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Digital Image Processing

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INTRODUCTION

In recent years, digital images and digital image processing have become part of everyday life. This growth has been primarily fueled by advances in digital computers and the advent and growth of the Internet. Furthermore, commercially available digital cameras, scanners, and other equipment for acquiring, storing, and displaying digital imagery have become very inexpensive and increasingly powerful. An excellent treatment of digital images and digital image processing can be found in Ref. [1].

A digital image is simply a two-dimensional array of finite-precision numerical values called picture elements (or pixels). Thus a digital image is a spatially discrete (or discrete-space) signal. In visible grayscale images, for example, each pixel represents the intensity of a corresponding region in the scene. The grayscale values must be quantized into a finite precision format. Typical resolutions include 8 bit (256 gray levels), 12 bit (4096 gray levels), and 16 bit (65536 gray levels). Color visible images are most frequently represented by tristimulus values. These are the quantities of red, green, and blue light required, in the additive color system, to produce the desired color. Thus a so-called "RGB" color image can be thought of as a set of three "grayscale" images—the first representing the red component, the second the green, and the third the blue.

Digital images can also be nonvisible in nature. This means that the physical quantity represented by the pixel values is something other than visible light intensity or color. These include radar cross-sections of an object, temperature profile (infrared imaging), X-ray images, gravitation field, etc. In general, any two-dimensional array information can be the basis for a digital image.

As in the case of any digital data, the advantage of this representation is in the ability to manipulate the pixel values using a digital computer or digital hardware. This offers great power and flexibility. Furthermore, digital images can be stored and transmitted far more reliably than their analog counterparts. Error protection coding of digital imagery, for example, allows for virtually error-free transmission.

OPTICS AND IMAGING SYSTEMS

Considering that optical images are our main focus here, it is highly beneficial to review the basics of optical image acquisition. During acquisition, significant degradation can occur. Thus in order to design and properly apply various image processing algorithms, knowledge of the acquisition process may be essential.

The optical digital-image acquisition process is perhaps most simply broken up into three stages. The first stage is the formation of the continuous optical image in the focal plane of a lens. We rely on linear systems theory to model this. This step is characterized by the system point spread function (PSF), as in the case of an analog photographic camera. Next, this continuous optical image is usually sampled in a typical fashion by a detector array, referred to as the focal-plane array (FPA). Finally, the values from each detector are quantized to form the final digital image.

In this section, we address the incoherent optical image formation through the system PSF. In the section "Resolution and Sampling," we address sampling and quantization. There are two main contributors to the system PSF, one of which is the spatial integration of the finite detector size. A typical FPA is illustrated in Fig. 1. This effect is spatially invariant for a uniform detector array. Spatial integration can be included in an overall system PSF by modeling it with a convolution mask, followed by ideal spatial sampling. More details will be supplied about this presently. Another contributor is diffraction due to the finite size of the aperture in the optics. Other factors such as lens aberrations[2,3] and atmospheric turbulence[4] can also be included in the image acquisition model.

Let us examine a uniform detector array and provide a mathematical model for the associated imaging system. We will closely follow the analysis given in Ref. [5]. The effect of the integration of light intensity over the span of the detectors can be modeled as a linear convolution operation with a PSF determined by the geometry of a single detector. Let this detector PSF be denoted by $d(x, y)$. Applying the Fourier transform to $d(x, y)$ yields

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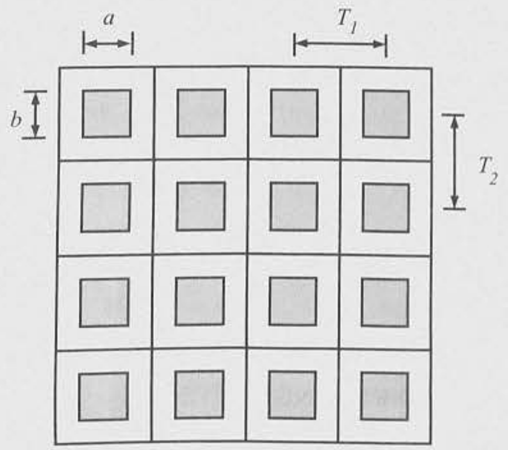

Fig. 1 Uniform detector array illustrating critical dimensions. (From Ref. [5].)

the effective continuous frequency response resulting from the spatial integration of the detectors[1,2,5]

$$D(u,v) = \mathcal{F}\{\mathrm{d}(x,y)\} \tag{1}$$

where $\mathcal{F}\{\cdot\}$ represents the continuous Fourier transform.

Next, define the incoherent optical transfer function (OTF) of the optics to be $H_o(u,v)$. The overall system OTF is given by the product of these, yielding

$$H(u,v) = D(u,v)H_o(u,v) \tag{2}$$

The overall continuous system PSF is then given by

$$h_c(x,y) = \mathcal{F}^{-1}\{H(u,v)\} \tag{3}$$

where $\mathcal{F}^{-1}\{\cdot\}$ represents the inverse Fourier transform.

If we intend to correct for this blurring in our digital image with postprocessing, it is most convenient to have the equivalent discrete PSF (the impulse-invariant system). The impulse-invariant discrete system PSF,[6] denoted as $h_d(n_1,n_2)$, is obtained by sampling the continuous PSF such that

$$h_d(n_1,n_2) = T_1T_2h_c(n_1T_1,n_2T_2) \tag{4}$$

where T_1 and T_2 are the horizontal and vertical detector spacings, respectively. This accurately represents the continuous blurring when the effective sampling frequency, $1/T_1$, exceeds two times the horizontal cutoff frequency of $H(u,v)$ and $1/T_1$ exceeds the vertical cutoff frequency by twofold.[6]

Let us now specifically consider a system with uniform rectangular detectors, as shown in Fig. 1. The shaded areas represent the active region of each detector. The detector model PSF in this case is given by

$$\begin{aligned} \mathrm{d}(x,y) &= \frac{1}{ab}\,\mathrm{rect}\left(\frac{x}{a},\frac{y}{b}\right) \\ &= \begin{cases} 1 & \text{for } |x/a| < 1/2 \text{ and } |x/b| < 1/2 \\ 0 & \text{otherwise} \end{cases} \end{aligned} \tag{5}$$

Let the active region dimensions, a and b, be measured in millimeters (mm). Thus the effective continuous frequency response resulting from the detectors is

$$D(u,v) = \mathrm{sinc}(au,bv) = \frac{\sin(\pi au)\sin(\pi bv)}{\pi^2 aubv} \tag{6}$$

where u and v are the horizontal and vertical frequencies measured in cycles/mm.

The incoherent OTF of diffraction-limited optics with a circular exit pupil can be found[2] as

$$H_o(u,v) = \begin{cases} \frac{2}{\pi}\left[\cos^{-1}\left(\frac{\rho}{\rho_c}\right) - \frac{\rho}{\rho_c}\sqrt{1-\left(\frac{\rho}{\rho_c}\right)^2}\right] & \text{for } \rho < \rho_c \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

where $\rho = \sqrt{u^2+v^2}$. The parameter ρ_c is the radial system cutoff frequency given by

$$\rho_c = \frac{1}{\lambda f/\#} \tag{8}$$

where $f/\#$ is the f-number of the optics and λ is the wavelength of light considered. Because the cutoff of $H_o(u,v)$ is ρ_c, so is the cutoff of the overall system $H(u,v)$.

Fig. 2 shows an example of $D(u,v)$, $H_o(u,v)$, $H(u,v)$, and $h_c(x,y)$ for a particular imaging system. The system considered happens to be a forward-looking infrared (FLIR) imager. The FLIR camera uses a 128×128 Amber AE-4128 infrared FPA. The FPA is composed of indium–antimonide (InSb) detectors with a response in the 3–5 μm wavelength band. This system has square detectors of size $a = b = 0.040$ mm. The imager is equipped with 100 mm $f/3$ optics. The center wavelength, $\lambda = 0.004$ mm, is used in the OTF calculation. Fig. 2a) shows the effective modulation transfer function (MTF) of the detectors, $|D(u,v)|$. The diffraction-limited OTF for the optics, $H_o(u,v)$, is shown in Fig. 2b). Note that the cutoff frequency is 83.3 cycle/mm. The overall system MTF, $|H(u,v)|$, is plotted in Fig. 2c). Finally, the normalized continuous system PSF, $h_c(x,y)$, is plotted in Fig. 2d). The continuous PSF is sampled at the detector spacing to yield the impulse invariant discrete system impulse response.

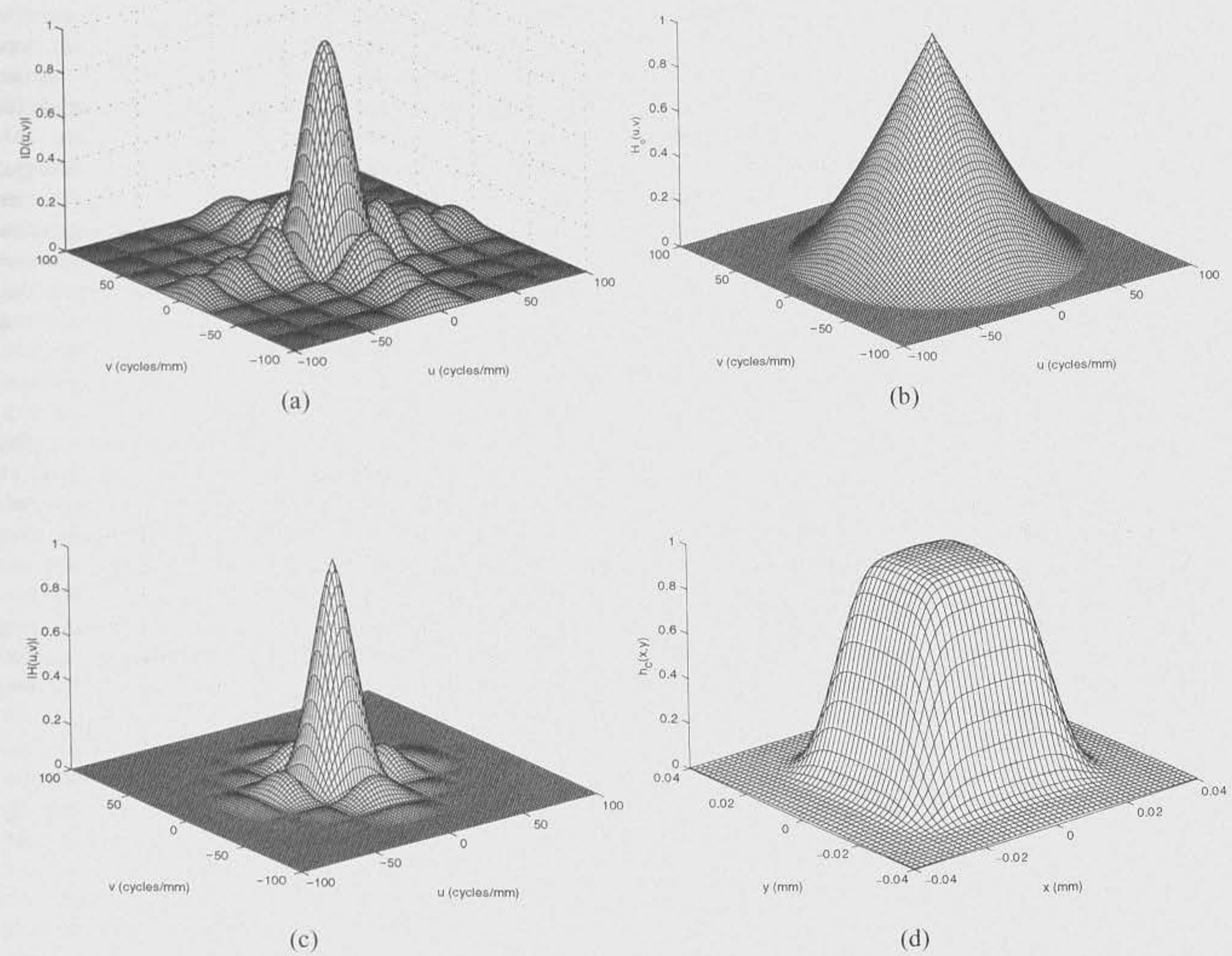

Fig. 2 (a) Effective MTF of the detectors in the FLIR imager; (b) diffraction-limited OTF of the optics; (c) overall system MTF; (d) overall continuous system PSF. (From Ref. [5].)

RESOLUTION AND SAMPLING

Resolution is generally thought of as the ability of an imaging system to preserve contrast in small, closely spaced objects. Thus resolution is tied to the ability of a system to preserve information necessary to resolve point sources at various separations. In this sense, resolution is affected by the three stages of image acquisition described above. We must consider the optical cut-off frequency, which limits the resolution of the optical image in the focal plane. Next, we must consider the ability of the sampling and quantization to preserve this optical resolution in our digital image.

The cut-off frequency of the optics and detector integration is a good means of quantifying the resolution of the optical image in the focal plane (prior to the spatial sampling and quantization). Another related means of quantifying optical resolution involves the Rayleigh distance.[1] The Rayleigh distance is related to the width of the PSF spot. For a diffraction-limited system with a circular aperture, the first zero of the PSF occurs at

$$r_0 = 1.22\frac{\lambda d}{a} \tag{9}$$

where λ is the optical wavelength, d is the focal length, and a is the aperture diameter. Thus the Rayleigh distance, r_0, basically describes the width of the PSF spot size (ignoring detector spatial integration). Thus according to the Rayleigh criterion, two point sources can be "resolved" in the focal plane image if they are separated by r_0 or greater.

Because of sampling and quantization, the diffraction-limited resolution does not tell the whole story for a digital imaging system. Another important aspect is the detector spacing which determines the spatial sampling rate.[7] The optical cut-off frequency and the Rayleigh distance lead to two different detector spacing criteria for "proper" sampling. The Nyquist criterion specifies that the sampling frequency must exceed two times the optical cut-off frequency. Note that the detector spacing in the focal plane determines the sampling frequency. Thus for a typical camera system with a cut-off frequency of $f_c = a/(\lambda d)$, the detector spacing for Nyquist sampling would be $(\lambda d)/(2a)$. Sampling at this rate means that the data are free from aliasing. Consequently, with proper interpolation, it is possible to recover the continuous image from its samples without error. Thus it is fair to say that the full optical resolution is preserved by Nyquist sampling.

The Rayleigh sampling criterion is less strict than the Nyquist criterion. According to the Rayleigh criterion, we space the detectors at one half of the Rayleigh distance, $0.5r_0$. By doing so, two resolvable adjacent spots in the focal plane image will remain resolvable in the sampled data. Thus for our typical camera system with a cut-off frequency of $f_c = a/(\lambda d)$, the detector spacing for Rayleigh sampling would be $0.61\lambda d/a$. Note that this is 22% larger than the spacing for Nyquist sampling. As a result, some aliasing will be present in the imagery, and it is not possible to perfectly reconstruct the continuous image from its samples. Many camera-system designs utilize a sampling rate lower than the Nyquist. This is partly attributed to the fact that little energy tends to exist at the higher aliased frequencies, and fewer detectors means less data (for the same field of view) and lower cost.

In infrared imaging systems, commercially available FPA arrays tend to have fewer detectors than in visible systems. This is attributed to the cost and fabrication complexity. This, coupled with the desire for a wide field of view (small focal length), means that aliasing is a significant problem in these systems. A number of algorithms have been developed which attempt to compensate for the aliasing in all types of images by post processing a sequence of frames with motion.[5,8–15] Related to these aliasing reduction algorithms are super-resolution techniques.[16–19] The term "super-resolution," is generally used to refer to algorithms that use post-processing to recover frequency information beyond that of the cut-off of the optics. This requires creating a new effective sampling grid denser than the Nyquist criterion dictates. Clearly, this is a far more ambitious goal than simply trying to realize the full resolution afforded by the optics. Such techniques require a priori information about the scene and its dynamics in some form.

IMAGE DEGRADATION AND NOISE

In almost all imaging systems, the very process of recording or acquiring of an image is accompanied by one or more forms of degradation and noise. This section deals with some of the prevalent sources of degradation and noise encountered in modern imaging systems.

There are many sources of degradation in imaging systems, and they can be categorized according to their spatial and temporal characteristics. *Point degradations* often refer to types of degradation where the values of individual pixels are affected without introducing any blur. In this case, the pixel values undergo a simple pointwise transformation. A good example of point degradation is the pixel saturation effect exhibited by visible and infrared cameras for which an excessive level of intensity will set the detector output to a saturation level. Practical imaging systems also introduce some form of image blur, in which case, the gray level of a pixel is affected by the gray levels of the neighboring pixels. These types of degradation are commonly referred to as *spatial degradations*. A prime example is the optical (or Rayleigh type) blur, which is particularly pronounced in small-aperture optical imaging systems. Another related example of spatial degradation is the blur introduced by the finite size of the active area of each detector in the array.

Other types of degradation involve chromatic or temporal effects. In some cases in hyperspectral imaging, for example, the PSF of the system can be strongly dependent on the optical wavelength of the incoming light, which may cause image deformation and additional blur. Another form of degradation occurs when imaging is performed in the presence of atmospheric turbulence. In this situation, the system PSF randomly fluctuates in time, according to the changes in the refractive index of the column of air between the object and the camera. This type of degradation may result in blur, tilt, or other aberration depending on the exposure time of the camera and atmospheric conditions.[4] Yet another important form of degradation involves the geometric deformation of the image, which can be attributed, for example, to aberration associated with the optical elements (e.g., lenses).

The above sources of degradation are all operational in nature. In other words, they can be thought of as some operator (or system) acting on the true image. This representation becomes particularly useful in image restoration, where the goal is to perform counter operations in an effort to "undo" degradation. However, such degradations are not the only cause of reduction of image quality because recording or acquisition of an image is always accompanied by measurement noise.

As in the case of image degradation, there are many sources of noise that can seriously degrade the quality of images. In principle, noise be classified into two categories: *signal-independent* and *signal-dependent*. Thermal noise (also known as Johnson noise), which is inherent in all electronic measurements, is an example of signal-independent noise. This type of noise is added to each pixel value and can become a limiting factor in cases when the object illumination is weak. Thermal noise is often modeled by a Gaussian process whose variance is dependent on the temperature, the resistance and the temporal bandwidth of the electronic circuitry.[20] In array sensors, however, there is additional noise because of the nonidentical responsivities of the individual detectors. In particular, any two detectors may respond slightly differently to the same intensity level. This results in a spatial pattern, which appears atop the image causing visual distortion and reducing the gray-level accuracy. This type of noise is commonly referred to as fixed-pattern noise; it can be a limiting factor in high-precision applications particularly in mid- to far-infrared imagers.[21–23] Fixed-pattern noise is a form of signal-dependent noise. For example, fluctuations in the gains of detectors are affected (in a multiplicative form) by the level of intensity. A number of techniques which attempt to correct for this nonuniformity[21,23–31] have been proposed.

The most fundamental source of noise in optical measurement, however, is quantum noise, which arises from the photon nature of light. Quantum noise represents the uncertainty in the number of photons collected in any time interval.[3,32] This random fluctuation in the photon number increases with the optical energy (or signal) per measurement time. Interestingly, the magnitude of quantum noise, relative to the mean photon number, is inversely related to the optical energy. Quantum noise therefore plays an important role in limiting the accuracy of optical imaging and vision in situations when the density of photons per measurement time is small, i.e., at low intensities of light.[33] These situations occur, for example, when imaging faint astronomical objects and in medical radiographic imaging.[34] Moreover, this type of signal-dependent noise is also important in high-intensity imaging applications whenever high levels of measurement accuracy is desired. For fully coherent light, the photon number distribution obeys a Poisson distribution. The Poisson distribution is also used as an approximation for partially coherent and thermal light as long as the measurement time and area (i.e., detector integration time and active area) are greater than the coherence time and area of the light, respectively.[35]

In any imaging application, the harm resulting from image degradation and measurement noise can be better overcome if the sources of degradation and noise are identified and properly modeled. Much of the available image restoration and model-based enhancement techniques often require a mathematical model for pertinent image-degrading effects.

OVERVIEW OF IMAGE PROCESSING TECHNIQUES

Digital image processing generally refers to the manipulation of the pixel values using a digital computer. The goals of such processing vary widely. In this work we describe six major categories of image processing algorithms. Each is addressed in detail in subsequent subsections.

Image Restoration

One important class of image processing problems is image restoration. In image restoration, the goal is to estimate an image free from some corruptive process based on corrupted observations. The corruptive process may include blur, noise, or aliasing, for example. Image restoration tends to be quantitative (rather than qualitative) and requires some knowledge of the corruptive process. The corruptive process modeled may include the imaging system itself.

Image restoration techniques can be divided into linear and nonlinear methods. Typical linear methods tend to be well suited for the restoration of images corrupted by a linear blur and additive Gaussian noise. Linear filters enjoy the benefits of having a well-established and rich theoretical framework. Furthermore, real-time implementation of linear filters is relatively easy because they employ only standard operations (multiplication and addition), and can also be implemented using fast Fourier transforms. In many cases, however, the restriction of linearity can lead to highly suboptimal results. In such cases, it may be desirable to employ a nonlinear filter.[36–38] Furthermore, as digital signal processing hardware becomes increasingly more sophisticated and capable, complex nonlinear operations can be realized in real-time. For these reasons, the field of nonlinear filters has grown, and continues to grow rapidly.

While many applications benefit from the use of nonlinear methods, there exist broad classes of problems that are fundamentally suited to nonlinear methods and which have motivated the development of many nonlinear algorithms. Included in these classes of problems are: suppression of heavy-tailed noise processes and shot noise; processing of nonstationary signals; superresolution frequency extension; modeling and inversion of nonlinear physical systems.

Image Enhancement

Another class of image processing techniques is image enhancement. Enhancement is the process of subjectively improving image quality. These techniques tend to be more qualitative than quantitative. Enhancement includes point operations which may modify the histogram of an image. A histogram of a grayscale image is simply a plot of the number of times each gray level is observed in the image. Changing the brightness or contrast using a linear scaling of each pixel value, for example, will change the histogram of the image. Enhancement includes many other operations including spatial smoothing and spatial sharpening. These can be accomplished with linear low-pass and high-boost filters, respectively. In a broader sense, enhancement can include edge detection, image resizing through interpolation, and other geometric transformations.

Multispectral and Hyperspectral Image Processing

A visible multispectral image is a collection of images of the same scene at different optical wavelengths. Each image or "band" typically corresponds to a narrow-spectral-band image of the scene. The term "hyperspectral" is generally reserved for multispectral images where hundreds of spectral bands are used. In a broader sense, some nonvisible images are described as multispectral when they are composed of a set of images, each measuring a different physical quantity. For example, in magnetic resonance imaging (MRI), the modality of the imager can be changed to collect several different types of images of the same area.

It may be that visible multispectral and hyperspectral images have most often found application in remote sensing. An excellent treatment of the subject can be found in Ref. [39]. The multiple wavelength information can provide a wealth of information about the scene. In the case of hypespectral imagery, each pixel provides significant information about spectral reflectance pattern or signature for the scene in that area. Such a spectral reflectance pattern can be used to distinguish the various materials in the scene with far more precision than with a single band. This is carried out by using multivariate clustering techniques. In some cases, it is even possible to perform material identification for each pixel based on the spectral reflectance signatures inferred from a hyperspectral image deck. This is referred to as pixel classification.

Image Segmentation

Segmentation is the process of grouping pixels in an image into similar classes.[40] This creates a set of nonoverlapping regions in the image. Segmentation is used in a number of ways. Perhaps the primary application is to isolate groups of pixels with similar properties so that these groups can then be classified together. This is performed extensively in remote sensing.[39] It is also carried out with nonvisible images such as MRI images. In the case of MRI, the different tissue types are segmented and may then be classified by a radiologist or by an automated system.

In automatic target recognition (ATR), described below, it is often necessary to isolate a single target object from the background prior to attempting to identify the object. This is carried out through image segmentation. Another use for segmentation is to allow one to perform different processing techniques on different groups of pixels (segments).[41] Segmentation can be accomplished using gray-level information, color or other spectral characteristics, local texture, boundaries, etc.

Automatic Target Recognition

ATR using image data remains an important problem in image processing. ATR refers to the processing of identifying an object in image data, based solely on an automated system (no human in the loop).[1] ATR capabilities are an important aspect of many autonomous vehicles, surveillance systems, and military systems. ATR is also important in a number of industrial applications such as automatic sorting of objects and quality control in an assembly line.

ATR is generally broken down into the steps of segmentation, feature extraction, and classification (pattern recognition).[42] Segmentation, described above, is used to isolate objects from one another and the background. Feature extraction is the process of converting the observed pixel data in the segment of interest into a compact and concise set of numerical observations. These "features" should be designed to offer maximum class separability with a minimum of redundant information. Such features can include shape analysis parameters, Fourier descriptors, edge locations, object symmetry parameters, size, color (spectral characteristics), etc.

Thus the features can be both spatial and spectral in nature. It is generally believed that a combination of these factors offers the most promise for many applications. Note that if only spatial information is used, this generally requires very high spatial resolution. If high-resolution spectral information is available, it may be possible to perform ATR with only one hyperspectral pixel on the object. Thus there is clearly an interesting trade-off between spatial and spectral resolution.

The pattern recognition step is the process of classifying (or naming) the objects based on the extracted features for those objects. This process can be accomplished using a number of frameworks including Bayesian analysis, neural networks, k nearest neighbor analysis, etc.[42]

Image sequences can aid ATR. For example, moving targets are easily segmented from the background in an image sequence. Furthermore, the motion parameters themselves could be used as features for ATR. Multiple looks from an image sequence from different viewing angles can also be a big aid, especially in the case of partially hidden or obscured objects.

Image Sequence Processing

With recent advances in video hardware and desktop digital video products, full-motion digital video and other image sequence data are becoming increasingly prevalent. Image sequences offer a wealth of information which can be exploited in image processing algorithms. Image restoration, enhancement, segmentation, and automatic target recognition can all benefit from image sequence information.[43] Consider the case of temporal noise, for example. Such noise can often be greatly reduced with a motion-compensated temporal-averaging filter.[43] Redundant information in sequences can also be exploited for dramatic video compression, as seen in the Moving Picture Experts Group (MPEG) standard. In many image sequence processing algorithms, scene motion parameters are frequently required. This may involve rigid object motion or full deformable optical flow. Thus motion estimation and optical flow estimation are fundamental problems associated with image sequence processing.

CONCLUSION

In this article, we have attempted to convey the basics of digital image representation and some aspects of visible image acquisition. We have also highlighted six major areas within the broad field of digital image processing, which are discussed in more detail in related articles. We hope that the reader will benefit from the references cited in this work, which provide a fuller treatment of these subjects.

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