# Digital Image Processing Techniques

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*Schlumberger-Doll Research*
*Ridgefield, Connecticut*



1984

ACADEMIC PRESS, INC.

*(Harcourt Brace Jovanovich, Publishers)*
*Orlando San Diego San Francisco New York London*
*Toronto Montreal Sydney Tokyo*

ACADEMIC PRESS, INC.
**Orlando, Florida 32887**

*United Kingdom Edition published by*
ACADEMIC PRESS, INC. (LONDON) LTD.
**24/28 Oval Road, London NW1 7DX**

Library of Congress Cataloging in Publication Data

Main entry under title:

Digital image processing techniques.

(Computational techniques ; v. )
Bibliography: p.
Includes index.
1. Image processing--Digital techniques. I. Ekstrom, Michael P. II. Series.
TA1632.D496 1983 621.36'7 83-22321
ISBN 0-12-236760-X (alk. paper)

PRINTED IN THE UNITED STATES OF AMERICA

84 85 86 87 9 8 7 6 5 4 3 2 1

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# Preface

Over the past decade the impact of computational techniques on all fields of information sciences has been both profound and widespread. This is perhaps nowhere more true than in the field of digital image processing, where digital approaches to the manipulation of imagery and other two-dimensional data sets have been employed almost exclusively in a broad range of scientific applications. Such processing has become an important, integral part of applications like computerized tomography, geophysical exploration, nondestructive testing, x-ray and radio astronomy, remote sensing, medical ultrasound, and industrial robotics. Indeed, it is difficult to conceptualize many of these applications without their image processing and display components.

What has caused this remarkable adoption of digital image processing? The availability of computing machinery capable of handling large-scale image processing tasks has been a primary element. The analog-to-digital conversion of image fields typically involves massive amounts of information. Sampling an image on a $1024 \times 1024$ grid, for example, with each picture element quantized to 10 bits, results in a data array of over 10 million bits. Although it remains true that the size of such arrays places severe demands on digital image processing systems, numerous systems do exist that have sufficient speed and memory to routinely process these large image arrays. In common with other digital signal processors, they are highly reliable, modular, and allow control of precision.

The evolution of increasingly sophisticated digital image processing algorithms has been a concurrent and complementary element. In this regard, a sort of "push-pull" relationship has existed between the processor hardware and algorithm development components: As processor capabilities have expanded, new algorithms have been developed to exploit their capabilities (and vice versa). The variety of algorithms considered is extensive, reflecting the variety of applications mentioned above. Contributions have been made from many disciplines including digital signal processing, computer science, statistical communications theory, control systems, and applied physics.

Our objective in preparing this volume is to provide a state-of-the-art review of digital image processing techniques, with an emphasis on the processing approaches and their associated algorithms. We have approached this by considering a canonical set of image processing problems. While this set is not all-inclusive, it does represent the class of functions typically required in most image processing applications. It also represents a reasonably accurate cross section of the literature presently being published in this field.

The volume is organized into two major sections. The first and principal section (Chapters 1–7) deals directly with processing techniques associated with the following tasks:

*Image Enhancement*—This processing involves subjectively improving the quality of various types of image information (e.g., edges), often in a perceptual context.

*Image Restoration*—Correcting for deblurring and/or other distorting effects introduced in the image forming process, usually performed with regard to an objective fidelity measure.

*Image Detection and Estimation*—Deciding on the presence or absence of an object or class of objects in an image scene and estimating certain of the object's features or parameters.

*Image Reconstruction*—Reconstructing a two-dimensional field from its one-dimensional projections, where the projections are taken at various angles relative to the object.

*Image Data Compression*—Encoding the imagery, based on information redundancy, to reduce its data storage/transmission requirements while maintaining its overall fidelity.

*Image Spectral Estimation*—Developing two-dimensional power spectral density estimates for image fields (used in many of the above tasks).

*Image Analysis*—Representing image information in a form compatible with automated, machine-based processing, usually in an interpretative context.

The emphasis in these contributions is on problem definition and technique description. Each chapter broadly addresses the following questions: What problem is being considered? What are the best techniques for this particular problem? How do they work? What are their strengths and limitations? How are the techniques actually implemented and what are their computational aspects?

The second section (Chapter 8) describes hardware and software systems for digital image processing. Aspects of commercially available systems that combine both processing and display functions are described, as are future prospects for their technological and architectural evolution. Specifics of system design trade-offs are explicitly presented in detail.

Some care has been taken in the preparation of all chapters to make the material as accessible as possible to the reader. To the extent practical, standard notation has been adopted, and each chapter concludes with an annotated bibliography, noting particularly important contributions, and an extensive list of references. This is intended to provide a useful entry point into the rich yet diverse literature of the field. For their consideration and cooperation in preparing these materials, I wish to publicly acknowledge the contributing authors.

# Contents

# 1 Image Enhancement

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## I. Introduction

Image enhancement is the processing of images to increase their usefulness. Methods and objectives vary with the application. When images are enhanced for human viewers, as in television, the objective may be to improve perceptual aspects: image quality, intelligibility, or visual appearance. In other applications, such as object identification by machine, an image may be preprocessed to aid machine performance. Because the objective of image enhancement is dependent on the application context, and the criteria for enhancement are often subjective or too complex to be easily converted to useful objective measures, image enhancement algorithms tend to be simple, qualitative, and ad hoc. In addition, in any given




ISBN 0-12-236760-X

application, an image enhancement algorithm that performs well for one class of images may not perform as well for other classes.

Image enhancement is closely related to image restoration. When an image is degraded, restoration of the original image often results in enhancement. There are, however, some important differences between restoration and enhancement. In image restoration, an ideal image has been degraded, and the objective is to make the processed image resemble the original as much as possible. In image enhancement, the objective is to make the processed image better in some sense than the unprocessed image. In this case, the ideal image depends on the problem context and often is not well defined. To illustrate this difference, note that an original, undegraded image cannot be further restored but can be enhanced by increasing sharpness through high-pass filtering.

Image enhancement is desirable in a number of contexts. In one important class of problems, an image is enhanced by modifying its contrast and/or dynamic range. For example, a typical image, even if undegraded, will often appear better when the edges are sharpened. Also, if an image with large dynamic range is recorded on a medium with small dynamic range, such as film or paper, the contrast and, therefore, the details of the image are reduced, particularly in the very bright and dark regions (see Fig. 1). The contrast of an image taken from an airplane is reduced when the scenery is covered by cloud or mist (see Fig. 2); increasing the local contrast

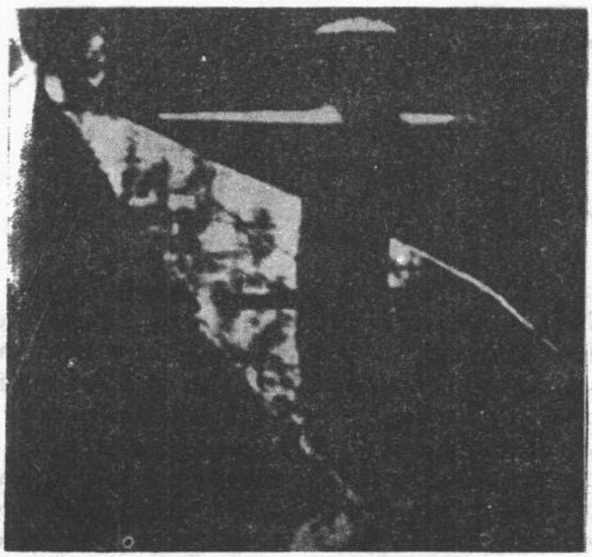


Fig. 1. Image with little detail in dark regions.

**Fig. 2.** **Image taken from an airplane through varying amounts of cloud cover.**

and reducing the overall dynamic range can significantly enhance the quality of such an image.

In another class of enhancement problems, a degraded image may be enhanced by reducing the degradation. When an image is quantized for the purpose of bit rate reduction, it may be degraded by random noise or signal-dependent false contours [31,32,80]. An example of an image with false contours is shown in Fig. 3. When a coherent light source is used, as in infrared radar imaging, the image may be degraded by a speckly effect [17,59]. An example of an image degraded by speckle noise is given in Fig. 4. An image recorded on film is degraded by film-grain noise. The speckle noise and film-grain noise, in some instances, can be approximately modeled by multiplicative noise [5,17,37]. When an image is coded and transmitted over a noisy channel or degraded by electrical sensor noise, as in a vidicon TV camera, degradation appears as salt-and-pepper noise (see Fig. 5). An image may also be degraded by blurring (convolutional noise) due to misfocus of lenses, to motion, or to atmospheric turbulence. In this case, high-frequency details of the image are often reduced, and the image appears blurred. An image degraded by one or more of these factors can be enhanced by reducing the degradation.

Another important class of image enhancement problems is the display of two-dimensional data that may or may not represent the intensities of an actual image. In two-dimensional spectral estimation, the spectral esti-

**Fig. 3.** Image with false contours due to signal-dependent quantization noise in a 2-bit PCM image coding system.

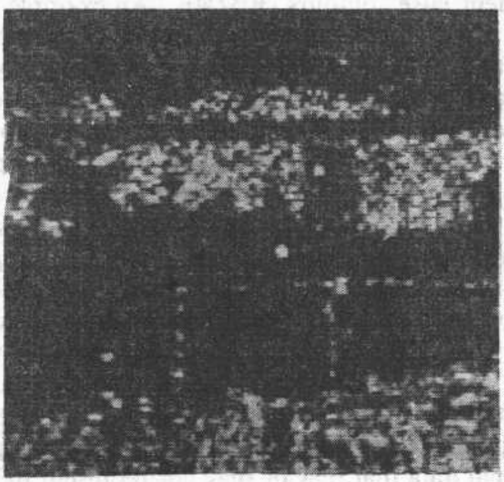


**Fig. 4.** Image degraded by speckle noise.

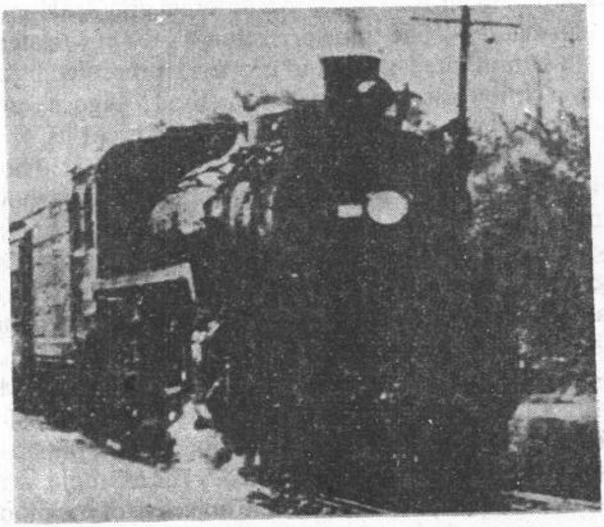


Fig. 5. Image degraded by salt-and-pepper noise.

mates have traditionally been displayed as contour plots. Even though such two-dimensional data displays are not images in the conventional sense, their appearance may be improved and information more clearly conveyed when enhanced with gray scale and/or color. In other applications, such as infrared radar imaging, range information as well as image intensities may be available. By displaying the range information with color, one can highlight relative distances of objects in an image. Even typical images may be enhanced by certain types of distortion. When an object in an image is displayed with false color, the object may stand out more clearly to a human viewer.

Thus, an image can often be enhanced when one or more of the following objectives is accomplished: modification of contrast or dynamic range; edge enhancement; reduction of additive, multiplicative, and salt-and-pepper noise; reduction of blurring; and display of nonimage data. In the next section, we shall discuss these methods of enhancement.

## II. Enhancement Techniques

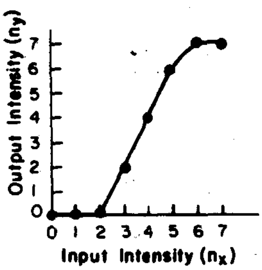
### *A. Gray-Scale Modification*

Gray-scale modification is a simple and effective way of modifying an image's dynamic range or contrast [28,29,34,35,46,80,100]. In this method the gray scale of an input image is changed to a different gray scale according to a specific transformation. The transformation $n_y = T[n_x]$ relates an input intensity $n_x$ to an output intensity $n_y$ and is often represented by a plot or a table. Consider a simple illustration of this method. Figure 6(a) shows an image of 4 × 4 pixels, with each pixel represented by three bits, so that there are eight reconstruction levels, that is, $n_x = 0, 1, 2, \ldots, 7$. The transformation that relates the input intensity to the output intensity is shown in Fig. 6(b) as a plot and in Fig. 6(c) as a table. For each pixel in the input image, the corresponding output intensity is obtained from the plot in Fig. 6(b) or from the table in Fig. 6(c). The result is shown in Fig. 6(d). By properly choosing the specific transformation, one can modify the contrast or dynamic range.

When the transformation is specified, gray-scale modification requires one table look-up per output point, and the table has $2^M$ entries, where $M$ is the number of bits used for the gray scale. The specific transformation desired depends on the application. In some applications, physical considerations determine the transformation selected. For example, when a display system has nonlinear characteristics, the objective of the modification may be to precompensate for the nonlinearities. In such a case, the most

| | | | |
|---|---|---|---|
| 3 | 3 | 4 | 4 |
| 2 | 3 | 4 | 5 |
| 2 | 3 | 4 | 5 |
| 2 | 3 | 4 | 5 |

(a)




(b)

| $n_x$ | $n_y$ |
|---|---|
| 0 | 0 |
| 1 | 0 |
| 2 | 0 |
| 3 | 2 |
| 4 | 4 |
| 5 | 6 |
| 6 | 7 |
| 7 | 7 |

(c)

| | | | |
|---|---|---|---|
| 2 | 2 | 4 | 4 |
| 0 | 2 | 4 | 6 |
| 0 | 2 | 4 | 6 |
| 0 | 2 | 4 | 6 |

(d)

**Fig. 6.** (a) Image of 4 × 4 pixels, with each pixel represented by 3 bits. (b) Gray-scale transformation function represented by a plot. (c) Gray-scale transformation function represented by a table. (d) Result of modifying the image in (a) using the gray-scale transformation function of (b) or (c).

suitable transformation can be determined from the nonlinearity of the display system.

A good transformation in typical applications can be identified by computing the histogram of the input image and studying its characteristics. The histogram of an image, denoted by $p(n_x)$, represents the number of pixels that have a specific intensity as a function of the intensity variable $n_x$. For example, the 4 × 4 pixel image shown in Fig. 6(a) has the histogram shown in Fig. 7(a). The histogram obtained in this way displays some important image characteristics that help determine which particular gray-scale transformation is desirable. In Fig. 7(a), the image's intensities are clustered in a small region, and the available dynamic range is not very well utilized. In such a case, a transformation of the type shown in Fig. 6(b) would increase the overall dynamic range, and the resulting image would appear to have greater contrast. This is evidenced by Fig. 7(b), which is the histogram of the processed image shown in Fig. 6(d).

Because computing the histogram of an image and modifying its gray scale for a given gray-scale transformation requires little computation (on the order of one table look-up and one arithmetic operation per output pixel), the desirable gray-scale transformation can be determined by a human operator in real time. Based on the initial histogram computation, the operator chooses a gray-scale transformation to produce a processed image. By looking at the processed image and its histogram, the operator can choose another gray-scale transformation, obtaining a new processed image. These steps can be repeated until the output image satisfies the operator.

When there are too many images for individual attention by a human operator, the gray-scale transformation must be chosen automatically. Histogram modification is useful in these circumstances. In this method, the gray-scale transformation that produces a desired histogram is chosen for each individual image. The desired histogram of the output image, denoted by $P_d(n_y)$, that is useful for typical pictures has a maximum around

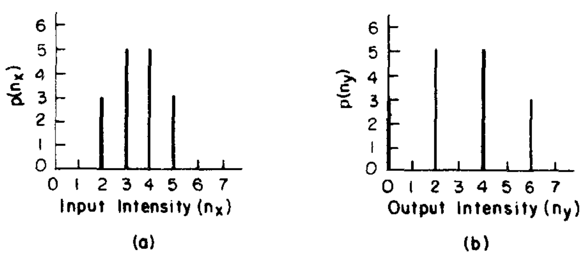



Fig. 7. Histogram of the 4 × 4 pixel image in Fig. 6(a). (b) Histogram of the 4 × 4 pixel image in Fig. 6(d).