Generalized methodology for the comparison of diagnostic imaging instrumentation

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INTRODUCTION.

Technology is providing exciting new ways to diagnose and characterize disease in a non-invasive manner. The decrease in morbidity and mortality that is realized by substituting pneumoencephalography and cerebral angiography by x-ray computed tomography (CT) and brain radionuclide imaging, or coronary angiography by radionuclide ventriculography and perfusion studies, cannot be easily quantitated by cost-effectiveness studies. The dollar value of peace of mind, patient dignity and comfort, avoidance of blindness or loss of limb, stroke, etc., cannot be derived from system analysis.

What some see as an unhealthy proliferation of diagnostic modalities has led to concern about excessive use. It can be argued that the marketplace in the form of medical history outcome, relative costs and patient acceptance, will eventually lead to convergent practice in the choice of diagnostic modalities. If such is the case, quantitative evaluation of instrumentation becomes redundant. In reality it serves many valuable purposes: a) at a minimum it provides a reasonable basis for quality control, b) it points the way toward an understanding of the diagnostic process and consequent possible improvements, c) it delineates the limits of a technique, and d) it provides the rationale for the exploration of improved techniques. This is only true if the instrument evaluation process is carried out in a competent manner. If not, it can have effects totally opposite to those listed above.

It is important to keep in mind that the evaluation of a new imaging technology in terms of the assumptions, parameters and procedures that have been found adequate for existing technology can yield misleading results. A case in point is presented by nuclear imaging, where evaluation has been based on considerations of instrument sensitivity and modulation transfer function (MTF) (mainly for scintillation cameras and scanners). For emission tomographic devices characterization has been in terms of sensitivity and spatial resolution (either point spread function, PSF, or line spread function, LSF). The use of high contrast objects such as bar patterns and point sources to measure contrast and/or resolution as well as the assumptions of uniform scatter contributions to the output image (1), can lead to evaluations of the instrument that are consistent only for the type of object being used for that evaluation: The effects on low contrast lesions due to structured backgrounds introduced by complex sources and scattering material distributions, long tails in the PSF, and texture introduced by the detectors or processing algorithms, are not properly accounted for. Instead, photon detection efficiency becomes an over-weighted parameter. In fact, we have experimentally demonstrated that detector efficiency is not as important a parameter as expected from traditional image evaluation methods (2,3).

The growth in intradisciplinary imaging methods (i.e., planar imaging, single-photon emission tomography and positron tomography in nuclear medicine), as well as interdisciplinary modalities (nuclear, x-ray computed tomography, and nuclear magnetic resonance, NMR (5), imaging) both point toward the need for techniques that allow for a meaningful intradisciplinary comparison, and which can, conceptually, be extended to interdisciplinary comparisons as well.

In a previous communication (6) we have adopted the Rose model (7) to allow us to characterize an imaging instrument by an estimate of the number of elements, T, that can be resolved within an image. Thus, we write

\[ T = \frac{NC^2}{k^2(1+C)} \]  

where N is the number of discrete events forming the image, k is the confidence factor, and C is the contrast, defined by Rose as the signal-to-background ratio, with a value between 0 and 1. The factor (1 + C) was added to take into account the effects of noisy signal as well as noisy background (6). For \( k=2 \) and \( k=3 \) we have a 97.7 and 99.8 percent confidence factor, respectively. Rose states that "the factor \( C^2 \) is a consequence of the contrast C and the random character of photon distributions; the factor \( k^2 \) reflects both the random character of the photon distribution and the need to avoid false alarms" (7).

Contrast is defined in Rose’s formulation as “a measure of the signal as a function of the background brightness, that is, \( C = \Delta B/B \) and \( 0 \leq C \leq 1 \)” (7) where \( \Delta B \) is the difference in intensity between the site of the lesion and background B. In nuclear imaging one must sometimes consider the case \( \Delta B/B > 1 \).

Analytically a false alarm occurs when an element in a uniform background appears somewhat brighter or some-
what dimmer than its surroundings, where this difference is due only to statistical fluctuations. On the other hand, in diagnostic imaging the physician usually searches for patterns that involve more than one resolved element, or for differences in intensity in certain parts of the field. Thus, not every false alarm necessarily generates a false diagnosis. In many other procedures (for instance, cardiac wall motion studies), the delineation of an area is sought, and the exact contrast difference between adjacent elements is less significant. Based on these considerations, it would appear that, depending on the type of study being performed, satisfactory diagnostic images can be obtained with values of \( k \) between 2 and 3. The estimate is in need of corroboration through systematic study, but does not affect the methodology presented here.

Rose’s formulation is particularly attractive in that it separates the statistics of the image (represented by \( N \) and \( k \)) from the physics of the imaging process, which affects the value of \( C \) in the output image. In this manner, the tradeoffs between instrument sensitivity and the parameters that yield contrast can be easily evaluated. Rose’s formulation also makes it explicit that contrast is independent of the number of counts in the image, the latter only affecting the certainty with which the contrast can be determined. Although very basic, and supported experimentally (8), this concept is sometimes overlooked in the evaluation of imaging instrumentation. In nuclear medicine, this misunderstanding has led to the concept that images are “statistics limited.” As a consequence, undue emphasis has been placed on instrument efficiency, to the detriment of consideration of other important instrument characteristics which degrade performance (2). In x-ray computed tomography, this leads to the belief that increased dose by itself can improve image quality, where in fact it may only lead to better definition of artifacts produced by beam hardening, motion, detector instability, misalignments, etc.

The extension of Rose’s model presented here is intended to provide a framework within which these pitfalls are avoided. Within the constraints that: a) it is understood that signal-to-noise (the basis for Rose’s model) is a necessary but not sufficient criterion of visibility, and b) factors other than optimal signal-to-noise can be legitimately used to choose a particular diagnostic imaging modality, we demonstrate that meaningful quantitative comparisons of these modalities can be obtained.

SUMMARY OF PRIOR WORK

Rather than to repeat here the detailed methodology used in expanding Rose’s model (7), we summarize the main results. We considered the following sources of degradation of the resolving power of an imaging system:

**Spatial resolution**

The finite area over which data from a point in the subject is distributed in the output image produces a loss of observed contrast. For a spherical lesion and an approximately Gaussian point spread function (PSF), the output contrast \( C \) can be conveniently approximated (6) by the expression

\[
C = C_0 \exp\left(-\frac{\text{FWHM}^2}{4D^2}\right)
\]

where \( C_0 \) is the object contrast, \( \text{FWHM} \) is the full width at half maximum of the Gaussian PSF and \( D \) is the lesion diameter. Equation 2 is valid only for \( \text{FWHM}/D < 1.5 \) (6).

**Texture**

If a uniform object is imaged, and the variability in resultant intensity with respect to the mean value is measured for regions in the image with area \( a \), one of three types of distributions are generally found:

i) Normal distribution in value and in space, the value being that which is expected on the basis of counting statistics only. This form of noise is the one treated by Rose.

ii) Same distribution as in i above, but with a value that exceeds by a noise magnification \( M \) that which is expected from counting statistics. Noise of this kind is introduced by the reconstruction algorithms used in 3-D reconstruction (9).

iii) Texture, where after correction for counting statistics a remnant \( \beta \) is found that is not normally distributed in value or in space. General consideration of this case is difficult, but it can be approximated as follows: In general the distribution of values for \( \beta \) can be approximated by a normal distribution, as we have demonstrated for the scintillation camera. In addition, even when \( \beta \) has a non-random distribution in space, the location of a lesion is randomly distributed with respect to background structure. Thus, for an ensemble of images, the effects of \( \beta \) can be approximated by those of a random distribution.

The effect of texture can be included in Rose’s formulation in a number of ways (6). We have chosen to include it as an explicit alteration of output contrast of the form

\[
C'^2 = C^2 - k\beta^2
\]

where \( \beta \) is the fractional value of the standard deviation of counts in a region of area \( a \) with respect to the counts in a surrounding (background) region, these corrected for pure counting statistics and \( M \). Thus, in the presence of texture, acquired quanta can be thought of as being partitioned into two groups—one which produces increased detectability of small structures and the other which serves to enhance the visibility of interfering texture in the background. This is an important effect, and in many situations typical of diagnostic nuclear medicine, the images produced by scintillation cameras are as much “texture limited” as they are “statistics limited,” and increases in count density with the accompanying increase in dose-time product will not yield commensurate increases in diagnostic efficacy.

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Other sources of alteration of contrast

Image contrast is altered by effects other than finite spatial resolution and texture. In general, we can write

\[ C = \frac{C_{sFF}}{1 + \Sigma f} \]  

(4)

where \( \Sigma f \) is a sum of factors, examples of which are

i) \( SF \), the scatter fraction as defined in Reference 1, with one important difference: Rather than being constant over the image, it is used only as a local parameter, defined in the immediate vicinity of the lesion. It can be different even over the area of interest and the chosen background region (10).

ii) \( P \), the accidental overlap rate (also locally defined). \( P \) is mostly important in coincidence imaging, but, as demonstrated by Lewellen (11), also affects scintillation camera images obtained at high rates.

iii) \( E \), the electronic noise normalized to real signal, a factor that is not important in photon-counting instruments, but can be significant in devices that obtain data by integration of large numbers of discrete events.

iv) \( CR \), the collimator crosstalk, which can be large in multi-peak and high-energy imaging, but is not trivial even under more favorable conditions (12).

\( FF \) is the filling factor, introduced to take into account the loss of contrast produced by the finite dimensions being sampled in a direction perpendicular to the image plane. In a planar camera \( FF \) is the fraction of the signal that is generated by the target as opposed to that generated by target plus non-target tissues present in the projection (accounting, of course, for attenuation effects). In a tomographic camera \( FF \) is the ratio of lesion size (in the direction mentioned above) to the slice thickness.

Combining Equations 2 and 4, we can write, for a spherical lesion,

\[ C = \frac{C_{sFF} \exp(-FWHM^2/D^2)}{1 + \Sigma f} \]  

(5)

where the \( FWHM \) refers to the sharp part of the PSF, and all parameters are considered in their local context. It is important to note that the parameters \( SF, P, E, CR, \) etc., are not generally independent of each other, as is often assumed.

DERIVED PARAMETERS

Effective spatial resolution

Equation 2 defines output contrast as a function of \( FWHM \) for a well behaved PSF (i.e., Gaussian or nearly Gaussian without appreciable tails).

If the sharp component of the PSF is accompanied by the presence of tails due to, for instance, the acceptance of scatter, or forced sharpening of resolution by image processing or reconstruction algorithms, equivalence between output contrast and PSF \( FWHM \) is lost.

To obtain a realistic measure of spatial resolution we can define as an effective resolution the \( FWHM_{\text{Eff}} \) that yields the measured contrast \( C \) for cylindrical or spherical lesions of known diameter \( D \) assuming that the system is well behaved. If the system is not well behaved \( FWHM_{\text{Eff}} \) will not be identical to the \( FWHM \) obtained from a point source. Thus, from Equation 2, for a sphere,

\[ FWHM_{\text{Eff}} = D[\ln(C_o/C)]^{1/2} \]  

(6a)

It can similarly be shown (6) that for a cylinder

\[ FWHM_{\text{Eff}} = D[\ln(C_o/C)]^{1/2} \]  

(6b)

The attractiveness of this definition of resolution is that it takes into account significant effects that are lost in the measurement of high contrast sources, it unmasks manipulations of the image, and presents results within the context of relevant diagnostic situations. An unattractive feature is that no single number may characterize resolution, which now becomes object-dependent. Unfortunately, reality does not necessarily permit characterization of the instrument in terms of simple parameters.

Needed sensitivity

For an instrument that obtains images by accumulating serially or in parallel a number of discrete events, \( N \) in Equation 1 can be expressed as

\[ N = N_oSt \]  

(7)

where \( N_o \) is the rate with which discrete events are generated for the purpose of forming an image (disintegration rate in nuclear imaging, x-ray tube output in x-ray CT, resonant nuclei in NMR, etc.); \( S \) is the sensitivity of the system, given as the fraction of all events that is incorporated in the output image; and \( t \) is the imaging time. The value of \( S \) can be reduced by dead time effects, which need be taken into account.

For low contrast images, the sensitivity needed to obtain a certain resolving power under a given set of imaging conditions is

\[ S_a = Tk^2M^2(1+C)/N_a(C^2-k^2\beta^2) \]  

(8)

where the number of resolved elements is \( T = A/a \), \( A \) being the area of interest and \( a \) defining the size of lesion being sought. To the extent that the actual sensitivity \( S \) can be less than \( S_a \), the instrument becomes inadequate for the particular imaging problem.

Imaging efficiency

If we define \( S_a \) as the sensitivity that a perfect instrument \( (C = C_o = \text{object contrast}) \) would need under the same imaging conditions, the imaging efficiency (relative to that per-
fect instrument) is

\[ S_p/S = (C^2 - k^2 \beta^2)/(1 + C_s)C_s M^2/(1 + C) \] (9)

This is an important parameter, since it allows us to obtain an understanding of how far an instrument is operating from its statistics-limited point for a particular imaging problem and to accurately appreciate the gains that can accrue from improvements in specific performance parameters.

**Resolving power**

Under conditions of adequate area over which background can be estimated (6), Rose’s formulation of resolving power can be modified to take into account texture as follows

\[ T = N(C^2 - k^2 \beta^2)/k^2/(1 + C) \] (10)

where for the moment we ignore \( M \). Recalling once more that \( T = A/a \) and \( N \) is defined over the area \( a \), Equation 10 can be expressed as

\[ a = Ak^2/(1 + C)/N(C^2 - k^2 \beta^2) \] (11)

The term \( A/N \) is the square of the normally distributed noise in the image except for texture, as defined before, measured for regions of area \( a \). Thus, in a case where \( N \) and \( M \) are not easily obtained (as with CT scanners, ultrasound or NMR), we can write

\[ a = k^2(\text{noise}^2)/(1 + C)/(C^2 - k^2 \beta^2) \] (12)

keeping in mind that both the noise and \( \beta \) vary as a function of \( a \). Note also that the parameter \( C \) takes into account the filling factor as well as any other sources of degradation of contrast.

Equation 12 allows us to estimate the resolving power of an instrument by choosing a test area \( a \), as test point, and observing whether the measured parameters in an image reduce to a result for Equation 12 such that \( a \approx a_r \). In that case, the instrument can resolve lesions of area \( a \) with a confidence \( k \). The resolving limit is, of course, the case where \( a = a_r \). Alternatively, Equation 12 can be expressed in terms of \( k \),

\[ k = C\left[\text{noise}^2/(1 + C) + \beta^2\right]^{1/2} \] (13)

Thus, the output characteristics of the instrument are sufficient to compare its imaging performance to any other modality operating on the same subject. For infinite counts Equation 13 reduces to \( k = C/\beta \).

**EXAMPLES OF COMPARISONS**

*Intradisciplinary comparisons*

**Nuclear imaging, same radiopharmaceutical and same modality (i.e., planar) with different instruments**

As an example of the results of this methodology we will compare a scintillation and high purity germanium camera (13) in two planar imaging conditions.

a. A lesion of 1cm diameter, with a 10:1 lesion to background tissue table, within a 19cm-diameter tissue sphere surrounded by a 0.5cm-wide shell with a 5:1 shell to background tissue label. The lesion is at a 5cm depth, and is imaged from a direction such that the distance between it and the collimator is minimum. We will assume that the background tissue contains 0.14 \( \mu \)Ci/cm\(^3\) of Tc-99m. This example attempts to represent a reasonable benchmark for brain tumor imaging. The product \( C_s FF \) is calculated to be 0.51. For the scintillation camera we will use the following parameters: With a high resolution collimator \( FWHM = 6.7\) mm (6), \( SF = 0.8 \) (14), \( \beta = 0.025 \) (6), \( M = 1 \), \( CR = 0.06 \) (12) and, at low rates both \( P \) and the dead-time will be assumed to be nil. The sensitivity, or product of detector efficiency times the collimator acceptance is 4.8 cts/sec/\( \mu \)Ci (13). The expected output contrast \( C \), calculated from Equation 5, will be 0.175. For \( k = 2 \), the factor \((C^2 - k^2 \beta^2) = 0.028\).

For the HPGe camera with a high resolution collimator \( FWHM = 4mm \), \( SF = 0 \), \( \beta = 0 \), \( M = 1 \), \( CR = 0.02 \), and the sensitivity is 2.5 cts/sec/\( \mu \)Ci (13). The resultant contrast will then be 0.426 and the term \((C^2 - k^2 \beta^2) = 0.182\).

Under identical imaging conditions (\( T, k, N \), and \( t \) equal), the ratio of sensitivities needed by the two devices will be, using Equation 8,

\[ \frac{S_{sc}}{S_{ge}} = \frac{(C^2 - k^2 \beta^2)_{sc}(1 + C)_{sc}}{(C^2 - k^2 \beta^2)_{ge}(1 + C)_{ge}} = 5.4 \]

while the actual ratio is just 1.9. Thus, while the scintillation camera is almost twice as sensitive as the HPGe camera, under the given imaging conditions it needs 5.4 times more counts than the HPGe camera to achieve equivalent signal to noise.

It can also be appreciated from Equation 9 that as a planar imaging device the scintillation camera is operating with an imaging efficiency of 14 percent, while the HPGe camera reaches an imaging efficiency of 74 percent. Neither device extracts all the available information, that is, neither is statistics limited. We also ask whether either instrument can achieve the signal to noise needed to resolve the lesion. For the given example the effective peak activity over the lesion is 1.32 \( \mu \)Ci, while it is 0.88 \( \mu \)Ci/cm\(^2\) over the surrounding area.

If we take an area of interest of 3cm in diameter (7cm\(^2\)), it will represent an effective activity of approximately 6\( \mu \)Ci, thus \( N_a = 2.22 \times 10^5/\text{sec} \). For \( k = 2 \), \( t = 400 \) sec and \( T = 7cm/0.78cm^2 = 9 \), from Equation 8, \( S_a = 1.70 \times 10^{-5} \). Since the actual sensitivity for the scintillation camera is 4.8cts/sec/\( \mu \)Ci or 1.3 \times 10^{-4}, this instrument can achieve the desired signal to noise. For the HPGe camera \( S_a = 3.2 \times 10^{-6} \), which is considerably smaller than the achieved value of 2.5 cts/sec/\( \mu \)Ci or 6.8 \times 10^{-5}, and which makes this instrument also under the given conditions.

b. The second example compares the performance of the scintillation camera and HPGe camera for TI-201. In this case we will simulate a cold lesion of 1cm-diameter and 5cm depth in an immediate 1cm-thick area that is fully labeled with 1.6\( \mu \)Ci/cm\(^2\) of activity. In modeling this perfusion imaging study in the heart we will neglect chest-wall background and activity, we will consider only the myocardial
walls proximal to the camera face (5 cm depth) and distal to the camera (15 cm depth). This far wall produces an effective output equivalent to 0.12 \( \mu \text{Ci/cm}^2 \), while the proximal wall provides the main effective activity contribution of 0.68 \( \mu \text{Ci/cm}^2 \). Thus, the background immediate to the lesion has an output of 0.80 \( \mu \text{Ci/cm}^2 \), while the lowest activity in the lesion is 0.12 \( \mu \text{Ci/cm}^2 \). This results in a peak contrast at the surface of the subject that is given by \( C_{FF} = 0.85 \).

In a 300 sec gated study the accumulation time would be \( t = 15 \) sec each at end systole and end diastole. For the scintillation camera this yields 450 cts in a 7 cm\(^2\)-area over the lesion, using a medium resolution collimator (13) and a 20 percent window (15). A HPGe camera with a medium resolution collimator will accumulate twice as many counts (13), using a narrow window encompassing the \( K_{\alpha 1}\) and \( K_{\alpha 2}\) peaks of Tl-201. While the spatial resolution of the HPGe camera will be of the order of 5 mm \( FWHM \) and \( SF = 0.1 \), the scintillation camera will be operating with a spatial resolution of 9.7 mm \( FWHM \) (15) and \( SF = 1 \). \( CR \) for both is almost zero for the 70 keV photons. The contributions of the 135 keV and 167 keV photons of Tl-201 cause part of the increase in \( SF \) for the scintillation camera, but do not affect the image when using the HPGe detectors. The resulting peak contrasts, as calculated from Equation 5, will be 0.166 and 0.60 for the scintillation and HPGe cameras, respectively. As demonstrated experimentally (10), for Tl-201 scatter introduces a background that is structured, with frequency components similar to those of interest. Consequently, a conservative estimate is \( \beta = 0.05 \) for the scintillation camera, while because of its scatter rejection and digital position readout \( \beta = 0 \) in the HPGe camera. From Equation 11 we can see that for a confidence factor \( k = 2 \) the scintillation camera can resolve a minimum area \( a = 4.1 \text{cm}^2 \) (2.3 cm-diameter) under these conditions, much larger than the 0.8 cm\(^2\) of the lesion. The HPGe camera can, on the other hand, resolve a minimum area \( a = 0.14 \text{cm}^2 \) (0.4 cm-diameter). Thus, while the scintillation camera cannot provide the resolving power necessary for this particular problem, the HPGe camera capabilities exceed those needed to perform the task.

**Nuclear imaging, different modalities (positron and planar) and radiopharmaceutical**

We compare the results of planar imaging for the brain model above with what can be realized with a commercially available positron camera using an optimal positron emitter, the positron camera’s parameters based on data of Reference 16. A comparison of this sort can be based on a number of criteria. For instance, the parameters \( N_a \) and \( t \) need not be the same for both cases, even though it is tempting to perform this comparison for \( t \) and \( N_a \) weighted so that the radiation dose delivered by both radiopharmaceuticals is equivalent. For cameras that image a slice at a time, the time \( t \) should be that used for examination of the full organ of interest, in this case, the brain. Even so, it is also meaningful to perform this comparison under conditions of “standard practice.” In fact, “standard practice” comparisons are valid and valuable. For instance, the dose from the positron emitter may be lower than that from the Tc-99m but larger dosages may not be possible because of instrument saturation or limits on production set by cyclotron and labeling parameters. More important, the dose-time product may have become standardized by empirical observation that image quality is not improved for larger dose-time products (8). This indicates that an instrument is no longer operating in a statistics-limited region. On the other hand, an improved device may be able to take advantage of the quanta provided by larger dosages or longer imaging times. When such is the case, comparisons should be performed for the “optimal” practical values of \( N_a \) and \( t \).

Using the quantities specified above for the brain model, and Equation 13, we find that for the scintillation camera used in a planar imaging mode \( k = 4.5 \). Similarly, for the HPGe camera \( k = 9.3 \). With these values as a benchmark, we estimate \( k \) for a positron camera under conditions of “standard practice” (16). We postulate a typical study with 10\(^5\) counts over a 19 cm-diameter field of view, with an average count density of 2820 cts over a 1 cm-diameter region. For a reconstruction where the pixel size is matched to this diameter (355 pixels) we expect (17) the product Mx-Poisson noise to be approximately 0.1. This agrees with the value measured for the positron camera (16) for objects of 19 cm-diameter and 10\(^5\) counts, except that noise measurements were made for areas of the order of 3 \( \times FWHM \), or 4.5 cm-diameter. This would yield a granularity of the order of 40 percent-cm if the granularity function is well behaved (17). In estimating \( k \) for the brain model under discussion we will use noise figures of 0.1 and 0.4 to provide a range for the result. Using line sources the spatial resolution was measured to be 1.57 cm \( FWHM \) for the sharp part of the LSF, but the shape is not Gaussian and contains an appreciable tail to the edge of the field of view, this tail due to the reconstruction process and random events. Given that a cylindrical cold lesion of 1 cm-diameter appears in the output image as containing approximately 82 percent of the average counts found in the background (16), \( C_{IC} = 0.18 \). The effective spatial resolution can be calculated from Equation 6b, yielding \( FWHM_{eq} = 1.86 \) cm for 1 cm objects. Because Equation 2 is not valid below 20 percent contrast modulation, the value of \( C_{IC} \) for a sphere has to be calculated from the exact expression (6). A useful approximation in this case is to treat the spherical lesion as a cylindrical one of 1 cm diameter and 1 cm height, with the axis orthogonal to the image plane. Thus, the contrast modulation by effective spatial resolution will be 0.18, the factor \( C_{FF} = 3.60 \) and the output contrast \( C = 0.18 C_{FF} = 0.65 \). Finally, while \( \beta \) was not determined explicitly, it is most likely contained in the noise figures that were measured. From Equation 13, \( k = 1.1 \) to 4.5: Although the positron camera eliminates the effects of over- and underlying activity, its large slice thickness and poor spatial resolution degrade contrast to the point that the modeled 1 cm lesion is better detected in a planar imaging mode.

**Interdisciplinary comparisons**

We will apply Equation 13 to the brain model used as a benchmark in the prior analysis. Imaging performance will

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be evaluated for a state-of-the-art x-ray CT scanner (GE 8800), and for two devices for which only data from prototypes exist: A HPGe single-photon emission computed tomography (ECT) imager (18) and a nuclear magnetic resonance (NMR) camera (5). The (unsupported) assumption is made that larger devices would maintain currently achieved specifications. The CT scanner has a spatial resolution of 1.8mm FWHM and a granularity of 0.5 percent-mm for a 1cm slice-width (19). The NMR camera in its present format has a spatial resolution of $2 \times 0.5$mm $FW$ and a slice thickness of 8.4mm, with a granularity of 5 percent-mm at NMR intensity midrange.

The prototype of the HPGe ECT imager shows a spatial resolution at depth of 4mm FWHM in the axial plane and 2mm FWHM in the longitudinal plane (slice thickness). The sensitivity in this mode is 2.5 cts/sec/$\mu$Ci for Tc-99m. We assume that a single camera is rotated about the subject, that imaging is performed in 18 min, and that the mean absorption path is 10cm of tissue. Based on these parameters, and assuming a lesion content of 1$\mu$Ci of Tc-99m, 680 counts will be accumulated in the region of the lesion if 5 slices (each 2mm wide) are added. For a reconstruction performed over a 20cm-diameter cylinder with a $2 \times 2$-mm$^2$ pixel, $M \sim 10$, resulting in a noise $= 0.4$. As previously shown (6), $\beta = 0$. For a 10:1 lesion to background tissue label, 68 cts/cm$^3$ will be found in the area contiguous with the lesion, thus noise $= 1.2$. This is the value that is used in Equation 13.

The final question is that of $C_o$ for each modality. If we assume that the lesion offers contrast of the type found between fat and brain tissue, $C_s = 0.035$ for CT (19), and $C_o = 1$ for NMR. For the nuclear study $C_s = 9$ and for a 4mm FWHM resolution contrast is degraded to $C/C_o = 0.85$ for a 1cm sphere. Questions not addressed here are motion, placement of the slice with respect to the object (we will use $FF = 0.7$, which results from felicitous placing), and dispersion in the parameter $C_s$. While the latter two are amenable to analysis, the effects of motion can only be considered in the context of the imaging problem. CT is seriously affected but is the fastest of the modalities. In NMR as developed at UCSF (5), motion will tend to produce a shift in the image. A blur is expected in the nuclear image. With these considerations in mind, and setting $\beta = 0$, we find that $k(CT) = 37$ for an object of 1 cm-diameter, $k(NMR) = 84$ and $k(ECT) = 1.6$, the low value due mainly to noise.

**DISCUSSION**

Rose's model has been extended to deal with the principal sources of noise found in diagnostic imaging. The model provides an understanding of the effects on the output image of the physical parameters of the object/instrument system. It also permits an analysis of performance that is based on the characteristics of the output image only. Comparisons among different modalities can be made for any desirable source configuration, thus freeing the results from the fallacies that are incurred when unrealistic objects such as bar patterns are used to evaluate a device. An apparent weakness of the model is that it does not yield a single figure of merit or performance index to characterize an instrument. Although pleasant, the belief that such an imaging number or universal curve of performance can be generated is simplistic within the context of the complexity of the diagnostic problem.

The model is limited to consideration of signal-to-noise only. It neglects factors such as the type of information provided, availability, convenience, reliability of operation of the instrument, physician and patient acceptance, cost, etc. Consequently (and fortunately) it does not pretend to have utility in selecting a certain modality for a given diagnostic study. Rather, we believe that this kind of analysis has utility in allowing us to understand the effects of the physical and engineering characteristics of the object/instrument system on the characteristics of the output image. It also has utility in helping to determine what parameters are of importance and need to be improved in future instrumentation. For instance, even the simple examples presented here, using relatively large benchmark lesions, point toward the importance of spatial resolution in diagnostic applications.

Finally, the model allows for quantitation of the potential of any one modality for obtaining information from the subject. Only when an instrument is working at its true "statistics limited" level can we say that no further improvements are possible in a particular imaging situation.

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