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An experimental method to correct drift-induced error in zero-frequency DQE measurement

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Abstract

In 1963, Shaw applied Fourier analysis to the zero-frequency DQE and developed the frequency-dependent DQE or DQE(k) and made it clear that DQE(k) is applicable to every frequency level within the system bandwidth, including the zero frequency. Over time, especially after entering the modern era of digital x-ray imaging, the experimental measurement methods of DQE(k) (particularly the measurements of the NPS which is an important element in DQE(k)) have evolved, and some measurement methods may generate nonphysical NPS and DQE results at k=0. As a result, an experimental DQE(k) curve is often cut off at certain low frequency above zero. This work presents a new experimental method to deal with two challenges: severe NPS(k=0) underestimation due to polynomial-based background detrending; severe NPS(k=0) overestimation due to the presence of faint but non-negligible system drift. Based on a theoretical analysis of the impact of drift to the measured autocovariance function, the error introduced by drift can be isolated, and corresponding correction can be applied to NPS(k=0). Both numerical simulation with known ground truth and experimental studies demonstrated that the proposed method enables accurate DQE(k=0) measurement.

1. INTRODUCTION

The zero-frequency DQE is an important objective performance metric of x-ray imaging systems. Fellgett and Shaw pioneered the concept of the zero-frequency DQE and provided the following famous formula:^{1,2}

$$DQE_0 = \frac{SNR_{out}^2}{SNR_{in}^2}. \quad (1)$$

Note that measurements of system input SNR (SNR_{in}^2) and output SNR (SNR_{out}^2) should be performed over a large area so that each SNR measurement can be considered statistically uncorrelated to similar measurements performed at other nonoverlapping areas.²

In 1963, Shaw applied the Fourier analysis to the signal and noise of the detector output separately, and then he combined the signal and noise power spectrum together using the

DQE framework in Eq. (1) to derive the frequency-dependent DQE for film-based imaging systems:²

$$\text{DQE}(k) = \frac{(\gamma \log_{10} e)^2 \text{MTF}^2(k)}{q_0 \text{NPS}(k)}, \quad (2)$$

where k denotes the spatial frequency vector, and NPS and MTF denote the noise power spectrum and modulation transfer function, respectively, of the imaging system. The quantity q_0 denotes the expected number of input photons per unit area, γ denotes the slope of the characteristic optical density vs. log-exposure curve of the film system.

Later, ICRU generalized the concept of the frequency-dependent DQE to both analog and digital imaging systems.³ The generalized DQE(k) formula is

$$\text{DQE}(k) = \frac{(\bar{d})^2 \text{MTF}^2(k)}{q_0 \text{NPS}(k)}, \quad (3)$$

where $(\bar{d})^2$ denotes the square of the mean signal of the detector output measured over a large area, and q_0 denotes the expected number of input photons per unit area.

In Shaw's original work that proposed the concept of DQE(k), the author made it very clear that DQE(k) is applicable to every frequency level within the bandwidth of the imaging system, including the zero frequency.² Overtime, however, the measurement methods of SNR and NPS have evolved, and some measurement methods may lead to quite unphysical DQE(k) results at $k = 0$ due to various reasons such as the Type I and Type II errors described in the next section. As a consequence, the DQE(k) curve is often cut off at certain low frequency level above zero; if the value of DQE($k = 0$) is needed, extrapolation or other estimation methods were often applied. The purpose of this work was to develop an experimental method to directly measure DQE(k) at $k = 0$ by addressing some inherent technical challenges encountered in the attempt for such direct measurement. The proposed experimental measurement method enables us to achieve consistent results with that measured by following the classical definition of the zero-frequency DQE in Eq. (1), i.e., $\text{DQE}(k)_{k=0} = \text{DQE}_0$.

2. METHODS

2.1. Challenges in experimental measurement of DQE(k) at k = 0

Strictly speaking, the term “SNR_{out}” used in the original definition of DQE₀ needs to be defined over a large area A in the output image.² As shown in Fig. 1(a), “S” (signal) refers to the expected value of the total quanta within area A , namely

$$\langle a_{\text{sum}} \rangle = \left\langle \sum_{m=1}^M \sum_{n=1}^M a_{m,n} \right\rangle = \sum_{m=1}^M \sum_{n=1}^N \langle a_{m,n} \rangle. \quad (4)$$

By definition, $\bar{d}$ in Equation (3) is given by

$$\bar{d} = \left\langle \frac{\sum_m \sum_n a_{m,n}}{MN} \right\rangle = \frac{1}{MN} \sum_{m=1}^M \sum_{n=1}^N \langle a_{m,n} \rangle. \quad (5)$$

Therefore, $\langle a_{\text{sum}} \rangle$ is related to $\bar{d}$ by

$$\langle a_{\text{sum}} \rangle = MN\bar{d}. \quad (6)$$

According to,² the definition of large area noise variance is given by

$$\sigma_{a_{\text{sum}}}^2 = \langle (\Delta a_s)^2 \rangle = \left\langle \left(\sum_m \sum_n \Delta a_{m,n} \right)^2 \right\rangle. \quad (7)$$

Note that the square operator should be taken outside the 2D summation operation; it is different from the pixel-by-pixel based noise variance measurements frequently performed on a CT console [Fig. 1(b)], where

$$\sigma_{a_{\text{pixel}}}^2 = \frac{1}{MN-1} \sum_{m=1}^M \sum_{n=1}^N (a_{m,n} - \overline{\text{ROI}})^2 \approx \langle (\Delta a_{m,n})^2 \rangle. \quad (8)$$

Assuming the input photon number follows the Poisson distribution, the input SNR^2 is given by

$$\text{SNR}_{\text{in}}^2 = \frac{\langle Q_A \rangle^2}{\sigma_{Q_A}^2} = \frac{\langle Q_A \rangle^2}{\langle Q_A \rangle} = \langle Q_A \rangle = q_0 MN \Delta x \Delta y, \quad (9)$$

where $x \times y$ denotes the pixel size of the digital image receptor. Based on Eqs. (7) and (9), DQE_0 in Eq. (1) can be expanded as

$$\text{DQE}_0 = \frac{\text{SNR}_{\text{out}}^2}{\text{SNR}_{\text{in}}^2} = \frac{MN(\bar{d})^2}{q_0 \Delta x \Delta y \langle (\sum_m \sum_n \Delta a_{m,n})^2 \rangle} \quad (10)$$

$$= \frac{MN(\bar{d})^2}{q_0 \Delta x \Delta y \left[\sum_m \sum_n \langle (\Delta a_{m,n})^2 \rangle + \sum_m \sum_n \sum_{m' \neq m} \sum_{n' \neq n} \langle \Delta a_{m,n} \Delta a_{m',n'} \rangle \right]}. \quad (11)$$

Note that the denominator in Eq. (11) contains not only noise variance of each pixel $\langle (\Delta a_{m,n})^2 \rangle$ but also noise covariance terms $\langle \Delta a_{m,n} \Delta a_{m',n'} \rangle$.

Now let us review the definition of another important component, NPS(k), in the DQE(k) formula. Based on its definition (Fourier transform of the autocovariance function), it can be derived that the digital form of 2D NPS is given by

$$\begin{aligned} \text{NPS}(u, v) &= \frac{\Delta x \Delta y}{MN} \left\langle \left| \sum_{m=1}^M \sum_{n=1}^N (a_{m,n} - \langle a_{m,n} \rangle) e^{-i2\pi \left(\frac{mu}{M} + \frac{nv}{N} \right)} \right|^2 \right\rangle \\ &= \frac{\Delta x \Delta y}{MN} \left\langle \left| \sum_{m=1}^M \sum_{n=1}^N \Delta a_{m,n} e^{-i2\pi \left(\frac{mu}{M} + \frac{nv}{N} \right)} \right|^2 \right\rangle, \end{aligned} \quad (12)$$

where $\langle a_{m,n} \rangle$ is strictly defined as the expected value of $a_{m,n}$. By using the NPS formula in Eq. (12), DQE(k) at $k = 0$ is given by

$$\begin{aligned} \text{DQE}(k)_{k=0} &= \frac{(\bar{d})^2 \text{MTF}^2(k)|_{k=0}}{q_0 \text{NPS}(k)|_{k=0}} = \frac{(\bar{d})^2}{q_0 \frac{\Delta x \Delta y}{MN} \left\langle \left(\sum_{m=1}^M \sum_{n=1}^N \Delta a_{m,n} \right)^2 \right\rangle} \\ &= \frac{MN(\bar{d})^2}{q_0 \Delta x \Delta y \left\langle \left(\sum_{m=1}^M \sum_{n=1}^N \Delta a_{m,n} \right)^2 \right\rangle}, \end{aligned} \quad (13)$$

which is the same as the DQE₀ formula in Eq. (10).

In practice, experimentally measured NPS(k) _{$k=0$} often deviates from the correct value, primarily due to the following two reasons.

Type I Error: Strictly speaking, the term $\langle a_{m,n} \rangle$ should be estimated via ensemble averaging of a large number of independent image acquisitions. In reality, a large number of repeated measurements is often associated with greater work load, or the problem listed in the Type II Error. As a result, $\langle a_{m,n} \rangle$ is often estimated by fitting the measured image $a_{m,n}$ using a 2D polynomial model $s_{m,n}$, as shown in the top row of Fig. 2. Notice that the 2D polynomial fit should be performed over the entire detector plane rather than the individual ROI. If the polynomial fit is mistakenly performed to each region-of-interest (ROI) used to calculate NPS, it can be proven that (Appendix A)

$$\sum_m \sum_n (a_{m,n} - s_{m,n}) \equiv 0. \quad (14)$$

If that is the case, $\text{NPS}(0) \equiv 0$. Another incorrect way to estimate $\langle a_{m,n} \rangle$ is take the average pixel value of an ROI, namely

$$\overline{\text{ROI}} = \frac{\sum_{m=1}^M \sum_{n=1}^N (a_{m,n})}{MN}. \quad (15)$$

Apparently,

$$\sum_m \sum_n (a_{m,n} - \overline{\text{ROI}}) \equiv 0. \quad (16)$$

When this happens, according to Eq. (12), $\text{NPS}(k)|_{k=0} \equiv 0$. The error caused by incorrect estimation of $\langle a_{m,n} \rangle$ is referred to as the Type I Error in this work. As a consequence of this error, $\text{DQE}(k)$ blows up at $k = 0$, namely $\text{DQE}(0) \rightarrow +\infty$, which is apparently nonphysical.

Type II Error: To better estimate $\langle a_{m,n} \rangle$, a large number of independent image acquisitions is required. In doing so, however, another technical challenge arises: a real experimental system is often associated with certain drift such as variation in the tube output over time. The requirements for “independent measurements” and “large number of measurement” determine that the total measurement time can not be arbitrarily reduced, making the influence of system drift somehow inevitable. Fig. 3 shows, as an example, the small but noticeable drifts measured from an experimental x-ray imaging system used in this work.

One may naively think that such a small drift in measurements does no harm to the final NPS and DQE measurements. Unfortunately, this is not the case. In the presence of system drift, an image measured at a time point t can be modeled as

$$a'_{m,n,t} = a_{m,n} + f_t, \quad (17)$$

where f_t denotes the drift function, and $a_{m,n}$ denotes the system output without drift. Appendix B shows that due to the presence of f_t , the measured autocovariance function becomes

$$K_{a'}(m', n') = K_a(m', n') + \sigma_f^2, \quad (18)$$

where m' and n' describe the relative distance between pixels, $K_a(m', n')$ is the true system autocovariance function, and the error item σ_f^2 is related to f_t by

$$\sigma_f^2 = \frac{1}{T-1} \sum_{t=1}^T \left[f_t - \frac{1}{T} \sum_{\tau=1}^T f_\tau \right]^2. \quad (19)$$

Here T denotes the total number of time frames. Since $\text{NPS}(k)|_{k=0}$ is equal to the area under the autocovariance function, the error term σ_f^2 will propagate to the zero-frequency NPS as follows

$$\begin{aligned} \text{NPS}_{a'}(0) &= \Delta x \Delta y \sum_{m'} \sum_{n'} K_{a'}(m', n') \\ &= \Delta x \Delta y \sum_{m'} \sum_{n'} K_a(m', n') + \Delta x \Delta y M N \sigma_f^2 \\ &= \text{NPS}_a(0) + A \sigma_f^2. \end{aligned} \quad (20)$$

Apparently, the drift error σ_f^2 in Eq. (19) is greatly amplified by a factor of A in the measured $\text{NPS}(0)$, leading to an underestimation of $\text{DQE}(k)$ at $k = 0$.

2.2. Experimental method to address the above challenges

In order to correct this error, we can utilize a priori knowledge that the true autocovariance function K_a goes to zero at long spatial distances (otherwise $\text{NPS}(0)$ may not be finite). The presence of system drift adds a positive offset to the measured autocovariance function $K_{a'}(m', n')$. Therefore, drift error σ_f^2 can be estimated from the plateaued tail of the measured autocovariance function as follows:

$$\sigma_f^2 = \frac{1}{MN - (2l)^2} \left[\sum_{|m'| \leq \frac{M}{2}} \sum_{|n'| \leq \frac{N}{2}} K_{a'}(m', n') - \sum_{|m'| \leq l} \sum_{|n'| \leq l} K_{a'}(m', n') \right], \quad (21)$$

where l is a distance threshold (units: pixels) beyond which the true autocovariance of the imaging system can be considered reasonably close to zero. In practice, this threshold can be determined based on the shape of the measured autocovariance function. Once σ_f^2 is estimated using Eq. (21), corrections to the measured $\text{NPS}(0)$ can be performed as follows:

$$\text{NPS}_{\text{corrected}}(0) = \text{NPS}_{\text{measured}}(0) - A \sigma_f^2. \quad (22)$$

In summary, the proposed method relaxes the need for polynomial fit-based background estimation, since it directly employ image ensemble-based method to estimate the background; the drift-induced error in the image ensemble-based NPS measurement can be

corrected based on the data itself without requiring a priori knowledge of the drift function itself.

2.3. Validation of the proposed method

To validate the proposed experimental methods, both numerical simulations and experimental studies were performed. The major advantage of numerical simulation is the availability of the ground truth for the $DQE(0)$, which was set to 0.8 in our study. An arbitrary drift function was generated by one of the co-authors; both the parameter/model of this drift function and the ground truth for $DQE(0)$ were hidden to other co-authors at the time of study. Other co-authors applied the proposed method to the simulated image ensembles to measure $DQE(k=0)$.

For the experimental study, a benchtop PCD (XCounter XC-FLITE X-1; 2 mm CdTe-based; 100 μm pixel) imaging system was used. Under the RQA5 beam condition, the system repeatedly acquired x-ray projections at two different energy threshold levels (20 and 35 keV) and two detection modes (single pixel and anti-charge sharing), all of which may impact zero-frequency DQE of the imaging system. For each mode/threshold, 1000 images were acquired. The measured exposure was 0.935 mR per image frame, which corresponds to an input q_0 of $2.47 \times 10^5 \text{ mm}^{-2}$. $DQE(0)$ was measured with and without the proposed method for comparison.

3. RESULTS

Table 1 summarizes the simulation results. The proposed method (image ensemble + drift correction) generated a zero-frequency DQE value of 0.799, which is consistent with the ground truth value of 0.8. In contrast, the zero-frequency DQE generated by the ROI ensemble method with improper background estimation significantly overestimated $DQE(k)|_{k=0}$. On the other hand, image ensemble without drift correction significantly underestimated $DQE(k)|_{k=0}$ due to the additional term of $A\sigma_f^2$ in $NPS(k)|_{k=0}$.

As shown in Fig. 3, a small but non-negligible system drift exist in each set of experimental images. Such output drift led to the overestimation of the autocovariance function (black circles in Fig. 4). After estimating and removing the drift error term, the $DQE(k)$ curves became continuous at $k=0$ (Fig. 5). In comparison, image ensemble without drift correction significantly underestimated $DQE(k)$ at $k=0$.

4. CONCLUSION

An experimental method was developed to 1) enable experimental $DQE(k)|_{k=0}$ measurements that is consistent with the classical and original definition of the zero-frequency DQE, and 2) mitigate drift-induced error in $DQE(k)$ and $NPS(k)$ at $k=0$. No extrapolation (which assumes certain $DQE(k)$ model) is required to extend the $DQE(k)$ curve to the point at $k=0$.

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Appendix A:: Summation of pixel values of detrended image

Let vector $\mathbf{y}$ denote the vectorized image data, and $\hat{\mathbf{y}}$ denotes the polynomial model of $\langle \mathbf{y} \rangle$. If each element in $\mathbf{y}$ is expected to have the same noise variance, the goal of the polynomial fit is to minimize the following objective function:

$$(\tilde{\beta}_0, \tilde{\beta}_1, \dots) = \operatorname{argmin}_{\beta_0, \beta_1, \dots} [\mathbf{y} - \hat{\mathbf{y}}(\beta_0, \beta_1, \dots)]^2, \quad (23)$$

where $(\beta_0, \beta_1, \dots)$ are parameters of the polynomial model. Taking the 2nd order polynomial fit as an example, the model is given by

$$\hat{\mathbf{y}} = \begin{pmatrix} 1 & x_1 & x_1^2 \\ 1 & x_2 & x_2^2 \\ \vdots & \vdots & \vdots \\ 1 & x_{MN} & x_{MN}^2 \end{pmatrix} \begin{pmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \end{pmatrix} \quad (24)$$

where x_j characterizes the spatial location of the j^{th} pixel. Let $\mathbf{x}^0$, $\mathbf{x}^1$, and $\mathbf{x}^2$ represent the 1st, 2nd, and 3rd column, respectively, in the $(MN) \times 3$ matrix in equation (24), then $\hat{\mathbf{y}}$ can be written as

$$\hat{\mathbf{y}} = (\mathbf{x}^0 \mathbf{x}^1 \mathbf{x}^2) \begin{pmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \end{pmatrix} = \beta_0 \mathbf{x}^0 + \beta_1 \mathbf{x}^1 + \beta_2 \mathbf{x}^2. \quad (25)$$

The corresponding objective function is

$$(\tilde{\beta}_0, \tilde{\beta}_1, \tilde{\beta}_2) = \operatorname{argmin}_{\beta_0, \beta_1, \beta_2} [\mathbf{y} - \beta_0 \mathbf{x}^0 - \beta_1 \mathbf{x}^1 - \beta_2 \mathbf{x}^2]^2. \quad (26)$$

The solution of $\tilde{\beta}_0$ satisfies the following condition:

$$\left. \frac{\partial [\mathbf{y} - \beta_0 \mathbf{x}^0 - \beta_1 \mathbf{x}^1 - \beta_2 \mathbf{x}^2]^2}{\partial \beta_0} \right|_{\beta_0 = \tilde{\beta}_0, \beta_1 = \tilde{\beta}_1, \beta_2 = \tilde{\beta}_2} = 0, \quad (27)$$

or equivalently

$$-2(\mathbf{y} - \tilde{\beta}_0 \mathbf{x}^0 - \tilde{\beta}_1 \mathbf{x}^1 - \tilde{\beta}_2 \mathbf{x}^2)^\top \mathbf{x}^0 = 0, \quad (28)$$

where $(\cdot)^\top$ denotes the matrix/vector transpose operator. Based on equation (28),

$$\begin{aligned} (\mathbf{y} - \hat{\mathbf{y}})^\top \mathbf{x}^0 &= (\mathbf{y} - \hat{\mathbf{y}})^\top \begin{pmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{pmatrix} \quad (29) \\ &= \sum_j (y_j - \hat{y}_j) \\ &= 0. \end{aligned}$$

In other words, after being subtracted by the polynomial fit of an image, the summation of the pixel values is zero. As a side note: through similar analysis, it can be shown that $\sum_j (y_j - \hat{y}_j)$ is always zero no matter what the highest order of polynomial fit is, as long as the polynomial model contains the zeroth order term.

Appendix B:: Impact of system drift to the measured autocovariance function

After acquiring a total of T images to generate an image ensemble, an ensemble average can be performed. Based on the model in equation (17), the average image is given by

$$\langle a'_{m,n} \rangle = \frac{1}{T} \sum_{t=1}^T a'_{m,n,t} = \langle a_{m,n} \rangle + \frac{1}{T} \sum_{t=1}^T f_t. \quad (30)$$

For an image acquired at time point t , its noise $a_{m,n,t}$ is given by

$$\begin{aligned}
\Delta a'_{m,n,t} &= a'_{m,n,t} - \langle a'_{m,n} \rangle \\
&= (a_{m,n} - \langle a_{m,n} \rangle) + \left(f_t - \frac{1}{T} \sum_{t=1}^T f_t \right) \\
&= \Delta a_{m,n} + \Delta f_t.
\end{aligned} \tag{31}$$

The corresponding autocovariance function is given by

$$\begin{aligned}
K_{a'}(m, n; m + m', n + n') &= \langle \Delta a'_{m,n} \Delta a'_{m+m', n+n'} \rangle \\
&= \frac{1}{T-1} \sum_{t=1}^T \Delta a'_{m,n,t} \Delta a'_{m+m', n+n',t} \\
&= \frac{1}{T-1} \sum_{t=1}^T (\Delta a_{m,n} + \Delta f_t)(\Delta a_{m+m', n+n'} + \Delta f_t) \\
&= \frac{1}{T} \sum_{t=1}^{T-1} (\Delta a_{m,n} \Delta a_{m+m', n+n'}) + 0 + 0 + \frac{1}{T-1} \sum_{t=1}^T (\Delta f_t)^2 \\
&= K_a(m, n; m + m', n + n') + \sigma_f^2,
\end{aligned} \tag{32}$$

where we utilized the fact that the drift function and the true pixel noise are uncorrelated. In equation (32), $K_a(m, n; m + m', n + n')$ denotes the true autocovariance of the system output in the absence of drift.

By averaging $K_{a'}(m, n; m + m', n + n')$ over all detector pixels, its dependence on the absolute pixel location (m, n) can be removed:

$$\begin{aligned}
K_{a'}(m', n') &= \frac{1}{MN} \sum_{m=1}^M \sum_{n=1}^N K_{a'}(m, n; m + m', n + n') \\
&= \frac{1}{MN} \sum_{m=1}^M \sum_{n=1}^N K_a(m, n; m + m', n + n') + \frac{1}{MN} \sum_{m=1}^M \sum_{n=1}^N \sigma_f^2 \\
&= K_a(m', n') + \sigma_f^2.
\end{aligned} \tag{33}$$

Therefore, drift adds a positive off set of σ_f^2 to the measured autocovariance.

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Figure 1.

(a) Ensemble statistics-based SNR method. (b) Single acquisition and single ROI-based SNR Method.

Figure 2.

Two background removal methods used in NPS measurements. The method in the top row uses a polynomial fit of the measured ROI image to estimate image background. The method in the bottom row uses the ensemble average of $a_{m,n}$ to estimate $\langle a_{m,n} \rangle$. For these two methods, the difference images between the measurement and estimated background may appear similar, but not the same.

Figure 3. Demonstration of system drift by plotting the measured detector output as a function of image frame index. The relative magnitude of drift is less than 1%.

Figure 4.

Autocovariance as a function of spatial distance between pixels. (a) ACS off; 20 keV energy threshold. (b) ACS off; 35 keV. (c) ACS on; 20 keV. (d) ACS on; 35 keV. The artifactual elevation of autocovariance at relatively large distance was removed after applying the proposed correction. Note that the vertical axis is broken at the the double wavy lines.

Figure 5.

Experimental DQE results. (a) ACS off; 20 keV energy threshold. (b) ACS off; 35 keV. (c) ACS on; 20 keV. (d) ACS on; 35 keV. The proposed drift correction generated smooth DQE within the entire bandwidth, including $k=0$.

Table 1.

Summary of the simulation results. The units of the NPS is $[\text{mm}^2]$. Other parameters are dimensionless.

	ROI ensemble	Image ensemble w/o drift correction	Proposed method	Ground truth
$\text{NPS}(k) _{k=0}$	2.32×10^{-20}	2.47×10^6	8010	8000
$\text{DQE}(k) _{k=0}$	2.76×10^{23}	2.59×10^{-3}	0.799	0.8