A method for modifying the image quality parameters of digital radiographic images

Robert S. Saunders, Jr.a)
Departments of Radiology and Physics, Duke University, Durham, North Carolina 27710

Ehsan Samei
Departments of Radiology and Physics, and Department of Biomedical Engineering, Duke University, Durham, North Carolina 27710

(Received 16 October 2002; accepted for publication 4 September 2003; published 23 October 2003)

A new computer simulation approach is presented that is capable of modeling several varieties of digital radiographic systems by their image quality characteristics. In this approach, the resolution and noise characteristics of ideal supersampled input images are modified according to input modulation transfer functions (MTFs) and noise power spectra (NPS). The modification process is separated into two routines—one for modification of the resolution and another for modification of the noise characteristics of the input image. The resolution modification routine blurs the input image by applying a frequency filter described by the input MTF. The resulting blurred image is then reduced to its final size to account for the sampling process of the digital system. The noise modification routine creates colored noise by filtering the frequency components of a white noise spectrum according to the input noise power. This noise is then applied to the image by a moving region of interest to account for variations in noise due to differences in attenuation. In order to evaluate the efficacy of the modification routines, additional routines were developed to assess the resolution and noise of digital images. The MTFs measured from the output images of the resolution modification routine were within 3% of the input MTF. The NPS measured from the output images of the noise modification routine were within 2% of the input NPS. The findings indicate that the developed modification routines provide a good means of simulating the resolution and noise characteristics of digital radiographic systems for optimization or processing purposes. © 2003 American Association of Physicists in Medicine. [DOI: 10.1118/1.1621870]

Key words: simulation, image quality, digital radiography, resolution, modulation transfer function, MTF, noise, noise power spectrum, NPS

I. INTRODUCTION

Currently, a number of image quality metrics exist which can objectively quantify the intrinsic physical performance of digital radiographic systems. The detective quantum efficiency (DQE), modulation transfer function (MTF), and noise power spectrum (NPS) are now commonly used to characterize the efficiency, resolution, and noise performance of these systems.1–7 These metrics adequately reflect the most important underlying physical processes in the formation of the image.8–12 In addition, these metrics are widely available for the majority of digital systems and, both commercially and in the literature, the performance of a system is reduced to these parameters to describe its general quality for clinical tasks.

One of the current dilemmas in digital radiography, however, is the extent to which these parameters affect clinical image quality.13–15 In comparing two systems, if one system has superior resolution and noise properties than another at all frequencies with all else equal, it is clear which system produces better diagnostic images. However, in many cases, the comparison between two systems is less straightforward. A system may only be superior in one metric while being inferior to another in the other metric. In these situations, it is unclear which characteristics may play a more prominent role for specific clinical tasks, for example the detection of lesions in chest radiographs. Even when one system has better resolution and noise characteristics than another, the quantitative difference in terms of diagnostic quality is unknown. As there are trade-offs associated with the improvement of each metric, it is necessary to understand how these parameters, collectively, impact the diagnostic quality of radiographic images.

As a first step to address these questions, the impact of image quality metrics on the appearance of radiographic images can be investigated by simulation studies. There have been limited prior studies on the simulation of radiographic image quality. In these studies, the more common approach has focused on modeling the effects of each stage of the detection process on image quality.16,17 While this approach sheds valuable insight into the physical processes underlying the detection process, it requires detailed knowledge of the system components and independent validation of the applied models with experimental measurements of the detector’s resolution and noise characteristics. Such characteristics are now easily measured and available for most imaging systems. Therefore, it is possible to model a system’s performance based on those characteristics alone, as suggested by Tinberg et al.18 An advantage of the latter approach to simu-
lation is that it isolates the resolution and noise characteristics; one is able to adequately model a system while ignoring other minor factors affecting image quality.

The present study takes a similar approach to emulate the influence of the resolution and noise characteristics of a digital detector on the appearance of a radiographic image. This approach allows modification of the noise and resolution characteristics for a given image in terms of the NPS and MTF independently, thus allowing one to quickly model various configurations of these characteristics.

II. IMAGE MODIFICATION ROUTINES

Two modification routines were developed to alter the resolution and noise attributes of digital images. Figure 1 includes schematics that outline the major steps of the routines. The original routines were written in MATLAB® Version 6.5, R13 (Mathworks, Natick, MA) and executed on UNIX workstations. Using a Sun Sparc Ultra-80 with 4 450-MHz Sparc processors, the modification routines could process a 2048×2048 pixel input image in approximately 2 h at 25% average processor usage. This level of processor usage was expected as the routines were implemented for single processor use. The routines have now been implemented in C, which has reduced processing time to several minutes.

A. Resolution modification routine

The resolution modification routine applies the resolution characteristics described by a presampled MTF to an input super-sampled digital image, and creates a more coarsely sampled digital image with resolution characteristics similar to those described by the input MTF. This routine includes the impact of both the MTF and digitization on the image resolution, and thus simulates the possible signal aliasing of the modeled system.

There are several requirements for the input variables to the resolution routine. The input image should be in a linear space or otherwise linearized to meet the requirements of linear systems theory. The input image should be representative of imaging with an ideal detector system, with very high resolution, low quantum noise, no electronic noise, and fine sampling. The input presampled MTF must be rotationally symmetric. In that way, the MTF is representative of an isotropic imaging system. This requirement is largely met by most current digital imaging systems.19,20 The resolution of the input image should be limited solely by its sampling such that the only source of blur for the modified image is from the resolution modification routine. As the presampled MTF describes the resolution independent of sampling, the modification should ideally be applied to an analog image. This requirement can be approximated if the input image is suffi-

![Figure 1. Schematic of the (a) resolution modification routine and (b) noise modification routine.](image-url)
ciently super-sampled, as described in Sec. III C. Previous studies describe how such high quality input images can be acquired for research purposes.\textsuperscript{21,22}

The resolution modification routine proceeds as follows. First, the input MTF is divided by the sinc function associated with the final sampling aperture, as the final sampling step causes the MTF to be multiplied by the corresponding sinc function. A cubic spline interpolation is also applied to the input MTF so the function may be evaluated at any arbitrary point. The input image is then transformed to Fourier space by a two-dimensional fast Fourier transformation (FFT) and multiplied by the MTF. An inverse two-dimensional FFT is taken of the output from the above-mentioned process. Finally, the modified image is reduced to the desired sampling size by a moving region of interest (ROI) method that averages the local pixel area of each ROI to form the pixels of the final image. This step, simulating the final sampling stage in the formation of a digital image, accommodates the possible signal aliasing inherent in digital imaging.

A requirement of Fourier analysis of the kind described above is that the image has wrap-around symmetry.\textsuperscript{23} This assumption may be fulfilled by forcing the edges of the image $I(x,y)$ to its mean pixel value with a generalization of the Hann window.\textsuperscript{24} The one-dimensional form of this window is

\[
I'(x,y) = \begin{cases} 
I(x,y) & d_0 < x < a - d_0 \\
I_0 + \frac{1}{2} \left[ 1 + \cos \left( \frac{d_0 - x}{d_0} \right) \right] (I(x,y) - I_0) & 0 \leq x \leq d_0 \\
I_0 + \frac{1}{2} \left[ 1 + \cos \left( \frac{a - x}{d_0} \right) \right] (I(x,y) - I_0) & a \geq x \geq a - d_0.
\end{cases}
\]

The window parameter $d_0$ is a user-defined variable that specifies the distance range over which the image will approach the mean of the image $I_0$, and $a$ specifies the length of a side of the square image. A similar filter was implemented along the $y$ direction. In this study, $d_0$ was chosen to ensure a large nonzero area as $d_0 = 0.95a$. Smaller values of $d_0$ do not affect the measured MTF of edge images (described in the following) while larger values introduce artifactual effects in the modified image.

**B. Noise modification routine**

Whereas the resolution modification routine changes the resolution characteristics of an input image, the noise modification routine changes its noise attributes. This routine adds noise described by an input NPS and a variance-mean functional relationship to an input image creating a digital image with noise characteristics corresponding to the noise inputs. Both quantum and electronic noise are simulated by the routine as they are both included in the NPS. As a NPS inherently includes sampling effects,\textsuperscript{25} the input image does not need to be supersampled, as in case with the resolution modification routine. Thus, the output of the resolution modification routine can conveniently serve as an input to the noise modification routine.

This routine makes several assumptions of the input variables. First, the input image should be in a linear space or otherwise linearized to meet the requirements of linear systems theory. Similar to the MTF, the input NPS must also be radially symmetric representing an imaging system with isotropic noise characteristics. Most current digital radiographic systems meet these requirements.\textsuperscript{26-28} Finally, the input image must have no or little quantum mottle compared to the noise level that will be added.

The noise modification routine uses a method similar to one suggested previously\textsuperscript{29} to create colored noise by filtering a white noise spectrum. The first step is to create an uncorrelated Gaussian noise array with mean of zero and unit variance. In Fourier space, this array will have an approximately constant magnitude and a random phase, which randomizes the appearance of the noise. As the initial noise array is uncorrelated, all later noise correlations will be described by the input NPS. In addition, this array has wrap-around symmetry as each pixel is an independent random variable with the same probability distribution. The initial noise array is then converted to Fourier space through a two-dimensional FFT. A noise frequency filter is then created by taking the square root of the input NPS, normalized to its value at zero frequency. A cubic spline interpolation is also applied to this filter function so it may be evaluated at any arbitrary point. The Fourier representation of the Gaussian noise array is then multiplied by the noise filter, and an inverse FFT is used to transform the results into the spatial domain. In this method, one is able to take only the real part of the image obtained from the inverse FFT because the Fourier spectrum is Hermitian and therefore its conjugate image is real.\textsuperscript{30} Finally, the resulting noise is added to the input image following a particular mean–variance relationship.

For a quantum limited imaging system, the noise will follow a Poisson process in which the variance is linearly related to the image mean. However, for systems with instrumentation noise, the noise variance and image mean may have a nonlinear relationship. Assuming no a priori relationship between the variance and mean, the actual relationship for an imaging system being simulated is used as an input to the routine. This method of noise application allows the routine to simulate various dose levels. Modified images with similar noise correlations indicated by the NPS but different noise magnitudes can be created by linearly scaling the pixel values of the linear input image and applying the variance–mean relationship.

The above-described method applies the noise pattern uniformly across the image. However, a realistic radiographic image is composed of structures from the varying attenuation of the image object. The noise will therefore have correspondingly different variances throughout the image, which must be accounted for in the noise application process. The noise modification routine assumed that the shape of the NPS is invariant with respect to exposure and there-

Medical Physics, Vol. 30, No. 11, November 2003
A. Resolution assessment methodology

A resolution assessment routine was developed based on an established edge technique. This technique uses an image of a perfectly sharp edge to determine the system or image MTF. In the new implementation of this technique, first the edge within the image is detected by a Sobel edge detection method. The angle of the edge line is determined by a double radon transform with 0.01° accuracy. The intercept of the edge line is determined from three samples of the line and averaging their intercepts. As the location of the intercept will only shift the location and not the spread of the edge spread function, this will provide sufficient accuracy. The image data are reprojected along the edge into bins of 0.1 pixels to compute the edge spread function (ESF). A fourth-order moving polynomial fit is applied to the ESF in order to reduce noise. This smoothing is more modest than the previous method to allow for more accurate measurement of the higher frequency response at the expense of a higher sensitivity to noise. No baseline correction is performed on the line spread function (LSF), as the systems investigated in this study did not show significant trending. As opposed to a Hann window, a Hamming window is used to window the LSF as it suppresses the highest sidelobe of the sinc more effectively than a Hann window. The MTF is finally computed as the normalized FFT of the LSF.

In order to verify the accuracy of the resolution assessment routine, two edge images were created with MATLAB software. Using a 0.2 mm pixel size and 256×256 matrix size, an edge line of 3° separated two distinct regions with pixel values of 10 000 and 4000 corresponding to a 40% edge transmission. The first image had no noise and therefore the first verification test did not utilize the smoothing portions of the assessment routine. As illustrated in Fig. 3, the MTF measured from this image corresponded to a sinc function, going smoothly to zero at the expected Nyquist frequency associated with the size of the subpixel bins (i.e., 0.1 pixels). However, as realistic images will have quantum noise, the smoothing step is necessary to reduce the fluctuations of the MTF associated with the measurement with a consequential dampening effect on the MTF at higher frequencies. To determine the extent of this effect, the second edge image, with identical edge angle and means, had quantum noise in the form of uncorrelated Poisson noise with a noise equivalent quanta (NEQ) of 250 000 mm⁻². This NEQ is consistent with the edge images acquired for MTF measurements. As shown in Fig. 3, the applied smoothing method caused a slight reduction of the measured MTF for the noisy edge calculated using smoothing compared to that measured from the noiseless image where no smoothing is utilized. However, compared to the ideal response, this reduction was limited to 0.01 at the image Nyquist frequency of 2.5 mm⁻¹.

The accuracy of the resolution assessment routine was also verified experimentally using an edge image obtained from a commercial digital radiographic system (Revolution RX/i, GE, Milwaukee, WI). An image of a 250 μm lead polished edge device was acquired at 120 kVp and 5.4 mR

III. EVALUATION OF MODIFICATION ROUTINES

In order to be able to evaluate the accuracy and precision of the modification routines by independent means, resolution and noise assessment routines were developed using established methods. In this section, first the methods and performance of these assessment routines are described. Using these verified assessment methods, the evaluation of the modification routines is then described.
exposure using RQA9 beam quality. The MTF computed from this image, illustrated in Fig. 4, showed excellent agreement with a previous measurement. The two curves were identical at lower frequencies. For the frequency range 0–5 mm$^{-1}$, the two curves differed by 2.03% calculated by the discrete form of an integral difference equation:

$$\frac{\Sigma_j \Delta_j |\text{Curve}_1 - \text{Curve}_2|}{\Sigma_j \Delta_j \text{Curve}_1} \times 100\%,$$

where $\Delta$ represents the interval width, Curve$_1$ the standard of comparison, and Curve$_2$ the curve to evaluate. The absolute differences at 0.25, 0.5, 0.75, and 1 mm$^{-1}$ were 0.0093, 0.0042, 0.0013, and 0.0097, respectively.

B. Noise assessment methodology

An independent means was also necessary to evaluate the performance of the noise modification routine. A noise assessment routine was thus developed for determining the NPS of an imaging system from a flat field image using an established method. In this method, first the flat field image is segmented into sequential ROIs of 128×128 pixels; the edges of the image are excluded. A second-order polynomial surface is then fit to each ROI and subsequently subtracted from the ROI to correct for any image nonuniformities. The ROI data are divided by the mean of the area and the pixel size in order to obtain the noise equivalent flux. A Hamming window is applied to each ROI to avoid noise aliasing; the rms value of this window is set to unity to preserve image scaling. To account for gross intensity variations in the image, each ROI is scaled by the ratio of the ROI mean to the mean of the ROI at the top-left-hand corner of the image. The two-dimensional fast Fourier transform of each ROI is then taken; the NPS is computed by averaging the magnitude squared of these FFTs. One-dimensional traces through the two-dimensional NPS are then extracted by vertical, horizontal, diagonal, or radial band averaging.

To evaluate the noise assessment routine, a synthetic 2048×2048 pixel flat field image was created with 0.2 mm pixel size, a mean pixel value of 10 000, and added uncorrelated Poisson noise. As illustrated in Fig. 5, the radial trace of the measured NPS from this image was flat, as expected for white noise. It varied from its theoretical value, determined by Parseval’s Theorem, by an absolute difference of 1.22%. The noise assessment routine was also benchmarked experimentally with a flat field image acquired using the digital imaging system specified earlier at 74 kVp and 0.274 mR exposure using RQA5 beam quality. This system had approximately isotropic behavior in its noise characteristics; therefore the radial trace of the NPS was utilized for comparison. The calculated NPS, also illustrated in Fig. 5, showed excellent agreement with previous measurements. The absolute difference between the two radial traces was 2.14%.

C. Evaluation of the resolution modification routine

1. Evaluation method

Once the accuracy of the resolution assessment routine was established, it was used to evaluate the performance of the resolution modification routine. As input images, four different sharp edge images were created, 51.2×51.2 mm in size, with array sizes of 2048×2048, 1024×1024, 512×512, and 256×256 pixels corresponding to pixel sizes of 0.025, 0.05, 0.1, and 0.2 mm, respectively. All four images were modified by the resolution modification routine to output images with 0.2 mm pixel size. Following Sec. III A, the images had two distinct regions with constant pixel values of 10 000 and 4000.
Three presampled MTF curves, two based on a theoretical model and one derived from an experimental measurement, were used in the evaluation. The experimentally obtained MTF curve was that from a commercial digital radiographic system (Revolution XQ/i, General Electric) used in Sec. III A, and previously reported in the literature.27 The theoretical MTF curves were formed from the Burgess model,

\[ \text{MTF}(u) = \left( \frac{1}{2} \right) \text{erfc} \left( \alpha \ln \left( \frac{u}{u_0} \right) \right), \]

which is shown to have good empirical correspondence with the MTF of most screen–film and computed radiography systems.36,28 In this relationship, \( \alpha \) is the slope, \( u \) is the spatial frequency, and \( u_0 \) is the frequency at a MTF of 0.5. Using \( \{\alpha = 0.8, u_0 = 0.5\} \) and \( \{\alpha = 0.8, u_0 = 1.25\} \) as the parameters, two MTF curves were created. The first curve had no power beyond 2.5 mm\(^{-1}\), the Nyquist frequency of the final modified image, while the second curve had notable power beyond \( f_N \). The MTF curves formed from this model were multiplied by Hamming windows to ensure a smooth approach to zero at specified frequency, 2.5 and 7.5 mm\(^{-1}\), respectively.

As the input image is to approximate an analog image, it was initially necessary to determine what amount of super-sampling is necessary for this approximation to be valid. Each of the four edge images was modified by the resolution modification routine using the second theoretical MTF described above and then reduced to a final pixel size of 0.2 mm. The presampled MTFs of each modified image were then measured by the resolution assessment routine to determine what minimum level of reduction is necessary to produce the desired presampled MTF. One consideration in this evaluation method is that some interplay exists between the bin sizes used for the measurement of the MTF and the reduction ratio used in the modification routine. However, these two refer to distinct physical processes and therefore should be considered independently.

Based on the preceding experiment (see Sec. III C 2), eight times reduction was found to provide sufficient super-sampling for the input image. Therefore, the input edge image of 2048×2048 pixels with a 0.025 mm pixel size was chosen for a subsequent experiment in which this input image was modified by all three previously described input MTFs and then reduced by a factor of 8 to an output pixel size of 0.2 mm. The MTFs of the modified images were then measured using the resolution assessment routine.

2. Evaluation results

Figure 6 shows the effect of the supersampling of the input image on the measured MTF. With no supersampling, the measured MTF differed from the input curve by 215.33% over the range of 0–10 mm\(^{-1}\). For supersampling ratios of 2:1, 4:1, and 8:1, those differences for the same frequency range were 66.90%, 1.98%, and 1.54%, respectively. The absolute modulation differences for the 8:1 supersampling ratio at 0.25, 0.5, 0.75, and \( 1f_N \) were 0.0008, 0.0016, 0.0019, and 0.0021, respectively. The peaks in the measured MTF for the smaller supersampling ratios appear to relate to the discrete nature of the input edge. The results demonstrate that at least a 4:1 reduction (optimally 8:1) is necessary to adequately model the presampled MTF of a digital image.

Figure 7(a) illustrates the results of the first evaluation test with a model MTF that goes to zero at the Nyquist frequency of the modified image. The absolute difference between the input MTF and the MTF measured from the modified image was 1.53% for the frequency range 0–2.5 mm\(^{-1}\). The absolute modulation differences at 0.25, 0.5, 0.75, and \( 1f_N \) were 0.0089, 0.0018, 0.0001, and 0.0002, respectively.

Figure 7(b) illustrates the results for a model MTF with significant power beyond Nyquist frequency, where there is the smaller supersampling ratios appear to relate to the discrete nature of the input edge. The results demonstrate that at least a 4:1 reduction (optimally 8:1) is necessary to adequately model the presampled MTF of a digital image.
significant potential for signal aliasing. For this case, the absolute difference between the two curves for the practical range 0–7.5 mm$^{-1}$ was 0.96%. The absolute modulation differences at 0.25, 0.5, 0.75, and 1 f$_N$ were 0.0002, 0.0006, 0.0021, and 0.0028, respectively.

Figure 7(c) illustrates the ability of the resolution modification routine to emulate the resolution characteristics of an actual digital radiographic system. The difference between the desired input MTF and the resultant output MTF of the routine was 3.39% for the frequency range 0–10 mm$^{-1}$, and 1.97% for the 0–5 mm$^{-1}$ range. The absolute modulation differences at 0.25, 0.5, 0.75, and 1 f$_N$ were 0.0139, 0.0085, 0.0031, and 0.0008, respectively.

The differences between the MTF measured from the output images and the input MTF are due to rounding errors in the resolution modification routine. Three prominent areas are bit-depth, thresholding to prevent dividing by zero, and aliasing. In spite of these rounding errors, the MTF measured from the output images are well within 4% deviation from the input MTFs.

D. Evaluation of the noise modification routine

1. Evaluation method

The noise modification routine assumes that the shape of the frequency spectrum of radiographic noise in an image is invariant of attenuation level from the imaged structure. To experimentally verify this assumption, 40 images were acquired on the General Electric XQ/i system of a Lucite™ low-angle ramp with an average thickness of 12.7 cm using 74 kVP and 10 mA $s$ with 19 mm aluminium filtration. The center of the Lucite ramp was placed 142 cm from the detector face in order to minimize scatter.

Two ROIs were extracted for analysis. One ROI was extracted from the section of the image containing the Lucite ramp (12.7 cm average Lucite thickness, 72% average attenuation level) while a second ROI contained only quantum noise. The following procedure was used to analyze the noise properties across the ensemble across the ROIs. First, the ensemble mean, $\overline{\tilde{X}}_{ij} = \frac{1}{n(n-1)} \sum_{k=1}^{n} X_{ijk}$, and the ensemble variance, $S^2_{ij} = \frac{1}{n(n-1)} \sum_{k=1}^{n} (X_{ijk} - \overline{\tilde{X}}_{ij})^2$, were computed, where $X_{ijk}$ represents the pixel in row $i$, column $j$, and in image $k$ of the ensemble. Relative noise was then computed as $X_{ijk}^* = (X_{ijk} - \overline{\tilde{X}}_{ij})/S_{ij}$, converting each pixel into a random variable with mean zero and unit variance. The noise frequency spectrum was subsequently computed from the relative noise for the three ROIs as NPS = $(1/n) \sum_{n=1}^{n} [\text{FFT}[X^*]]^2$. The radial trace of the NPS was examined in order to compare the two frequency spectra in terms of any change in the shape of the spectrum as a function of signal.

The noise modification routine was also evaluated using the verified noise assessment routine described previously. A synthetic 2048×2048 pixel flat field image with 0.2 mm pixels was created with a constant pixel value of 10,000. This image was used as the input into the noise modification routine.

Two NPS curves, one based on a theoretical model and one based on an experimental measurement, were used as inputs. The theoretical input NPS was generated using a noise model suggested by Siewerdsen et al. Based on the previous study, the parameters used to create the theoretical NPS curve for a typical radiographic system were a quantum efficiency of 0.28, a quantum gain of 600, a Poisson excess of 410, a sharpness factor of 0.20, a fill factor of 0.35, a coupling efficiency of 0.8, and a fitting parameter describing relative blur of 0.1. The experimentally acquired NPS was from a digital radiographic system (General Electric, Revolution RX/i), previously measured at 0.274 mR exposure using RQA5 with one image acquired at each of the following exposure levels: 0.12, 0.24, 0.50, 1.05, 2.12, and 4.31 mR. After converting the image values to exposure levels, the spatial variance, $S^2$, and the spatial mean, $\overline{\tilde{x}}$, were computed from the central 80% of the image area as

$$\overline{\tilde{x}} = \frac{1}{n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} I_{ij}, \quad S^2 = \frac{1}{n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} I_{ij}^2 - (\overline{\tilde{x}})^2. \quad (4)$$

where $I_{ij}$ represents the image at pixel location $i$, $j$. The relationship between the spatial variance and the image exposure, or spatial mean, was found using a least-squares fit,

$$S^2 = (7.939 \times 10^{-5})\overline{\tilde{x}}^2 + (9.433 \times 10^{-5})\overline{\tilde{x}} - 3.879 \times 10^{-6}. \quad (5)$$

where both the variance and mean have exposure units. This equation was an excellent fit to the data with the goodness-of-fit parameter $R^2 > 0.99997$.

The NPS of the output images from the noise modification routine were then measured by our independently verified noise assessment routine (Sec. III B). The radial trace of the output NPS of the assessment routine was compared with that of the input NPS to the modification routine to assess the accuracy of the noise modification routine.

2. Evaluation results

Figure 8 verifies the independence of the shape of the NPS from the exposure level, an underlying assumption behind the noise modification routine. The radial trace of the ensemble NPS for the flat, unattenuated portion of the image has been shifted to the same magnitude as the radial trace for the portion of the image with a Lucite ramp. This was done by scaling the flat trace by the ratio of the mean value of the ramp trace to the flat trace. The relative difference between the scaled flat trace and ramp trace, and therefore the difference between their two shapes, is 4.8%. The ramp trace has some low frequency artifacts below 0.25 mm$^{-1}$, which are
likely due to the movement of the detector\textsuperscript{39} (Warp, 2003 #2323) and the shape of the Lucite ramp. Even with these artifacts, however, the shape of the two curves is remarkably similar indicating that the shape of the NPS remains constant over an almost order of magnitude change in exposure.

Figure 9\textsuperscript{~a} illustrates the outcome of the first evaluation test for the noise modification routine using the theoretical input NPS. For the frequency range 0–2.5 mm\textsuperscript{-1}, the difference between the input NPS and the radial trace of the NPS measured from the modified image was 1.40%. The measured NPS exhibited some fluctuations centered on the input curve due to the limited number of ROIs used to determine the NPS.

Figure 9\textsuperscript{~b} shows the ability of the noise modification routine to model actual imaging systems. The difference between the input NPS and the radial trace of the NPS calculated from the modified image was 1.42%. The measured output curve showed similar fluctuations around the input curve at lower frequencies but closely matched the shape of the curve.

E. Evaluation of the combined modification routine

1. Evaluation method

To model the image quality characteristics of a radiographic system, the resolution and noise modification routines should be applied in combination. The order of application is important. As the resolution modification can significantly alter the noise characteristics of the image, it is best to apply the noise modification after the resolution modification. However, in this envisioned order of application, one must still ensure that the noise modification does not affect the resolution properties of the image. An experiment was conducted to investigate the potential for this interdependence.
An edge image with 102.4×102.4 mm area and pixel size of 0.025 mm was created. This larger field of view was used in order to have a greater area to use for qualitative evaluation. The resolution of this input image was modified by the previously used theoretical MTF with power beyond Nyquist frequency. An 8:1 reduction was used to generate a 512×512 pixel output image with 0.2 mm pixels. The output image of the resolution modification routine was then used as an input to the noise modification routine in conjunction with the input theoretical NPS calculated from the Siewerdsen model.

The MTF of the final resolution/noise-modified output image was measured using the resolution assessment routine. A similar experiment was also conducted using the experimentally measured MTF and NPS and noise variance properties of the XQ/i radiographic system. The resultant MTFs were compared with the original input MTFs to the resolution modification routine to assess any additional modification of the resolution by the noise modification routine.

2. Evaluation results

Figure 10 illustrates the resolution of the images after the combined resolution and noise modification routines. For the image modified by the theoretical MTF and NPS [Fig. 10(a)], the absolute difference between the MTF of the modified image and the original input MTF was 5.38% within the 0–7.5 mm⁻¹ frequency range. The MTF had some fluctuations at higher frequencies caused by the excessively high level of noise in the edge image. Note that usually higher exposure edge images are used for MTF measurements. Nevertheless, the two curves were very similar. The absolute modulation differences at 0.25, 0.5, 0.75, and 1fN were 0.0015, 0.0007, 0.0019, 0.0069, respectively. For the image
modified by the experimentally obtained MTF and NPS, [Fig. 10(b)] the absolute difference between the MTF curves was 2.52% within the 0–5 mm⁻¹ frequency range. The absolute modulation differences at 0.25, 0.5, 0.75, and 1f_N were 0.0147, 0.0113, 0.0043, 0.0027, respectively.

Figure 11 compares the modified edge image of the modification routines with experimentally obtained input MTF and NPS (Revolution XQ/i, GE) versus an edge image captured experimentally on this digital radiographic system at the exposure condition corresponding to the employed MTF and NPS. A qualitative comparison indicates that the two images are very similar in appearance with respect to blur and mottle characteristics.

To test the performance of the modification routines on anatomical images, a high-quality image of the human lung, acquired at high exposure with an industrial film detector and digitized with 0.01 mm pixel size, was modified according to the resolution and noise characteristics of a
clinical radiographic system (Revolution XQ/i, GE). The image size was reduced such that the output pixel size equaled that of the modeled digital radiographic system (i.e., 0.2 mm). A qualitative comparison of the input and modified images in Fig. 12 shows the change in appearance due to the change in blur and mottle as well as pixelation effects.

IV. DISCUSSION

In radiographic imaging, two primary image quality metrics have commonly been used to describe the performance of an imaging system: the noise power spectrum and the modulation transfer function. These metrics have been utilized extensively to evaluate various imaging systems. However, a difficulty has existed in knowing how these metrics affect image quality in digital radiographic systems, where there are potentials for signal and noise aliasing.

Simulation studies of image quality attributes for x-ray systems using computer methods have been undertaken by few investigators, and shown to be an effective means of evaluating various elements of the image formation process. Some previous studies have simulated each stage in the imaging process, which requires detailed knowledge of the imaging system and often limits the utility of the simulation routines to a specific type of imaging system. Assuming a background knowledge about the imaging detector and relying only on the experimentally measured MTF, NPS, and noise variance properties, in this study, we developed a method to model the resolution and noise characteristics of digital radiographic systems (Fig. 12). A thorough evaluation of the method with modeled and measured resolution and noise characteristics indicated that the developed approach is capable of emulating those characteristics in ideal input images with high accuracy.

The image modification routines developed in this study have certain potential limitations in terms of their underlying assumptions. First, the routines assume isotropic behavior of the simulated image system; it is inferred that the NPS and MTF curves are to be radially symmetric. Some systems differ slightly from this behavior. For example in computer radiography (CR), the MTF varies by several percent in the scan and subscan directions. However, for most current digital radiographic systems, including CR, the response in orthogonal directions does not differ dramatically. Second, using Fourier analysis to define digital radiographic systems does not have universal support within the medical physics community. Some have raised concerns that the reduction of the system performance to global metrics in the spatial frequency space does not fully describe the system performance for specific clinical tasks. However, the image quality metrics utilized by this analysis (i.e., the MTF and NPS) are measured for most radiographic systems. Although the general debate continues, these metrics do contain some representation of clinical image quality and can serve as good approximations of the actual system performance. Research is clearly needed to determine the level and sufficiency of these approximations.

Our method for modifying the image quality characteristics of an image shows promise as a process for modeling various digital radiographic systems. The image quality metrics of the modified images show close agreement with the desired input characteristics. Thus, this type of simulation can be accurately utilized to model various types of detector systems quickly. With this ability, one can begin to quantitatively determine how various performance metrics impact specific clinical tasks.

ACKNOWLEDGMENTS

This work was supported in part by a grant from the National Institutes of Health (R21CA91806). The authors thank James T. Dobbins, III and James Bowsher for helpful conversations and G. Allen Johnson for use of his computer facilities. The authors also thank Christoph Hoeschen for the use of the high-quality lung images used in this study.


