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INTRODUCTION TO DIGITAL IMAGE PROCESSING TECHNIQUES

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1. INTRODUCTION

In the last two decades conventional and relatively simple image processing techniques such as image enhancement, gray-level mapping, texture analysis, etc. have been modified for biomedical images and successfully applied for processing and analysis.
This paper discusses some image analysis techniques that are widely used for biomedical image processing and that will be devoloped, during the laboratory sessions, using conventional image processing systems.

2. SYSTEM REQUIREMENTS FOR BIOMEDICAL IMAGE PROCESSING

The efforts to build image processing systems were started in the late 1960s and early 1970s with the development of mainframe computers and minicomputers. At that time, image processing systems were used only in laboratories, and were stand-alone minicomputer-based systems with limited image processing capabilities. The system architecture of the late 1970s established a model that is still prevalent. Today, the image processing systems are being designed for a variety of applications. Some applications require interactive and real-time processing and for these reasons the systems are often augmented with other processors (configuring parallel processing) or with dedicated array processors. We shall discuss the requirements of a conventional but advanced biomedical image processing and analysis system.
More details about advances in the image processing systems architecture can be found in references 1, 2, 3.

The basic components of the system are:

a) image acquisition system
b) digital computer (analysis system)
c) image display environment

a) image acquisition system

The image acquisition system must have some means of converting the image from the source to a digital picture.
For X ray radiograph the acquisition system usually includes a suitable light source to illuminate the radiograph (the film) and a digitizing camera to convert the analog image into a digital picture. Other means of digitizing an image include several types of microdensitometers and laser scanners.

b) digital computer

This is the main processing unit (or host computer) with sufficient and appropriate memory which is used to store the digitized information for furher processing. A general-purpose computer or a specific-purpose processor can be used as the processing unit.

c) image display environment

Usually it includes a frame buffer (multiple memory planes) where are stored the images to be viewed, pixel processors for real time image processing operations, LUTs (look-up tables) that generate the color representing the intensity level of each pixel. The output of each LUT is sent to a digital to analog converter. These D/A converters produce, in real time, the three analog signals for the RGB video output.
Depending on the application, there may be a large variation in the requirements of image display environment in terms of display capabilities such as resolution, number of gray-levels, number of colors etc.

3. IMAGE PROCESSING TECHNIQUES

The basic sequence of preprocessing, processing, feature detection and feature analysis for a biomedical image analysis system is shown in fig. 1

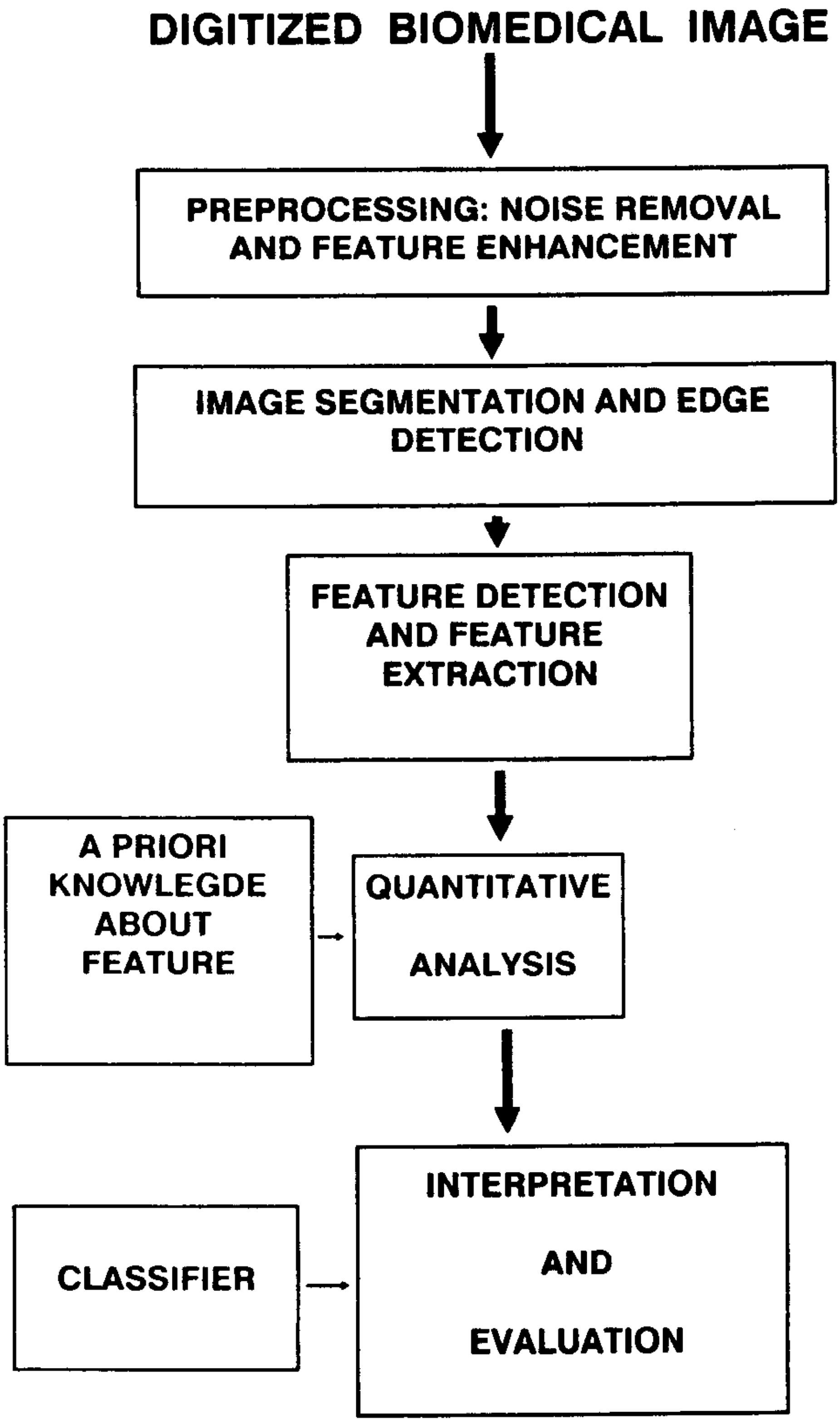
3.1 IMAGE PREPROCESSING AND CONTRAST ENHANCEMENT

To evaluate the content of an image automatically by a computerized analysis, or by visual inspection, usually it becomes necessary to improve the image quality by reducing the noise, enhancing the contrast or correcting the imperfections of the image acquisition system.
In the following sections, we will discuss some filtering operations and enhancement methods used to improve visibility and subjective quality of the image. These methods are not recognized as formal image restoration methods. They may be categorized as ad-hoc methods but are found very useful and popular in biomedical image processing. They can be classified as follow:

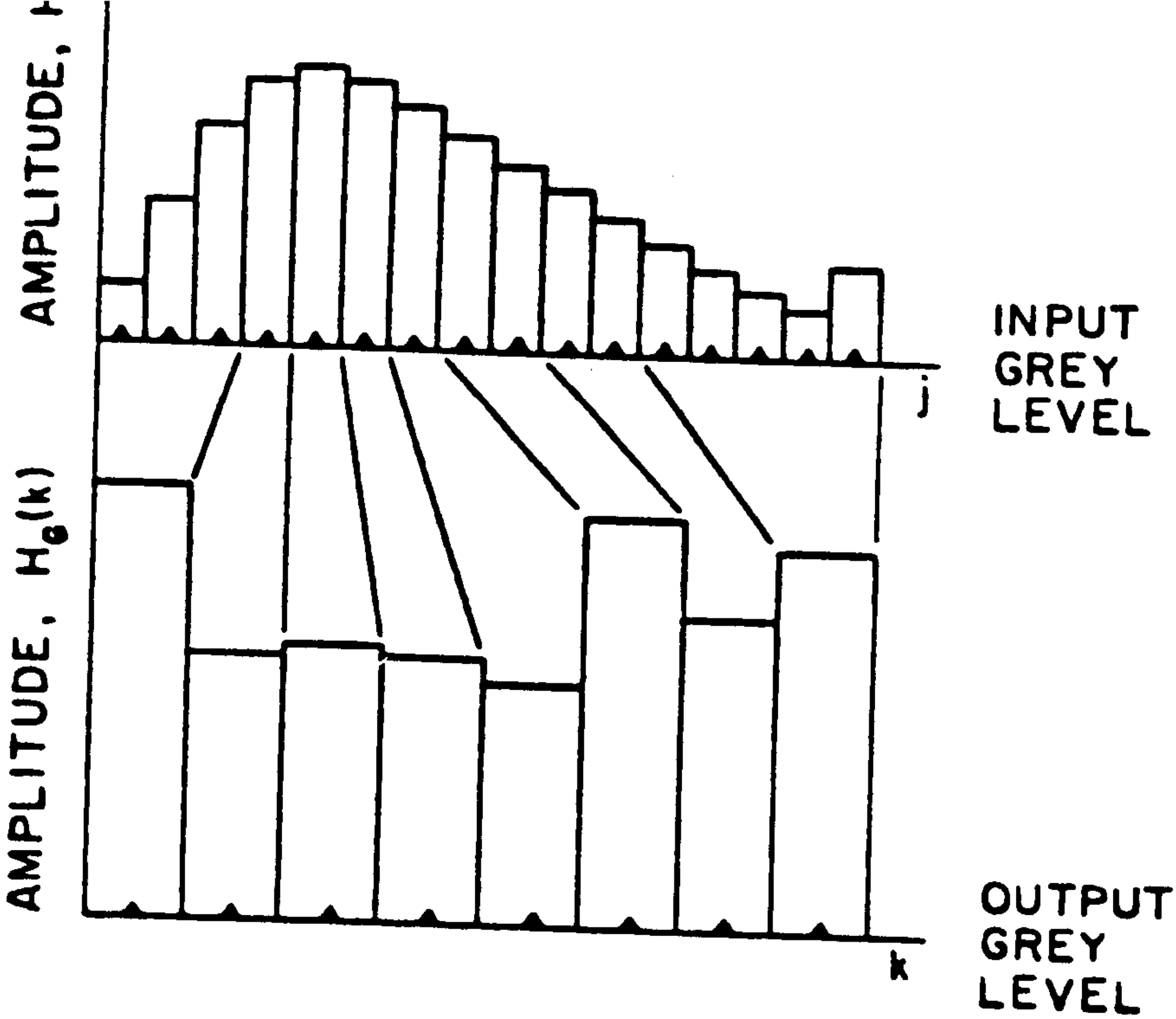
a) enhancement based on point operations
b) filters based on neighborood operations

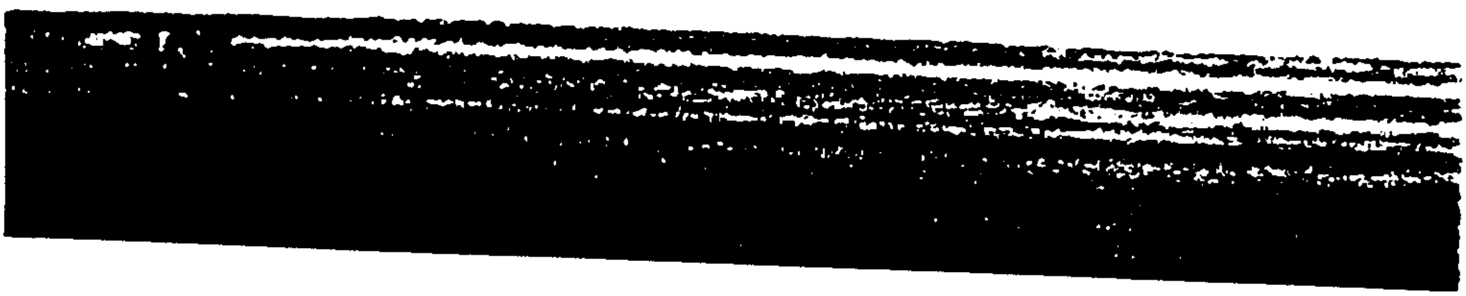
a) enhancement based on point operations

In a point operation, the gray level of each pixel is modified according to a predefined transformation to create an output image.
One simple but very efficient type of contrast enhancement is histogram equalization (4), in which the original image is rescaled so that the histogram of the gray-level distribution of the output image is forced to be uniform (fig. 2).
Such a trasformation provides equal opportunity to all gray-levels to appear in the image. As a result the overall contrast of the image can be improved, if the original image utilizes only a part of the full gray-scale.
The histogram modification process can be considered a monotonic


DIGITIZED BIOMEDICAL IMAGE
PREPROCESSING: NOISE REMOVAL AND FEATURE ENHANCEMENT
IMAGE SEGMENTATION AND EDGE DETECTION
FEATURE DETECTION AND FEATURE EXTRACTION
A PRIORI KNOWLEGDE ABOUT FEATURE
QUANTITATIVE ANALYSIS
CLASSIFIER
INTERPRETATION AND EVALUATION

2A


AMPLITUDE, H
INPUT GREY LEVEL
j
AMPLITUDE, H_G(k)
OUTPUT GREY LEVEL
k



point transformation $G(x,y) = h(f(x,y))$, where $f(x,y)$ is the input image, $G(x,y)$ is the enhanced image and h is the transformation function.
The transformation function h, depending on the requirement, may be linear, logarithmic, or exponential.

b) Filtering based on neighborhood operations (4)

These methods allow the convolution of the input image with a specific mask to selectively enhance or reduce specific spatial frequency components in an image.
This filtering operates on each pixel of the original image, replacing that particular pixel by a combination of it and its nearest neighbors. The mask defines the size of the grid nearest neighbors to be used. For the case illustrated mask 3x3 are employed, but in other cases one may use a 5x5, 7x7, 3x1 grid and so forth.
Low pass filtering has been called smoothing because it tends to blur, or smooth, abrupt transitions in the image. These rapid transitions, representing high-spatial-frequency information, are attenuated, while the low-frequency information is left unchanged
Several convolutions arrays of low-pass form are listed below.

LOW - PASS DIGITAL SPATIAL FILTERING

(SMOOTHING)

SEVERAL CONVOLUTION ARRAYS (NOISE CLEANING MASKS):

MASK 1 $$H = 1/9 \begin{vmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{vmatrix}$$

MASK 2 $$H = 1/10 \begin{vmatrix} 1 & 1 & 1 \\ 1 & 2 & 1 \\ 1 & 1 & 1 \end{vmatrix}$$

MASK 3 $$H = 1/16 \begin{vmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{vmatrix}$$

The high-pass filter enhances edges and attenuates smooth transitions. Besides it increases the background random noise level.

Several typical high-pass masks are listed below

THE MASK DEFINES THE SIZE OF THE GRID

NEAREST NEIGHBORS TO BE USED.

HIGH PASS MASKS:

MASK 1

$$H = \begin{vmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{vmatrix}$$

MASK 2

$$H = \begin{vmatrix} -1 & -1 & -1 \\ -1 & 9 & -1 \\ -1 & -1 & -1 \end{vmatrix}$$

MASK 3

$$H = \begin{vmatrix} 1 & -2 & 1 \\ -2 & 5 & -2 \\ 1 & -2 & 1 \end{vmatrix}$$

3.2 EDGE DETECTION

Edge detection is the process of identifying edges of interest in the image. Often the process is an integral step of boubdary detection, and plays a very important role in the feature detection and image analysis. A large number of edge-detecting operators and algorithms have been developed (4). Most commonly used edge detection methods in biomedical image analysis use different masks for detecting edges. Several convolving masks are listed below.

GRADIENT MASKS:

- HORIZONTAL EDGE DETECTION MASK:

$$H = \begin{vmatrix} -2 & -2 & -2 \\ 0 & 0 & 0 \\ 2 & 2 & 2 \end{vmatrix}$$

- VERTICAL EDGE DETECTION MASK:

$$H = \begin{vmatrix} -2 & 0 & 2 \\ -2 & 0 & 2 \\ -2 & 0 & 2 \end{vmatrix}$$

LAPLACIAN MASKS

EDGE SHARPENING WITHOUT REGARD TO EDGE DIRECTION

MASK 1 $$H = \begin{vmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{vmatrix}$$

MASK 2 $$H = \begin{vmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{vmatrix}$$

MASK 3 $$H = \begin{vmatrix} 1 & -2 & 1 \\ -2 & 4 & -2 \\ 1 & -2 & 1 \end{vmatrix}$$

3.3 FEATURE DETECTION: TEXTURE ANALYSIS

Texture provides important informations for the analysis of many types of images. Textural techniques have been widely used in the field of remote sensing (images from air-craft or satellite platforms), and, more recently, they have been employed in the fields of microscopy and biomedical imaging.
Despite its importance in image data, a precise definition of texture does not exist. Textural analysis can be regarded as a set of ad hoc techniques that allows to determine images features useful to classify images and to detect objects in an image.(5)
These techniques have been successfully applied in several imaging modalities, such as feature detection of chest radiographs (6,7,8), ultrasonic tissue characterization (9) etc.
As a preliminary approach statistical feature extraction methods will be considered. They can be classified as follows.

3.3.1 Analysis in spatial domain

a) Pixel

- First order statistics on grey level distributions. They describe the shape of the grey levels histogram (e.g. mean grey level, variance, skewness, curtosis etc).

The shape of an image histogram provides many clues as to character of the image. For example, a narrowly distributed histogram indicates a low-contrast picture while a bimodel histogram suggests regions of differing brightness. The following measures have been formulated as a concise means of describing the shape of first-order image histograms.

1st ORDER STATISTICS OF GRAY LEVEL HISTOGRAM:

MEAN: $$\overline{b} = \sum_{b=0}^{L-1} b \, P(b)$$

VARIANCE: $$s_b^2 = \sum_{b=0}^{L-1} (b - \overline{b})^2 \, P(b)$$

SKEWNESS: $$b_s = 1/s_b^3 \sum_{b=0}^{L-1} (b - \overline{b})^3 \, P(b)$$

KURTOSIS: $$b_K = 1/s_b^4 \sum_{b=0}^{L-1} (b - \overline{b})^4 \, P(b)$$

ENERGY: $$b_N = \sum_{b=0}^{L-1} [\, P(b) \,]^2$$

- Co-occurence matrix (Haralick et al.). A matrix is computed in wich each element P(i,j) is a probability that a pixel separated by a fixed displacement d(x,y) from a pixel of gray level i will have gray level j

- Difference statistics histogram (Weszka et. al) the k-th element of wich is the probability that two pixels separated by displacement d will have a grey-level difference k

- Run-length matrix (Galloway et. al.) each element (i,j) of wich is the frequency with wich j pixels of gray level i continue in direction theta.

b) Edge element

Edge elements (edgels) are detected by a gradient operator. An edgel is characterized by the edge value, the edge direction and the edge size. The average values of edgel density or edge size are correlated with the coarsness of the texture. The directionality of the texture can be measured from the edge direction histogram.

c) Extrema

Local maxima and minima of greylevel (extrema) are detected by scanning the image in the horizontal and vertical directions. An extrema is characterized by the size (corresponding to the contrast of the texture), and the frequency of extrema of different sizes is computed.

3.3.2 Analysis in frequency domain

The power spectrum is computed, which gives the magnitude of the frequency components in the Fourier trasform of an image. (4)

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