1 INTRODUCTION

In our daily life, our vision and actions are influenced by an abundance of geometry and color information. When crossing a street, we identify a technical apparatus by its geometry as a traffic light. However, only by analyzing color information do we subsequently decide whether we are to continue, if the light is green, or stop, if the light is red. A camera-assisted driving information system should be able to evaluate similar information and either pass the information on to the driver of a vehicle or directly influence the behavior of the vehicle. The latter is of importance, for example, for the guidance of an autonomous vehicle on a public road. Something similar to this applies to traffic signs, which can be classified as prohibitive, regulatory, or informative signs based on color and geometry.

The assessment of color information also plays an important role in our individual object identification. We usually do not search in a bookcase for a book known to us solely by its title. We try to remember the color of the cover (e.g., blue) and then search among all of the books with a blue cover for the one with the correct title. The same applies to recognizing an automobile in a parking lot. In general, we do not search for model X of company Y, but rather we look for a red car, for example. Only when we see a red vehicle do we decide, according to its geometry, whether that vehicle is the one for which we are looking. The search strategy is driven by a hierarchical combination of color and form. Such hierarchical strategies are also implemented in automatic object recognition systems.

While in the past color image processing was limited essentially to satellite imagery, it has gained importance in recent years on account of new possibilities. This is due, among other things, to the high information level that color images contain in relation to gray-level images. This information allows color image processing to succeed in areas where "classical gray-level image processing" currently dominates. The decision confidence level for various techniques can be greatly improved by the additional classification markers color can provide. The applied procedures are thereby made simpler, more robust, or even applicable in the first place.

The fundamental difference between color images and gray-level images is that in a color space, a color vector (which generally consists of three components) is assigned to a pixel of a color image, while a scalar gray value is assigned to a pixel of a gray-level image. Thus, in color image processing, vector-valued image functions are treated instead of the scalar image functions used in gray-level image processing. Color image processing techniques can be subdivided on the basis of their principal procedures into two classes:

1. *Monochromatic-based techniques* first treat information from the individual color channels or color vector components separately and then combine the individual results.
2. *Vector-valued techniques* treat the color information as color vectors in a vector space provided with a vector norm.

The techniques from the first class can also be designated as *rental schemes* [Zhe et al. 93], since they frequently borrow methods from gray-level image processing and implement them separately on each color component. Thereby the dependencies between the individual color components (or vector components) are usually ignored. The monochromatic-based techniques make it clear that the transition from scalar to vector-valued functions, which can be mastered with color image analysis, is not yet generally known.

Color attributes such as hue or saturation are also used in monochromatic-based techniques. However, the analysis or processing of color information occurs separately for each component, for example, only the hue component or only the saturation component is treated (as in a gray-level image). In contrast, vector-valued techniques treat the color information in its entirety and not separately for each vector component.

While monochromatic-based techniques were predominantly regarded in the early days of color image processing, in recent times vector-valued techniques are being more frequently discussed. The difference between the two techniques serves as a systematization of the procedure in order to point out the respective conditions of developments from monochromatic-based techniques to vector-valued techniques. Better or more robust results are often attained with monochromatic-based techniques for color image processing than with techniques for gray-level processing. The monochromatic-based techniques, however, do not define a new way of image processing but rather demonstrate only transference of known techniques to color images. In contrast, the analysis and processing of vector-valued image information establishes a new step in image processing that simultaneously presents a challenge and a new possibility for analyzing image information. One difficulty with vector-valued techniques has been that the signal-theoretical basics for vector-valued color signals have not yet been presented.

In the past, the application of techniques for color image processing was restricted by additional factors. One factor was limited data memory and the "slow" processors: a three-channel color image of 1024×1024 pixels occupies, for example, 3 MB. For a geometric stereo analysis technique at least two images (6 MB) are needed, and for a photometric stereo analysis technique generally three images (9 MB) are necessary. These must be treated at a processing speed appropriate for the requirements of the application. Using more modern computers, the limitations on memory space and processing speed are not totally eliminated; however, the importance of this problem continues to decrease. Thus, the processor requirements for implementing digital color image processing today are satisfied.

Another factor that limited the applicability of color image processing in the past was color camera technology. In recent years, the availability of robust and low-cost color CCD cameras has made the acquisition of high-quality color images feasible under many varying acquisition conditions. However, in spite of enormous advances in camera technology there is a lack, as already mentioned, of extensive signal-theory investigations of vector-valued color signals. Here an urgent need for basic research exists.

In areas such as photogrammetry and remote sensing, images with more than three "color" channels are frequently analyzed. Newer areas of application analyze color images that represent three-channel spectral transmissions of visible light. Knowledge of the processing occurring in the human eye and brain of the signals that come from the three sensitive (with regard to different wavelengths) receptors in the retina can be used for the development and evaluation of techniques for color image processing.

The three different receptor types in the human retina are also the reason that commercial CCD-color cameras likewise implement measurements in three different wavelength areas of visible light. These cameras deliver a three-channel signal and the three channels are represented separately on a monitor or screen for the observer. Furthermore, the color attributes hue and saturation are defined only within the spectral area of visible light. In this book, techniques for the analysis of three-channel color images are presented whose spectral transmissions lie within the visible area of light.

As an example, correspondence analysis in stereo images shows that red pixels do not correspond with blue pixels, even when their intensity values are similar. The segmentation of color images based on classification of color values is generally substantially more differentiated than segmentation based exclusively on intensity values.

The evaluation of color information in the image creates additional new possibilities for solving problems in computer vision. Many image processing techniques still assume that only matte (Lambertian) surfaces in the scene are analyzed. This assumption does not hold for real scenes with several reflecting (non-Lambertian) surfaces. However, this limitation can be overcome under certain conditions by highlight elimination in color images. Furthermore, physically determined phenomena, such as shadows or interreflections, can be analyzed more easily in color images than in gray-level images. For this, predominantly vector-valued image processing techniques are used that employ reflection models derived from physical optics for modeling image functions. These techniques are denoted as *physics-based vision techniques*. The invariant extraction of color information in relation to varying lighting conditions and description of image characteristics represents another problem in computer vision. Here promising vector-valued techniques for so-called color constancy can make an important contribution.

1.1 GOAL AND CONTENT OF THIS BOOK

Color information is gaining an ever-greater meaning in digital image processing. Nevertheless, the leap to be mastered by the transition from scalar to vector-valued image functions is not yet generally known. One goal of this book is to clarify the significance of vector-valued color image processing. The present state of the art in several areas of digital color image processing is represented in regard to a systematic division into monochromatic-based and newer vector-valued techniques. The more recent potentials and the requirements in vector-valued color image processing are shown. Here references will be made to the fundamentals lacking in many areas of digital color image processing.

While a terminology for gray-level image processing has been established for the most part, corresponding terms do not yet exist for vector-valued color images. Fundamental ideas in color image processing are specified within the context of this work. Monochromatic-based techniques still dominate in many practical applications of digital color image processing, such as in medicine, agriculture, and forestry, as well as industrial manufacturing. A few examples of monochromatic-based and vector-valued techniques of color image analysis in practical usage are presented in Section 1.3.

This book is organized in regard to advanced techniques for three-dimensional scene analysis in color images. In the first four chapters, the fundamentals and requirements for color image processing are illustrated. In the next four chapters, techniques for preprocessing color images are discussed. In subsequent chapters, the area of three-dimensional scene analysis using color information is viewed. In the final three chapters, case studies on application of color image processing are presented. For some selected areas of digital color image processing, such as edge detection, color segmentation, interreflection analysis, and stereo analysis, techniques are discussed in detail in order to clarify the respective complexities of the solution for the problem.

Knowledge of the human visual system is frequently utilized for designing procedures in digital image processing (see, e.g., [Mar82], [Ove92], and [Wat88]). This also applies for digital color image processing. In Chapter 2, an introduction to human color vision is presented whereby color blindness of a section of the population and the phenomenon of color constancy are given special attention. For the representation and treatment of color images, a suitable form of representation for the data must be selected. Different color spaces used in color image processing are presented in Chapter 3. Chapter 4 contains the technical requirements for color image processing (color camera, color filter, standard illuminants, color charts, etc.) as well as techniques of photometric and colorimetric calibration that are necessary for the further treatment of color images.

Techniques for noise suppression and contrast enhancement in color images are the subject of Chapter 5. An important task in preprocessing color images is the extraction of edges in the image. Various procedures for color edge detection are discussed in Chapter 6. A comparison of the results of one monochromatic-based and two vector-valued color edge operators are also given. An overview of different techniques for color image segmentation is presented in Chapter 7. There, a robust technique for the segmentation of color images based on the watershed transformation is presented.

An interesting challenge and at the same time a new possibility of color image processing is the analysis of physical phenomena, such as the analysis of highlights and interreflections. In Chapter 8, an overview of the techniques for highlight analysis and a new method for minimizing interreflections in real color images is presented. In addition, different procedures for achieving color constancy are discussed.

A detailed description of the use of color information for static stereo analysis is given in Chapter 9. There, investigations for edge-based as well as area-based color stereo techniques can be found. Also shown is how stereo matching results can be significantly improved by projecting color-coded light patterns onto the object. The inclusion of color information into dynamic and photometric stereo analysis is the subject of Chapter 10.

Chapter 11 addresses case studies of color use in an automated video tracking and location system that is under development at the University of Tennessee's Imaging, Robotics and Intelligent Systems (IRIS) Laboratory in Knoxville, Tennessee. Chapter 12 discusses the acquisition and analysis of multispectral images. Their use in face recognition is outlined as an example of multispectral image processing. The application of color coding in x-ray imaging is the subject of Chapter 13.

1.2 TERMINOLOGY IN COLOR IMAGE PROCESSING

There is agreement concerning the terminology used in the processing of gray-level images [HarSha91]. In contrast, a corresponding transference onto vector-valued color images does not yet exist. For example, it has not yet been established what a color edge is, what the derivative of a color image is, or what should be understood as the contrast of a color image. In color image processing, the terms are used very differently and also somewhat imprecisely. In the following section, terminology used in color image processing is established.

1.2.1 What Is a Digital Color Image?

The central terminology of color image processing is that of the digital color image. A *digital image* is defined for image pixels that are assumed in the real plane or could be elements of a discrete set of points. A gray-level image E assumes an *image value* $E(\mathbf{p}) = E(x, y)$ in an *image pixel* $\mathbf{p} = (x, y)$ as a uniquely determined function value, approximately a numerical *gray value* u, which characterizes a determined gray tone. For this, $E(x, y) = u$ is written formally. (Note that for the sake of simplification, the double parentheses is omitted in the coordinate equation $E(\mathbf{p}) = E((x, y))$ for $\mathbf{p} = (x, y)$.) The triple $(x, y, E(x, y)) = (x, y, u)$ is indicated as *pixel* (from *picture element*), where x and y are the coordinates in the image plane. The points in the image plane are converted by the image acquisition equipment into integer-valued, device-dependent coordinates of the row and column position.

Discrete image pixels and discrete image values distinguish a digital image. The index domains $1 \le x \le M$ and $1 \le y \le N$ are presupposed. The values M and N mark the image resolution. The value $A = M \cdot N$ marks the image size. For the possible image values $E(x, y)$ of a digital gray-level image E, $G_{\max} + 1$ gray values, $G_{\max} \ge 1$, are assumed. The representation of (continuously distributed) image values and gray tones into a limited number of gray values is called *quantization*. For the $G_{\max} + 1$ gray values, a connected interval of non-negative integers is assumed. For an integer gray value u holds

$$0 \le u \le G_{\max} .$$

The standard value for gray-level images is $G_{\max} = 255$.

A *color image* corresponds intuitively to the perceived representation of our colored environment (i.e., to one's individual visual sensory perception). Computationally, a color image is treated as a vector function (generally with three components). The range of the image function is a vector space, provided with a norm that is also called a *color space*. For a (three-channel) *digital color image* $\mathbf{C}$, three vector components u_1, u_2, u_3 are given for one image pixel (x, y):

$$\mathbf{C}(x, y) = \left(u_1(x, y), u_2(x, y), u_3(x, y)\right)^T = \left(u_1, u_2, u_3\right)^T . \qquad (1.1)$$

The colors represented by concrete value combinations of the vector components u_1, u_2, u_3 are relative entities. Each of the vectors $(u_1, u_2, u_3)^T$ with the generally integer components $0 \le u_1, u_2, u_3 \le G_{max}$ characterizes a color in the basic color space. Examples of color spaces are the *RGB* color space, which is used for representing a color image on a monitor (additive color mixture), or the *CMY(K)* color space, which is used for printing a color image (subtractive color mixture).

A color image is denoted as *true-color image* if the vector components of the digitalized color image represent spectral transmissions of visible light. The generation of a true-color image results as a rule by using a color CCD camera, which commercially has a quantization of eight bits per color channel and/or vector component (see Section 4.1).

A *false-color image* corresponds essentially to a true-color image, however, with the difference that areas of wavelengths outside the visible light are also allocated to the vector components of the color image. An example of that is an infrared image whose information content does not come from visible light. For its representation and visualization, the information of the infrared spectrum is transformed into the area of visible light.

The term *pseudocolor image* is used if selected image pixels are recoded or colored, that is, for these image pixels, the associated image value (gray value or color vector) is replaced by a given color vector. The original image can be a gray-level image in which the significant areas should be recoded into color (e.g., areas in a digital x-ray image to be used for aiding the radiologist in a diagnosis). The selection of the color vectors is often arbitrary and serves solely for better visualization of different image domains.

Another example of a pseudocolor image is a true-color image in which color vectors were recoded. This can be used for the special emphasis (coloring) of certain image areas or for reducing the number of differing color vectors in the image. The last case is implemented for reducing color quantization (e.g., to 256 colors). While in early years many workstations could represent only 256 colors, most workstations today offer a true-color representation with a quantization of eight bit per color component (i.e., altogether 24 bits per image pixel or ca. 16 million colors). Reducing the number of differing color vectors in the image can also be used for reducing the amount of image data to be stored. An image in 8-bit mode needs less storage space than an image in 24-bit true-color mode. Less data needs to be transferred for representing an image in the Internet saved with 8-bit color quantization.

A color quantization is realized in general by using *indexed colors*. After, for example, 256 color vectors are selected for an image (based on a quantization algorithm), these are placed on a *colormap* or *palette*. For each image pixel the associated index number is listed. On the basis of this number the indexed color is selected for representing the color image on a monitor. In the graphic data formats GIF (Graphics Interchange Format) and TIFF (Tagged Image File Format), the associated colormap is contained along with the indexed color image. In general, a colormap of this type contains *RGB* entries suited to the nonlinear monitor that are meant for the direct representation of a color image (without additional correction) on the monitor. By using indexed colors for true-color images, the color information of the image is reduced and in the process the quality of the color image is also impaired. Such color images are just barely suitable for further treatment with image analysis techniques.

In the image examples discussed so far, color vectors with three components or three color channels were always observed so that we could talk of three-channel images. This technique can also be expanded to n (color-) channels. It concerns, then, a so-called *multichannel* or *multiband image*,

$$\mathbf{C}(x,y) = \left(u_1(x,y), u_2(x,y), \ldots, u_n(x,y)\right)^T = \left(u_1, u_2, \ldots, u_n\right)^T , \qquad (1.2)$$

whose special case for $n = 1$, for example, can be a gray-level image or intensity image and for $n = 3$ can be a three-channel true-color image.

Another special case is the *multispectral image*, in which data is acquired of a given scene in a number of more than three different spectral bands. Some (or all) of the spectral bands may lie outside the visible light (e.g., in LANDSAT images with the spectral areas 500 - 600 nm (blue-green), 600 - 700 nm (yellow-red), 700 - 800 nm (red-infrared), and 800 - 1100 nm (infrared)). The image values in a LANDSAT image are represented by vectors with four components. Other examples of multichannel images are radar images in which the individual channels represent the received signals for differing wavelengths and polarizations. Recent research activities also include the acquisition, representation, and processing of multispectral color images with more than three channels of information for the visible light spectrum. Images with, for example, six color bands can be visualized with very high fidelity when special hardware is used. Digital images with more than a hundred spectral bands are called *hyperspectral images*. However, there exists no common agreement on the minimum number of spectral bands in a hyperspectral image. The acquisition and analysis of multispectral images will be presented in more detail in Chapter 12.

1.2.2 Derivative of a Color Image

For a color component or a gray-level image $E(x,y)$ the *gradient* or the *gradient vector* is given by

$$grad(E) = \left(\frac{\partial E}{\partial x}, \frac{\partial E}{\partial y}\right)^T = \left(E_x, E_y\right)^T . \qquad (1.3)$$

Here, the indexes x and y are introduced as abbreviations that indicate the respective partial derivative of the function, that is, it holds

$$E_x = \frac{\partial E}{\partial x} \quad \text{and} \quad E_y = \frac{\partial E}{\partial y}.$$

The absolute value of the gradient,

$$\|grad(E)\| = \sqrt{\left(\frac{\partial E}{\partial x}\right)^2 + \left(\frac{\partial E}{\partial y}\right)^2}\ , \tag{1.4}$$

is a measurement for the "height change" of the gray-level image function. It takes on the extreme value of zero for a constant gray-level plateau (in the ideal case $E(x, y) = const$).

A three-channel color image can be described by a function $\mathbf{C}: Z^2 \to Z^3$. This definition can be easily expanded to n-channel color images. However, color images with three vector components will be examined in this book. The differential of function $\mathbf{C}$ is given in matrix form by the *functional matrix* or *Jacobian matrix* $\mathbf{J}$, which contains the first partial derivatives for each vector component. For a color vector in a color space with $\mathbf{C}(x, y) = (u_1, u_2, u_3)^T$ the derivative is described at a location (x,y) by the equation $\Delta\mathbf{C} = \mathbf{J}\Delta(x, y)$. It holds

$$\mathbf{J} = \begin{pmatrix} \frac{\partial u_1}{\partial x} & \frac{\partial u_1}{\partial y} \\ \frac{\partial u_2}{\partial x} & \frac{\partial u_2}{\partial y} \\ \frac{\partial u_3}{\partial x} & \frac{\partial u_3}{\partial y} \end{pmatrix} = \begin{pmatrix} grad(u_1) \\ grad(u_2) \\ grad(u_3) \end{pmatrix} = \begin{pmatrix} u_{1x} & u_{1y} \\ u_{2x} & u_{2y} \\ u_{3x} & u_{3y} \end{pmatrix} = (\mathbf{C}_x, \mathbf{C}_y). \tag{1.5}$$

Both vectors are indicated with $\mathbf{C}_x$ and $\mathbf{C}_y$:

$$\mathbf{C}_x = (u_{1x}, u_{2x}, u_{3x})^T \text{ and } \mathbf{C}_y = (u_{1y}, u_{2y}, u_{3y})^T .$$

1.2.3 Color Edges

While in gray-level images a discontinuity in the gray-level function is indicated as an edge, the term *color edge* has not been clearly defined for color images. Several different definitions have been proposed for color edges. A very old definition [Rob76] states that an edge exists precisely in the color image if the intensity image contains an edge. This definition ignores, however, possible discontinuities in the hue or saturation values. If, for example, two equally light objects of various colors are arranged in juxtaposition in a color image, then the edges determining the object geometry cannot be determined with this technique. Since color images contain more information than gray-level images, more edge information is expected from color edge detection in general. However, this definition delivers no new information in relation to gray-value edge detection.

A second definition for a color edge states that an edge exists in the color image if at least one of the color components contains an edge. In this monochromatic-based definition, no new edge detection procedures are necessary. This presents the problem of accuracy of the localization of edges in the individual color channels. If the edges in the color channels are detected as being shifted by one pixel, then the merging of the results produces very wide edges. It cannot be easily determined which edge position in the image is the correct one.

A third monochromatic-based definition for color edges [Pra91] is based on the calculation of the sum of absolute values of the gradients for the three color components. A color edge exists if the sum of the absolute values of the gradients exceeds a threshold value. The results of the color edge detection by the two previously named definitions depend heavily on the basic color spaces. An image pixel that, for example, is identified in one color space as an edge point must not eventually be identified in another color space as an edge point (and vice versa).

All previously named definitions ignore the relationship between the vector components. Since a color image represents a vector-valued function, a discontinuity of chromatic information can and should also be defined in a vector-valued way. A fourth definition for a color edge can result by using the derivative, described in the previous section, of a (as a rule in digital color image processing three-channel) color image. For a color pixel or color vector $\mathbf{C}(x,y)=(u_1,u_2,u_3)^T$, the variation of the image function at position (x,y) is described by the equation $\Delta\mathbf{C}=\mathbf{J}\Delta(x,y)$. The direction along which the largest change or discontinuity in the chromatic image function is detected is represented in the image by the eigenvector $\mathbf{J}^T\mathbf{J}$ corresponding to the largest eigenvalue. If the size of the change exceeds a certain value, then this is a sign for the existence of a color edge pixel.

A color edge pixel can also be defined applying vector ordering statistics or vector-valued probability distribution functions. The various techniques for the extraction of edges in color edges are the subject of Chapter 6.

1.2.4 Color Constancy

The colors of the surfaces of an object represent important features that could be used for identifying the object. However, a change in lighting characteristics can also change the several features of the light reflected from the object surfaces to the sensor. *Color constancy* is the capability of an invariant color classification of surfaces from color images with regard to illumination changes.

The human visual system is nearly color constant for a large area of surfaces and lighting conditions. As an example, a red tomato appears red in the early morning, at midday, and in the evening. The perceived color is therefore not the direct result of the spectral distribution of the received light, which was the assumption for many years (see [Zek93] for a detailed representation). A brief introduction to this subject is presented later in Section 2.4.

Color constancy is likewise desirable for a camera-based vision system when its use should occur under noncontrollable lighting conditions. Achieving color constancy in digital color image processing is, however, a problem that is difficult to solve since the color signal measured with a camera depends not only on the spectral distribution of the illumination and the light reflected on the surface, but also on the object geometry. These characteristics of the scene are, as a rule, unknown. In digital image processing, various techniques are identified for the numerically technical realization of color constancy. Color constancy techniques (in digital color image processing) can be classified into three classes with regard to the results that they intend to obtain:

1. The spectral distribution of the reflected light is to be estimated for each visible surface in the scene.
2. A color image of the acquired scene is to generate in the way it would appear under known lighting conditions.
3. Features are to be detected for the colored object surfaces in the image that are independent from lighting conditions (invariant to illumination changes).

The examination of all three techniques or procedures for achieving color constancy is the subject of Section 8.3.

1.2.5 Contrast of a Color Image

The term *contrast* is used ambiguously in the literature. In the following, several examples (without claiming completeness) are introduced.

1. Contrast describes the relation between the brightness values in an image or section of an image. As measurement for the size of the contrast, for example, the Michelson Contrast $(I_{\max} - I_{\min} / I_{\max} + I_{\min})$ is used [Gil94], whereby the largest-appearing brightness value is indicated by $I_{\max}$ and the smallest-appearing brightness value is denoted by $I_{\min}$. This is described as *relative brightness contrast*.
2. The perceptual phenomenon of brightness perception of a surface in dependence on the lightness of the background is likewise indicated as contrast. For the illustration of this phenomenon, a gray surface surrounded by a white surface and a gray surface of the same lightness surrounded by a black surface is used. The gray-on-white background is perceived as somewhat darker than the gray-on-black background. This phenomenon is called *simultaneous brightness contrast* [Gil94]. An example is given in Fig. 1.1.
3. In a color image with low brightness contrast, details can be distinguished from the background on the basis of differing color saturation. The relation between the saturation values in a color image can be described as *relative saturation contrast*.

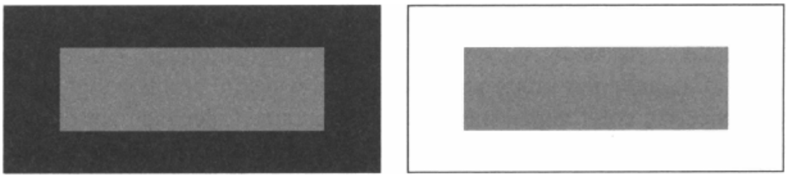

Figure 1.1. *Example of simultaneous (brightness) contrast: The left-hand grey rectangle appears lighter than the right-hand one.*

4. The detection of a colored surface depends likewise on the color of the surface surrounding it. A gray surface surrounded by a red ring appears, e.g., bluish-green [Zek93]. For the description of *induced color*, influenced by the color of the surrounding surface, the opponent color model is frequently implemented [Kue97]. This type of contrast is also denoted as *simultaneous color contrast*. Davidoff [Dav91] describes the effect of color contrast as the change of color constancy in a systematic manner.
5. Another type of contrast is the *successive (color) contrast*. This occurs when a colored area is observed over a long period of time and a neutral area is subsequently fixed. An *afterimage* of the previously observed area appears either in the opponent colors (negative afterimage) or approximately in the previously observed colors (positive afterimage) [Kue97]. Afterimages appear also with closed eyes.

Apart from the contrast definitions named here, the question is posed for digital color image processing as to what should be affected by the computer-aided change of contrast of a color image. The goal of enhancing the contrast in an image is generally to improve the visibility of image details. Only in rare cases is the goal of the technique the systematic influence of color constancy.

In many technical-based books, the contrast of a color image is regarded solely as brightness contrast in the sense of definition 1 (see, e.g., [Poy96]). Most display devices have implemented this definition for contrast control. On a color monitor (or television) the (nonlinear) area between the darkest and lightest pixel is adjusted with the "contrast control." With the "lightness control," a positive or negative offset for the lightness to be represented is established according to the adjustment. Also in the image-editing software program Adobe Photoshop TM the function of contrast change refers to the lightness values of the image.

Digital color image processing offers the opportunity of changing the relative brightness contrast as well as the possibility of including perception-based observations if the need arises. In addition, color attributes such as saturation and intensity can also be set in relation to each other in the vector-valued color signals. A fact to be remembered is that the term *contrast of a color image* should not be used without the use of an adjective (e.g., *relative* or *simultaneous*) or an appropriate definition of the term.

1.2.6 Noise in Color Images

Until now, not much has been published on the subject of noise in color images. It is generally assumed [BarSan97] that the individual components of the vector-valued color signal are degraded separately from each other by noise and that not all components are equally affected. This can be described, for example, by various additive overlays of the signals in the individual color components by malfunctions or Gaussian noise. Here the model

$$\mathbf{y} = \mathbf{x} + \mathbf{n}$$

is used as a basis, whereby **x** denotes the undisturbed image vector at a position (i,j) in the color image. The corresponding vector with noise is indicated by **y** and **n** is an additive noise vector at position (i,j) in the image.

It cannot be concluded from the assumption of the existence of differing overlays in the individual color components that monochromatic-based techniques for separate noise suppression in the individual color components provide the best results. Vector-valued techniques allow, in general, a better treatment of noise in color images (see, e.g., [PitTsa91], [Pla et al. 97], and [Zhe et al. 93]). Vector-valued techniques are dealt with later in Section 5.3.

1.2.7 Luminance, Illuminance, and Brightness

The terms *luminance*, *lightness*, and *brightness* are often confused in color image processing. To clarify the terminology we borrow three definitions from Adelson [Ade00]:

1. *Luminance* (usually L in formulas) is the amount of visible light that comes to the eye from a surface. In other words, it is the amount of visible light leaving a point on a surface in a given direction due to reflection, transmission, and/or emission. *Photometric brightness* is an old and deprecated term for luminance. The standard unit of luminance is *candela per square meter* (cd/m^2), which is also called *nit* in the United States, from Latin *nitere* = "to shine" (1 nit = 1 cd/m^2).
2. *Illuminance* (usually E in formulas) is the amount of light incident on a surface. It is the total amount of visible light illuminating (incident upon) a point on a surface from all directions above the surface. Therefore illuminance is equivalent to *irradiance* weighted with the response curve of the human eye. The standard unit for illuminance is *lux* (lx), which is *lumens per square meter* (lm/m^2).
3. *Reflectance* is the proportion of incident light that is reflected from a surface. Reflectance, also called *albedo*, varies from 0 to 1, or equivalently, from 0% to 100%, where 0% is ideal black and 100% is ideal white. In practice, typical black paint is about 5% and typical white paint about 85%. (For the

sake of simplification, we consider only ideal matte surfaces, for which a single reflectance value offers a complete description.).

Luminance, illuminance, and reflectance are physical quantities that can be measured by physical devices. There are also two subjective variables that must be discussed:

1. *Lightness* is the perceived reflectance of a surface. It represents the visual system's attempt to extract reflectance based on the luminances in the scene.
2. *Brightness* is the perceived intensity of light coming from the image itself, rather than any property of the portrayed scene. Brightness is sometimes defined as perceived luminance.

1.3 COLOR IMAGE ANALYSIS IN PRACTICAL USE

In many practical applications the analysis of gray-level images is not sufficient for solving the problems. Only by evaluating color information in the images can the problem be solved or be resolved considerably more easily than in gray-level images. Even now the monochromatic-based techniques predominate in practical applications. Only in recent times have vector-valued techniques been discussed. In the following, examples are presented in which the necessity of analysis of color images arises directly from the demands of the applications. None of the posed tasks could be solved with the techniques from gray-level image processing. In order to clarify the differences and common features, categorization is introduced for the techniques. The following nomenclature indicates:

M: Monochromatic-based techniques, and
V: Vector-valued techniques.

Furthermore, it will be differentiated in this section as to whether

α: The techniques deliver better results by evaluating color information than by evaluating gray-level information, or
β: The techniques are possible only by the evaluation of color information.

For example, a $V\beta$-technique is a vector-valued technique that is possible only by evaluating color information. One difficulty in assigning a technique to one of the classes listed above is that no one class of techniques will be followed continually in every case. For example, the vector-valued color signal can be evaluated in one processing step while in another processing step only gray-level information is analyzed. For systematization only the part of the procedure that refers to the evaluation of color information is used as a basis. The technique in this example is denoted as a V-technique.

Another difference between the techniques can result from the use of true-color or pseudocolor images. If not mentioned otherwise, the use of true-color images is always assumed in the following. The information on the basic color space for the representation of color values in the image is without further specification. The discussion of color spaces is, as previously mentioned, the subject of Chapter 3. The following examples should illustrate the diverse possibilities of using color image processing.

There are a roughly equal number vector-valued and monochromatic-based techniques in these examples. However, this does not reflect the actual level of development. In fact, nearly all the vector-valued techniques of color image analysis in practical usage known to the authors are presented here, while only a few examples of monochromatic-based techniques used in practice are named. The reason for this is that, according to our estimation, the vector-valued techniques are the more interesting of the two. As previously mentioned, better results are frequently obtained with monochromatic-based techniques than with techniques of gray-level image analysis, but the techniques used are as a rule identical or similar to the known techniques from gray-level image analysis. On the other hand, the vector-valued approaches of color image analysis present a new procedural class that obtains special consideration in this work.

1.3.1 Color Image Processing in Medical Applications

In many medical applications, x-rays, which traditionally exist as gray-level images, must be evaluated for a diagnosis. By transferring the gray values into pseudocolors the visualization of small nuances can be improved considerably, especially in x-rays with 12-bit quantization. The application of color coding used in x-ray imaging is the subject of Chapter 13.

Some research studies exist on the use of color image processing in the classification of skin tumors. An accurate evaluation of a pigment sample and a hue typical of a melanocyte is necessary for the classification. In [Ros et al. 95], the automatic classification of skin tumors is discussed without practical realization. Two $M\alpha$-procedures can be found in [Sto et al. 96] and [Umb et al. 93]. In both techniques, principal component analysis is first implemented in order to obtain less correlated values. In [Sto et al. 96], a best channel for a gray-value segmentation is subsequently selected. For the color classification the centers of gravity of the intensity values within each segmented region are compared in every color channel. In [Umb et al. 93] a quantization (in four colors) for the segmentation of a skin cancer image is implemented applying principal component analysis. An $M\beta$-technique is proposed in [Xu et al. 99]. There, a gray-level image is created for skin cancer image segmentation. The gray-level image is obtained after mapping colors into intensities in such a way that the intensity at a pixel is proportional to the CIELAB color distance of the pixel to the average color of the background. Another $M\beta$-technique is presented in [Gan et al. 01], where several components of the *RGB*, the CIELAB, and the *HSI* color space are used for melanoma recognition.

Peptic ulcers (*Ulcera ventriculi*) represent a frequent and serious illness in humans. Approximately 1 - 5 % of stomach ulcers are malignant. Here, early detection is necessary for a successful cure. By evaluating the contour of ulcers in color endoscope images, a doctor can be aided considerably in his or her diagnosis of an ulcer (malignant or benign). In [Pau et al. 93], a vector-valued color variant of the Sobel operator is suggested for determining the contour. In order to calculate the difference between the color vectors in the *RGB* space, a distance measurement similar to the Euclidian distance is used. The individual vector components are, however, without more exact motivation, weighed differently. This technique constitutes a $V\alpha$–procedure.

An $M\beta$-procedure for a quantitative description of the severity of an inflammation of the larynx (laryngitis) is presented in [Sch et al. 95]. The severity of the illness is assessed by the doctor subjectively on the basis of redness of the mucous membrane of the larynx in a laryngoscopic color image. The finding can be evaluated using color information in the CIELUV color space. In [Sch et al. 95], the classification of the redness is implemented solely by an observation of the U component of the CIELUV color space.

1.3.2 Color Image Processing in Food Science and Agriculture

The visual appearance of food is a deciding factor in assessing its quality. An important part of quality control in the food industry is, therefore, based on visual inspection. This is traditionally carried out by the human eye. Apart from the absence of reliable quantitative assessment criteria, visual assessment by human beings is time consuming and cost intensive. Until now, the tools needed for implementing automatic quality control using color criteria were lacking. The introduction of color image analysis has decisively changed this. By using analysis in the production process, it can be automatically determined, for example, whether baked goods have the desired size and color appearance [Loc et al. 96].

Another application of color image processing in food control is automatic counting of the number of pepperoni slices and olives on a pepperoni pizza [Ste95]. At first sight, this application does not seem sensible. But if one considers that each customer who buys a pepperoni pizza containing only one slice of pepperoni will probably never buy another pizza from this company again, the economic damages caused by this type of situation become obvious. In [Ste95], a $V\beta$–procedure is presented for segmentation (e.g., of pepperoni slices and olives) in the image with the help of color vector comparisons in the *RGB* space. Another $V\beta$-technique for automatic pizza quality evaluation applies segmentation in the *HSI* space [SunBro03].

At the University of Genoa, an agriculture robot with a color stereo camera system is tested [Bue et al. 94]. Its purpose is to monitor tomato cultivation in a hothouse. Tomatoes ripe for the harvest should be selected with the help of segmentation of color images. Simultaneously, a possible fungus attack should be detected and automatically treated with pesticides. For segmentation in the *HSI* space, a *Mβ*-procedure is suggested that fixes the regions by separate threshold value formation in the *H* and *S* components of the image. Subsequent stereo matching of the segmented regions (for determining the distance between grasping arm and tomato) results without considering color information.

1.3.3 Color Image Processing in Industrial Manufacturing and Nondestructive Materials Testing

To avoid any possibility of confusion and to enable a clear identification, colored markings are used in the electronics industry and pharmaceutical industry. For example, electrical resistors [Asa et al. 86] or ampoules filled with medicine [Bre93] can be automatically determined and selected by an analysis of their color code. In [Asa et al. 86], evaluation of the color code occurs with the help of a monochromatic-based subdivision of the hue and saturation components in the *HSI* color space. In [Bre93], no information on the selection process is given. The information from the signal processors used for increasing the processing speed suggests, however, a monochromatic-based technique.

Furthermore, for the identification of medicine a pharmaceutical code is employed that is composed of a variable number of thick and thin rings applied to ampoules. The use of color image processing is important in this case for legibility since many colors (e.g., yellow) do not have sufficient relative lightness contrast in the gray-value representation. In each case, a defectively marked ampoule must be automatically detected and removed. The use of color image processing can ensure this [Bre93].

1.3.4 Additional Applications of Color Image Processing

A cost-efficient inspection and monitoring of the air quality is another example of a use for color image processing. The active examination of lichens (e.g., *Parmelia sulcata* and *Hypogymnia physodes*) produces a valuable indicator for this [BonCoy91]. Direct conclusions about air quality can be drawn from irregularities in growth, form, or coloring of the lichens. In general (see [BonCoy91]), a series of tests over a period of seven days is conducted, whereby the abovenamed criteria (growth, form, and coloring) are recorded daily. Digital color image processing serves as an effective aid for the automatization of these mass screenings.

Bonsiepen and Coy [BonCoy91] combine the individual components of the color vectors in the *RGB* color space into a scalar feature and segment the scalar feature image produced by this as a gray-level image. More exact segmentation results can be expected here by using a vector-valued technique.

Another possible application is the digitization of maps. These are generally read by flatbed scanners. Chromatic distortions result through errors in the mechanical adjustment and chromatic aberration of the scanner's lens system, by which brown or blue lines in the maps are no longer represented as a blue or a brown, but rather by a class of blue and brown tones. Automatic classification of colored lines requires that the chromatic distortions first be removed. A *Vβ*-technique for this is based on determining eigenvectors in the *RGB* color space [KhoZin96].

1.3.5 Digital Video and Image Databases

Just as the CD has replaced the long-playing record in recent years, the videotape is now being replaced by the DVD ("digital versatile disc" or "digital video disc"). This results in another new range of applications results for color image processing. The main activities in this area still relate at the present to an efficient coding and decoding of color images. This extensive subject area is not covered further here. Interested readers are referred to the following publications on this subject: [ArpTru94], [CarCae97], [Che et al. 94], [MemVen96], [Mit et al. 96], [Ove et al. 95], [Sag et al. 95], [Sch95], [VauWil95], [Wu96], [ZacLiu93], and [ZhaPo95]. A detailed representation of techniques for digital image coding is presented in [RaoHwa96]. Activities in this area are also influencing the development and design of techniques for videophones, teleconferences, and digital cinema.

Additional research deals with the retrieval of image sequences or individual images in image databases (*image retrieval*). For example, at the Massachusetts Institute of Technology, image content oriented search techniques are being researched (see [Pen et al. 96] and [Pic95]). Additional research in the area of color image retrieval deals with search techniques based on histograms of features in the *HSI* color space [RicSto96], with the selection of a "best" color space (*RGB, HSV, YUV*, or Munsell [WanKuo96]; see Chapter 3 for the definition of color space), or various definitions of the *RGB* color space [Lu96] for representing color images using fuzzy techniques in connection with color histograms [StrDim96], distinction of color images in image databases [FauNg96], [GevSme96], [GonSak95], and special techniques for color indexing [SawHaf94], [SmiCha96]. The techniques of color indexing employed here or of color histogram evaluation are similar to those that are also used in color object recognition.

1.4 FURTHER READING

An introduction to various color spaces and the transformations between the spaces are given in [Pra91]. Very worth reading is the (968-page) standard book on color by Wyszecki and Stiles [WysSti82]. The treatment of color information in the human visual system is presented in detail by Zeki [Zek93]. An extensive presentation of techniques for digital image coding (JPEG, MPEG, fractal coding, etc.) can be found in [RaoHwa96]. Mathematical foundations for vector analysis are contained, for example, in [Mat96] and [Sha97].

An interesting overview of the fundamentals of physics-based color image processing has been published by Healey, Shafer, and Wolff [Hea et al. 92]. This is a compilation of 28 selected publications from a number of authors. A technical introduction to the area of digital video is presented by Poynton in [Poy96]. Also recommended is an overview by Poynton of various technical questions regarding color, which can be found on the Internet at http://www.poynton.com/Poynton-color.html. This site also contains links to other color related sites.

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