Digital Filtering in Nuclear Medicine

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Digital filtering is a powerful mathematical technique in computer analysis of nuclear medicine studies. The basic concepts of object-domain and frequency-domain filtering are presented in simple, largely nonmathematical terms. Computational methods are described using both the Fourier transform and convolution techniques. The frequency response is described and used to represent the behavior of several classes of filters. These concepts are illustrated with examples drawn from a variety of important applications in nuclear medicine.

J Nucl Med 23: 66–72, 1982

The use of computers in nuclear medicine has increased dramatically in recent years. Advanced computer techniques are being introduced rapidly, some with potential for important clinical application. This paper will describe digital filtering techniques, which are very powerful mathematical tools that can be used to extract additional quantitative information and to improve the quality of nuclear medicine images. Familiarity with these techniques is important both for the computer-oriented investigator and the clinician who wants to understand whether these new methods, offered to him by the computer manufacturers, will be of value in his practice. The basic concepts of object- and frequency-domain analysis will be developed without recourse to detailed mathematics. These concepts lead naturally to the design of versatile digital filters. After discussing the principal computational techniques, current and future applications will be described.

BASIC CONCEPTS (*1-3*)

Object and frequency domains. Nuclear medicine data usually represent images in terms of spatial coordinates (x − y) or dynamic functions varying in time (t). This representation of data in terms of spatial or temporal functions is called the "object domain" representation. The Fourier series, described below, can be used to represent these data as a series of trigonometric functions characterized by varying frequencies and amplitudes. This description in terms of spatial or temporal frequencies is termed the "frequency-domain" representation.

Digital filters can be applied to data either directly in the object domain (x − y or t) through a "convolution" operation or after transformation to the frequency domain. Because of the exact mathematical equivalence between the object-domain representation and the frequency-domain representation, the results of the digital filtering will be the same. However, as discussed below, many digital filters are best described and evaluated by computing the change in the frequency distribution of the data that they produce.

Fourier series and Fourier transform. Mathematical functions that are repetitive in space or time (periodic functions) can be represented exactly as the sum of a series of sine and cosine waves of differing frequencies and amplitudes. Expressed mathematically, for a temporal function f(t) this "Fourier series" is

$$\begin{aligned} f(t) = A_0 &+ A_1 \cos(\omega t) + B_1 \sin(\omega t) \\ &+ A_2 \cos(2\omega t) + B_2 \sin(2\omega t) \\ &+ A_3 \cos(3\omega t) + B_3 \sin(3\omega t) \\ &+ \ldots, \end{aligned} \quad (1)$$

where the A's and B's are the amplitudes of the cosine

Received Sep. 9, 1980; revision accepted Sep. 17, 1981.

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and sine waves, respectively, and $\omega = 2\pi/T$ where T is the period of the periodic function f(t). Alternatively, the Fourier series can be represented completely by cosine waves alone with differing phases or shifts of the crests of the waves from t = 0. In this form,

$$\begin{aligned} f(t) &= a_0 + a_1\cos(\omega t - \Phi_1) + a_2\cos(2\omega t - \Phi_2) \\ &\quad + a_3\cos(3\omega t - \Phi_3) + \ldots \qquad (2) \\ &= a_0 + \sum_{n=1}^{\infty} a_n\cos(n\omega t - \Phi_n), \end{aligned}$$

where the a_n are the amplitudes and the Φ_n are the phases. The series in Eqs. (1) and (2) can be terminated when the amplitudes become insignificantly small.

The Fourier series, illustrated here for a periodic temporal function f(t), applies equally to spatial functions f(x,y) (e.g., images) where the image is considered to be the sum of cosine waves running across the image in the x and y directions. To satisfy the periodicity requirement, the image intensity can be smoothly tapered to zero at the edges of the image. Thus, the data for each row or column will appear as a continuous periodic function with continuity at the edges. The Fourier series representation of the image consists of the Fourier transforms of each individual row and column.

To illustrate the use of Eq. (2), a left-ventricular time-activity curve (TAC) from a gated cardiac study is shown in Fig. 1 along with the Fourier series representation of this curve. In this case, frequency components above the third are omitted because their contribution to the TAC is negligible.

The process of determining the amplitudes in Eq. (1) or the amplitudes and phases in Eq. (2) is called Fourier transformation. In mathematical notation,

$$F(\omega) = \mathcal{F}\{f(t)\}, \qquad (3)$$

where $\mathcal{F}$ denotes the Fourier transform operation and $F(\omega)$ is the Fourier transform, a function of the frequency ω. The process of going back from the frequency domain to the object domain is called inverse Fourier transformation, written $\mathcal{F}^{-1}$, i.e.,

$$f(t) = \mathcal{F}^{-1}\{F(\omega)\}. \qquad (4)$$

Digital filtering in the frequency domain. The computations involved in digital filtering may be performed either in the frequency domain or in the object domain. In frequency-domain filtering, the relative contributions of the frequencies that comprise the data are modified by filter coefficients. Digital filtering of the function f(t) described by the Fourier series of Eq. (2) leads to the filtered function f′(t):

$$\begin{aligned} f'(t) = Hf(t) &= H_0a_0 + H_1a_1\cos(\omega t - \Phi_1) \\ &\quad + H_2a_2\cos(2\omega t - \Phi_2) \\ &\quad + H_3a_3\cos(3\omega t - \Phi_3) + \ldots \qquad (5) \\ &= H_0a_0 + \sum_{n=1}^{\infty} H_na_n\cos(n\omega t - \Phi_n), \end{aligned}$$

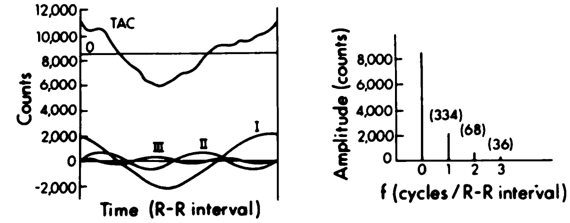

FIG. 1. Left panel: Time-domain representation. A representative time-activity curve (TAC) from a gated cardiac blood-pool study is shown at top. Constant term and first three frequency terms that comprise the TAC are labeled 0, I, II, III, respectively. Right panel: Frequency-domain representation. Amplitude of constant term and first three harmonics of the TAC in left panel are displayed as vertical bars. Phase of each harmonic is shown in parentheses.

where the digital filter consists of the H_n terms of the "filter transfer function" multiplying the amplitudes a_n of the Fourier series representation of the data.

Using the Fourier transform notation of Eqs. (3) and (4), the operation of filtering in the frequency domain may also be written as

$$\begin{aligned} F'(\omega) &= H(\omega)\cdot F(\omega) \\ f'(t) &= \mathcal{F}^{-1}\{F'(\omega)\}. \end{aligned} \qquad (6)$$

In other words, to perform digital filtering in the frequency domain, first compute the Fourier transform of the function to be filtered $[F(\omega) = \mathcal{F}\{f(t)\}]$, then multiply by the filter transfer function $H(\omega)$ and perform the inverse Fourier transform $\mathcal{F}^{-1}$ to obtain the filtered function f′(t).

To clarify the concept of frequency-domain filtering further, we may draw a useful analogy with the familiar modulation transfer function (MTF) widely used in nuclear medicine to characterize scintillation-camera performance (*4*). The camera may be thought of as a filter that blurs the distribution of activity emanating from the organ of interest to yield the resulting degraded image. This "filtering" function is described by the MTF in terms of the camera's effect on the spatial frequency components that comprise the image. In the same way, a digital filter acts to modify the frequency components of an image with its effect described by the filter transfer function $H(\omega)$.

Methods for determining the filtering function will be described below along with examples of several popular filters.

Digital filtering in the object domain. Filtering may be performed directly in the object domain without Fourier transformation to the frequency domain. In this case, a convolution operation is performed where the data (image or temporal function) are "convolved" with the filter function. For unfiltered and filtered temporal functions f(t) and f′(t),

$$f'(t) = h*f = \int h(\alpha)f(t-\alpha)d\alpha, \qquad (7)$$

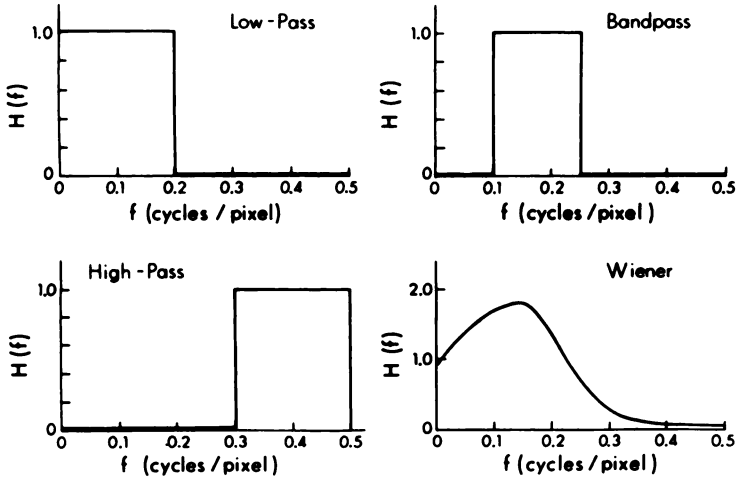

FIG. 2. Typical frequency response functions H(f) for low-pass, band-pass, high-pass, and Wiener filters. Here, $f = \omega/2\pi$.

where h is the digital filter function in the object domain, $*$ denotes the convolution operation, and α is a dummy variable of integration. For discrete functions,

$$f'(t) = h*f = \sum_{n=-N}^{N} h_n f(t-n), \qquad (8)$$

where the filter is of length 2N + 1.

Just as an analogy can be drawn between the filter transfer function H and the MTF, the filter function h in the object domain can be compared with the point-spread function (PSF) used to characterize scintillation-camera performance (*4*). The blurring of the imaged organ is represented as a convolution of the PSF with the distribution of radioactivity within the organ. In the same way, in digital filtering the filter function h is convolved with the image to yield the filtered image.

Convolution theorem. As is evident from the above discussion, object-domain and frequency-domain filtering are closely related. This association is expressed mathematically in the convolution theorem, which states that the convolution of two functions in the object domain is equivalent to multiplication of their Fourier transforms in the frequency domain. In other words, if f(t) and h(t) are two functions with Fourier transforms $F(\omega)$ and $H(\omega)$ respectively, then

$$h(t)*f(t) = \mathcal{F}^{-1}\{H(\omega) \cdot F(\omega)\}. \qquad (9)$$

Thus, the convolution operation in the object domain may be computed by multiplying the Fourier transforms and taking the inverse transform.

DESIGNING A FILTER

The first, and most difficult, task of the filter designer is choosing the desired frequency response. For each frequency a number is specified that multiplies the amplitude of the corresponding frequency term in the Fourier series to obtain the filtered frequency terms. As is evident from Eq. (5), the factor 1 implies no modification of the frequency component, while attenuation is indicated by values less than one and amplification by numbers greater than one.

The desired form of the filter transfer function can be determined by considering the actual frequency spectrum of the data and comparing it with the desired frequency spectrum after filtering. For a function f(t) with frequency spectrum (Fourier transform) $F(\omega)$, the desired frequency spectrum, represented by the Fourier transform $F'(\omega)$ is, as in Eq. (6),

$$F'(\omega) = H(\omega) \cdot F(\omega). \qquad (10)$$

Thus, the required filter transfer function is

$$H(\omega) = F'(\omega)/F(\omega). \qquad (11)$$

A widely used class of filters is the so-called "smoothing" filters, whose effect is reduction in high-frequency noise while leaving unaffected the lower frequencies where the signal predominates. An example of this group, perhaps better called "low-pass" filters, is shown in Fig. 2A. Other filters, the band-pass and high-pass filters, are shown in Figs. 2B and 2C; they are named for the parts of the frequency spectrum unaffected by the filter (*3*). Frequency components outside these ranges are completely attenuated. Also shown is the response of a typical Wiener filter, a more sophisticated filter based on the principle of minimizing the mean squared error between the original, undegraded image and the filtered image (*5*). Examples of the use of some of these filters will be presented below.

After the desired frequency response is selected, the actual digital filtering operation is performed using one of the techniques discussed below.

DIGITAL FILTERING TECHNIQUES

In doing digital filtering, one always characterizes the filter in terms of its effect on the frequency components of the data. However, the actual computations can be performed in either the frequency domain or the object domain.

Fourier transform method. Here, the frequency components are actually calculated using the Fourier transform, then the filter is applied, and finally the inverse Fourier transform is performed. This is the basic frequency-domain method discussed above.

A very attractive feature of the direct Fourier transform technique is the availability of the fast Fourier transform (FFT), a computer algorithm that performs the Fourier transform very rapidly (*1*). There are, however, several computational pitfalls, described in the Appendix, that must be avoided to prevent the introduction of serious processing artifacts.

Convolution method—FIR filters. In the convolution method, the computation is performed in the object domain, as discussed above, without Fourier transformation to the frequency domain (*2,6*). However, the design and performance of these filters, often called finite impulse response (FIR) filters, is always characterized by the effect of the filter on the frequency components of the data. As is evident from the convolution theorem, the Fourier transform and convolution methods are mathematically identical. There are, however, important computational differences and differences in local versus global properties that are discussed below.

To illustrate in detail the mathematical computations, consider an image i(x, y) processed to yield a filtered image i′(x, y) according to the convolution equation

$$i'(x, y) = \sum_{l=-N}^{N} \sum_{m=-N}^{N} h_{lm} i(x - l, y - m), \quad (12)$$

where the h_{lm} are the FIR coefficients for a square filter of size (2N + 1) × (2N + 1). The coefficients are chosen so that this spatial-domain filter will handle the frequency terms of the image as if an actual Fourier transform had been performed. An example of an FIR filter is the familiar "nine-point smooth" widely used in nuclear medicine (*7*). While this filter is not generally recognized as such, it is in fact one of the simplest possible FIR filters. This filter is shown in Fig. 3 along with the frequency response determined by generating test "images" of sine waves of differing frequencies and applying the filter. To clarify the meaning of Eq. (12), the magnitude of the filtered image at a point (x_0, y_0), i.e., $i'(x_0, y_0)$, is, for this filter,

$$\begin{aligned} i'(x_0, y_0) = {} & 0.25\, i(x_0, y_0) + 0.125[i(x_0 - 1, y_0) \\ & + i(x_0 + 1, y_0) + i(x_0, y_0 - 1) + i(x_0, y_0 + 1)] \\ & + 0.0625\, [i(x_0 - 1, y_0 - 1) \\ & + i(x_0 + 1, y_0 - 1) + i(x_0 - 1, y_0 + 1) \\ & + i(x_0 + 1, y + 1)]. \quad (13) \end{aligned}$$

The complete filtered image is obtained by running this FIR "mask" over all values of x_0 and y_0 in the image.

There are a number of ways to determine the FIR coefficients after the filter designer specifies the desired

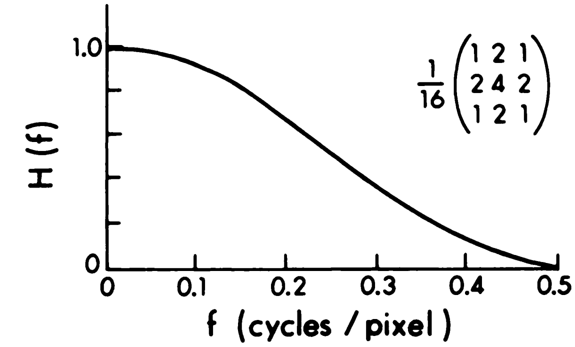

FIG. 3. Frequency response function H(f) shown for the widely used 3 × 3 smoothing FIR filter. Filter coefficients are shown in inset. Here, f = ω/2π.

frequency response (*6*). The simplest approach would be to take the Fourier transform of the filter transfer function, i.e.,

$$h = \mathcal{F}\{H(\omega)\}. \quad (14)$$

Unfortunately, as discussed in the Appendix, this method will introduce spurious terms in the FIR coefficients arising from the "leakage" phenomenon. To correct this problem, a "window" must be applied to the coefficients (*2*).

The most widely used method of determining the FIR coefficients is based on a mathematical technique called Chebyshev optimization. McClellan et al. (*8*) have written a versatile Fortran computer program to determine the one-dimensional coefficients by this method. A second program is available to obtain two-dimensional coefficients from the one-dimensional terms (*6*).

A filtering method theoretically related to the FIR filter is the infinite-impulse response (IIR) filter (*9*). While a casual analysis of this method suggests certain advantages over the FIR technique—especially in speed of computation—closer inspection reveals several practical disadvantages that make the FIR filter the preferred method in most applications.

COMPARISON OF FOURIER TRANSFORM AND FIR METHODS

The Fourier transform method of digital filtering using the FFT is older than the convolution (FIR) method and it is still very popular. However, the FIR technique has been thoroughly developed in recent years, and it is now widely used both for one-dimensional digital signal processing and two-dimensional image processing.

Basically, either method will work in most applications of interest in nuclear medicine. Indeed, as discussed above, the fundamental identity of the two techniques is expressed in the convolution theorem. However, the choice of method in a particular application depends primarily on two considerations: (a) computational issues (see the Appendix) and (b) the "local" nature of the FIR filter. The FIR filter operates only on the data in a local region surrounding each individual point to be filtered. In other words, the filtered value for any given point depends only on the nature of the data in the adjoining area. This FIR property permits "adaptive" filtering where the characteristics of the filter are adapted, or changed, to match the nature of the data on a point-by-point basis. Furthermore, since the performance of the filter is insensitive to characteristics of the data outside the range of the filter mask, any artifacts or corruption of the data—e.g., falloff of TAC counts in late diastole due to beat-length variability—will not affect the filtered result far from those regions. Of course, when only a fixed, or global, filter is required and the data are of good quality, the Fourier transform method is often quite satisfactory.

Propagation of noise through a digital filter is an important consideration in most nuclear medicine applications. The choice of a filter to reduce data noise is often a major concern of the filter designer. Although this complex topic is beyond the scope of this paper, note that the Fourier transform and FIR techniques treat noise in essentially the same way, since the primary determinant of noise response is the nature of the filter, not the way it is implemented.

Digital filters may be used to reduce temporal or spatial blurring. Here, too, this important goal is related to the choice of frequency response of the filter and not to whether the Fourier transform or FIR technique is used to realize the filter design.

APPLICATIONS

Digital filtering techniques pervade the digital signal-processing and image-processing literature. Since many excellent books and review articles (*5,6,10,11*) are available describing applications outside nuclear medicine, the discussion here will be limited to recent work in nuclear medicine.

Studies of the heart lend themselves naturally to digital-filtering analysis since the heart functions periodically in time. Verba et al. (*12*), in their program for automatic analysis of the gated cardiac blood-pool study, rely extensively on Fourier transform filtering both in space and time. They perform a two-dimensional (spatial) Fourier transform to smooth the cardiac images and, additionally, smooth the pixel-by-pixel TAC curves in time. They believe that this combined filtering—essentially a three-dimensional Fourier transform—is critical to the performance of their program.

The Fourier transform is the central component of the so-called "phase" analysis of the gated cardiac study (*13*). A time-activity curve is formed for each picture element ("pixel") of the two-dimensional image. The first harmonic (first frequency term) of the Fourier series representation of each pixel's TAC is then computed. Two static "functional images" are formed, one with the gray level or color of each pixel proportional to the maximum amplitude of the first harmonic of the corresponding TAC, and the other with the pixel value proportional to the phase angle. The amplitude image separates the beating atria and ventricles from the adjoining static structures and areas of ventricular hypokinesis. The phase image shows dramatically the progression of the electrical conduction wave through the heart, and serves to highlight areas of chamber dyskinesis.

Applications of digital filters to nuclear medicine images are reviewed by Todd-Pokropek (*14*). Examples of representative FIR filters applied to the gated cardiac study are shown in Fig. 4. The widely used nine-point (3 × 3) FIR filter of Fig. 3 is shown along with 7 × 7 low-pass and Wiener filters similar to those diagrammed in Fig. 2. Note the noise reduction or "smoothing" effect of the low-pass filter and the edge sharpening of the Wiener filter. These and other related FIR filters are discussed in Ref. (*15*).

It is not necessary to compare specific images filtered with the Fourier transform and FIR methods. As discussed above, the two filtering techniques give essentially identical results. The differences between them lie in the realm of computation time, adaptive properties, and details of their implementation.

HARDWARE AND SOFTWARE REQUIREMENTS

Most popular minicomputers and microprocessors used in nuclear medicine can be programmed to do

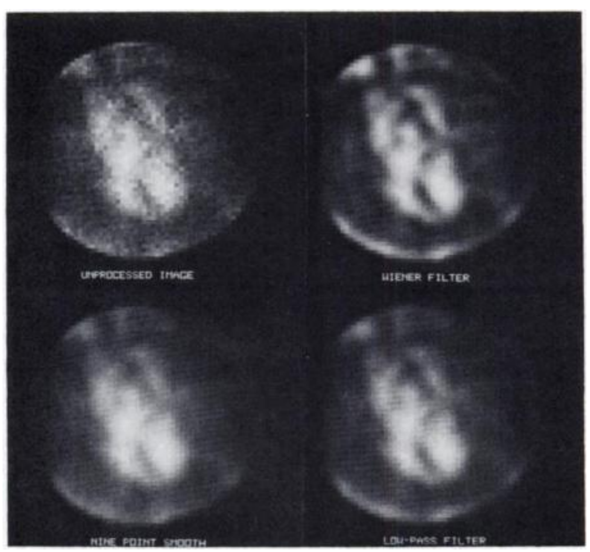

FIG. 4. Single frame from 35° LAO view of gated cardiac blood-pool study. Unprocessed image at upper left. Same image is shown at right, processed with a 7 × 7 FIR Wiener filter similar to that shown in Fig. 3. Bottom images are same view after filtering with the 3 × 3 (nine point) filter of Fig. 4 and a 7 × 7 FIR low-pass filter similar to that shown in Fig. 3. Note edge sharpening evident with Wiener filter and noise suppression obtained with nine-point and low-pass filters.

digital filtering by either the Fourier transform or FIR methods. The required programs are available in the literature for those wishing to develop their own software (*1*,*6*,*8*), and several computer manufacturers are now beginning to supply integrated software packages to do frequency-domain analysis. Indeed, users with minimal training in computer applications should very soon have access to these powerful techniques on a "turn-key" basis, just as they can now perform elaborate cardiac analysis without detailed knowledge of the internal workings of the programs.

A major advance in computer hardware, the low-cost array processor, should have great impact on the feasibility of complex computations in routine data processing in nuclear medicine. These powerful machines perform arithmetic operations on arrays of data at rates 100 to 200 times faster than in conventional minicomputers. These units, now available as optional accessories for nuclear medicine computers, make practical many sophisticated filtering applications that could not have been considered in the past because of the prohibitively long computation time required with conventional minicomputers.

FUTURE OF DIGITAL FILTERING IN NUCLEAR MEDICINE

Digital filtering techniques are ubiquitous in digital signal-processing and image-processing applications outside nuclear medicine. Indeed, the methods described here are routine mathematical tools that are used widely in such diverse contexts as astronomy, oil exploration, telephone communication, and planetary imaging. In recent years, these techniques have been applied successfully to increase the diagnostic power of studies in nuclear medicine. As more advanced equipment, including array processors, and more complex programs become commonplace in nuclear medicine, these digital techniques are sure to assume a still more prominent role both in research and in day-to-day clinical nuclear medicine.

ACKNOWLEDGMENTS

We thank Drs. Barry A. Siegel, Daniel R. Biello, and Stuart A. Jones for their helpful suggestions. We are grateful to Lorraine DiPlacido for her assistance in the preparation of the manuscript.

This study was supported in part by the National Institutes of Health Grant No. HL13851.

APPENDIX

Computational pitfalls. Serious artifacts may arise in frequency-domain analysis if certain computational details are not adhered to. These considerations, except for the aliasing problem referred to below, arise principally when the direct Fourier transform method is used. Indeed, the absence of most pitfalls in the FIR method constitutes an important reason why some users prefer that technique. These problems are related to the subtle but important differences between the continuous Fourier transform—applicable to continuous functions—and the discrete Fourier transform used with digital computers where the function must be sampled at discrete points.

Leakage (*1,16*). When the function to be analyzed by the Fourier transform is not periodic, spurious frequency terms, called "leakage," are introduced. To suppress leakage, the beginning and end of the function should be smoothly tapered to zero with a "window" function to restore periodicity.

If the periodic function is sampled over precisely one period, as in Fig. 1, then leakage will not occur and a window need not be applied unless there is data loss at the end of the cycle leading to violation of the periodicity requirement.

Wraparound error (*1,3,16*). In a convolution operation, the two convolved functions are assumed to be periodic. If the periods are too short, the functions will overlap or "wrap around" at the edges, leading to erroneous results. For convolution of images (Eq. (12)) or one-dimensional data (Eq. (8)), the problem can be avoided by stopping the convolution mask N-1 pixels before each edge of the image or by padding the convolved functions with zeros to lengthen the periods.

Aliasing (*2,5*). According to the sampling theorem, a function must be sampled at least twice in every wavelength of the highest frequency component in the function (Nyquist interval). If the sampling is too coarse, low-frequency artifacts will be introduced through the aliasing phenomenon. To avoid this pitfall, a relatively fine sampling interval should be chosen initially and the Fourier transform computed to determine the highest significant frequency component in the data. Then, if desired, subsequent sampling can be performed at a wider interval up to the limit set by the sampling theorem.

Speed of computation. It is difficult to make dogmatic statements about the time required to run different filters, because of the wide variability in floating-point processor speed and memory among different computers. If speed is a critical issue in a particular setting, both the direct Fourier transform and FIR methods should be tried.

A few generalizations do, however, usually hold:

(1) The FIR method is faster for filters up to about length 11 (11 × 11 for a 2D filter) (*5,6*). This relatively large FIR filter is adequate for many applications. If larger filters are required, the Fourier transform method using the FFT is usually preferred.

(2) Elaborate algorithms are available to increase the speed of large FIR filters (*17*) and to perform FFT calculations on large two-dimensional arrays (*5*). However, the efficiency of these complex methods may be severely limited on computers without very large memories because they require many disc transfers to move segments of the data in and out of memory.

The advent of the array processor may obviate most considerations of speed. Both one- and two-dimensional FFTs and large FIR filters should run so rapidly with this new hardware that the major considerations may become user preference and attention to computational pitfalls rather than speed of computation.

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