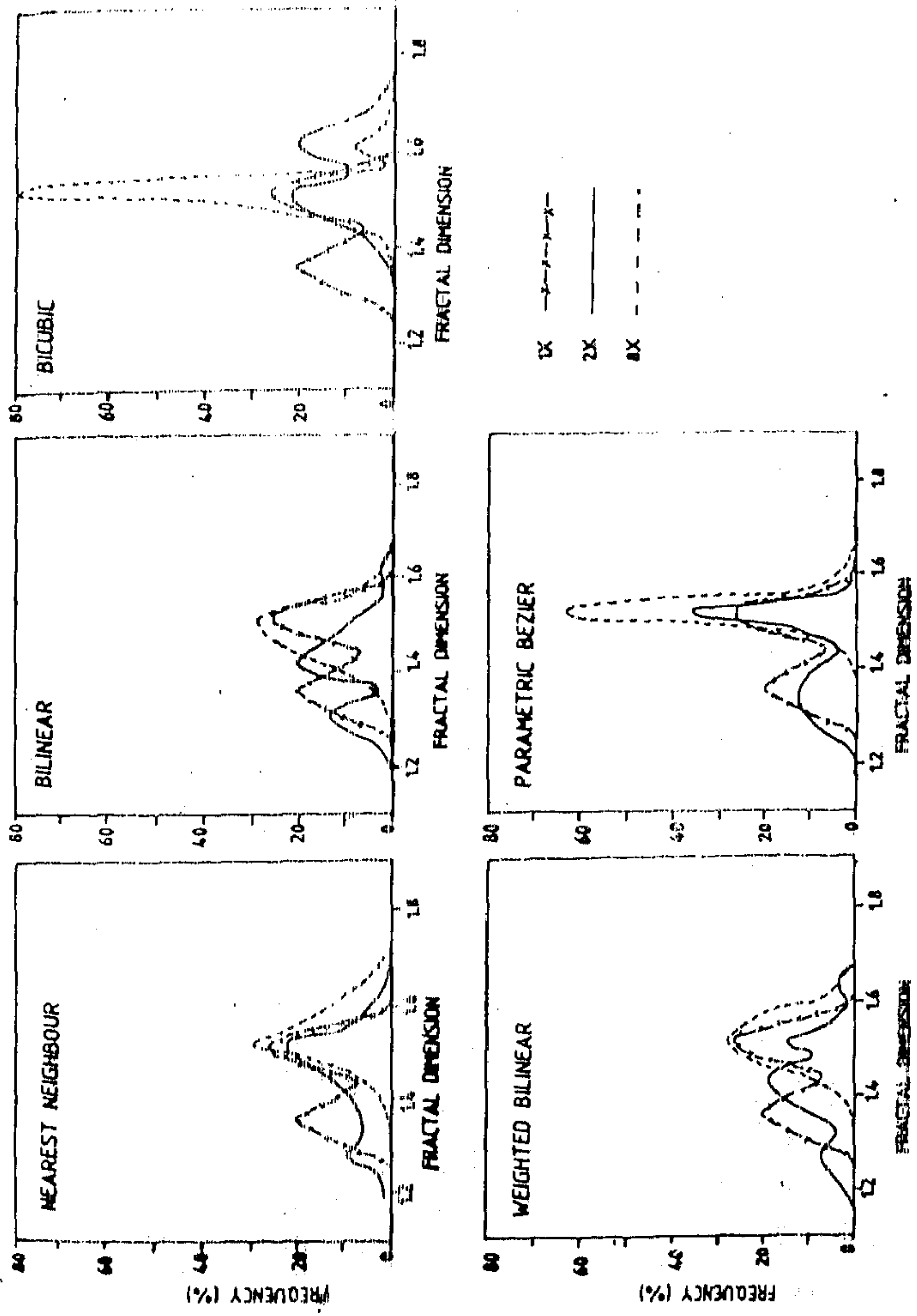


FIG.4.5 FREQUENCY DISTRIBUTION OF FRACTAL DIMENSION AFTER MAGNIFICATION OF IMAGE 1

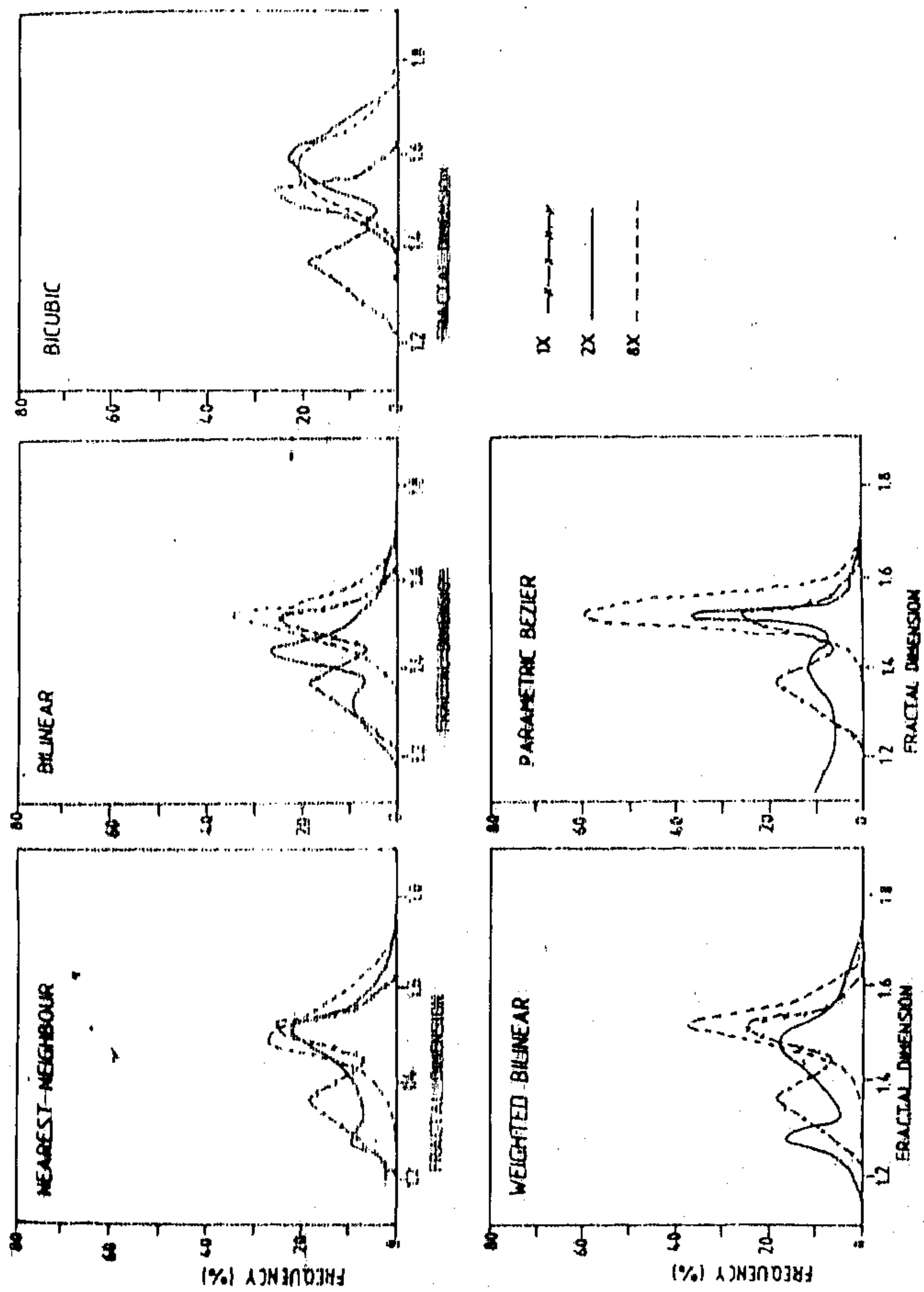


FIG. 4.5 FREQUENCY DISTRIBUTION OF FRACTAL DIMENSION AFTER MAGNIFICATION OF IMAGE 2

TABLE 4.1(a) Results of Kolmogorov-Smirnov test on Image 1

Method	Magnification Scale			
	2x	4x	6x	8x
Nearest Neighbour	A	A	R	R
Bilinear	A	A	R	R
Bicubic	R	A	R	R
Weighted bilinear	A	A	R	R
Parametric Bezier	A	R	R	R

A - Accepted at 5% level

R - Rejected at 5% level

TABLE 4.1(b) Result of Kolmogorov-Smirnov test on Image 2

Magnification Scale

Method	2x	4x	6x	8x
Nearest Neighbour	A	A	A	R
Bilinear	A	A	A	A
Bicubic	R	R	R	R
Weighted bilinear	A	A	A	A
Parametric Bezier	A	A	R	R

A - Accepted at 5% level

R - Rejected at 5% level

CHAPTER 5

LINEAR FEATURE DETECTION

5.1 INTRODUCTION

Multi-source satellite data having different scales can be brought to a common scale by magnifying the coarse resolution data sets to a scale equivalent to the data set having the maximum resolution. In the previous chapters we discussed the problem of image magnification as an image reconstruction problem; surface interpolation techniques to be used for reconstructing the image. An interactive surface interpolation technique was proposed for magnifying images. Fractal dimension criterion could be used to decide the suitability of a particular magnification technique for a given data set.

Once the images are brought to a common scale they have to be processed to extract information. Image analysis can be considered as a process of image abstraction. Since it is difficult to integrate the radiometric values from multi-source satellite data, segmented image outputs from each data set can be combined. Although it is not necessary to bring the images to a common scale for this purpose, image magnification sometimes helps in interpretation.

The objective of image segmentation is to generate segments

which correspond to objects in an image. If we know the geometric characteristics of an object, we can design a mask or template of the object and compare the input image at every pixel with the mask. If the matching is perfect in any region of the image, then in principle, the object is located. The implementation of this approach is rather involved. If on the other hand, the shape of an object is known, then some shape detection algorithm (Parui, 1984) can be applied. Another approach to image segmentation which is suitable for syntactic pattern recognition is to extract features such as edges, arcs, curves from an image. These can be used as primitives for subsequent syntactic processing.

Extraction of primitives from images is an important task in image processing. Linear features are attractive primitives particularly while processing satellite images. In geology lineaments express the zones of weakness or structural displacement in the crust of the earth. A lineament is defined as a "mappable simple or composite linear feature of a surface, whose parts are aligned in a straight or slightly curving relationship, and which differs distinctly from the patterns of adjacent features and presumably reflects a subsurface phenomenon" (Sabins, 1978). The other linear features that occur in a satellite image are roads, rails, canals and river courses. The linearity of a feature depends to quite an extent on the scale of observation. Ideally, a

linear feature must have one pixel width. Thus in satellite images, roads, rails and canals can be expected to be linear while in aerial images, the same roads appear like a region. Similarly some river courses have a single pixel width while there may be occasions when they are as much as 10 pixels wide.

The spectral channels and the time of observation also dictate the appearance of a linear feature in a satellite image. A road for instance, will not be visible in all bands. The background on either side of a road will either aid or hinder its detection. Thus, a road with barren soil on either side may be clearly picked up by a sensor operating in the region 0.7-0.8 μ m and would be missed if there are built up areas on both sides. If the features on both sides of the road are dynamic, then the road may appear only when the contrast between the grey values of a road and its background are significant. This is true of any linear feature.

A clear cut distinction between edges and linear features exist; often though edge detection algorithms have been used to detect both edges and lines. This happens because at high resolutions, linear features appear like a region. An edge refers to the boundary between two adjacent components in an image. Along this boundary the grey value distributions similar to one of the components. On the other hand, along a

linear feature, the grey value distribution is uniform and the grey value distribution on either side are also generally identical. In extracting edges, we are inherently trying to extract the homogeneous regions while in extracting linear features, we primarily concentrate on the linearity of the feature.

In this chapter we present the geometric description of a linear feature and some definitions that are a prerequisite for subsequent presentation. We then review some of the existing techniques of linear feature detection and describe the template based techniques in a little more detail. A new technique for linear feature detection will be described in the next chapter.

5.2 DEFINITIONS

FIRST ORDER NEIGHBOURS

For a pixel (X,Y) a pixel (u,v) is its first order neighbour if $\max(|X-u|, |Y-v|) = 1$. A pixel (X,Y) has two types of first order neighbours characterized as follows-

$$(i) \quad |X-u| + |Y-v| = 1$$

$$(ii) \quad |X-u| = |Y-v| = 1$$

Those neighbours that satisfy (i) are called 4-neighbours and those that satisfy (i) and (ii) are together known as 8-neighbours of (X,Y) . Fig 5.1 shows the first order neighbours

of the center pixel R. Here, the pixels A, C, E and G are 4-neighbours of R and A, B, C, D, E, F, G, H are 8-neighbours of R.

SECOND ORDER NEIGHBOURS

For a pixel (X, Y) , a pixel (u, v) is its second order neighbour if

$$\max (|X-u|, |Y-v|) \leq 2$$

A pixel has three types of second order neighbours characterized as follows-

$$(i) |X-u| + |Y-v| = 2$$

$$(ii) |X-u| + |Y-v| = 3$$

$$(iii) |X-u| = |Y-v| = 2$$

If (i) is satisfied (u, v) is a second order 4-neighbour, if (i) and (iii) are satisfied then (u, v) is a second order 8-neighbour of (X, Y) and if (ii) is satisfied (u, v) is a 4-8 or 8-4 neighbour of (X, Y) . In Fig. 5.2, A, E, J and M are the second order 4-neighbours, A, C, E, G, I, K, M, O are the second order 8-neighbours and B, D, F, H, J, L, N, P are the 4-8 neighbours of R.

Note that a pixel has eight first order neighbours and sixteen second order neighbours.

PATH

A set of pixels $P_0, P_1, \dots, P_n$ defines a path if P_{i-1} is a first order neighbour of P_i for $1 \leq i \leq n$.

BINARY IMAGE

A particular case of a digital image wherein the pixels assume grey values either 0 or 1. The image contains just an object and background.

In Fig 5.3 the pixel (1,1) is a first order neighbour to (2,2) and the sequence of pixels ((1,1), (2,2), (3,3), (4,3), (5,3)) define a path. The pixel (3,5) has no first order neighbour and is called an isolated pixel.

Any two pixels P and Q are said to be connected if there exists a path from P to Q. This connectivity relation is an equivalence relation and the equivalence classes under this relation are the connected components. Rosenfeld (1979) gives the definition of digital arc and digital closed curve based on first order neighbours as follows.

DIGITAL ARC

A set S of connected pixels $P_0, P_1, P_2, \dots, P_n$ of an image I is an arc if all but two points of S have exactly two neighbours in S and those two have exactly one.

DIGITAL CLOSED CURVE

A set S of connected pixels $P_0, P_1, \dots, P_n$ of an image I is a closed curve if every point of S has exactly two neighbours in S.

The above definitions consider only the immediate neighbours of an arc pixel. Thus, the sequence (5,2), (4,2), (3,3), (2,3) in Fig 5.4 defines an arc, but if we include (2,4), then the sequence will not be a digital arc.

Extraction of linear features from an image requires two steps -(i) Detection of pixels that belong to a linear feature and (ii) building up the linear feature from these detected pixels. The detection can be done either as a local operation or a global one. Local methods of line pixel detection apart from being simple allows parallel implementation, thus ensuring speed. Global methods on the other hand, have a better handle on noisy images. We will now briefly review the local and global techniques of line detection.

5.3 LOCAL METHODS OF LINE DETECTION

Local methods of line detection employ templates that are of size 3 x 3 or 5 x 5 which are operated over the image. The resulting response is analyzed to decide whether the pixel corresponding to the center of the template belongs to a linear feature or not. Of these, linear detector designed by Prewitt (Rosenfeld, 1982), non-linear detector of Rosenfeld and Thurston(1971) and the semi-linear detector of Vanderbrug (1975,1976) are important. Frei and Chen (1977) designed templates to detect edges, lines and points in an

image. A rule based line detector proposed by Paton (1979) is also a local method for line detection.

5.31 PREWITT LINEAR DETECTOR

Prewitt designed the following 3 x 3 template to detect dark vertical lines amidst a light background.

-1/2	1	1/2
-1/2	1	1/2
-1/2	1	1/2

The template is moved from pixel to pixel through the image and the response at every pixel recorded. The pixels that have a response greater than a threshold T are labeled as line pixels.

Examples 5.1

Let A denote a sub-image with a vertical line.

	b	b	b	a	b	b	b
	b	b	b	a	b	b	b
	b	b	b	a	b	b	b
A:	b	b	b	a	b	b	b
	b	b	b	a	b	b	b
	b	b	b	a	b	b	b

The response obtained by operating the Prewitt operator on A

is,

$$R(A) = \begin{bmatrix} -3/2 (a+b) & 3a & 3/2 (3b-a) \\ -3/2 (a+b) & 3a & 3/2 (3b-a) \\ -3/2 (a+b) & 3a & 3/2 (3b-a) \end{bmatrix}$$

When $a > b$, the response of these line pixels will be the maximum. Thus the threshold can be set as $T = (\text{max response} - 1)$

Example 5.2

Suppose that in the same image, there is a region that has grey values identical with the line grey values as shown below:-

```

      a   a   a   b   b   b
      a   a   a   b   b   b
      a   a   a   b   b   b
B:    a   a   a   b   b   b
      a   a   a   b   b   b
      a   a   a   b   b   b

```

Notice that there is a vertical edge between the two regions spanned by the a's and b's. The response of the Prewitt

operator on B will be -

$$\begin{array}{rcccc}
 & -3a & 1/2(3b - a) & 3/2(3b - a) & 3b \\
 R(B) : & -3a & 1/2(3b - a) & 3/2(3b - a) & 3b \\
 & -3a & 1/2(3b - a) & 3/2(3b - a) & 3b \\
 & -3a & 1/2(3b - a) & 3/2(3b - a) & 3b
 \end{array}$$

If the responses were to be thresholded with 'T' defined as in Example 1, then a portion of the region having grey values 'a' get detected as line pixels,

Example 3.

Consider a sub-image C, consisting of an isolated pixel with gray value 'a' surrounded by background grey values b.

$$\begin{array}{ccccc}
 b & b & b & b & b \\
 b & b & b & b & b \\
 C: & b & b & a & b & b \\
 b & b & b & b & b \\
 b & b & b & b & b
 \end{array}$$

The response of the prewitt operator in this case will be,

$$\begin{array}{r}
 -1/2 (5b + a) \quad 2b + a \quad 1/2 (5b - a) \\
 R(C) : \quad -1/2 (5b + a) \quad 2b + a \quad 1/2 (5b - a) \\
 -1/2 (5b + a) \quad 2b + a \quad 1/2 (5b - a)
 \end{array}$$

In this case, the threshold T defined as in Example 1, will not allow isolated pixels to be picked up as line pixels. To conclude, the Prewitt operator responds to vertical lines in an image as well as regions having grey values same as the line pixels. It does not respond to isolated pixels.

5.32 ROSENFELD'S NON-LINEAR DETECTOR

The non-linear detector requires that line pixels have a grey value greater than it across the line. Thus in a 3 x 3 neighbourhood, if the grey value distribution is,

$$\begin{array}{ccc}
 a & b & c \\
 d & e & f \\
 g & h & i
 \end{array}$$

with $b > a$ and $b > c$

$e > d$ and $e > f$

$h > g$ and $h > i$

then the central pixel is detected as a line pixel. Unlike

the linear detector it will be seen that, this detector will not respond to edges.

5.33 VANDERBRUG'S SEMILINEAR DETECTOR

To detect a vertical line, Vanderbrug suggests the following strategy. The average grey value along the line must be greater than the average grey value on both sides of the line considered separately. That is, in the 3 x 3 neighbourhood considered earlier for the non linear detector,

$$b + e + h > a + d + e \quad \text{and}$$

$$b + e + h > c + f + i$$

In this case the vertical lines get definitely detected. Regions having grey values identical to the line pixels are however, ignored as they should be. But it is possible that a few isolated pixels may be detected as a line pixel.

An image can have linear features oriented in different directions. In particular over a 3 x 3 neighbourhood, one can expect lines to occur in eight directions. Vanderbrug (1976) has suggested 14 templates to detect lines of all orientation (See Fig. 5.5) In the figure the set of b's represent a line. The maximum of the response obtained by operating the 14 templates is then taken as the response at a pixel.

5.34 FREI AND CHEN OPERATORS

A set of orthogonal templates to detect lines, edges and points simultaneously was developed by Frei and chen (1977) For a 3 x 3 neighbourhood the templates proposed by them are shown in Fig. 5.6. The first four masks are suitable for edges; the second set for lines; and the last template is added to complete the basis.

Let r_e , r_l , r_0 denote the root mean square responses of the edge templates, line templates and the average template respectively and r the root mean square response of all the templates. Then the orientations are defined as,

$$\theta_e = \cos^{-1} r_e/r$$

$$\theta_l = \cos^{-1} r_l/r$$

$$\theta_0 = \cos^{-1} r_0/r$$

If $\theta_e < \theta_l, \theta_0$, then we say that the corresponding pixel has more of edge characteristics. If $\theta_l < \theta_e, \theta_0$ then we say that the corresponding pixel has more of line characteristics and if $\theta_0 < \theta_e, \theta_l$, the pixel is probably part of a region. A threshold T can be defined to decide whether the differences among θ_e , θ_l and θ_0 are significant to warrant classifying the pixel as an edge or a line pixel.

5.35 PATON'S LINE DETECTOR

Paton (1979) proposes eight templates that operate on a 9×9 neighbourhood to detect lines. The technique is capable of detecting line segments in an image that are of varying widths in the presence of noise. The method proposed consists of a set S of sampling configurations, a rule E for evaluating the evidence for a line segment in a single direction, and a rule C for comparing the evidence for line segments in different directions.

5.36 OTHER METHODS

Nevatia and Babu (1980) use edge detection templates to extract linear features. Their approach is to determine edge magnitude and direction by convolution with a number of edge masks; thinning and thresholding these edge magnitudes and then linking the edge elements based on proximity and orientation. Finally, the linked elements are approximated to define piecewise linear segments.

Recently, Chen and Tsai (1988) have proposed the estimation of line location and width to subpixel accuracy based on the moment preserving principle. Their line detector locates a digital line segment with any thickness by its central line that is, the skeleton of the 'thick' line, and determines its width, according to certain criterion. Any line within

the mask is characterized by three parameters q, b and H ; where H is the width of the line; b is the normal distance from the origin to the central line and q is the angle between the line and the x-axis.

Using a circular mask, the first three moments of the grey values inside the mask are first obtained. Then the grey value intensity h_1 and h_2 for the line and its background respectively are estimated as functions of these moments. If $h_2 - h_1 > \delta$ then a line pattern is supposed to exist in the circular region. This is confirmed by additionally checking whether

$$\frac{h_2' - h_1'}{h_2' - h_1'} \geq \sqrt{\quad}$$

Where h_1' , h_2' are the mean of the observed grey values in the line region and the background region respectively. Once it is confirmed that a line exists in the circular region, then, the three parameters q, b and H are determined.

The local methods of line detection it is observed aim at identifying pixels that are a part of the linear feature. No attempt is made to build up the line segments from the recovered pixels. Global techniques attempt to perform both these operations simultaneously.

5.4 GLOBAL TECHNIQUES OF LINE DETECTION

These techniques do not use templates; some transformation is applied to the data that enables easier recognition of linear features. Hough transform (Duda and Hart, 1972) is one of the commonest ploy employed to extract lines. Hough transform approach for extracting linear features is based on the principle that if a line exists in an image passing through a point P with pixel and line coordinates (x,y) , then the equation of the straight line has the form $y = mx$, when p is taken as the origin. Thus if $P_1, P_2, \dots, P_n$, be a set of points that are possible candidates for a linear feature then we can construct an array in which the value at position w is the number of P_i 's such that $y_i/x_i = w$. If $P_1, P_2, \dots, P_n$ is indeed a linear feature passing through the point P then a significant mode should occur at the position w in the array. One of the attractive features of this approach is that the linear feature need not be continuous, for it is only the modal value that is looked for. Modifications of this technique to detect linear features from grey level images have been proposed by Sklansky(1978).

Optimal decision rules have been tried to detect linear features by Griffith(1973) and Montanari(1971). Montanari proposes a technique based on the determination of the optimal system of curves in a picture with respect to a given

figure of merit. This figure of merit is defined considering the properties of a curve such as its curvature.

Chittineni (1983) has developed a technique that uses multiband data to detect lines and edges in a satellite image. The multiband picture function is modelled as a weighted sum of orthogonal basis functions with a noise term where the noise is assumed to be Gaussian and independent from pixel to pixel. Masks are defined to estimate the coefficients of the model. Expressions are obtained to calculate the means and variances of the estimated coefficients. This enables a statistical test to be performed on the transformed data to decide whether the centre pixel on a 3 X 3 neighbourhood forms part of a line or an edge.

5.5 SUMMARY

Satellite images constitute a very large data base and for effectively utilizing them quick processing techniques are a must. The local techniques currently in use, however, require as many as 14 templates to be operated on every pixel to detect lines in eight directions. The thresholding of response is done heuristically. We propose a simple technique that works reasonably well for the detection of linear features from a satellite image.

D	C	B
E	R	A
F	G	H

FIG.5.1 FIRST ORDER NEIGHBOURS OF R

G	F	E	D	C
H	.	.	.	B
I	.	R	.	A
J	.	.	.	P
K	L	M	N	O

FIG.5.2 SECOND ORDER NEIGHBOURS OF R

	1	2	3	4	5
1	1	0	0	0	0
2	0	1	0	0	0
3	0	0	1	0	1
4	0	0	1	0	0
5	0	0	0	0	0

FIG.5.3 EXAMPLE OF A PATH

1	2	1	1	0	-1	0	-1	-2	-2	-1	0
0	0	0	2	0	-2	1	0	-1	-1	0	1
-1	-2	-1	1	0	-1	2	1	0	0	1	2

EDGE TEMPLATES

0	1	0	-1	0	1	1	-2	1	-2	1	-2
-1	0	-1	0	0	0	-2	4	-2	1	4	1
0	1	0	1	0	-1	1	-2	1	-2	1	-2

LINE TEMPLATES

1	1	1
1	1	1
1	1	1

AVERAGING TEMPLATES

Fig 5.6 FREI AND CHEN OPERATORS

CHAPTER 6

PROPOSED METHOD OF LINEAR FEATURE DETECTION

6.1 INTRODUCTION

The local methods of line detection described in the last chapter use a large number of templates to detect lines oriented in eight different directions. The maximum of the response when these templates operate upon the first order neighbours of a candidate pixel is taken as the response at the candidate pixel. A linear feature in a satellite image apart from its geometrical property has a spectral component. This spectral property will depend on the type of linear feature, that is, whether it is a road, canal, rail or a lineament, etc. Linear features in a satellite image may therefore be light toned with a dark background or dark toned in light background. Both types of linear feature can be expected in an image. In order that a linear feature get detected, the grey values of the linear feature should have a minimum contrast with respect to its background. Although, it is difficult to specify what this minimum should be, generally it is observed that the grey value distribution on either side of the line pixels are similar in the sense that their statistical characteristics are not significantly different.

Satellite images we must note are not noise-free. In addition, all linear features will not appear in all bands. Detection of linear features from remote sensing data has to be preceded by feature selection and enhancement processes. The type of enhancement will depend upon the spectral nature of the linear features. Pelletier (1985) has shown that high-pass filtering of thermal IR images improves the contrast of linear features. Pointing out that the road materials are highly reflective in the 0.4 - 0.45 μm , Rao and Mahabala(1983) attempted extraction of road network from aerial images. Similarly Ton et al. (1987) and Bajcsy and Tavakoli (1976) suggest that Band 3 and Band 7 of Landsat TM are most suitable for road detection. In these studies techniques used are specifically meant to detect roads. Some of the image enhancement techniques that are used for improving the contrast of an image are discussed in the following section.

6.2 IMAGE ENHANCEMENT

The objective of enhancement techniques is to alter the appearance of an image so that certain features are more readily seen in the resultant image. Clearly, there is no general theory of image enhancement. The suitability of an enhancement technique depends very much on the object to be emphasized in the image and the background in which the object is found.

Image enhancement techniques can be of two types - the frequency domain method and the spatial domain methods. Frequency domain methods are based on modifying the Fourier transform of an image. The latter method enhances an image by manipulating the grey values in the image.

One of the simplest approaches to pixel grey value manipulation is contrast stretching. Suppose that we want to emphasize the grey values in the range $[m,n]$ of a k -level image. Then this is achieved by darkening the grey values in the range $[0,m)$ and brightening the grey values in the range $(n,k]$. One can think of producing a binary image with the grey values $[m,n]$ being mapped to 0 and grey values $[0,m)$ and $(n,k]$ mapped to 1.

Most image enhancement techniques aim at modifying the grey values or the fourier transform of a single image. Thus there are techniques such as Histogram equalization, image smoothing, lowpass filtering, image sharpening with gradient operators such as Robert's operator, high pass filtering, etc. (Gonzalez and Wintz, 1983). In the case of satellite images, we have multiband data, and often, by combining the different band data, image features can be enhanced. We will briefly describe some of the techniques commonly used for the enhancement of satellite images.

6.21 IMAGE SUBTRACTION

Suppose that $I_1(x,y)$ and $I_2(x,y)$ represent the image of an area observed in two bands, then a difference image can be obtained as,

$$I_d(x,y) = I_1(x,y) - I_2(x,y)$$

This operation is carried out pixel by pixel. If both the images have a radiometric range 0 to 255, then in principle, the difference image can take values between -255 and 255. Before this image can be used for subsequent analysis, the grey values have to be normalised to the range 0 to 255. This can be done by linearly stretching the actual range of the difference image to the range 0 to 255. Differencing of two images is useful not only as an enhancement tool but also to detect changes that have occurred over a period of time. This is done by differencing images of a scene observed at two different time points.

6.22 IMAGE RATIO

This is very commonly used in enhancing remote sensing images (Mather, 1987). Certain aspects of the shape of spectral reflectance curves of different earth surface cover types can be brought out by ratioing. In addition, the effect of variable illumination can be reduced by ratioing two bands. As in the case of image subtraction, image ratioing is also a

pixel to pixel operation. In this case we define the ratioed image $I_r(x,y)$ as,

$$I_r(x,y) = I_1(x,y) / I_2(x,y)$$

In taking band ratios, however, care has to be taken to ensure that the denominator is not 0. This can be done by setting $I_r(x,y)$ as 0 or some appropriate value if $I_2(x,y)$ is 0. Again the output grey values need to be normalised to the range 0 to 255. In the case of remotely sensed images the spectral reflectance curves suggest the bands that could be ratioed. However, if we are interested in enhancing edges, linear features or some similar features, it is difficult to decide which band ratios will work the best.

6.23 BAND COMBINATIONS

Image differencing and image ratios consider only pairs of bands. The idea can be extended to combine several bands of an image. The type of combinations to be attempted is again determined by the spectral reflectance curve of the different features.

The false colour composite (FCC) is one of the simplest means to generate an enhanced combined image (Hord, 1985). In this technique red green and blue colours are assigned to each band; and three band images are combined to give a resultant image. This resultant image has a visual clarity better than

any of the original band images. The question of which three bands need to be combined is difficult to answer. However, Hord(1986) suggests that the band triplet that provides the ellipsoid of maximum volume can be selected for FCC generators. He has shown that in the case of Landsat thematic mapper the band combinations 145 in the order blue, red, green is usually the best triplet.

Another way of combining different bands is to generate some indices. That is, define,

$$I_d(x,y) = [I_1(x,y) - I_2(x,y)] / [I_1(x,y) + I_2(x,y)]$$

The popularly used normalized difference vegetation index (NDVI) is obtained in this manner. Justice et al.(1985) used bands 1 and 2 of TIROS/NOAA AVHRR images to generate global vegetation maps. There are many more ways of combining different band; most of them are empirical.

6.24 PRINCIPAL COMPONENT TRANSFORMATION

Principal component transformations is a statistical way of combining n - dimensional data to give an $m < n$ dimensional output. The technique is based on the premise that the n - dimensional data are mutually correlated. By transforming the data into m - dimensional, mutually uncorrelated data, the redundancy in the original data set is eliminated. In the case of n band satellite images, it is well known that the

data are correlated (Ready and Wintz, 1973). Uncorrelated linearly transformed components are derived from the original data such that the first principal component accounts for the maximum possible variation in the original data set, and subsequent components for the remaining residual variance.

The principal component transformation involves,

- * Calculation of the variance covariance matrix for the image data sets.
- * Computation of the eigen vectors and eigen values.
- * Linear transformation of the data.

Unlike other techniques, this is not a pixel by pixel operation although the linear transformation is carried out for each pixel. The principal component analysis has been used primarily for data compression; because the first principal component transformed image accounts for most of the variation, this transformed image will be found to have enhanced certain features. It must be noted that the principal component analysis is very much scene dependent. A general conclusion on which of the features will be enhanced in the first component cannot be made.

Techniques have also been developed exclusively to enhance edges in an image. These are Sobel's operator, Robert's operator, Laplace operator etc. (Jensen, 1986). The

suitability of these techniques in enhancing linear features however, remains unanswered. It is easier to design filters to enhance edges since edges are high frequency components of an image. Linear features however, cannot be considered as either high frequency components or low frequency components. Thus, it becomes necessary to try various enhancement techniques to decide their suitability for linear feature enhancement before attempting to detect the linear features.

Linear features that we try to detect on satellite images rarely have sizes larger than the pixel resolution. As a result the grey value noted for a line pixel is an average of the linear feature reflectance and its background; dominated by the former. Thus the contrast between the linear feature and its first order neighbours will not be large. In other words the first order neighbour pixels can be considered as noisy pixels as far as the linear feature pixels are concerned. This point has been noted by other authors too (Fischler et al. 1981; Ton et al., 1987). In the local methods of line detection discussed in chapter 5 templates operate on the first order neighbours of a candidate pixel. As a result it is possible that quite a few line pixels get omitted. We propose templates that operate on the second order neighbours of a pixel. The technique is capable of detecting both dark and light lines in an image. In the

following section, we extend the definitions of digital arc and digital closed curve over a second order neighbourhood.

6.3 DEFINITIONS

DIGITAL ARC

A set S of connected pixels $P_0, P_1, \dots, P_n$, is an arc if all but four pixels have at least two second order neighbours in S . These four pixels have at least one second order neighbour in S . In any case the total number of second order 8 - neighbours for an arc pixel cannot exceed 6.

DIGITAL CLOSED CURVE

A set of connected pixels $P_0, P_1, \dots, P_n$, is a closed curve if every pixel in S has atleast two second order neighbours in S . The total number of second order 8-neighbours for a closed curve pixel cannot exceed 6.

The above definition of digital arc includes arcs as complicated as in Fig. 6.1.

6.4 TEMPLATE DESIGN

In the proposed technique templates are designed to operate in two stages (Lalitha and Dutta Majumder). In the first stage the two templates Δ_1 and Δ_2 operate on the image (Fig. 6.2). The response of Δ_1 is denoted as CON4 and that of Δ_2 as CON8. These templates respond to horizontal or vertical lines and diagonal lines respectively. If the line is

horizontal or vertical CON4 will be less than CON8. If diagonally oriented CON8 will be less than CON4. In any case the minimum absolute value of the response (CMIN) lies between T_1 and T_2 where T_1 and T_2 are line contrast parameters. Otherwise the center pixel in the template is not a line pixel. In the second stage the presence of a line pixel and its orientation is confirmed. This is done by ensuring that the grey value distribution on either side of the probable line are identical. If CON4 is minimum, then the two templates Δ_{11} and Δ_{12} (Fig.6.3) operate on the neighbourhood of the candidate pixel. The responses are denoted as CON41 and CON42 respectively. Then for a line pixel the maximum absolute value of these responses (QMAX) cannot exceed a threshold T_1 , if it does the candidate pixel is not accepted as a line pixel. If CON8 is minimum, the templates Δ_{21} and Δ_{22} (Fig.6.4) operate on the pixel giving the response CON81 and CON82 respectively. For a line pixel the maximum of the absolute value of these responses cannot exceed a threshold T ; if it does the candidate pixel is not accepted as a line pixel. Thus by operating four templates in two stages, a pixel oriented in one of the eight directions get detected. In Fig.6.5 the flow chart of the steps in implementing the technique are given. Generally, this technique does not respond to zig zag lines. Line segments having the property

No. of turning points

----- > 0.5

No. of pixels in the line segment

are not detected by this technique. An important aspect of the proposed line detection process is to specify the threshold or the line contrast parameters T_1 and T_2 .

6.5 THRESHOLD SELECTION

Threshold setting is an important problem in image processing particularly for segmentation of images. Yet, there has not been any fool-proof technique that determines the threshold to be specified. For the purpose of linear feature detection using templates, thresholding of the responses should be done preferably automatically and must form part of the response calculation process. The line contrast parameter T should depend on the grey value distribution in the image being analysed. We propose a histogram based criterion for selecting the threshold. In principle, the various classes in an image can be discriminated provided there is a significant contrast difference between the adjacent classes. Since we do not know apriori the significant contrast difference or the number of classes, we take the number of modes in the histogram to represent the number of classes and the modal values as the representative grey value for the particular class. Suppose that m_1, m_2, m_3 are the three modes of a histogram with d as the average interclass distance. Then the

grey value distance between two adjacent modes is called the interclass distance for the two classes (Fig. 6.6). Then for a line pixel the responses of Δ_1 and Δ_2 will result in a minimum along the line. This minimum CMIN will have to be atleast d and it cannot exceed $3d$. Note that if the centre pixel is part of a region then CMIN will be very small and could be zero. Also if the centre pixel is an isolated pixel then CMIN could be as much as $4d$ or more. For a line pixel the second stage ensures that the grey value distribution on either side of the line are similar. In such a case the response due to the second pair of templates has to be small. In any case the absolute maximum response (QMAX) cannot exceed d . In the case of edge pixels this QMAX could be larger than d and in the case of a pixel belonging to a region, QMAX could be small. It is expected that a pixel belonging to a region gets rejected at the first stage itself. Thus we see that T_1 could be chosen as d and T_2 as $3d$. Essentially the average interclass distance d is a single parameter to be specified for line detection. The technique thus requires that the modes of the histogram be detected initially. Detection of modes from a histogram is by itself a very important problem in statistics as well as image processing. We have used a simple approach, that provides a quick means to set the threshold parameter.

MODE DETECTION

The problem of estimation of the number of modes is closely related to the problem of statistical probability density function estimation. Histograms are amongst the easiest descriptive tools that indicate what the density is likely to be. However, one of the vexing problems has been how to decide the width of the bins of the histogram. It is possible that a very small width will give rise to a clutter of hills and valleys and too wide a bin may tend to overly smoothen the distribution. In addition, with satellite data where the number of data points are quite large, quick generation of the histogram and smoothing of the histogram are important. As a result techniques such as the penalized likelihood method very effectively put to use by Good and Gaskins (1980) for mode detection in scattering and meteorite data cannot be applied here.

In the present context we need to determine the modes of the image histogram and the intermodal distance. For this purpose a technique for smoothing the histogram is necessary. The average shifted histogram technique proposed by Scott(1985) is a very good alternative to other techniques of density estimation such as that of Parzen(1965). The technique has been implemented for multivariate remote sensing data by Scott(1986). Following his method we used a triangular kernel with different widths to smoothen the original histogram.

Thus for a triangular kernel of width m , the weighting function is

$$W_m(i) = \begin{cases} 1 - \frac{i}{m} & , \quad i < \text{or} = m-1 \\ 0 & , \quad \text{Otherwise} \end{cases}$$

and the smoothed ordinate value at a point is obtained as the weighted average of the ordinate value of the original histogram. It turns out for the data we analysed, that with $m=3$ to 5 a smooth histogram can be obtained; thus enabling us to locate the modes immediately. Automatic detection of modes from the smoothed histogram can be done using techniques proposed by Boukharouba et al. (1985) or Eklundh and Rosenfeld (1979) or Rosenfeld and De La Torre(1983). In our study we displayed the smoothed histogram and visually detected the modes.

6.7 EXPERIMENTAL RESULTS ON NOISE FREE IMAGES

In order to study the performance of the proposed technique we generated artificial images with linear features. The image contains three arcs, a closed curve and two regions having grey values identical with that of the lines. Fig. 6.7 shows the image where L and M correspond to the grey value of the lines; A, B, C are the background values. By specifying

the different values for A,B,C,L and M the contrast between the lines and the background can be changed and the detectability studied. For these synthetic images the line contrast parameter was obtained as the average inter class distance, where A, B, C, L, and M are assumed to be representative values of different classes. Figures 6.8 to 6.10 show the results of operating the image with linear, semi linear and the new detector. Numbers at the top indicate the values specified for A, B, C, L and M and the threshold used in each case.

When the grey value difference between the line and its background is greater than 25, the line is detected almost exactly by the proposed detector. This is irrespective of whether the line grey value is greater or smaller than the background grey value. The new detector recognizes closed curves; does not respond to edges. Sometimes responds to isolated points. To a limited extent the detector responds to lines which are two pixels wide. The linear and semi linear detectors respond to edges as well as lines. They do not detect closed curves. In an image where two types of lines exist, that is, lines having grey values larger than the background grey values and lines having grey values smaller than the background grey values; the linear and semi linear detectors respond to only one type of line.

6.8 LINEAR FEATURE DETECTION IN SATELLITE SUBSCENES

Prior to the detection of linear features from a satellite image, some kind of pre-processing and enhancements have to be carried out. As already pointed out there is no single enhancement technique that will enhance the linear features alone. The detector we have proposed is meant to detect dark and light toned lines and no attempt is made to recognize what the feature really is. Attempts are made to digitally pick up the linear features seen visually.

Fig 6.11 shows an urban subscene of a Landsat TM image in the bands 1, 2, 3, 4, 5 and 7. Band 6 was not considered because of its coarse resolution. It is readily seen that the linear features are clearly seen in the bands 3, 4 and 5. False colour composites using the band triplets 234, 145, 345 and 147 were then generated. The band triplets 234 are the standard bands used to generate FCC, while the other three bands were tried as per the ranks given by Hord(1986). It was found that the FCC using bands 3, 4 and 5 gave the best results (Fig.6.12). Yet it is seen that the FCC image has the effect of enhancing the overall image features and not particularly the linear features. A principal component analysis of bands 2, 3, 4, 5 and 7 was then carried out. The first three principal component images are shown in Fig. 6.13. The first principal component image has enhanced urban

features. However, none of the components enhanced the linear features. An FCC of the first three component images (Fig.6.14) can be effectively used for urban land use mapping. Although edge detectors have been used to detect linear features, it was found that edge enhancement techniques such as Robert's operator did not, in any way enhance the linear features in the image under study (Fig.6.15). Of the various band ratios tried, it was found that the ratio image generated using Band 4 and Band 1 significantly highlighted the linear features (Fig.6.16). A small portion (64 X 64 pixels) of this ratioed image is used to illustrate the application of the proposed technique for linear feature detection from satellite images. A line printer output of this image is shown in Fig.6.17(a). The linear features noted in this image are road networks as depicted in the map (Fig.6.17(b)). The histogram of this portion of the image (Fig.6.18) was then generated to obtain the line contrast parameter. Using the average shifted histogram technique, the histogram was smoothed with a triangular kernel of width equal to 3 units. In the process two modes could be located. The line contrast parameter T was then found to be 38. Implementing the line detector with this value of T indicated that the number of isolated pixels that got detected was high (see Fig. 6.19 (a)) while the number of line pixels were few. By progressively increasing the value

of T , the number of line pixels that get detected also increased. However, the number of isolated pixels that get detected does not decrease as we would like it to. For $T = 45$, the maximum number of line pixels get detected; for this value of T the number of isolated pixels were also many. Using the definition of linear features based on the second order neighbours, some of the isolated pixels were eliminated and the resultant image is shown in Fig.6.19(b). It is noted that the major road pixels were picked up by the linear feature detector. The pixels that are part of minor roads could not be however detected. In Fig.6.19(c) and Fig.6.19(d) are shown the outputs of operating the linear and semi linear detectors to the ratioed image. The linear detector responds to fewer non line pixels than the semi linear detector. However, both the techniques do not pick up all the line pixels. The study clearly suggests the need for cleaning up the noise before applying any line detector. However, once the image is cleaned up, with guide line provided by the modes of the image histogram, line detection can be done using the proposed technique.

Fig. 6.20(a) - 6.20(c) shows a subscene taken from the Indian Remote sensing satellite. The area is part of Calcutta City and the map of the area is shown in Fig.6.20(d). The ratio of Band 3 and Band 1 gave the best enhanced image for this area. In this area a road runs parallel to a canal in the centre of

the scene and the linear features are mostly canals. In analysing this scene with the proposed detector it was found that the ratioed image had four modes. Taking the average interclass distance as the line contrast parameter and operating the templates for line detection resulted in a large number of noise pixels and very few line pixels. Further analysis pointed out that the linear features are being missed mainly because there was no significant contrast between the line pixel and its background. The ratioed image was then density sliced to retain the water pixels and the rest of the pixels were set as background pixels (Fig.6.20e). In this case the histogram would have only two modes that of water category and the background. Choosing the line contrast parameter as $T=170$, the pixels detected are shown in Fig.6.20(f). Even in this case the number of non - line pixels picked up are many, in comparison with the linear and semilinear detectors, however they are few (Fig. 6.20(g) - (h)). The analysis of this image suggests that the proposed technique performs reasonably well only when the input image is enhanced enough to retain a good contrast between linear features and its background. In the first satellite image the original image had a grey value range of 128 while the second image had a grey value range of 64. Thus detection of linear features became more difficult in the second case. Further the few linear features picked up were that of canals; no

roads were picked up due to a lack of good contrast between the roads and its surroundings.

6.9 CONCLUSION

Templates have been designed to detect the pixels that are part of a linear feature. Once this is accomplished, the linear feature can be built up using techniques such as Hough transform techniques. The gaps between line segments can be filled up aided by extraneous data such as topo maps and / or ground truth. In comparison with other line detectors, this method requires fewer templates and thus can be used to detect linear features in real time. Both dark lines in a light background and light lines in a dark background can be detected. The importance of enhancement of an image prior to the application of the linear feature detectors is illustrated for a satellite subscene. It is found that a general criterion cannot be laid down to select the enhancement operation that will enhance the linear features. In one of the subscene under study it is found that the ratio of bands 4 and 1 improved the contrast of the linear features. In the second scene ratio of bands 3 and 1 proved to be the best. This cannot be generalised for all images, however. The background in which a linear feature is found will decide the efficacy of an enhancement technique. Linear features such as roads do not necessarily have identical

background features in all subscenes. In fact in the second image canals were detected but not the roads. As a result, a trial and error process has to be resorted to, to enhance images before attempting to detect linear features from an image. It is also possible that the season in which the data is obtained may help in detecting the roads in the second subscene. Data obtained during the dry summer months will not display the canals as clearly as the present one. The present data was for the month of February when most canals in this part are with water.

```

      X  X  X  X
    X
      X  X  X
                X
      X  X  X  X  X
  
```

FIG.6.1 EXAMPLE OF DIGITAL ARC

		-2		
-1		4		-1
		-1		

-1				-1
		4		
-1				-1

FIG.6.2 TEMPLATES PROPOSED FOR THE FIRST STAGE

-1				1
-1				1
-1				1

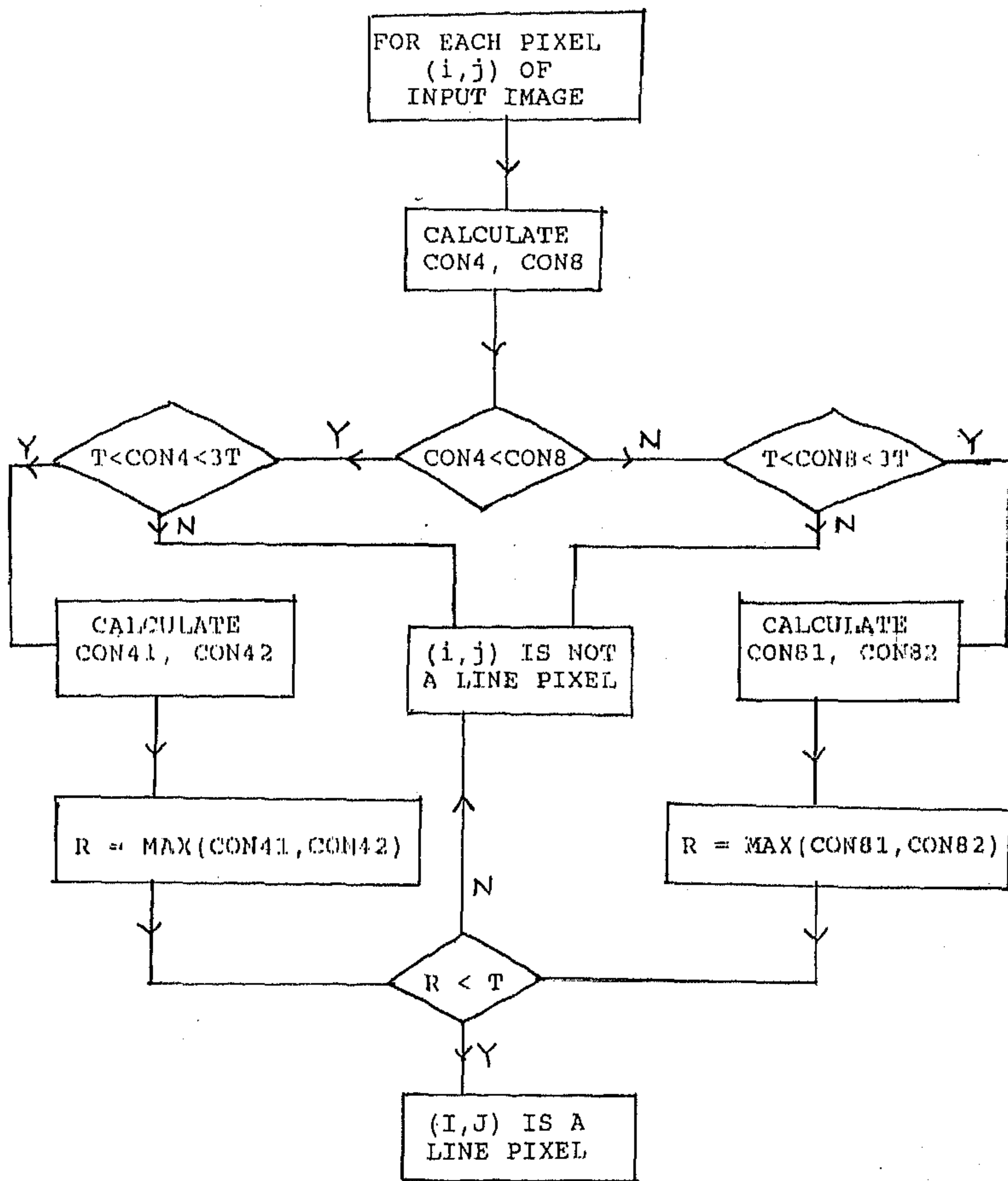
-1		-1		-1
1		1		1

FIG.6.3 TEMPLATES PROPOSED FOR THE SECOND STAGE TO DETECT LINES ORIENTED HORIZONTALLY OR VERTICALLY

		1		1
-1				1
-1		-1		

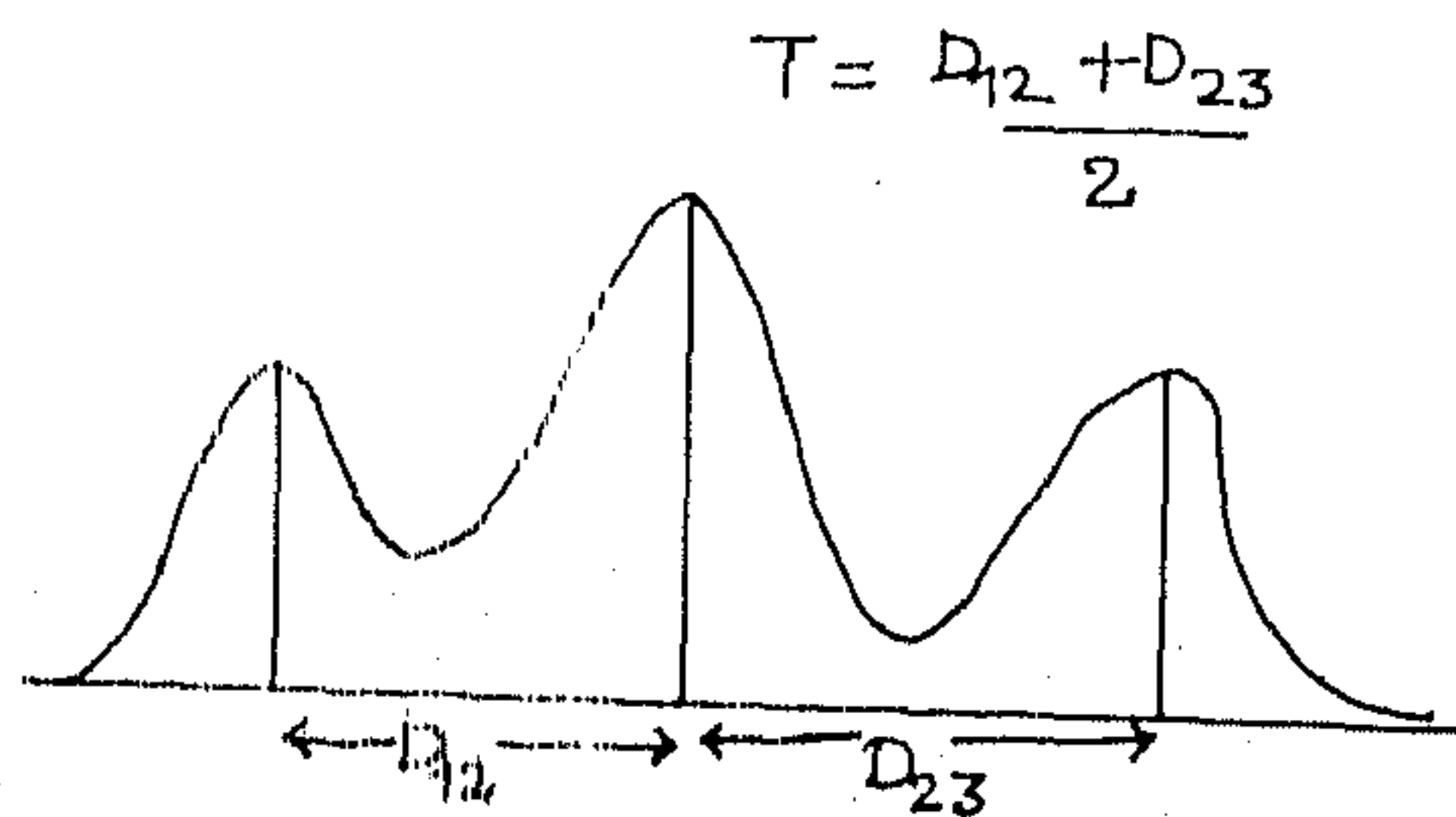
1		1		
1				-1
		-1		-1

FIG.6.4 TEMPLATES PROPOSED FOR THE SECOND STAGE TO DETECT LINES ORIENTED DIAGONALLY



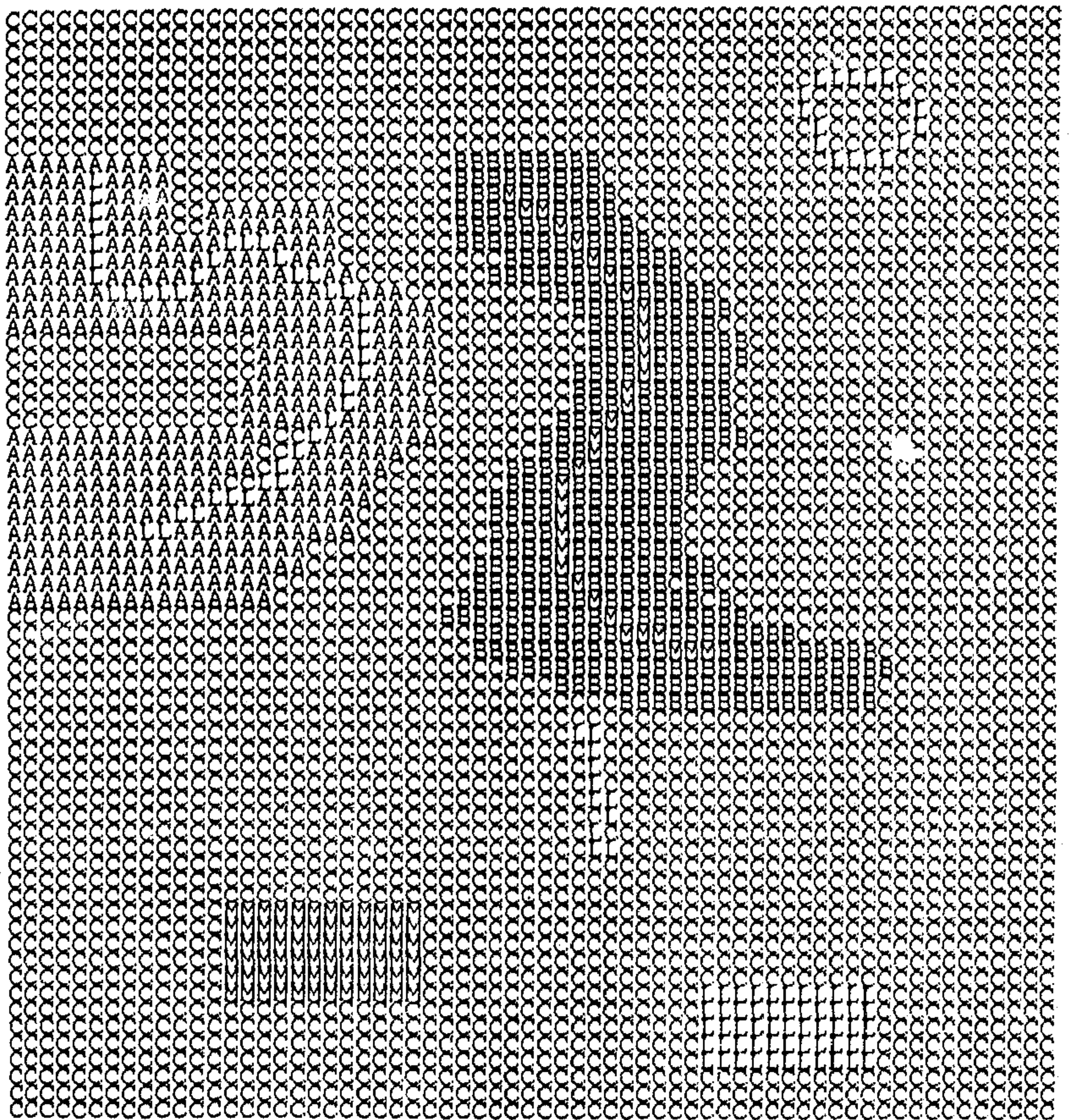
6.5

FLOW CHART OF STEPS IN IMPLEMENTING THE PROPOSED
TECHNIQUE



6.6

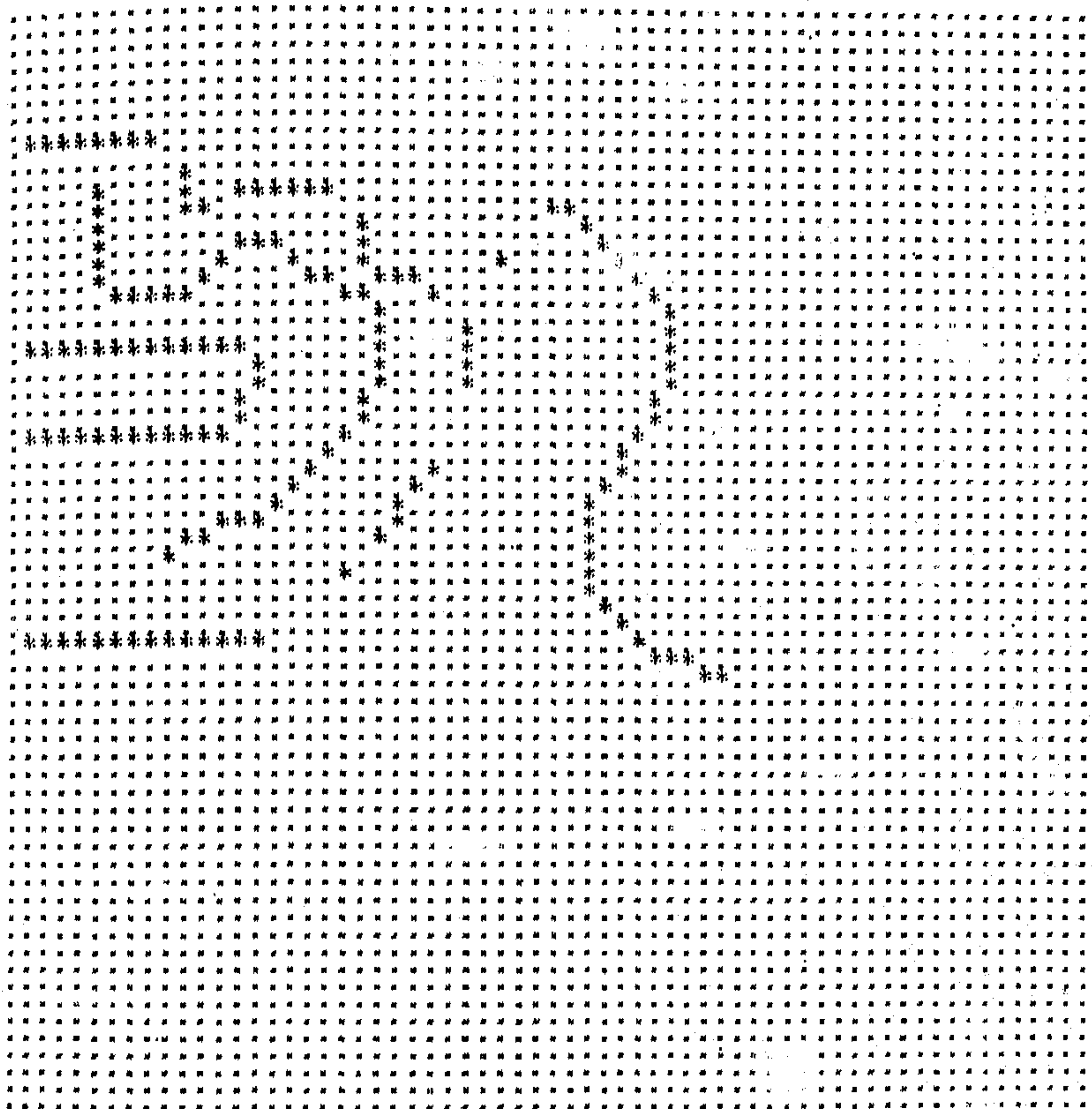
ILLUSTRATION OF THE AVERAGE INTER CLASS DISTANCE



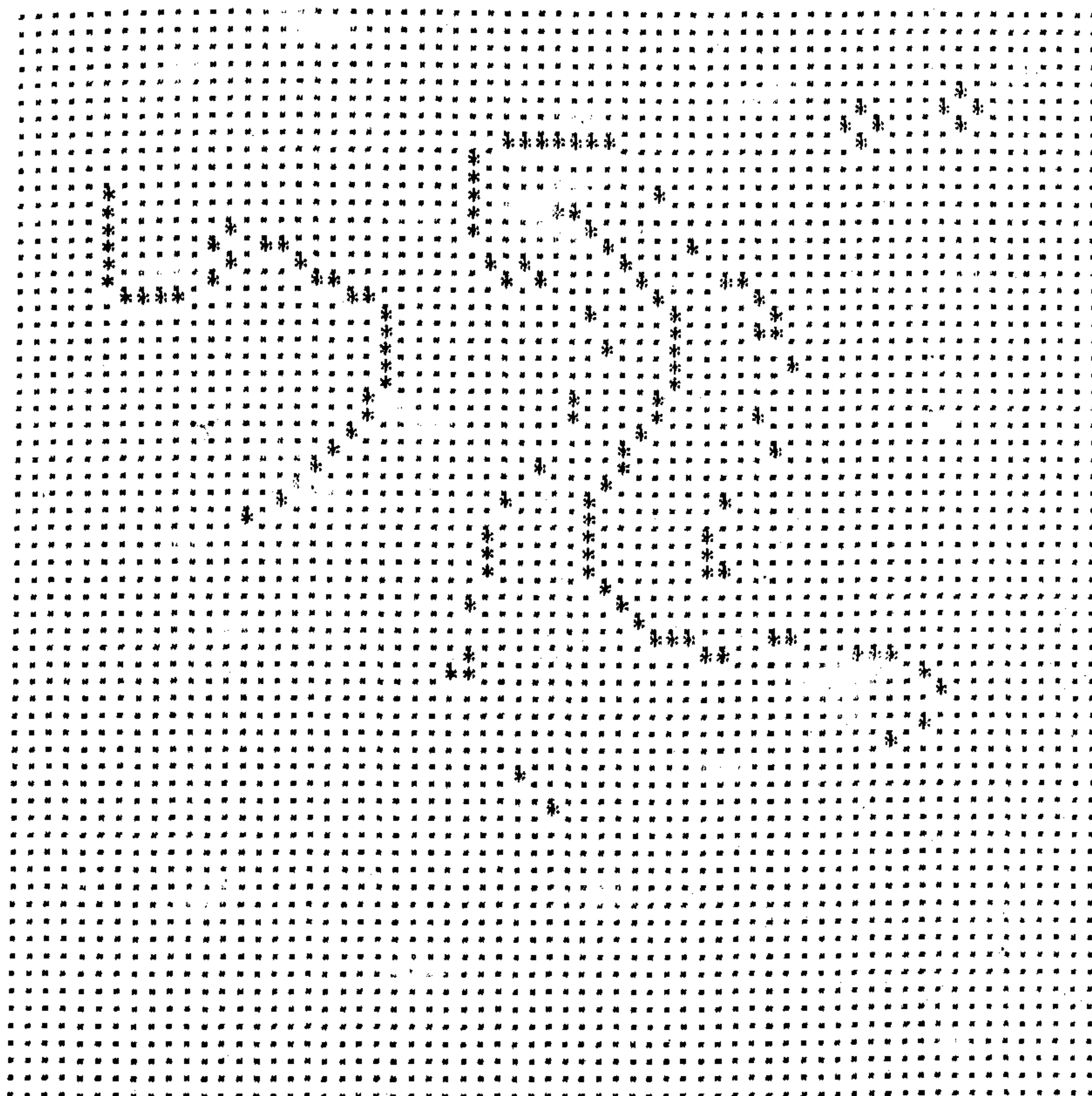
6.7

ORIGINAL SYNTHETIC IMAGE

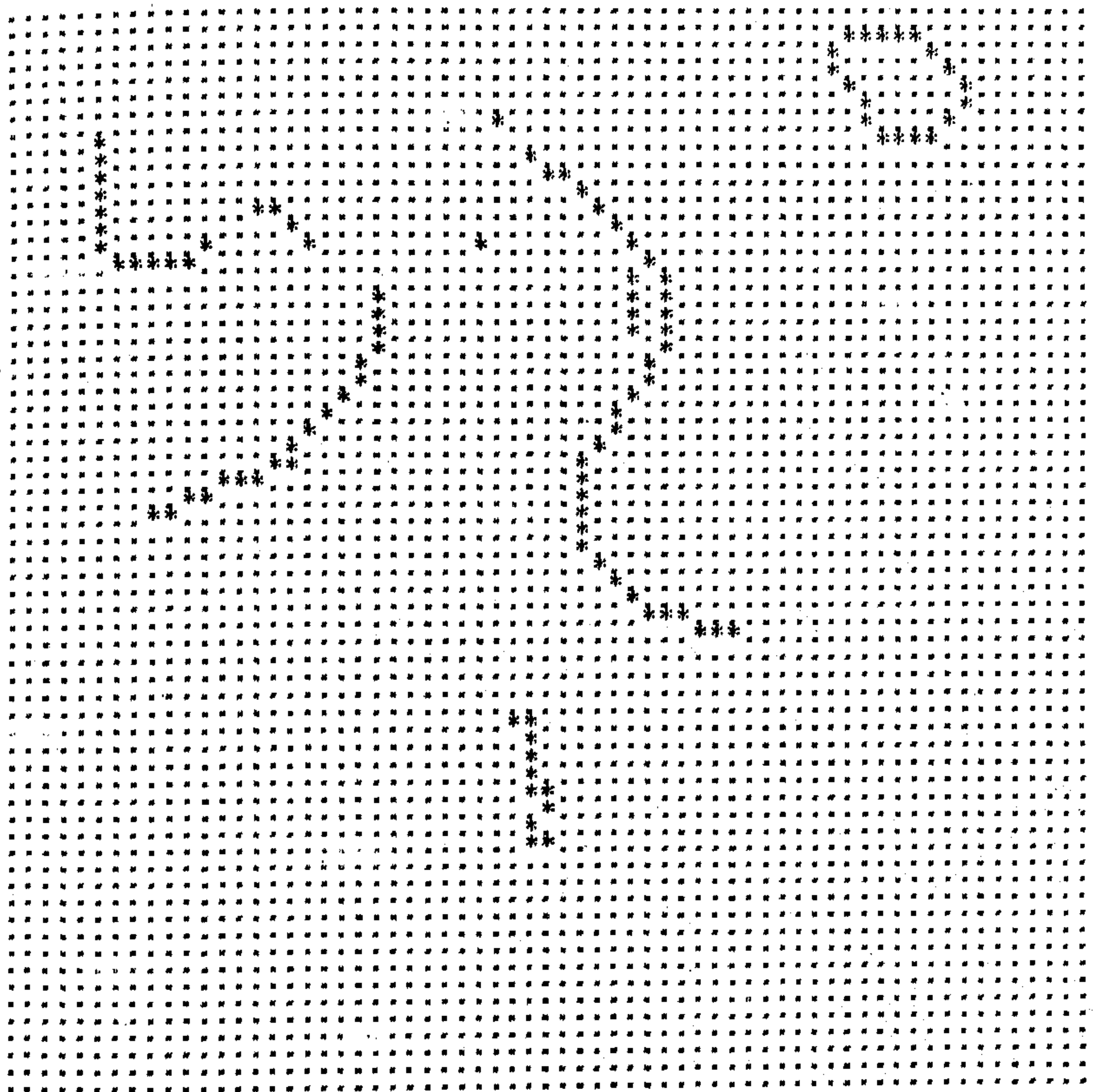
RESPONSE OF LINEAR DETECTOR
(A=5 B=20 C=60 L=35 M=50 T1=35 T2=30)



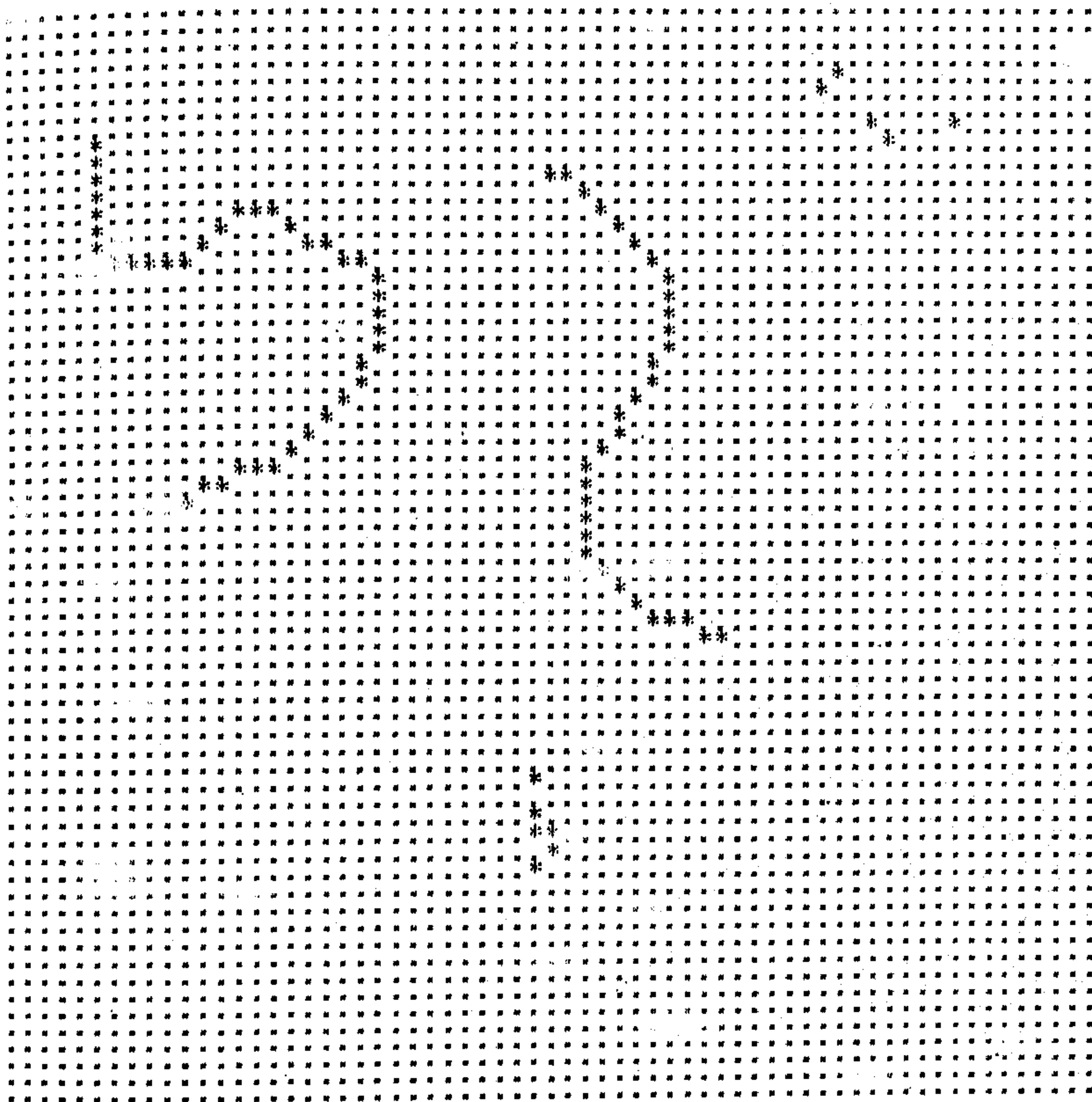
RESPONSE OF SEMILINEAR DETECTOR
(A=5 B=20 C=60 L=35 M=50 T1=25 T2=30)



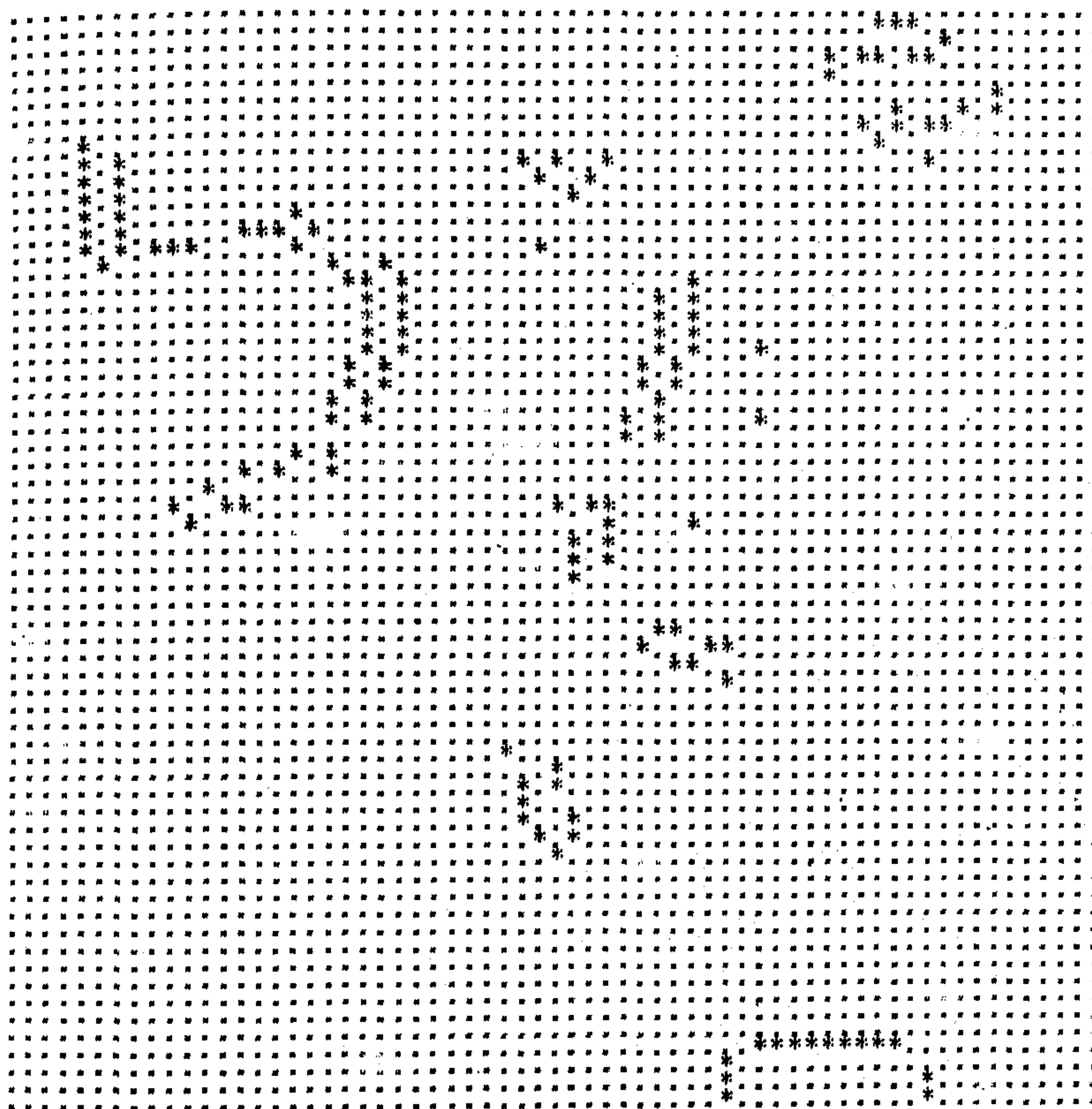
RESPONSE OF PROPOSED DETECTOR
(A=5 B=20 C=60 L=35 M=50 2T=27)



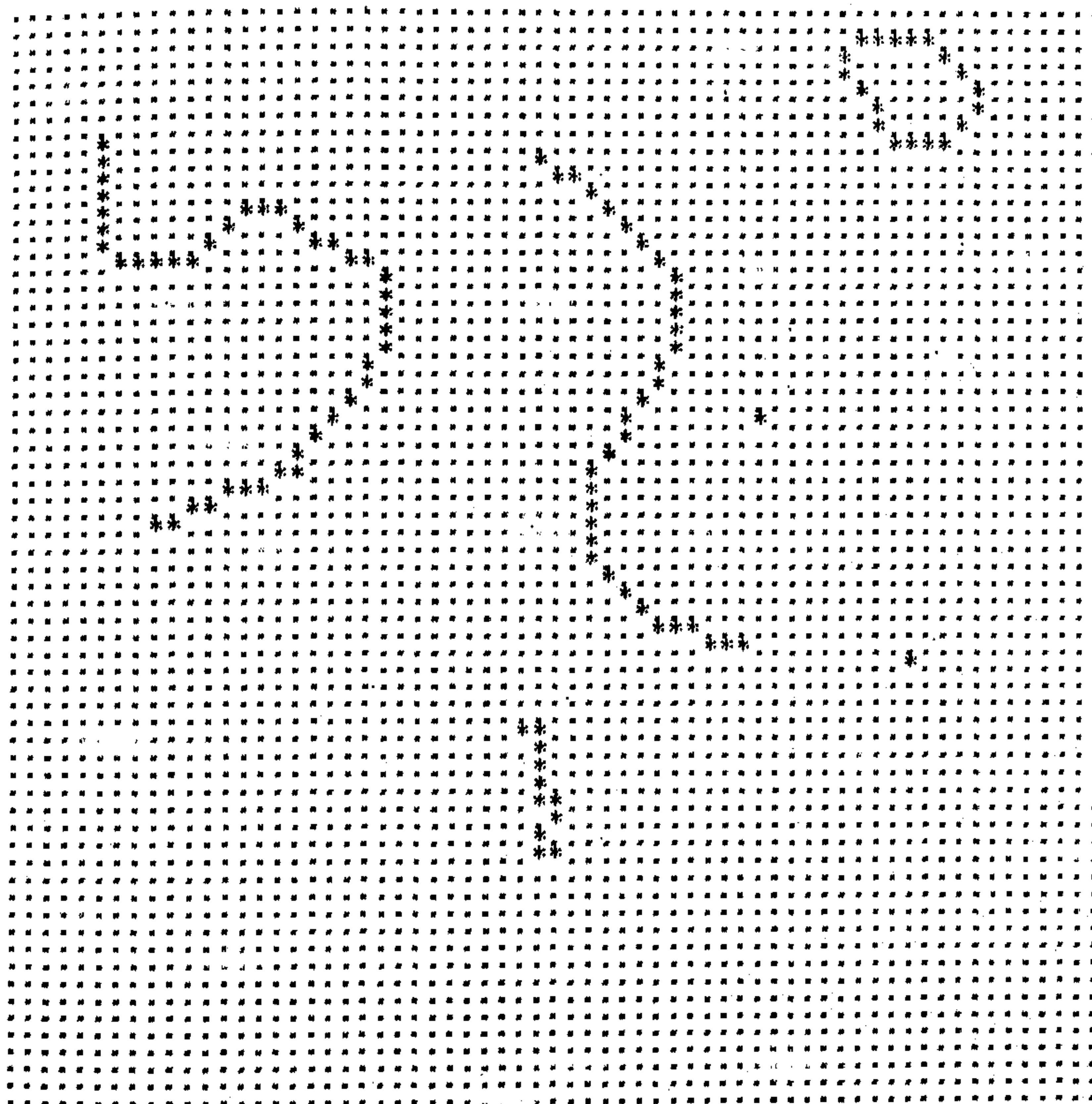
RESPONSE OF LINEAR DETECTOR
(A=35 B=60 C=40 L=5 M=30 T1=25 T2=30)



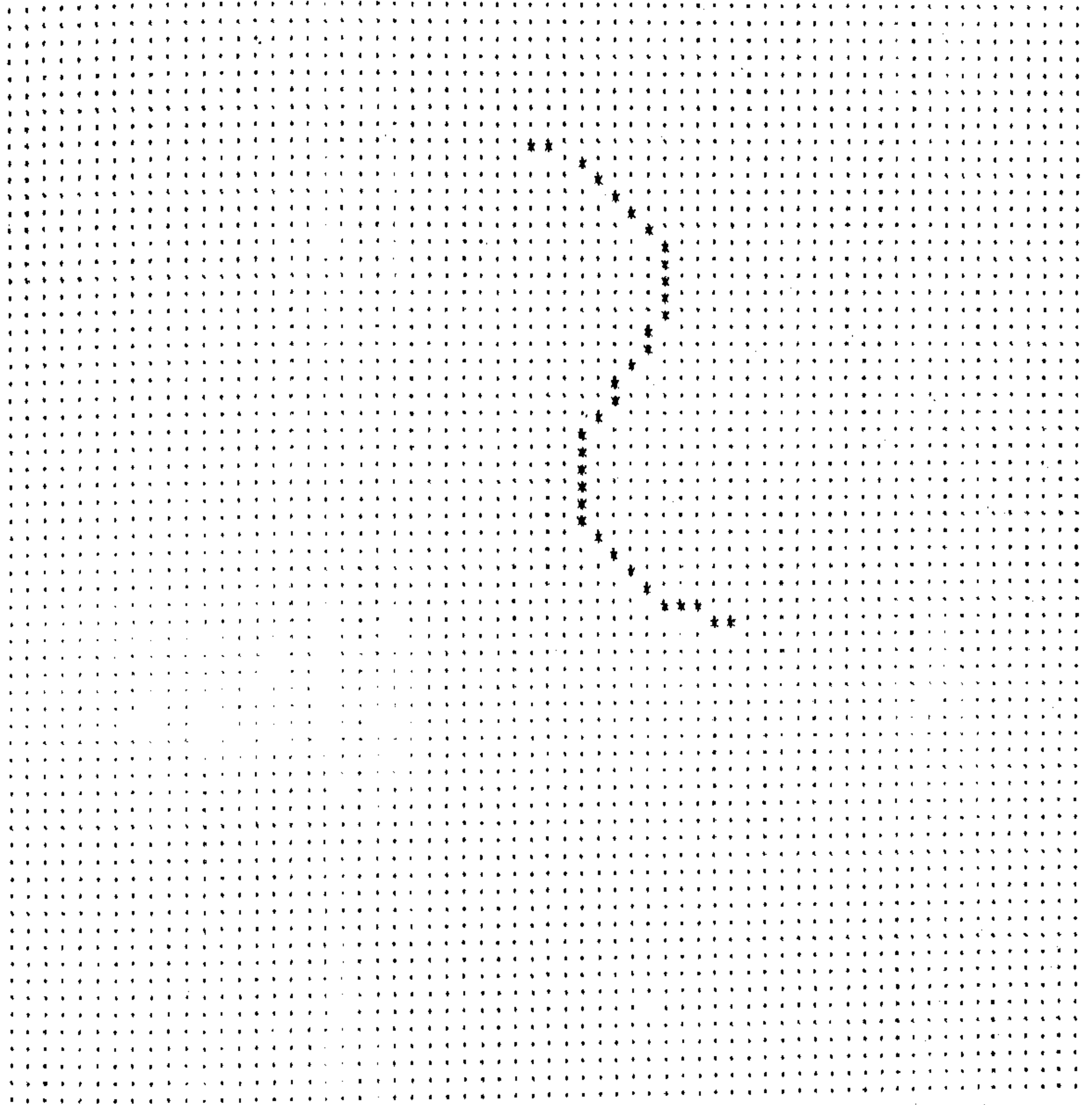
RESPONSE OF SEMILINEAR DETECTOR
(A=35 B=60 C=40 L=5 M=30 T1=20 T2=27)



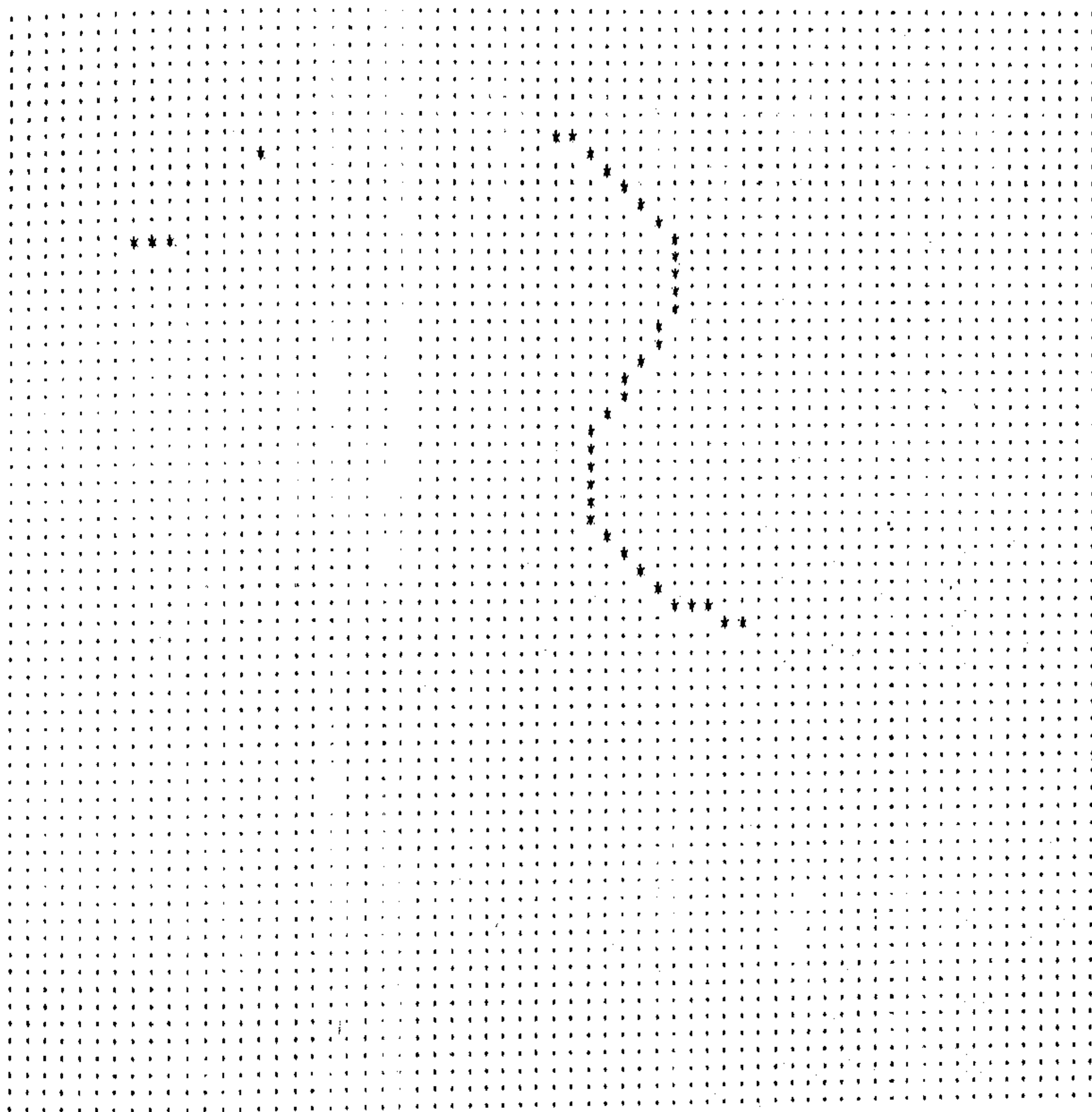
RESPONSE OF PROPOSED DETECTOR
(A=35 B=60 C=40 L=5 M=30 2T=28)



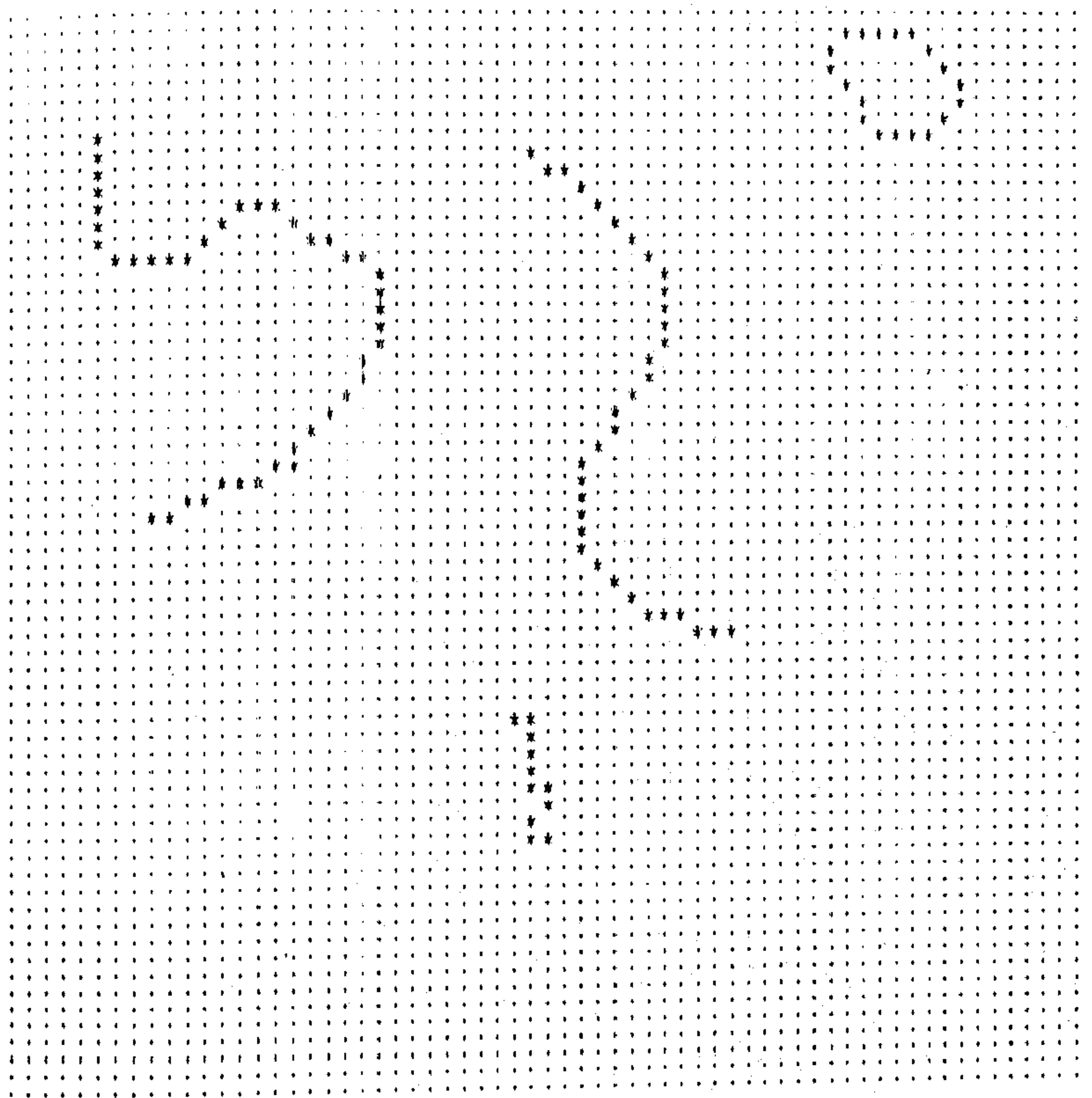
RESPONSE OF LINEAR DETECTOR
(A=35 B=30 C=40 L=5 M=60 T1=25 T2=30)

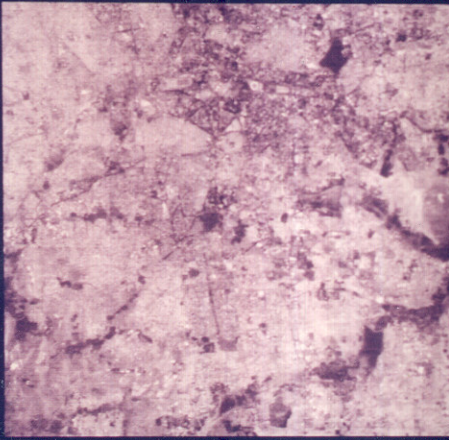


RESPONSE OF SEMILINEAR DETECTOR
(A=35 B=30 C=40 L=5 M=60 T1=25 T2=30)



RESPONSE OF PROPOSED DETECTOR
(A=35 B=30 C=40 L=5 M=60 2T=28)





PART OF AN
URBAN
TM SCENE
MAR '85
BAND1

6.11(a) A LANDSAT TM SUBSCENE -- BAND1



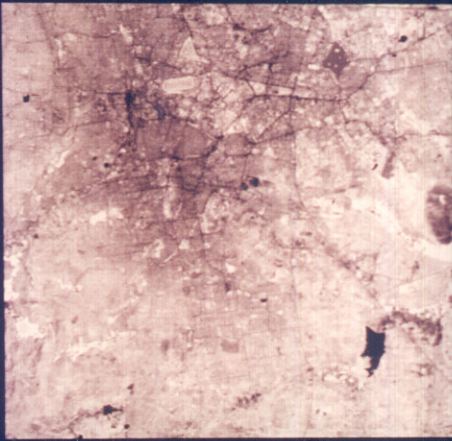
PART OF AN
URBAN
TM SCENE
MAR '85
BAND2

6.11(b) A LANDSAT TM SUBSCENE -- BAND2



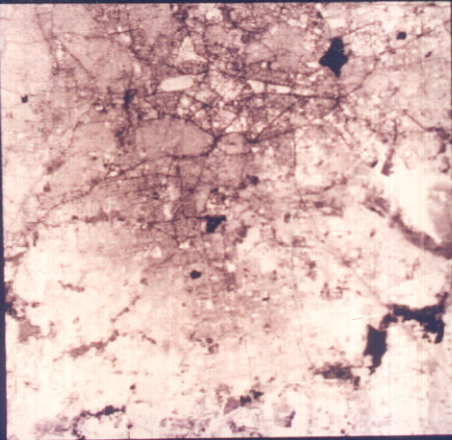
PART OF AN
URBAN
TM SCENE
MAR '85
BAND3

6.11(c) A LANDSAT TM SUBSCENE -- BAND3



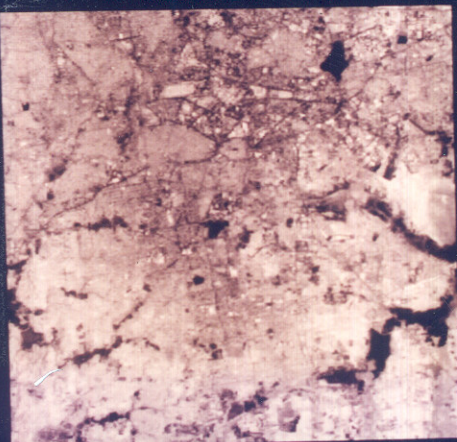
PART OF AN
URBAN
TM SCENE
MAR '85
BAND4

6.11(d) A LANDSAT TM SUBSCENE - BAND4



PART OF AN
URBAN
TM SCENE
MAR '85
BAND5

6.11(e) A LANDSAT TM SUBSCENE - BAND5



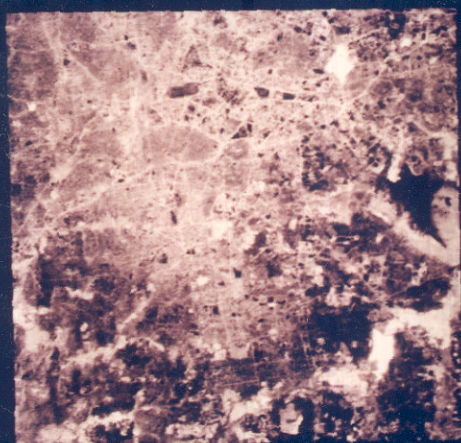
PART OF AN
URBAN
TM SCENE
MAR '85
BAND7

6.11(f) A LANDSAT TM SUBSCENE - BAND7



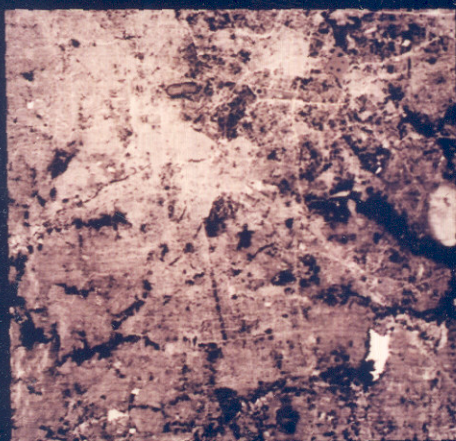
FCC
BANDS 345
OF PART
OF AN URBAN
TM SCENE
MAR '85

6.12 FCC OF BANDS 3 4 5



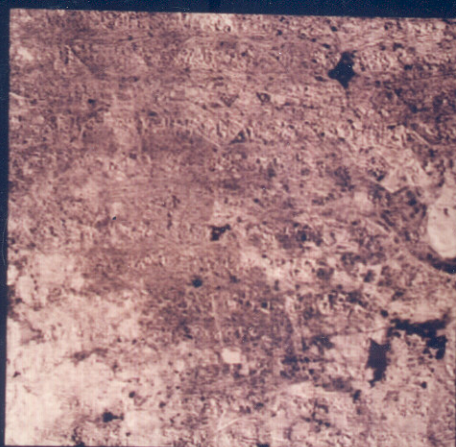
FIRST
PRINCIPAL
COMPONENT
TM SCENE
MAR '85
BANDS USED
23457

6.13(a) FIRST PRINCIPAL COMPONENT IMAGE



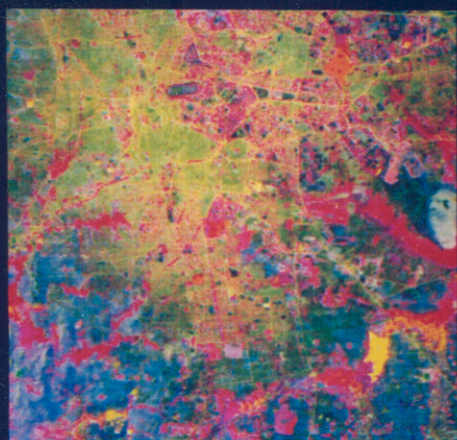
SECOND
PRINCIPAL
COMPONENT
TM SCENE
MAR '85
BANDS USED
23457

6.13(b) SECOND PRINCIPAL COMPONENT IMAGE



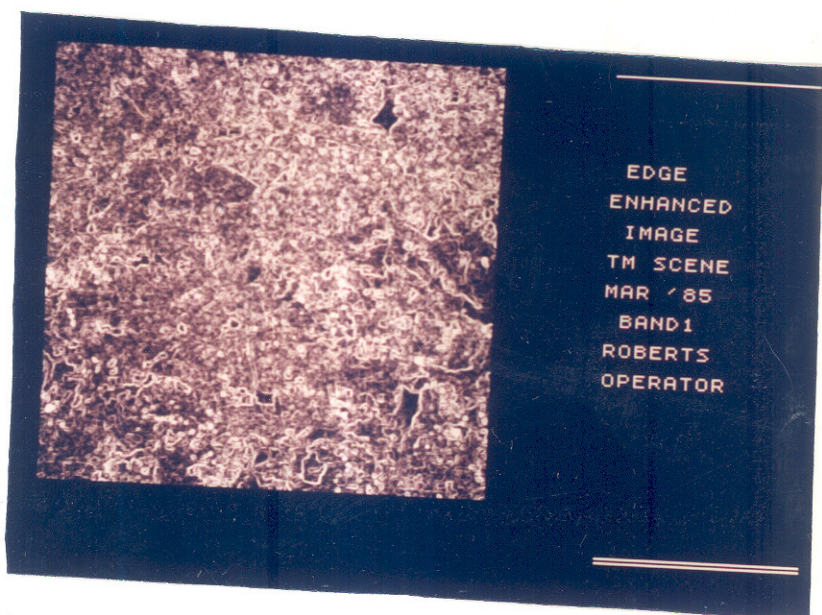
THIRD
PRINCIPAL
COMPONENT
TM SCENE
MAR '85
BANDS USED
23457

6.13(c) THIRD PRINCIPAL COMPONENT IMAGE

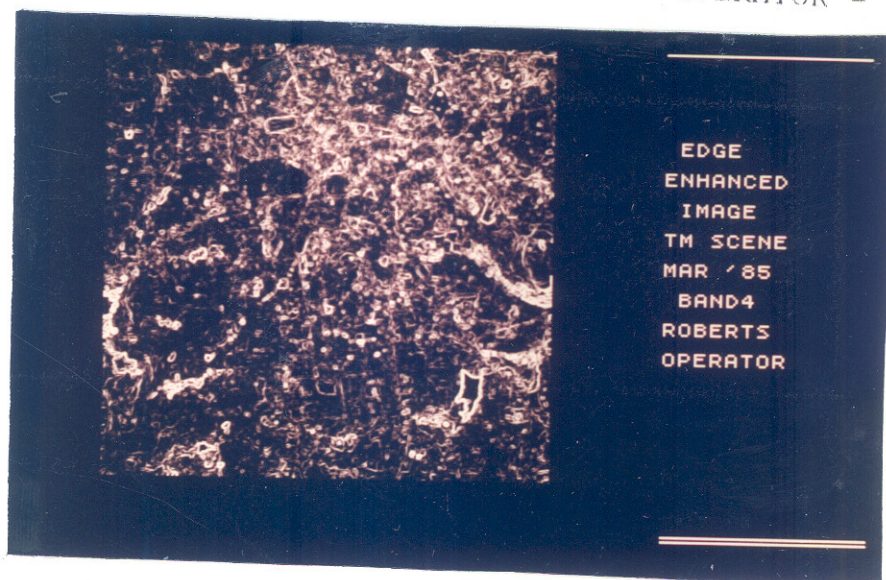


FCC
FIRST 3
PRINCIPAL
COMPONENTS
TM SCENE
MAR '85
RED PC1
GREEN PC2
BLUE PC3

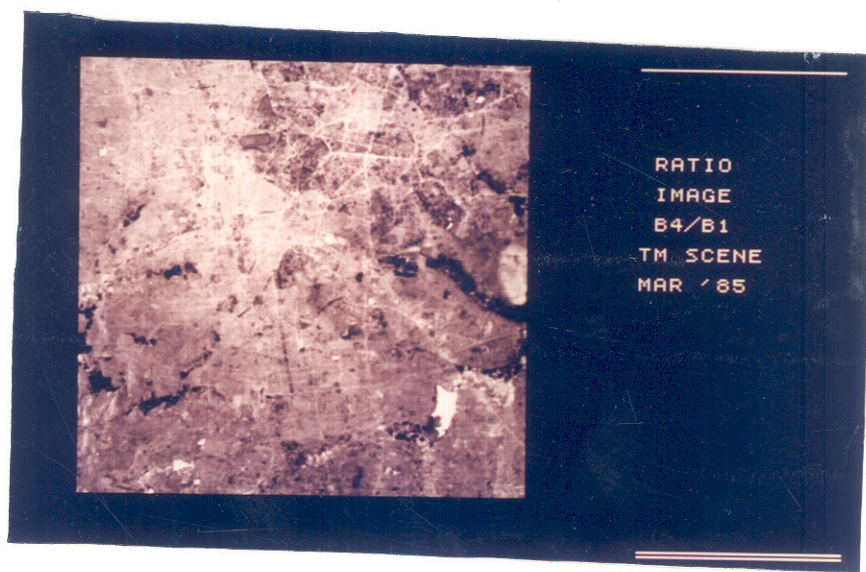
6.14 FCC OF THE FIRST THREE PRINCIPAL COMPONENT IMAGES



6.15(a) EDGE ENHANCED WITH ROBERT'S OPERATOR - BAND1



6.15(b) EDGE ENHANCED WITH ROBERT'S OPERATOR - BAND4



6.16 RATIO IMAGE - BAND4/BAND1

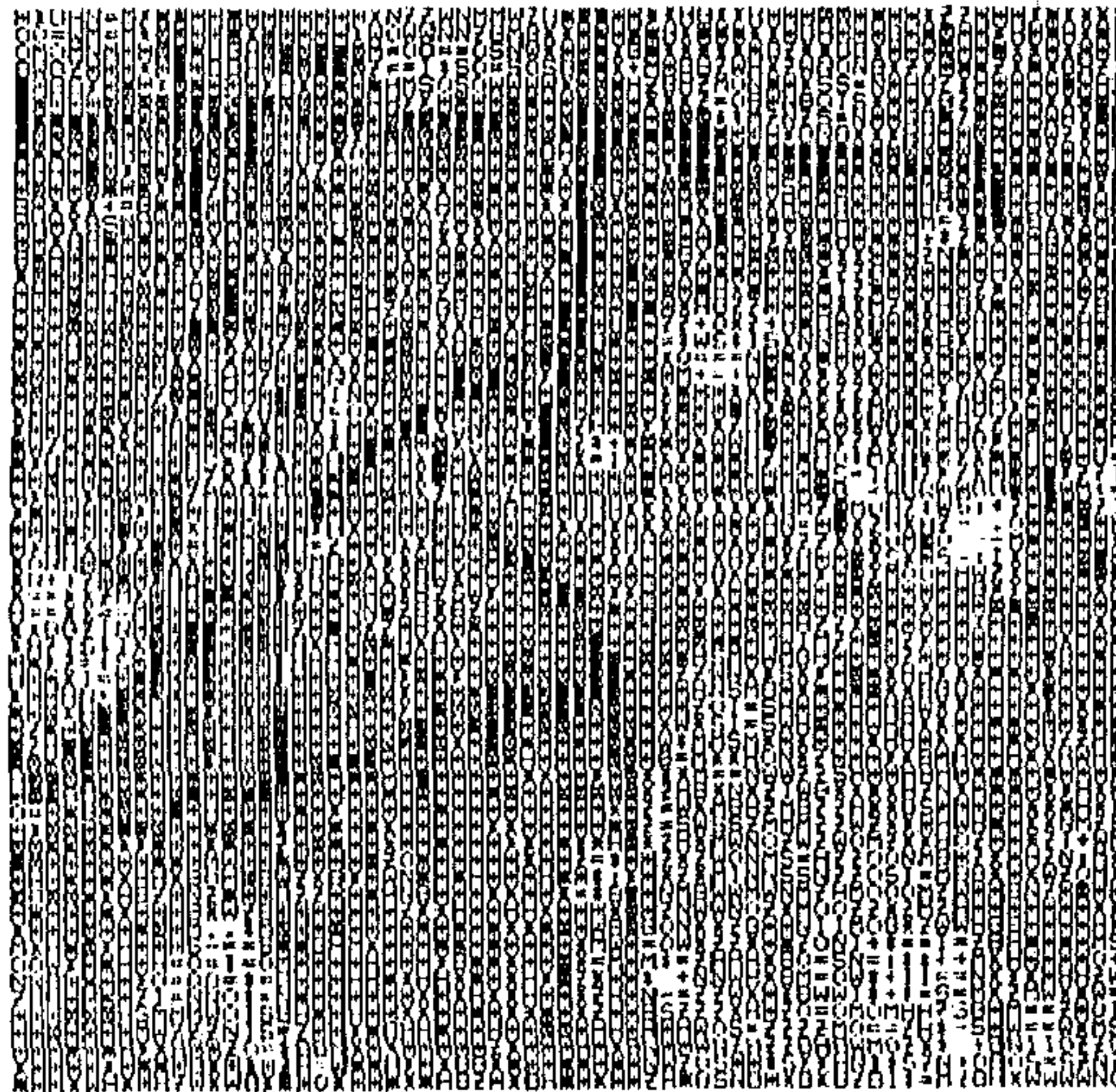


FIG.6.17 A LINE PRINTER OUTPUT FOR A PART OF THE RATIOED IMAGE

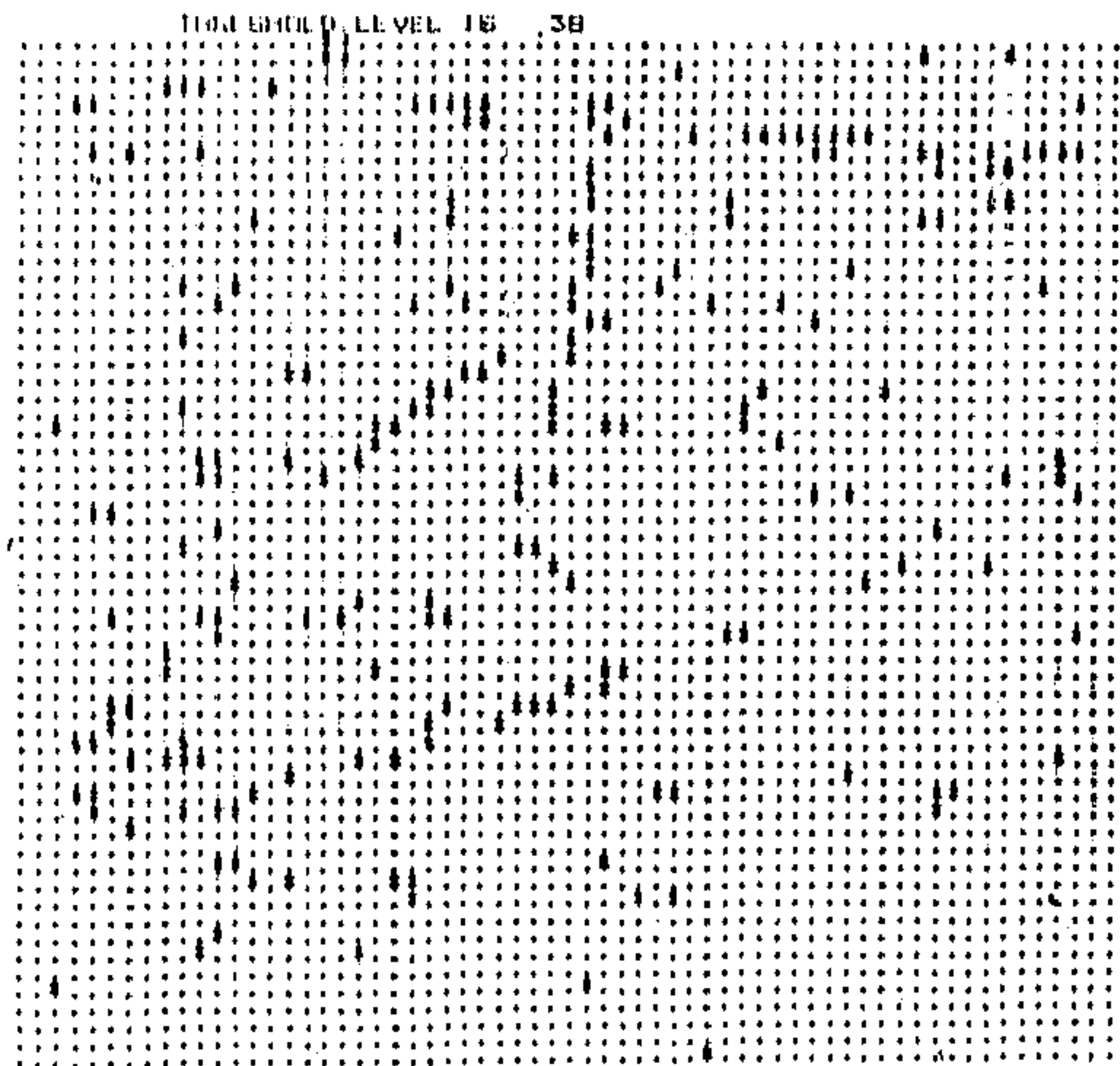
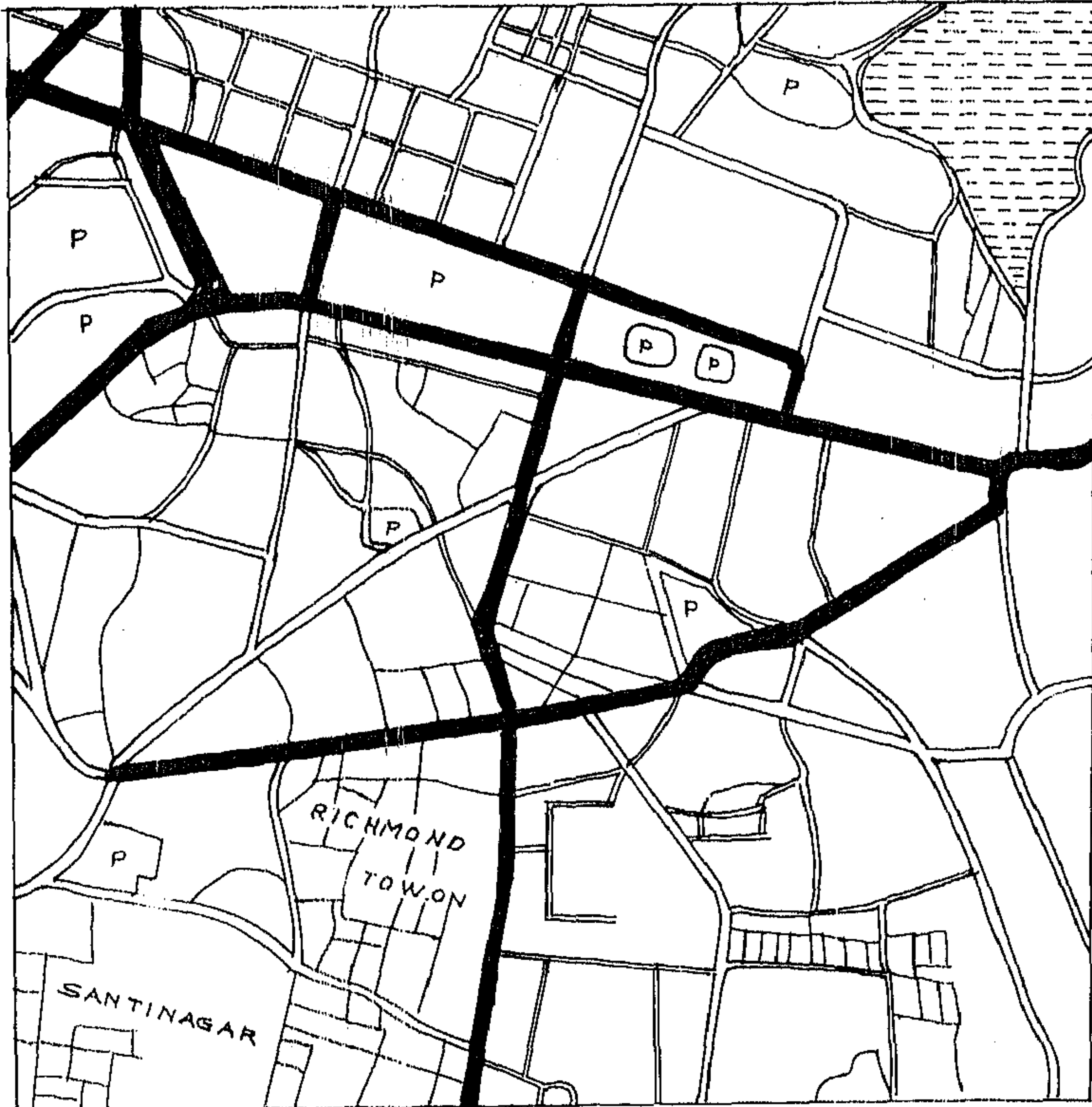
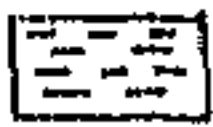


FIG.6.19(a) LINEAR FEATURE PIXELS DETECTED WITH PROPOSED TECHNIQUE T = 38

6.17(b) A MAP OF THE AREA SHOWN IN 6.17(a)



SYMBOLS

1. Roads according to importance **thick line** **double line** **single line**
2. Parks = P
3. Tonks 

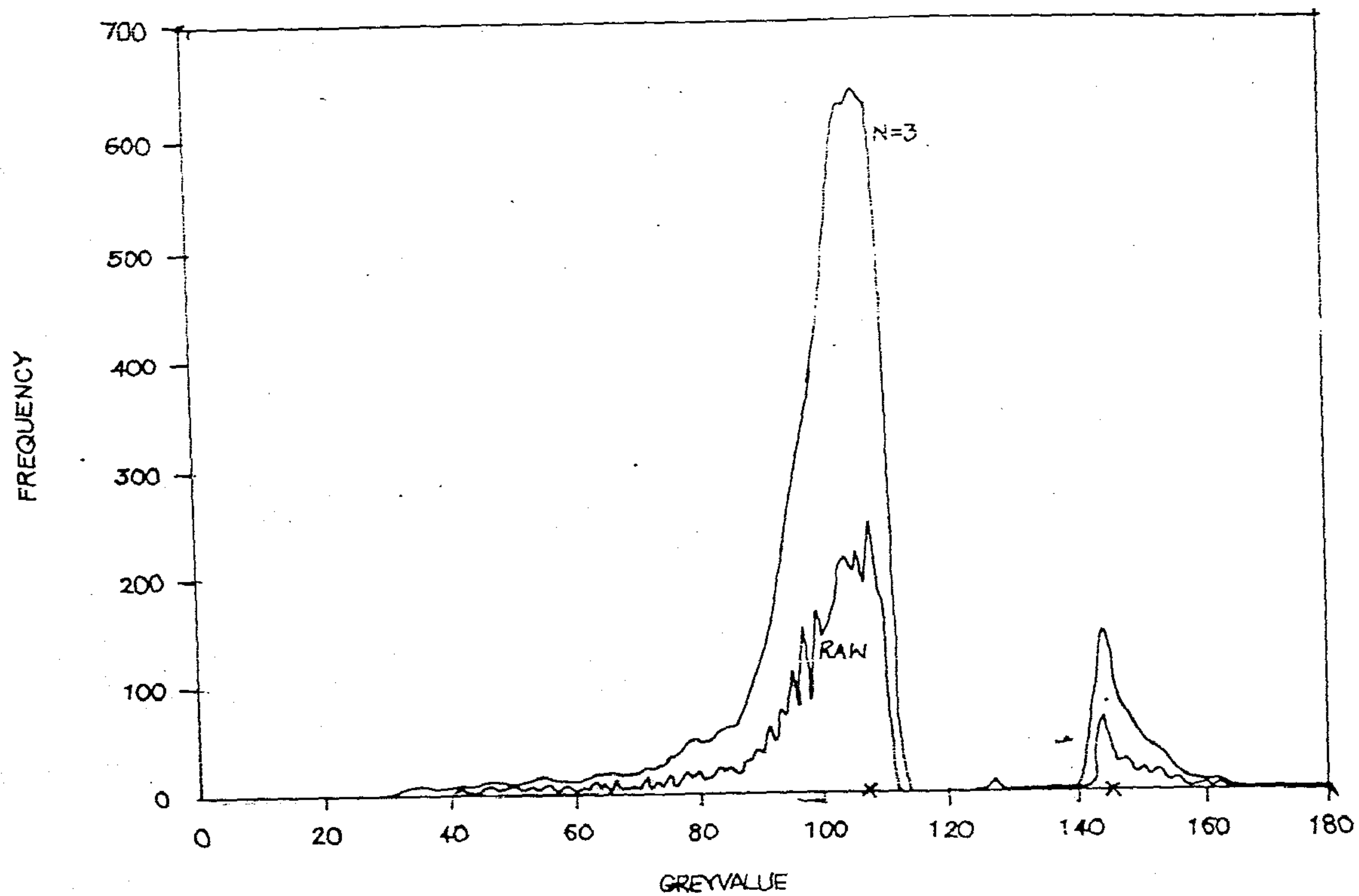


FIG. 6.18 HISTOGRAM OF IMAGE IN FIG. 6.17

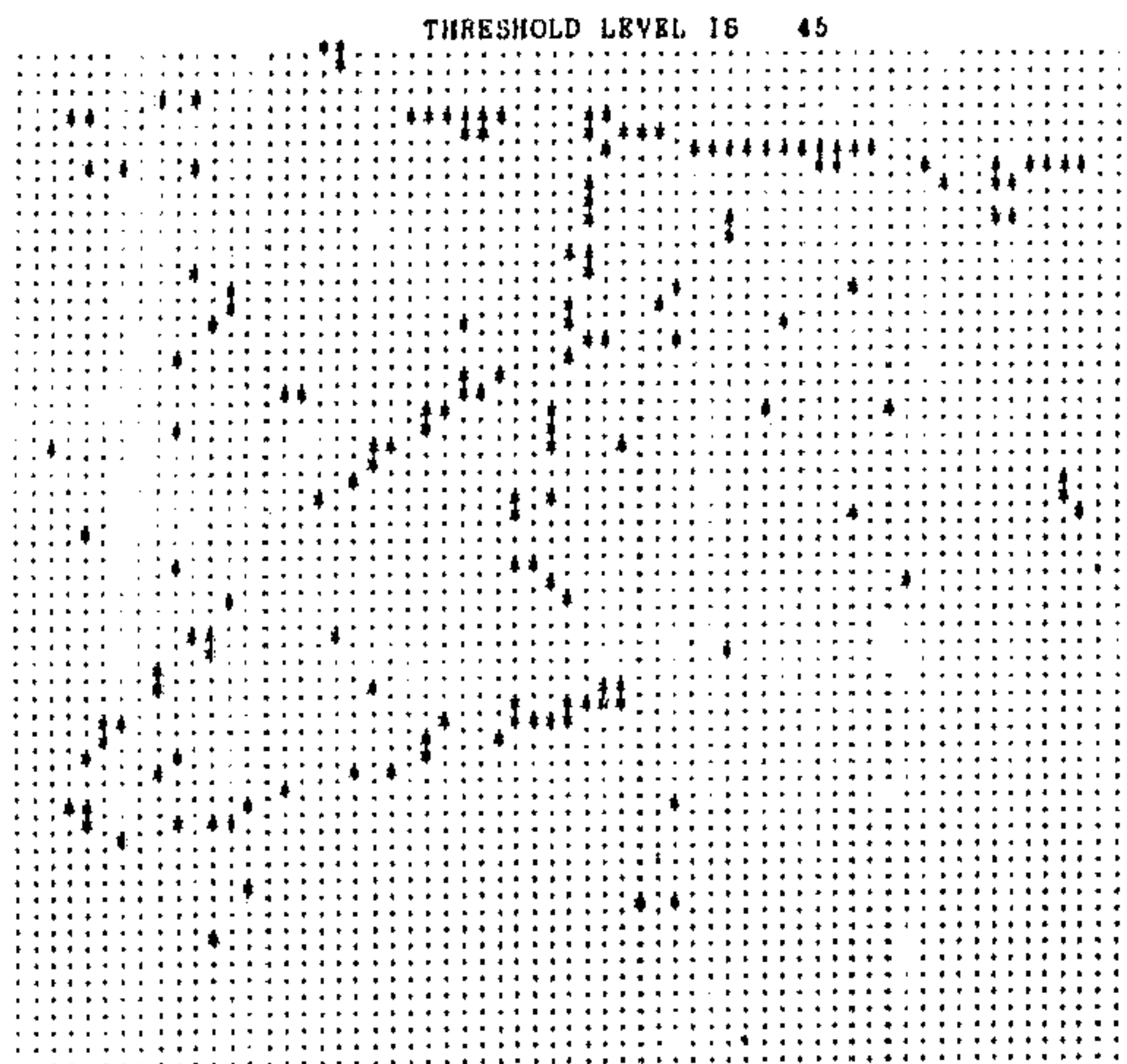


FIG.6.19(b) LINEAR FEATURE PIXELS DETECTED WITH
PROPOSED TECHNIQUE $T = 45$

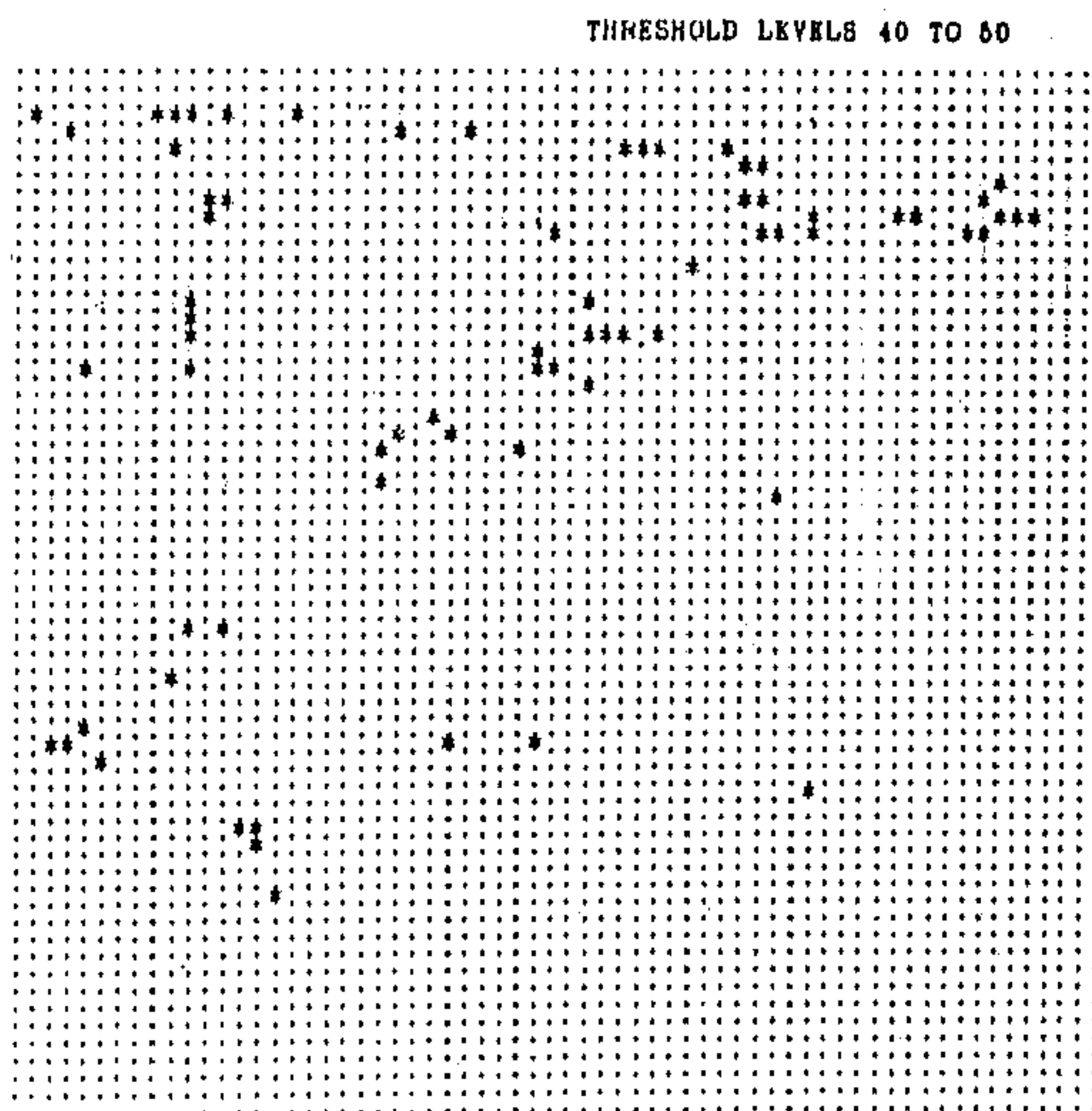


FIG.6.19(c) LINEAR FEATURE PIXELS DETECTED WITH
LINEAR DETECTOR

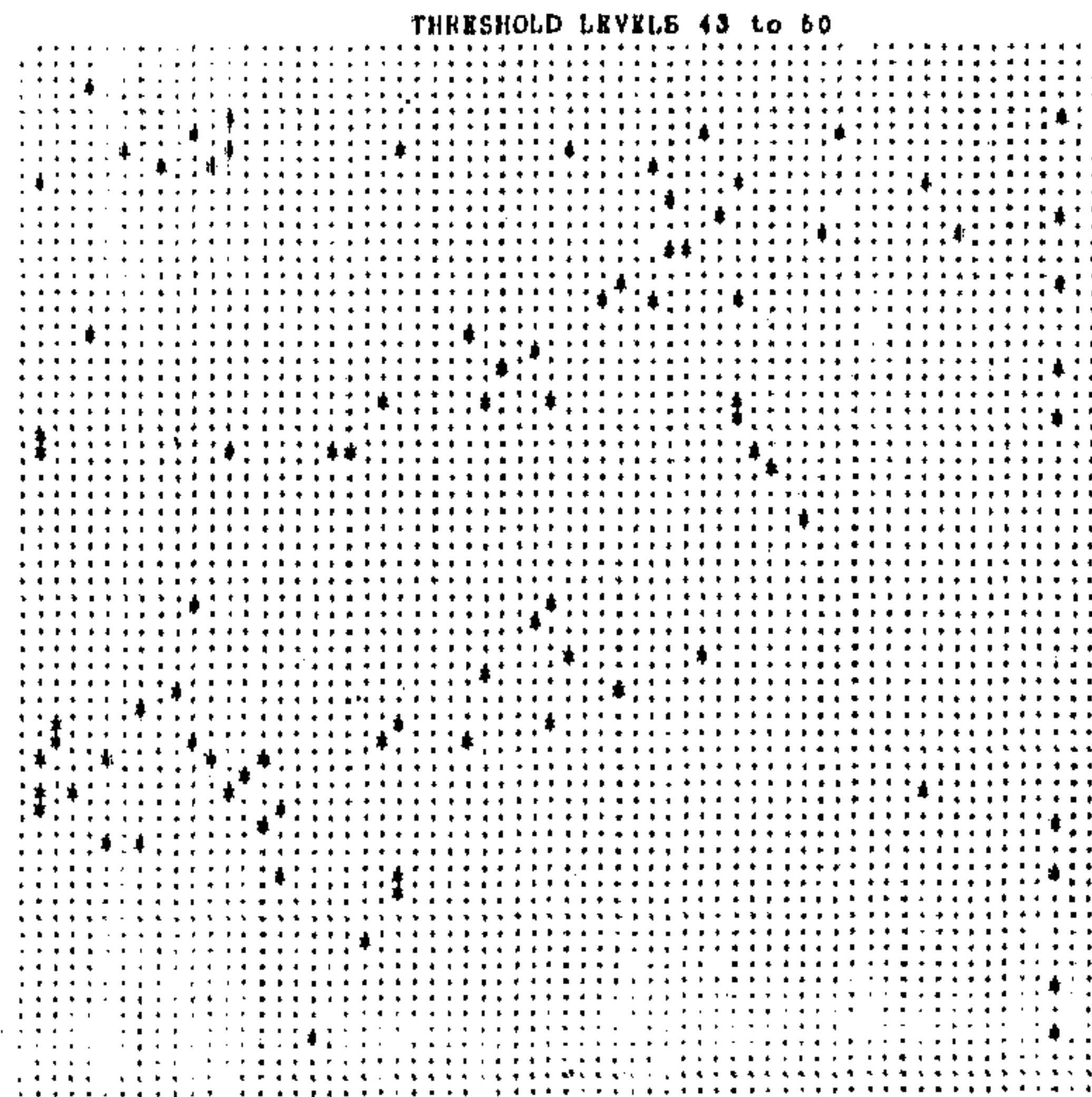
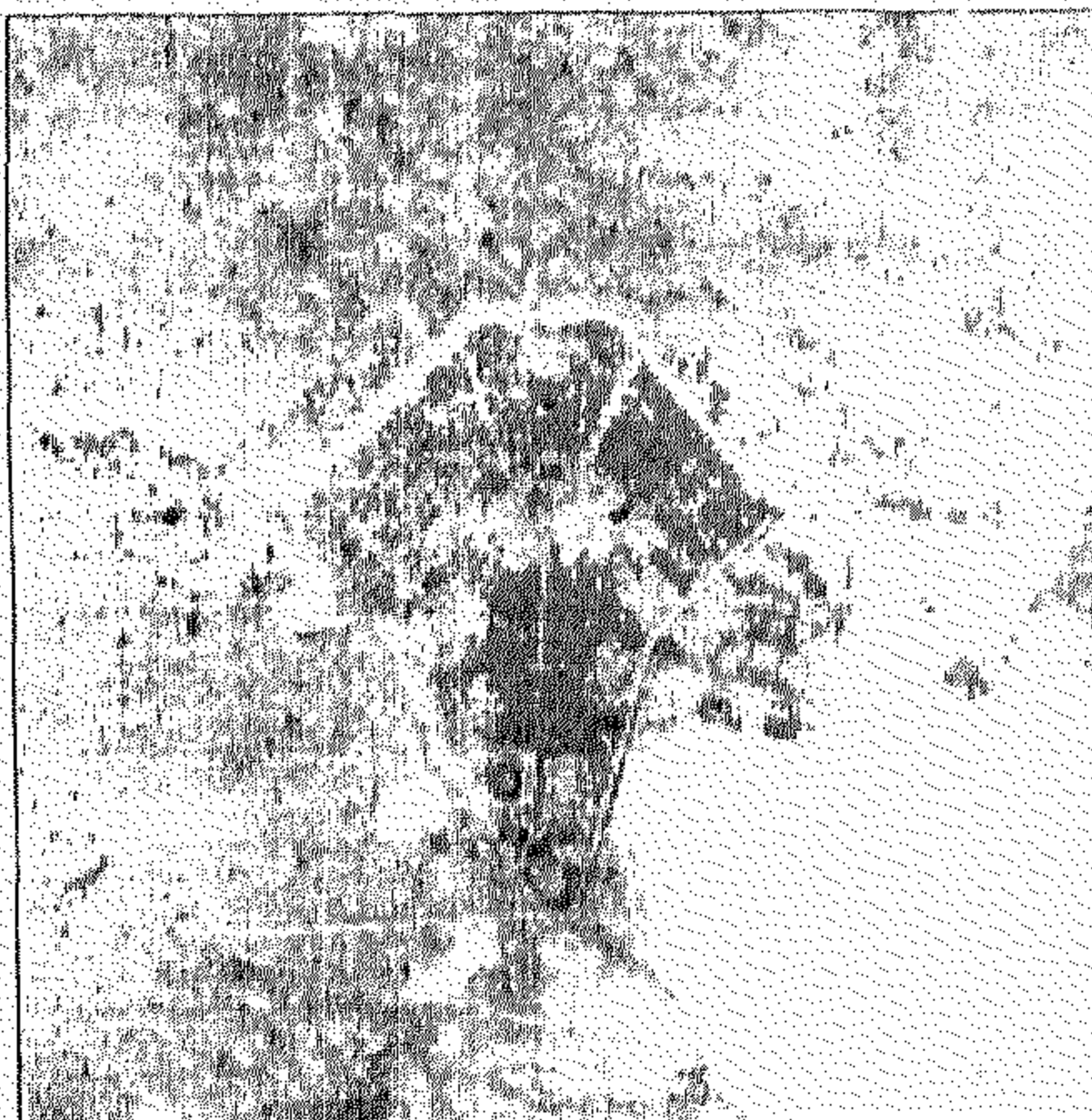


FIG.6.19(d) LINEAR FEATURE PIXELS DETECTED WITH
SEMILINEAR DETECTOR



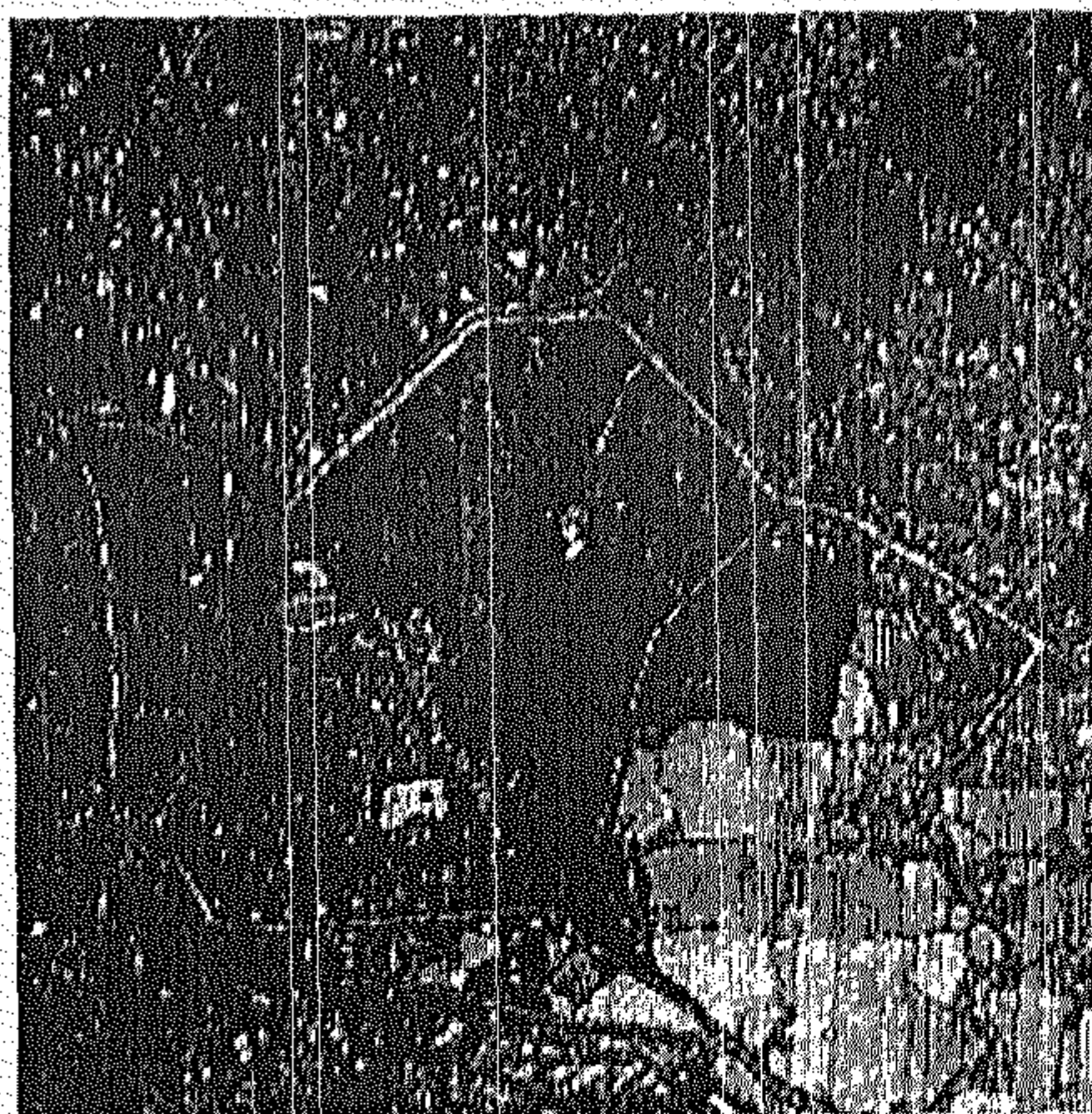
6.20(a) PART OF AN IRS SCENE - BAND1



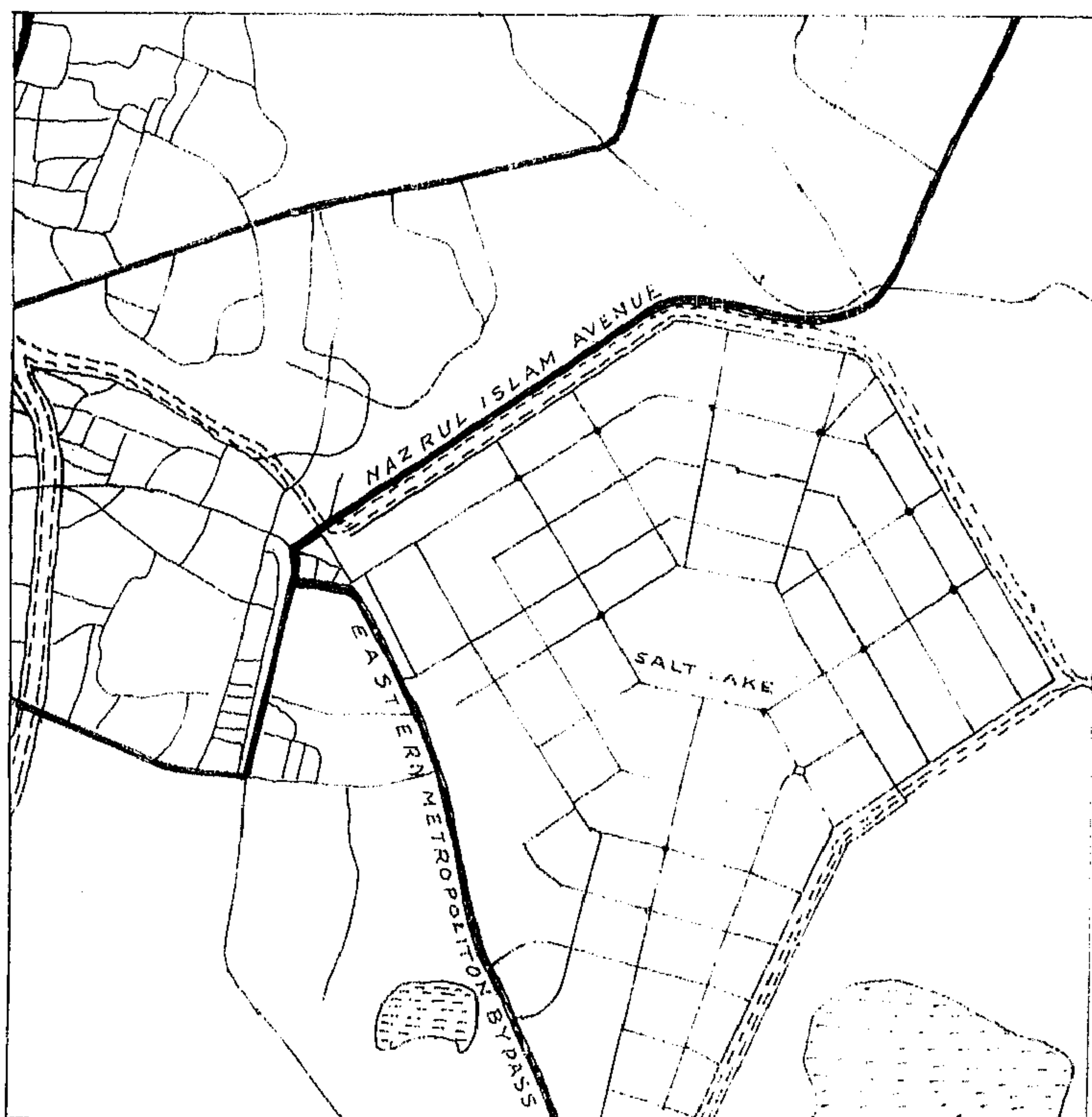
6.20(b) PART OF AN IRS SCENE - BAND3



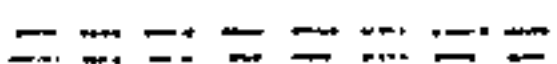
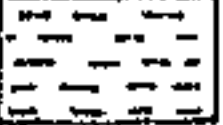
6.20(c) RATIOED IMAGE - BAND3/BAND1



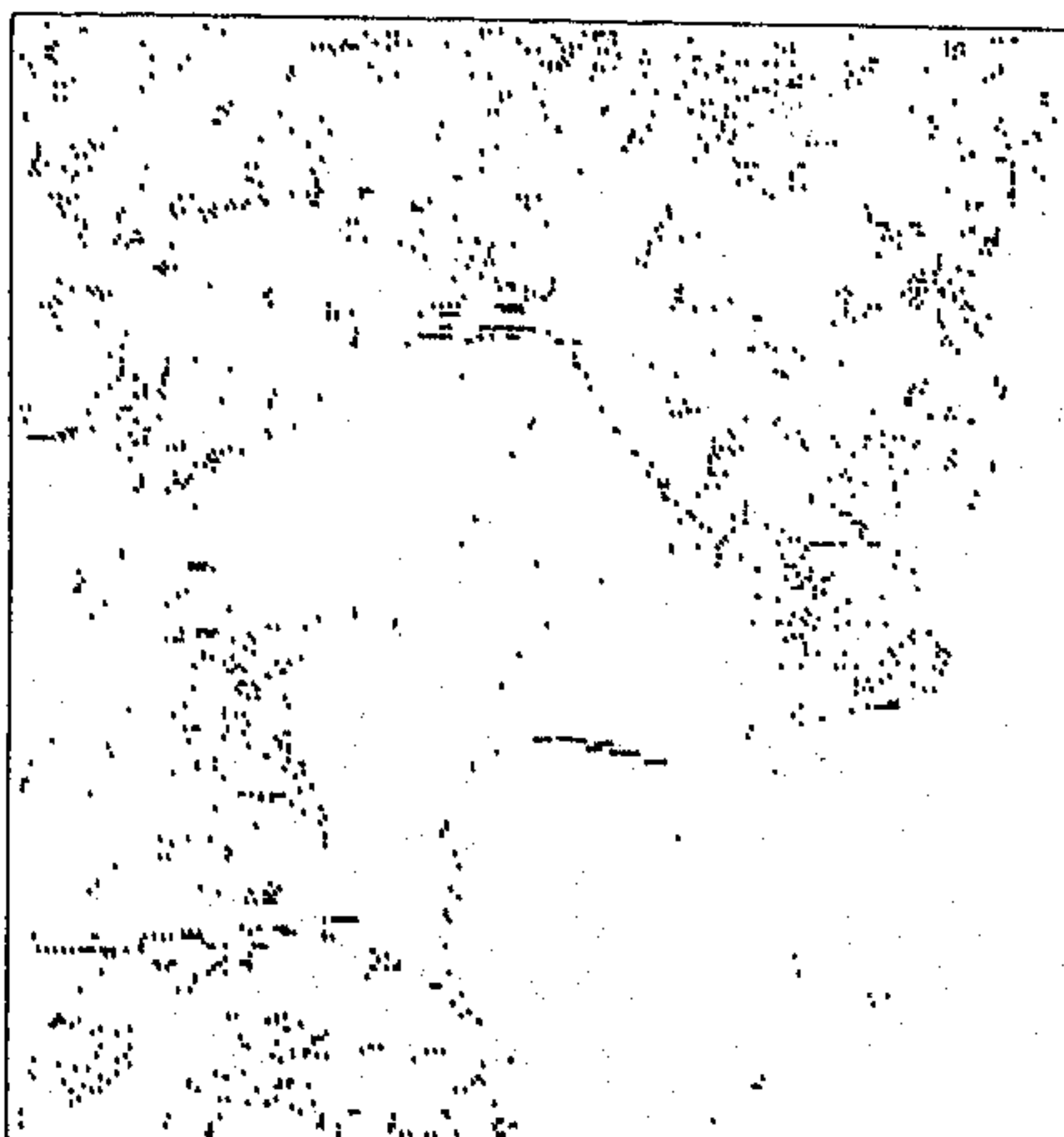
6.20(d) DENSITY SLICED IMAGE OF 6.20(c)



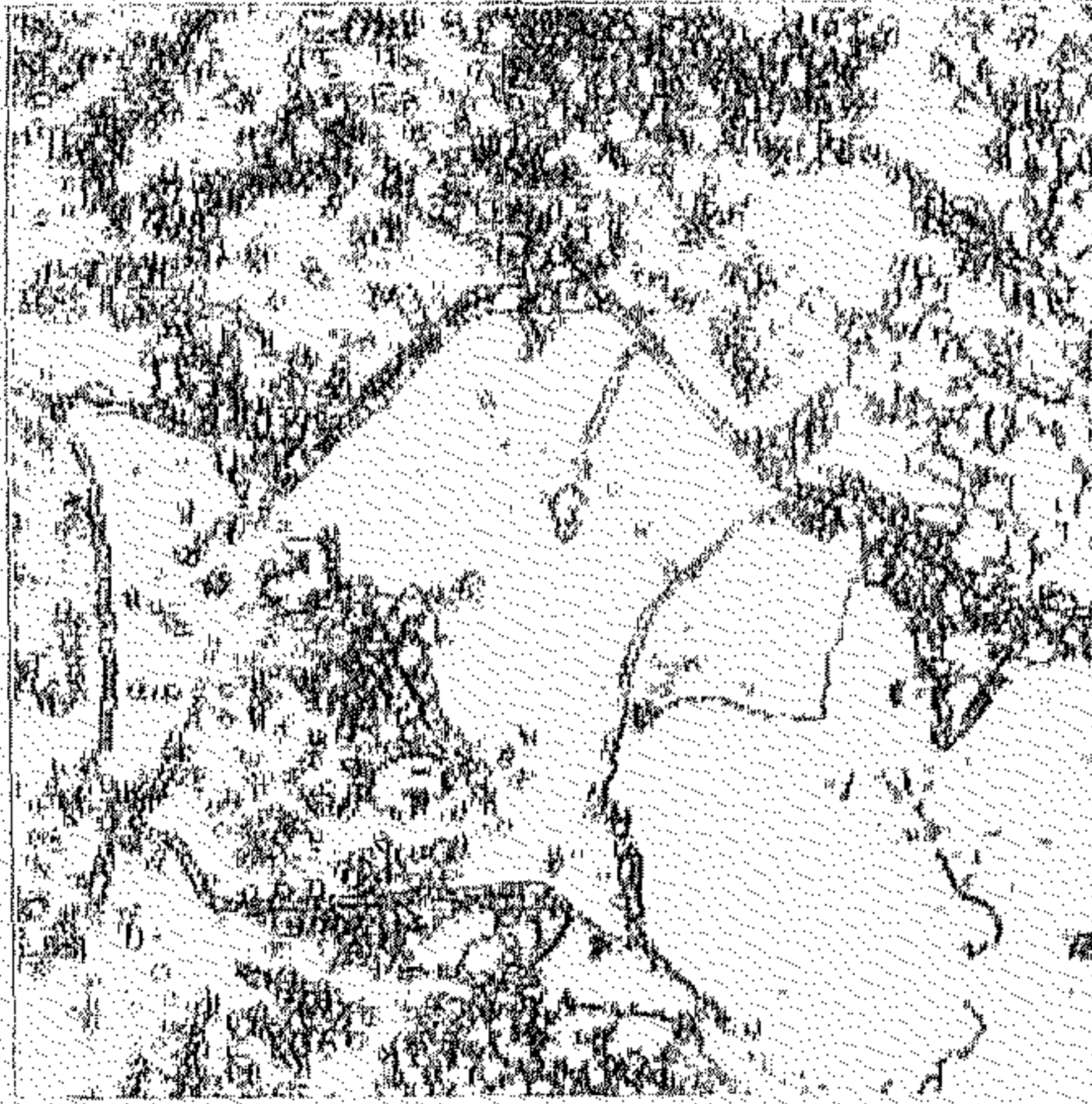
SYMBOLS

1. Roads according to importance 
2. Drains 
3. Lakes 

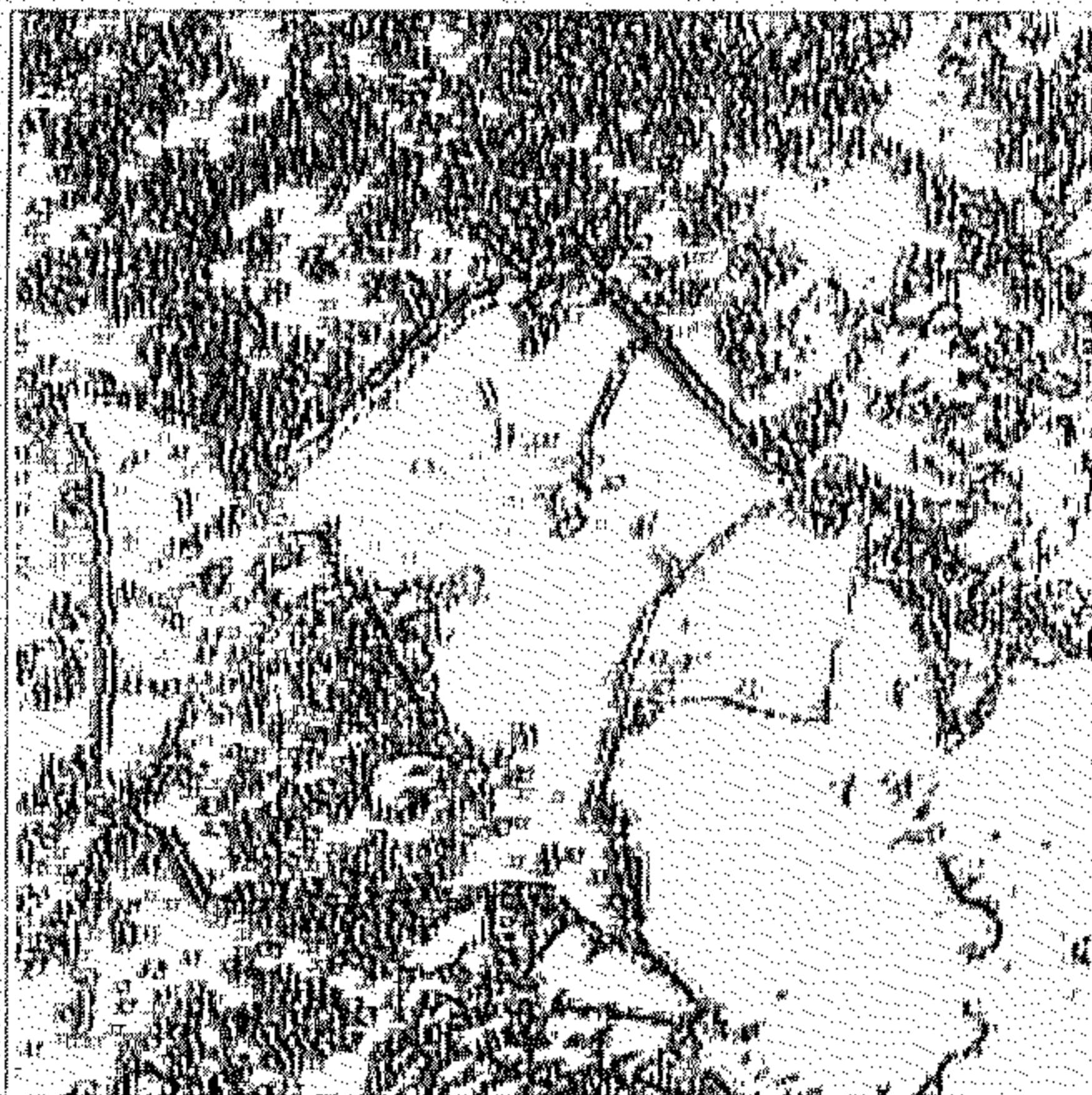
6.20(e) MAP OF THE AREA SHOWN IN (6.20(a))



6.20(f) LINEAR FEATURE PIXELS DETECTED WITH THE PROPOSED
TECHNIQUE $T = 85$



6.20(g) LINEAR FEATURE PIXELS DETECTED WITH THE LINEAR
DETECTOR



6.20(h) LINEAR FEATURE PIXELS DETECTED WITH THE SEMILINEAR
DETECTOR

CHAPTER 7

CONCLUSION

7.1 SUMMARY

Highlighting the importance of integrating multi-source satellite data, a framework for analyzing such data is proposed. The need for bringing all data sets to a common scale is stressed; to be followed by primitive extraction to enable syntactic or structural pattern recognition. In chapter 2 the focus was on image magnification using digital techniques. The importance of defining the coordinates of the magnified image independent of the technique to be used and the surface patch size was stressed. After defining the parametric form of Bezier and bicubic interpolation techniques, their mathematical properties were dealt with. The computational effort involved in implementing the bicubic interpolation techniques is higher than that required for bilinear interpolation technique. The general belief is that bilinear technique being a simple average, tends to smooth out the edges in an image while bicubic interpolation sharpens the edges. The latter feature it has been pointed out by Schowengerdt(1983) may not be very desirable when subsequent processing of the magnified image is intended. We propose a modification of the bilinear technique where in the

gradient at each pixel is taken as an additional weighting factor. If all the four pixels have the same gradient, the usual bilinear technique is resorted to. Visual comparison of the magnified image generated using this technique and the standard technique does not however, show any significant improvement. By specifying two parameters, the bilinear technique can be suitably modified to magnify an image. This technique is an extension of parametric Bezier technique developed for curve approximation. In applying this technique the parameter specification is made in such a way to ensure a first order continuity between adjacent patches. The two parameters are not independent. A look-up table of possible values that the parameter can take is provided. The effect of using different values can be studied interactively with little effort.

Observing the inadequacy of visual means of comparing the suitability of different interpolation techniques for image magnification, an objective criterion is suggested. This criterion is based on the fractal dimensions of an image and its magnified form. The appropriateness of this criterion is discussed in chapter 4. The method is illustrated for two small subscenes which are magnified 2X, 4X, 6X and 8X times using nearest neighbour, bicubic and parametrized bicubic techniques. It is seen that bilinear techniques preserve the

fractal dimensions of an image up to 4X magnification factor. This observation calls for a cautious application of bicubic techniques for digital magnification purposes specially when subsequent processing of the magnified image is intended. Linear features are important primitives in a satellite image and detection of pixels that form part of a linear feature is discussed in chapters 5 and 6. After a review of local methods of line detection a new technique for line detection is proposed. The technique has to be implemented in two stages. A pair of templates are proposed for the first stage. The templates are designed to operate on the second order neighbours of a candidate pixel. The responses of the operation at this stage are thresholded to decide whether the candidate pixel forms part of a line or not. If it is not, the second stage of operating with another pair of templates is skipped; otherwise the response of operating with the second pair of templates is thresholded to confirm whether the candidate pixel is a line pixel or not. The setting of the threshold is guided by the modes of the image histogram. Results of applying the technique on noise-free images bring out the superiority of the technique over the linear and semilinear detectors normally used for line detection. However, experimental studies with satellite images show that prior to using the technique of satellite images, enhancements of the images is a must. The attractiveness of

the technique lies in its simplicity.

7.2 SCOPE FOR FUTURE WORK

Once the image from different satellites have been brought to a common scale and primitives such as linear features are extracted, for subsequent integration, and further processing, we need to establish a one-to-one correspondence between the pixels of the image data set. This is normally done using control points in the different sets of the images. However, the extracted primitives can be utilised to carry out the registration process. This approach is called a model based registration (Henderson et al., 1985) and is particularly attractive for image to image registration. A very simplistic approach to register the image sets will be to treat the corner points of a linear feature as pseudo control points. Given a linear feature extracted in the two images to be registered, we can translate one image with the other image called the reference image so that one of the end-points coincide. Then we locate the co-ordinates of the corner points on the linear feature in the image to be registered. Using a minimum distance criterion, the co-ordinates of the corresponding corner point in the reference image is located. The coefficients of the transformation model are estimated from these set of points. This is illustrated for a set of synthetic image (Fig. 7.1). One can

think of extending this approach for satellite data sets with suitable modifications.

The idea of using fractal dimensions as a criterion for evaluating the performance of different image magnification techniques can be generalized to decide apriori, which technique is most appropriate for a given image and specified scaling factor. This kind of generalization can be evolved after studying the fractal dimensions of a variety of image data sets vis-a-vis, the capability of different techniques to preserve this fractal dimensions at different scales.

With the advent of integrated geographical information systems, the need for handling data of different scales has become very necessary. In addition if remote sensing data can be input in vectorized form; specially the linear features, a lot of computational effort can be saved. The proposed technique of linear feature detection would serve as a very useful tool for this purpose. Bringing of different satellite images to a common scale and extraction of primitives such as linear features will be extremely useful for developing Knowledge - based systems (Wu et al., 1988) for natural resources assessment and military reconnaissance. They also play an important role in developing expert systems for satellite data processing.

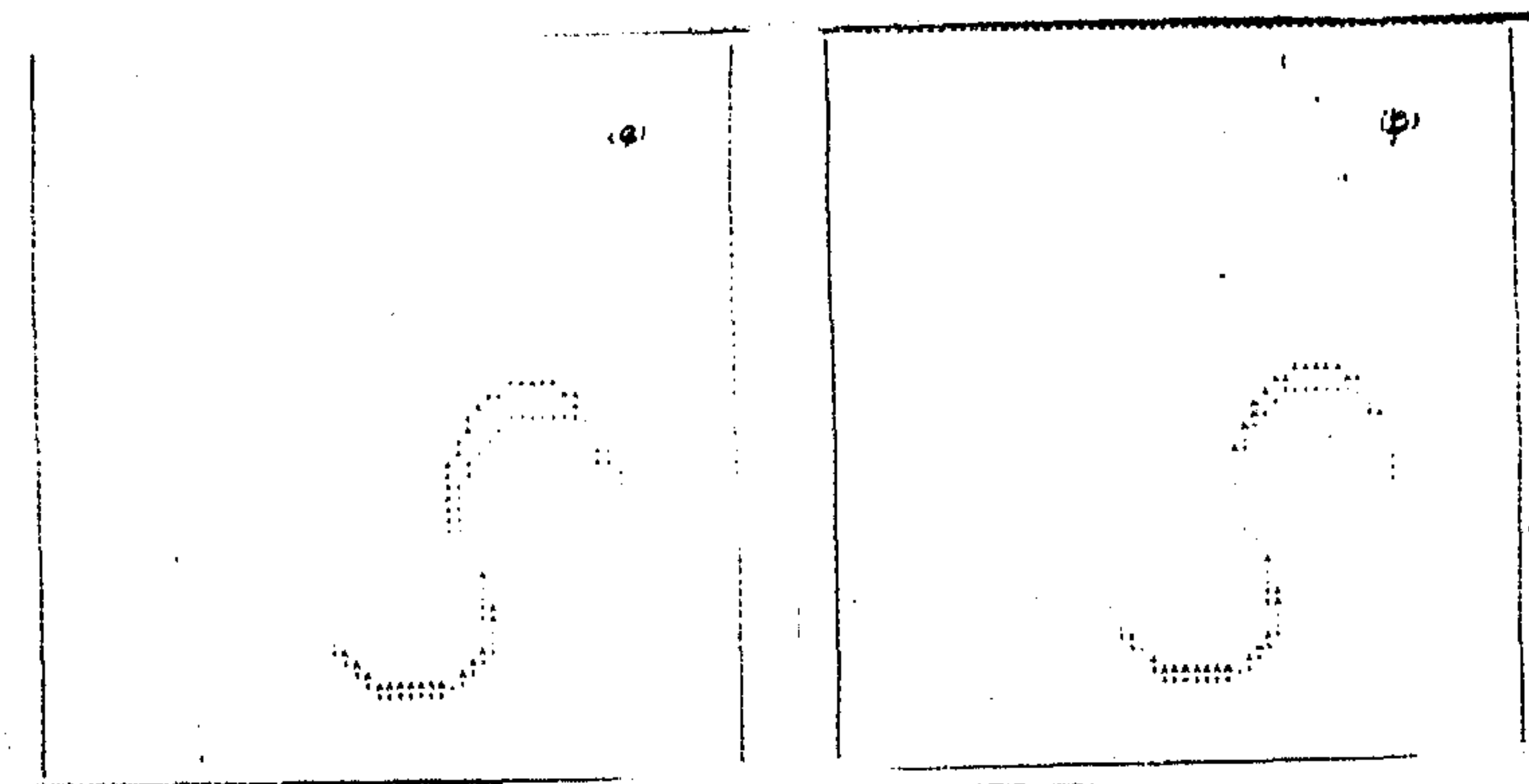


FIG.7.1 ILLUSTRATION OF IMAGE TO IMAGE REGISTRATION

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