

# Grayscale Image

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## PNN-based classification of retinal diseases using fundus images

Jitendra Virmani, ... Kriti, in [Sensors for Health Monitoring, 2019](#)

### 11.3.2.2 Multiplication of gray image with vasculature of raw image (retinal vessel mask)

Multiplication of [grayscale image](#) showing whole fundus, with its vasculature image also called the retinal vessel mask (which is an image just showing retinal vessels of that particular fundus image), has been done in order to obtain a grayscale image consisting only of retinal vessels present in our original grayscale fundus image. Every element of the gray scale image is multiplied by the corresponding element in the retinal vessel mask and in the resultant image only those parts are retained that fall under the white region (value = 1) of the mask, in this case the retinal vessels. The results are represented in Fig. 11.7. The vascular retinal mask of the fundus images is obtained from the HRF dataset.

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## A Set of Texture-Based Methods for Breast Cancer Response Prediction in Neoadjuvant Chemotherapy Treatment

Mohammed Ammar, ... Drisis Stylianos, in [Soft Computing Based Medical Image Analysis, 2018](#)

### SFTA Extraction Algorithm

*Require; Grayscale image I and number of thresholds*

**Ensure:** Feature vector  $V_{SFTA}$

- 1:  $T \leftarrow \text{MultiLevelOtsu}(I, n_t)$
- 2:  $T_A \leftarrow \{\{t_i, t_{i+1}\} : t_i, t_{i+1} \in T, i \in [1 .. |T| - 1]\}$
- 3:  $T_B \leftarrow \{\{t_i, n\} : t_i \in T, i \in [1 .. |T|]\}$
- 4:  $i \leftarrow 0$
- 5: **for**  $\{(t_i, t_u) : \{t_i, t_u\} \in T_A \cup T_B\}$ . **do**
- 6:  $I_b \leftarrow \text{TwoThresholdSegmentation}(I, t_l, t_u)$
- 7:  $\Delta(x, y) \leftarrow \text{FindBorders}(I_b)$
- 8:  $V_{SFTA}[i] \leftarrow \text{BoxCounting}(\Delta)$
- 9:  $V_{SFTA}[i + 1] \leftarrow \text{MeanGrayLevel}(I, I_b)$
- 10:  $V_{SFTA}[i + 2] \leftarrow \text{PixelCount}(I_b)$
- 11:  $i \leftarrow i + 3$
- 12: **end for**
- 13: **return**  $V_{SFTA}$

SFTA requires the user to set the parameter  $n_t$  that defines the number of thresholds that will be employed in the input image decomposition.

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## Basic Image Filtering Operations

E.R. Davies, in [Computer and Machine Vision \(Fourth Edition\)](#), 2012

### 3.8.2 Generalization to Grayscale Images

To extend these results to [grayscale](#) images, first consider the effect of applying a [median filter](#) near a smooth step edge in 1-D. Here the median filter gives zero shift, since for equal distances from the center to either end of the neighborhood there are equal numbers of higher and lower intensity values and hence equal areas under the corresponding portions of the intensity histogram. Clearly this is always valid where the intensity increases monotonically from one end of the neighborhood to the other—a property first pointed out by Gallagher and Wise (1981) [for more recent discussions on related “root” (invariance) properties of signals under [median filtering](#), see Fitch et al. (1985) and Heinonen and Neuvo (1987)].

Next, it is clear that for 2-D images, the situation is again unchanged in the vicinity of a straight edge, since the situation remains highly symmetrical. Hence the median filter gives zero shift, as in the binary case.

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# Mathematical Morphology

E.R. Davies, in [Computer and Machine Vision \(Fourth Edition\)](#), 2012

## 7.4 Grayscale Processing

The generalization of morphology to [grayscale](#) images can be achieved in a number of ways. A particularly simple approach is to employ “flat” structuring elements. These perform morphological processing in the same way for each of the gray levels, acting as if the shapes at each level were separate, independent [binary images](#). If dilation is carried out in this way, the result turns out to be identical to the effect of applying a maximum intensity operation of the same shape: i.e., we replace set inclusion by a magnitude comparison; needless to say, this is mathematically identical in action for a normal binary image, but when applied to a [grayscale image](#) it neatly generalizes the dilation concept. Similarly, erosion can be carried out by applying a minimum intensity structuring element of the same shape as the original binary structuring element. This discussion assumes that we focus on light objects against dark backgrounds<sup>7</sup>: these will be dilated when the maximum intensity operation is applied, and eroded when the minimum intensity operation is applied; we could of course reverse the convention, depending on what type of objects we are concentrating on at any moment, or in any application. We can summarize the situation as follows:

(7.45)

(7.46)

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# Image Processing Education

Umesh Rajashekhar, ... Reginald L. Lagendijk, in [Handbook of Image and Video Processing \(Second Edition\)](#), 2005

## 4.3.2 Histogram and Point Operations (Gray Scale)

To demonstrate the effects of elementary gray-scale image processing, VIs that perform linear (offset, scaling, and full-scale contrast stretch) and nonlinear (logarithmic range compression) point operations on images are included in SIVA. A more advanced VI shown in Fig. 11 demonstrates the effects of histogram shaping. The histograms of the input image and the resulting image after the [linear point operation](#) are also displayed on the front panel to verify the results of the shaping (e.g., the histogram in Fig. 11(d) is inverse Gaussian-like).

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# The SIVA Image Processing Demos

Umesh Rajashekhar, ... Dinesh Nair, in [The Essential Guide to Image Processing](#), 2009

## 2.2.2.1 NI Vision

NI Vision is the image processing toolkit, or library, that adds high-level machine vision and image processing to the LabVIEW environment. NI Vision includes an extensive set of MMX-optimized functions for the following machine vision tasks:

- Grayscale, color, and [binary image](#) display
- Image processing—including statistics, filtering, and geometric transforms
- Pattern matching and geometric matching
- Particle analysis
- Gauging
- Measurement
- Object classification
- Optical character recognition
- 1D and 2D barcode reading.

NI Vision VIs are divided into three categories: Vision Utilities, Image Processing, and Machine Vision.

**Vision Utilities VIs** Allow you to create and manipulate images to suit the needs of your application. This category includes VIs for image management and manipulation, file management, calibration, and region of interest (ROI) selection.

You can use these VIs to:

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# Imaging of tendons and ligaments in animal models

Johanna Buschmann, Gabriella Meier Bürgisser, in [Biomechanics of Tendons and Ligaments](#), 2017

## 5.2.4 Correspondence of US with biomechanics

Correlations not only between gray-scale images in US and histomorphometric information have been attempted but also between echo intensities in US images and biomechanical properties of healing tendons (Chamberlain et al., 2013). Such an approach is valuable because mechanical data are typically obtained by extracting tendons and subsequent *in vitro* biomechanical [tensile testing](#). In contrast, a noninvasive method as US allows a direct *in vivo* longitudinal evaluation of the same specimen during the regeneration period. The theory behind the correspondence of US imaging and mechanical characteristics is found in acoustoelasticity, where the acoustic properties of a material are dependent of its stiffness and are changed when the material is deformed under load. Such changes in acoustic properties of a material result from the [elastic deformation](#), which by itself can be measured as a change in the wave propagation velocity and amplitude of the reflected wave (Kobayashi and

Vanderby, 2005, 2007).

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## Image filtering and morphology

E.R. Davies, in [Computer Vision \(Fifth Edition\)](#), 2018

### 3.14 Morphology in Grayscale Images

The generalization of morphology to [grayscale](#) images can be achieved in a number of ways. A particularly simple approach is to employ “flat” structuring elements. These perform morphological processing in the same way for each of the gray levels, acting as if the shapes at each level were separate, independent [binary images](#). If dilation is carried out in this way, the result turns out to be identical to the effect of applying an intensity maximum operation of the same shape: i.e., we replace set inclusion by a magnitude comparison; needless to say, this is mathematically identical in action for a normal binary image, but when applied to a [grayscale image](#) it neatly generalizes the dilation concept. Similarly, erosion can be carried out by applying a minimum intensity structuring element of the same shape as the original binary structuring element. This discussion assumes that we focus on light objects against dark backgrounds. In fact, this is the opposite convention to that employed in Chapter 2, Images and Imaging Operations, but, as we shall see below, in grayscale processing it is probably more general to focus on intensities rather than on specific objects. Thus, light objects will be dilated when the maximum intensity operation is applied and eroded when the minimum intensity operation is applied; we could of course reverse the convention, depending on what type of objects we are concentrating on at any moment or in any application. We can summarize the situation as follows:

(3.54)

(3.55)

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## Mathematical Morphology

E.R. DAVIES, in [Machine Vision \(Third Edition\)](#), 2005

### 8.5 Gray-scale Processing

The generalization of morphology to gray-scale images can be achieved in a number of ways. A particularly simple approach is to employ ‘flat’ structuring elements. These perform morphological processing in the same way for each of the gray levels, acting as if the shapes at each level were separate, independent binary images. If dilation is carried out in this way, the result turns out to be identical to the effect of applying an intensity maximum

carried out in this way, the result turns out to be identical to the effect of applying an intensity maximum operation of the same shape. That is, we replace set inclusion by a magnitude comparison. Needless to say, this is mathematically identical in action for a normal binary image, but when applied to a gray-scale image it neatly generalizes the dilation concept. Similarly, erosion can be carried out by applying an intensity minimum structuring element of the same shape as the original binary structuring element. This discussion assumes that we focus on light objects against dark backgrounds.<sup>7</sup> These will be dilated when the maximum intensity operation is applied, and they will be eroded when the minimum intensity operation is applied. We could of course reverse the convention, depending on what type of objects we are concentrating on at any moment, or in any application. We can summarize the situation as follows:

(8.47)

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