Detector Modeling Project

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IMGS-442 Imaging System Analysis Modeling, Dr. Hailstone

ABSTRACT

In this project, computer simulations are used to help better understand the performance limitations of electronic imaging devices. To do this, the theory surrounding how photons interact with detector arrays must be well understood. When photons are treated as individual particles, the photon detector array problem simply becomes a question of probability. Using Poisson statistics photon detection can be quantified and modeled. Noise can also be taken into account using this model by including those terms in the equations. Using MATLAB, equations can be used to model detector quantum efficiency, DQE. The DQE calculation takes into account different types of noise including, A-to-D conversion noise and read noise. The effect of noise, as well as the effects from pixel size is explored.

Keywords: Detectors, Noise, Detector Modeling, Imaging Systems

1. INTRODUCTION

Modern imaging systems are made up of several different components in order to successfully capture an image. One of those components is the imaging detector. An ideal detector is an array of individual photon detectors, or pixels, that can detect photons and read out a response as a one to one relationship. Like most technology, limitations exist, but they can be estimated to make a realistic model of how a detector should behave.

It is assumed that the detector array is made up of individual photon detectors, pixels. These pixels record incident photons independently of neighboring photons and have a unique and distinguishable image state dependant only on the number of photons on that pixel. These detectors cannot read an infinite number of pixels, so some upper threshold must be established so that after that many photons, all further photons will go undetected. This threshold, L, is the max saturation on that detector. Up to that fixed level, L, the detector will act with 100% efficiency while after L the efficiency is zero. It is assumed that the incident number of photons, k reaching the detector follows Poisson statistics, so that if the mean number of photons $\bar{q}$ then the probability is given by

$$P(k) = \frac{e^{-\bar{q}}\bar{q}^k}{k!} \tag{1}$$

Knowing that the detector behaves following Poisson statistics, measurements of the overall efficiency can be estimated. One useful measurement is the fraction of detectors that reached the saturation level, which can be calculated by taking the sum of equation 1 from L to infinity. Another useful measurement is the relationship between mean count level, l, and the mean exposure, $\bar{q}$. The mean count level, l can be easily calculated using the equation

$$l = \sum_{k=1}^{\infty} \frac{e^{-\bar{q}}\bar{q}^k}{k!} + \sum_{k=2}^{\infty} \frac{e^{-\bar{q}}\bar{q}^k}{k!} + ... + \sum_{k=L}^{\infty} \frac{e^{-\bar{q}}\bar{q}^k}{k!}) \tag{2}$$

In Figure 1, mean count level, l is plotted against the mean exposure, $\bar{q}$. There is a linearity between 0 and L that can be observed. After the max exposure, L, the mean count level l reaches is max and plateaus. Since there are L summations on the right side of Eq. (2), is can be rewritten as

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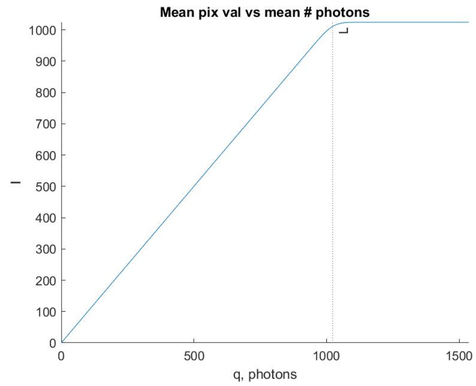


Figure 1. Mean output level vs mean number of input photons/ counter.

$$l = L(1 - f_1) \tag{3}$$

where

$$f_1 = \frac{1}{L}\left(e^{-\bar{q}} + \sum_{k=0}^{1} \frac{e^{-\bar{q}}\bar{q}^k}{k!} + \sum_{k=0}^{2} \frac{e^{-\bar{q}}\bar{q}^k}{k!} + ... + \sum_{k=0}^{L-1} \frac{e^{-\bar{q}}\bar{q}^k}{k!}\right) \tag{4}$$

Another characteristic to examine is the rate of change of mean count level with exposure, which is the gradient, or contrast, or gamma, or gain, G. Gain can be derived from l and f_1, but can be simplified as

$$G = Lf_2 \tag{5}$$

where

$$f_2 = \frac{1}{L}\sum_{k=0}^{L-1} \frac{e^{-\bar{q}}\bar{q}^k}{k!} \tag{6}$$

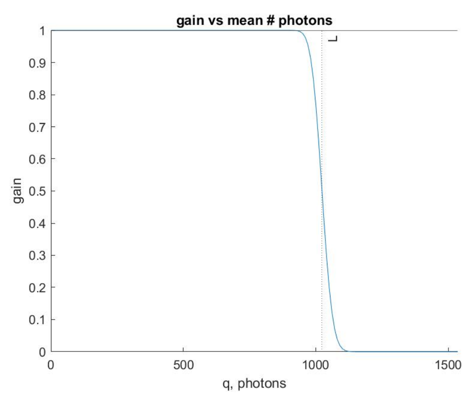


Figure 2. Gain vs mean number of input photons

In Figure 2, Gain is compared to the mean number of photons $\bar{q}$. As mentioned before in Figure 1, there is a linear relationship between l and $\bar{q}$, therefore the derivative would of course be 1. This is why the gain is 1 from 0 to nearly L. Just around L the gain shifts from 1 to 0 as the l value is shifting from linearly increasing to constant value L. This kind of plot shows clearly over what exposure region the imaging system is ideal.

Natural fluctuations will occur in the image spatially due to the statistical distribution of incident photons. This is what is known as photon noise. These fluctuations can be modeled and estimated by calculating the variance. The variance equation is derived using the second moment of the distribution about the origin m_2 which is written as

$$m_2 = \sum_{k=1}^{L-1} k^2 \frac{e^{-\bar{q}}\bar{q}^k}{k!} + \sum_{k=L}^{\infty} L^2 \frac{e^{-\bar{q}}\bar{q}^k}{k!} \tag{7}$$

When rearranged,

$$m_2 = L^2(1 - f_3) \tag{8}$$

where

$$f_3 = \frac{1}{L^2}(e^{-\bar{q}} + 3\sum_{k=0}^{1} \frac{e^{-\bar{q}}\bar{q}^k}{k!} + 5\sum_{k=0}^{2} \frac{e^{-\bar{q}}\bar{q}^k}{k!} + ... + (2L-1)\sum_{k=0}^{L-1} \frac{e^{-\bar{q}}\bar{q}^k}{k!}) \tag{9}$$

now the variance can finally be written out as

$$\sigma_l^2 = m_2 - l^2 = L^2[(1 - f_3) - (1 - f_1)^2] \tag{10}$$

Variance is compared to the mean number of input photons in Figure 3. Note that the relationship has a slope of 1 for the initial q values, but as the q values approach L, the variance drops off to zero. This tells us that there is a linear, one to one relationship between photon noise and the mean number of incident photons. This makes sense, as there are more photons there will be more variability. After L, the photon noise is zero, because the system will no longer be photon limited. This means that after L, the noise cannot be separated out from the signal because the max signal is already reached.

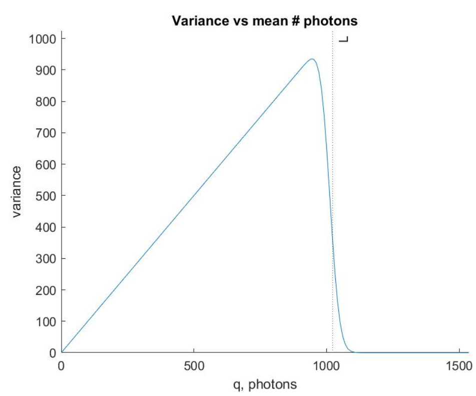


Figure 3. Variance vs mean number of input photons.

Aside from photon noise, another type of noise that is introduced to the system is analog to digital conversion noise. It makes sense that there is some loss when converting from analog to digital because in a sense, the values have to get rounded to the nearest integer value. The decimals become lost. A-to-D noise is a function of how many quantization levels, b there are in the output image. As the quantization levels are increased, the noise is decreased.

$$\sigma_{A-D}^2 = \frac{(L)^2}{12 * 2^{2b}} \tag{11}$$

A final, and maybe the most common, metric for characterizing the detectors performance is detector quantum efficiency, DQE. This is the ratio between the signal to noise out and the signal to noise in. It is saying how much loss there is in the detector, where 1 is no loss and 0 is total loss of signal. The textbook definition of DQE is

$$DQE = \frac{(S/N)_out^2}{(S/N)_in^2} \tag{12}$$

However, given that the detector follows Poisson statistics and the signal to noise can be written out in terms of the noise, gain, and $\bar{q}$; we get

$$DQE(\bar{q}) = \frac{\bar{q}G^2}{\sigma_l^2} \tag{13}$$

and subbing in for G and σ_l^2 from Eqs. (5) and (10)

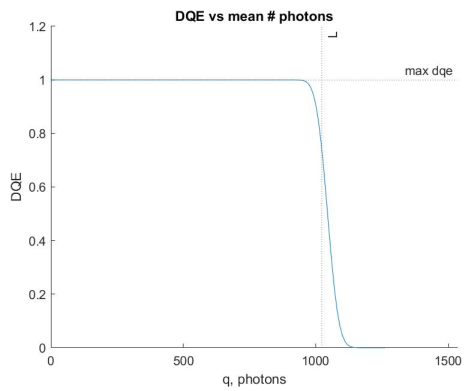


Figure 4. DQE vs input photons

$$DQE(\bar{q}) = \frac{\bar{q}(f_2)^2}{(1 - f_3) - (1 - f_1)^2} \tag{14}$$

Again as another comparison metric, DQE can be plotted against mean number of photons $\bar{q}$. In an ideal detector, the max detector quantum efficiency (DQE) is 1. In the same linear segment from the previous graphs, between 0 and L, the DQE is ideal at 1. After the max saturation, L, the DQE is zero since all of the extra photons reaching the detector after L can not be absorbed and recorded out.

It was assumed that the incident photons reaching the detector are absorbed 100% of the time, but realistically this is not true. Since the detectors rarely if ever have 100% absorption, a new term η must be introduced. The primary quantum efficiency, η, is used to represent this fact that detectors will lack 100% absorption. Using properties of Poisson statistics, η can be incorporated into DQE using

$$DQE(\eta\bar{q}) = \eta DQE(\bar{q}) \tag{15}$$

Now, a sufficient model has been built up to explore the effects of noise on the detector. Several metrics are described as useful measures for detector performance and efficiency. In an ideal case, the detector will perform with 100% efficiency up to some max saturation value, L. However, realistically, noise is introduced to the system by the fundamental properties of physics. These noise terms can be estimated and added to the model to make it more realistic. Adding those terms to the model can also help us understand what the effect of that individual noise term is. In this lab the effects of read noise, A-to-D conversion noise, and pixel size is explored.

2. SIMULATION

Under the assumption that photon detector arrays follow Poisson statistics, the detectors performance can be modeled. In this exercise, DQE is calculated for a detector as a function of . Using a mathematical software package, like MATLAB, this computation can be done relatively quick.

2.1 Task 1

2.1.1 Simulation Method

In this experiment, the maximum saturation level L = 1024 electrons. For a range of mean photons, from 0 to 8001, and using the DQE equations () and (); the DQE can be calculated for $\eta = 0.125$, 0.25, 0.5, and 1.0. This should be done once with the assumption that every photon produces a distinguishable output signal and there is no A-D noise. Then, repeat the DQE calculations again at every η, but with a read noise of 10 electrons and 4 bit quantization. This will help understand the general effect of noise on a detector array.

2.1.2 Results

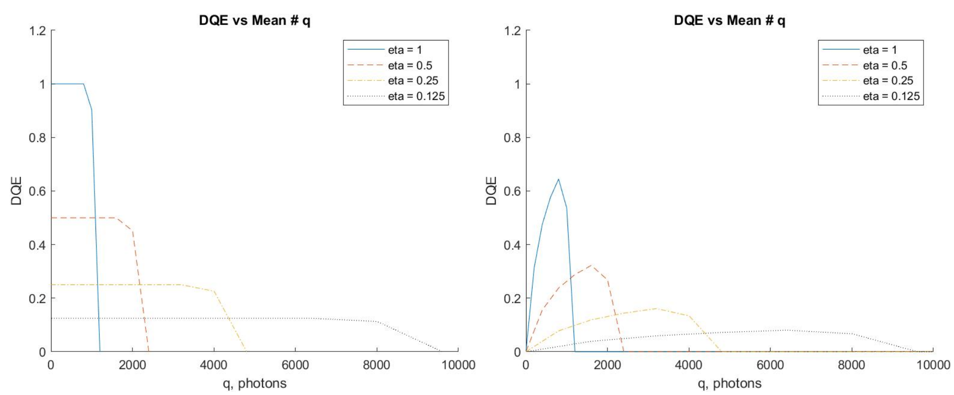


Figure 5. (a) DQE vs mean photon count with no read or A-D noise. (b) DQE vs mean photon count with 10e- read noise and 4-bit A-D noise.

In task 1, two plots are made; DQE of a detector with no noise and DQE of a detector with 10 electron read noise and 4-bit A-to-D conversion noise. Comparing these two plots can help understand what the general effect of noise on the detector system is. For the most part, both types of noise have the strongest effect at lower light levels. This is expected since at low light levels, the number of photons incident on the detector may be less than or equal to the amount of noise being read off the system. The plot in task 1 can also help explain the effect of η on the DQE. As η gets closer to zero, the DQE peak decreases but the maximum q value increases. This means that low η systems perform well at high light levels, but at the cost of overall DQE.

2.2 Task 2

2.2.1 Simulation Method

Now, with a constant $\eta = 0.5$ and the same parameters from task 1, the individual effects of noise on DQE can be investigated. First, vary the read noise between 1, 3, and 10 electrons and note the effect on the detectors DQE. As the noise increases, DQE will decrease. Then, with a read noise of 0 electrons, vary the A-to-D quantization between 2 bits, 4 bits, and 8 bits and note the effect on DQE.

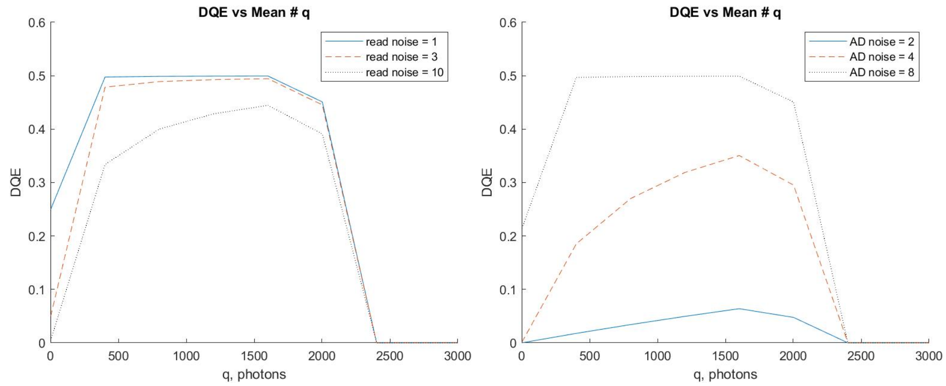


Figure 6. (a) DQE vs mean photons with no A-D noise, and varying read noise. (b) DQE vs mean photons with no read noise, and varying A-D noise.

2.2.2 Results

In task 2, the individual effects from read noise and A-to-D noise are explored. In Figure (a) read noise is varied while no A-to-D noise is present. It can be observed that there is a steep drop off for low photon levels at higher read noise. In Figure (b) A-to-D noise is varied while no read noise is present. The effect from A-to-D noise is much more drastic than that of read noise. The DQE flattens out as the AD quantization level is decreased.

2.3 Task 3

2.3.1 Simulation Method

The effect of pixel size on the detectors performance can be explored. For the next three tasks, square pixel diameters of 5, 10, and 20 μm are used. Calculate a mean level response by using the normalized count level l/L. This will be plotted against log E where exposure E,

$$E = n_A A\bar{q} \tag{16}$$

is the photons/ area. n_A is the number of pixels per area, A. This should be calculated and plotted for each pixel size.

2.3.2 Results

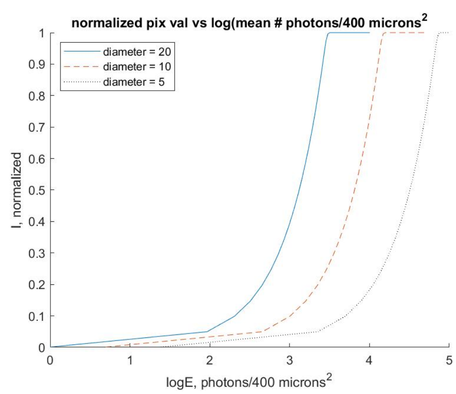


Figure 7. normalized pixel value vs log E.

Pixel size has an effect of the detector performance as well. In the figure, normalized count level is compared to log E. It can be observed that the general shape remains constant as the square pixel diameter increases, but the plot shifts leftwards. This means that at a normalized mean value, l for a detector, the corresponding log E value will decrease as pixel size increases. This is a result of E, photons per pixel, being dependant on pixel size.

2.4 Task 4

2.4.1 Simulation Method

Again keeping the same parameters as the last tasks, calculate the noise variance of the detector array. The variance should be calculated for each pixel size and plotted against the normalized mean count level as well as the log E that was calculated in task 3.

2.4.2 Results

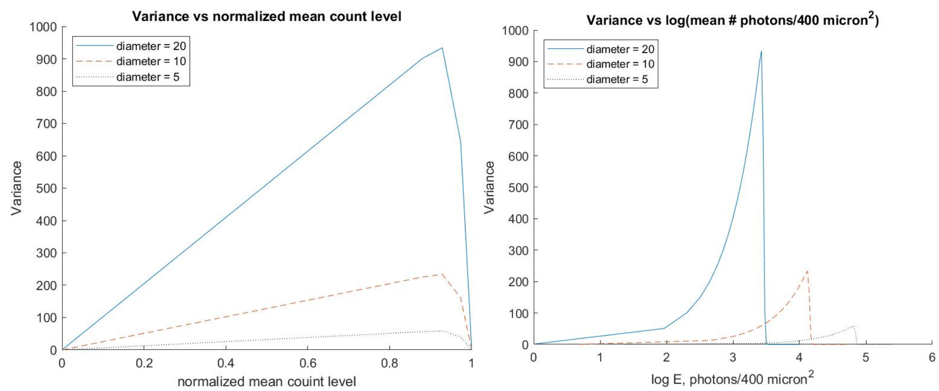


Figure 8. (a) Variance vs normalized mean count level. (b) Variance vs log E.

Next, variance was calculated for each of the three pixel sizes using equation . The variance is plotted against both normalized mean count and log E. In figure (a) as the pixel size increases, the scale of the variance increases. In figure (b) as the pixel size increases, the scale of the variance increases again, however the max log E decreases.

2.5 Task 5

2.5.1 Simulation Method

Finally, for each of the three pixel sizes, calculate DQE. The DQE should be plotted against logE to understand the relationship between pixel size, exposure, and DQE. A plot of the DQE and normalized count should be plotted against log E for a 20 μm pixel.

2.5.2 Results

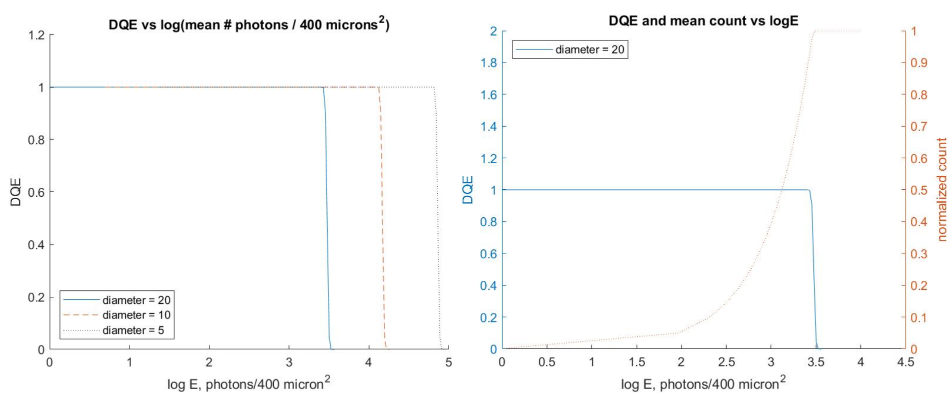


Figure 9. (a) DQE versus log E for various pixel sizes. (b) DQE and mean count level vs log E

Finally, DQE is plotted against log E for each of the three pixel sizes. It is observed that as pixel size increases the DQE drop off occurs at a lower log E value. DQE is equal to its max value, 1, until that threshold. When the plot is overlaid with normalized count versus log E, it becomes clear that the normalize count reaches 100% at that same log E threshold value.

3. DISCUSSION

3.1 Multiple levels

How does the ability of a detector array to detect multiple levels of incident photons affect its DQE?

A detector array's ability to detect multiple levels of incident photons has a direct effect on the Detector's Quantum Efficiency (DQE). In an ideal detector array, each pixel is an individual photon detector that returns one value for each incident photon. The DQE of an ideal detector will be 100% efficient up until some maximum saturation, L. After this point, the DQE falls off. In a real detector, with read noise and A-to-D quantization noise, the DQE is not perfectly efficient until that maximum saturation. Rather, when noise is introduced to the detector, the DQE is very low at low levels of incident photon counts. This is because the number of photons on the detector is less than or equal to the noise, so there is not enough contrast to know if it is a photon response or noise. In both cases, DQE is high after the noise levels through the maximum saturation value.

3.2 Pixel Size

How does pixel size affect DQE and noise?

Pixel size is an important characteristic of detectors since pixels act as bins to catch incident photons. Larger pixels can cover a larger area and will therefore have more photons incident upon it. The change in area will directly have en effect on the exposure, E due to equation . At some mean photon level, l, the log E value will decrease as pixel size is increased. Similarly DQE shifts leftwards when pixel size increases. This means that the DQE fall-off occurs are smaller log E values as the pixel size and area is increased, meaning smaller pixels can have a larger log (mean number of photons per area).

3.3 Dynamic Range

How is the dynamic range achieved in electronic systems and what does this mean in terms its DQE?

Dynamic range in a detector array is the change in log E between where photons can be detected above the read noise and the full well capacity/ max saturation. In an ideal, noiseless system the dynamic range would be log E where max saturation occurs. In figure 9b from Task 5, the saturation curve is overlaid on the DQE. This makes it obvious that the DQE cut-off occurs at the same log E as max saturation. The conclusion to be made here is that the DQE cut-off occurs at dynamic range, so as pixel size increases dynamic range decreases. This result can be seen visually in Figure 9a from Task 5.

3.4 Noise Limited

Under what conditions is the detector photon-noise limited, and under what conditions is it detector-noise limited?

Real imaging detectors experience noise. In the system as a whole, the greatest source of noise is known as the noise limit. So when the detector has a log E less than the read noise, the noise is greater than the signal and the system is detector noise limited. After that threshold, photons being absorbed by the detector are above the noise and can be distinguished. Above the log E of read noise, the system is considered photon limited, meaning the output is limited by how many photons are incident upon the detector array.

4. CONCLUSION

Imaging detectors consist of an array of individual photon detectors. When photons are treated as individual particles, they follow properties of Poisson statistics. Using probability, photon detection can be quantified and modeled. This model can be used to calculate the detector quantum efficiency (DQE). Although the equations are expansive and would take a long time to calculate by hand, computer software can be utilized to speed up this calculation. In this implementation, MATLAB was used to program the DQE functions, along with functions for variance based on pixel size to help understand the detectors performance.

The functions for DQE can include both read noise as well as A-to-D conversion noise. Plots are made to see the individual effects of noise on the detector. In both cases, low light levels were effected the most. This is well expect since in a real system, if the number of photons incident upon the detector is less than the noise then the signal will not be strong enough to stand out against that noise. The effects from pixel size are explored as well.

As pixel size is increased, the dynamic range of the detector is decreased. This may be an important take away while designing a new detector.

In this project, computer simulations are used to better understand the performance limitations of the electronic imaging devices. This is done by calculating the detective quantum efficiency for various assumed properties of these devices. From DQE estimations of dynamic range can be made.

APPENDIX A. MATLAB CODE

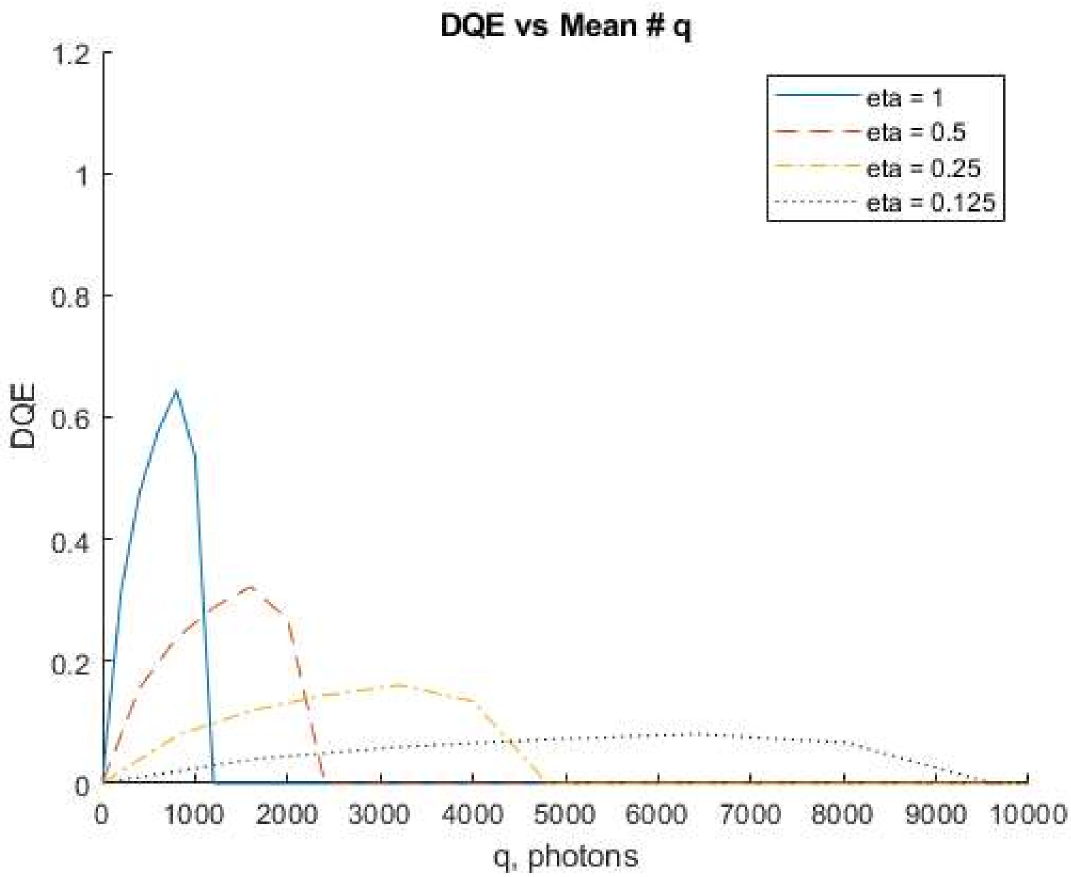
Imaging System Analysis Modeling

Project: Detector Modeling Author: Jared Gregor (jmg2586@rit.edu) Date: Oct 5 2020

Contents

Task 1

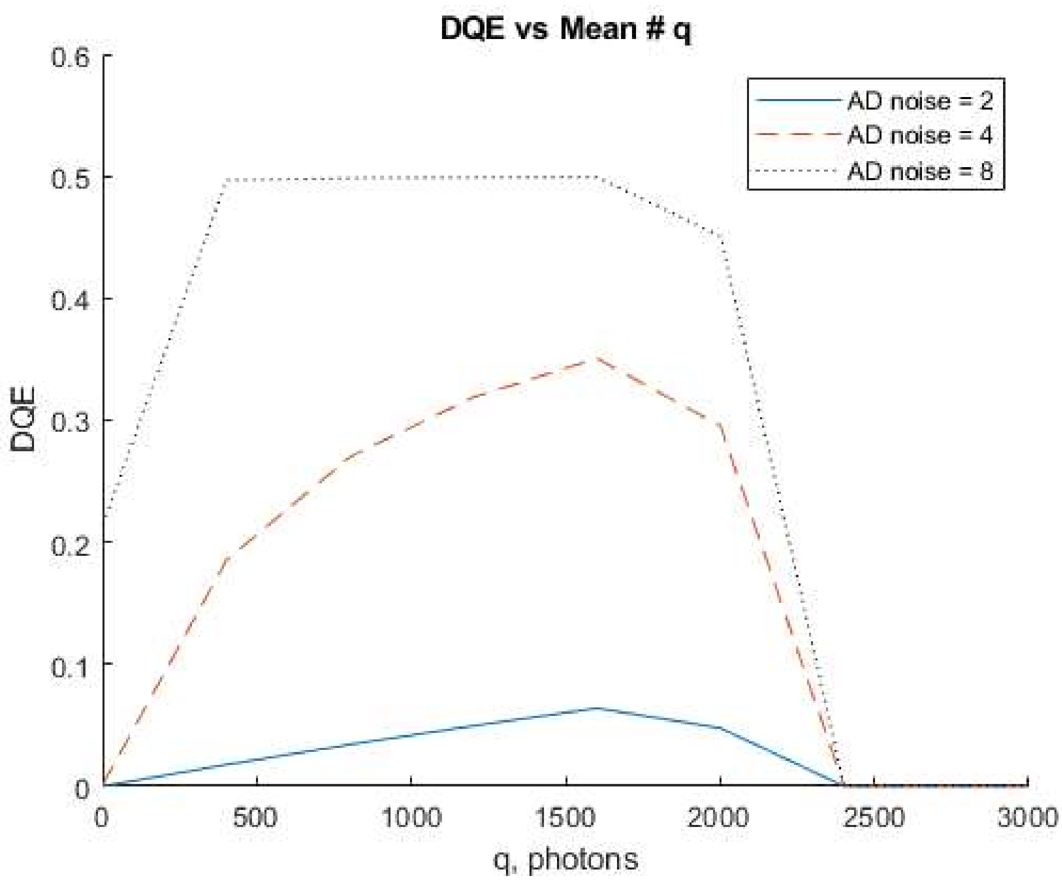
```
clear
close all

% Given Variables
L = 1024; % Saturation level
eta = [1.0, 0.5, 0.25, 0.125];
q = [1:200:8001]; % Lambda/ Mean exposure
q_scaled = [q;q;q;q]; % Scale q for each eta
q_scaled = q_scaled ./ eta';


noise_read = 0; % Electrons
noise_AD = 0;

% Calculate dqe with 0 noise
dqe(1,:) = DQE(L, q, eta(1), noise_AD, noise_read);
dqe(2,:) = DQE(L, q, eta(2), noise_AD, noise_read);
dqe(3,:) = DQE(L, q, eta(3), noise_AD, noise_read);
dqe(4,:) = DQE(L, q, eta(4), noise_AD, noise_read);

% Plot DQE vs q
Plot1(q_scaled, dqe)

% Add noise
noise_read = 10; % Electrons
AD = 4; % bits
noise_AD = NoiseAD(L, AD);

% Calculate dqe with constant read and AD noise
dqe(1,:) = DQE(L, q, eta(1), noise_AD, noise_read);
dqe(2,:) = DQE(L, q, eta(2), noise_AD, noise_read);
dqe(3,:) = DQE(L, q, eta(3), noise_AD, noise_read);
dqe(4,:) = DQE(L, q, eta(4), noise_AD, noise_read);

% Plot DQE vs q with noise
Plot1(q_scaled, dqe)
```



Task 2

```
clear

% Given Variables
L = 1024; % Saturation level
eta = 0.5;
q = [1:200:3001]; % Lambda/ Mean exposure
q_scaled = q ./ eta;

% DQE varying read noise
noise_read = [1,3,10];
noise_AD = 0;

% Calculate DQE varying read noise and 0 AD noise
dqe(1,:) = DQE(L, q, eta, noise_AD, noise_read(1));
dqe(2,:) = DQE(L, q, eta, noise_AD, noise_read(2));
dqe(3,:) = DQE(L, q, eta, noise_AD, noise_read(3));

Plot2(q_scaled, dqe,["read noise = 1", "read noise = 3", "read noise = 10"])

% DQE varying bit level
noise_read = 0;
AD = [2,4,8];
noise_AD = NoiseAD(L, AD);

% Calculate DQE varying AD noise and 0 read noise
```

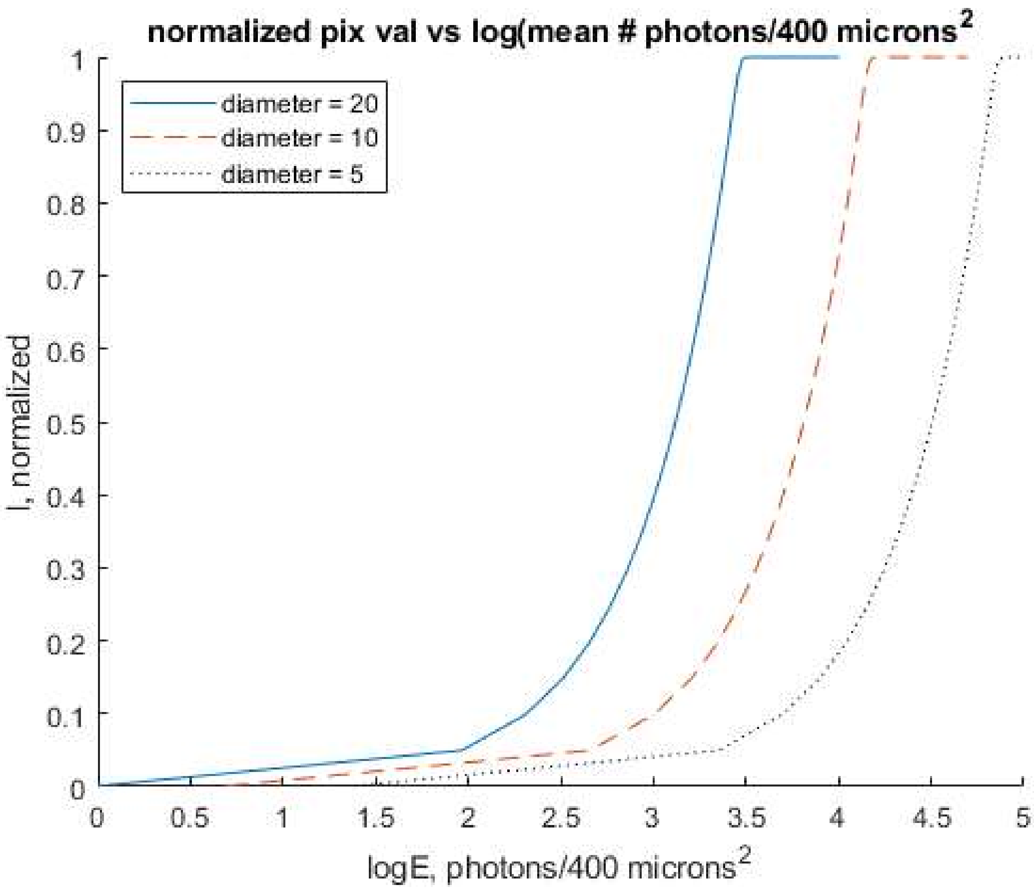
```
dqe(1,:) = DQE(L, q, eta, noise_AD(1), noise_read);
dqe(2,:) = DQE(L, q, eta, noise_AD(2), noise_read);
dqe(3,:) = DQE(L, q, eta, noise_AD(3), noise_read);

Plot2(q_scaled, dqe,["AD noise = 2", "AD noise = 4", "AD noise = 8"])
```



Task 3

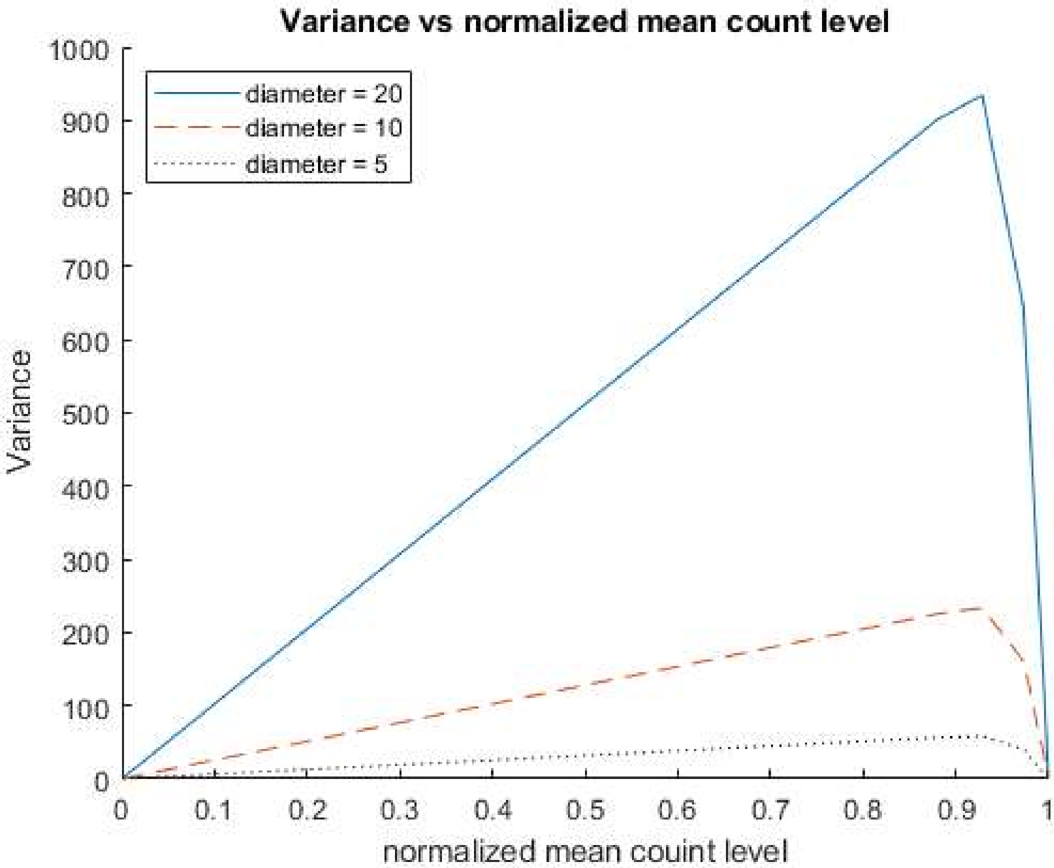
```
clear

% Given Variables
noise_read = 0;
noise_AD = 0;


q = [1:50:3001]; % Lambda/ Mean exposure
L = 1024; % Saturation level
l_norm = (1 - F1(L, q)); % count

diameter = [20,10,5]; %Square Pixel diameter microns
area = diameter.^2; %microns^2
multiplier = area(1) ./ area;

% Calculate E for each area
E(1,:) = q;% ./ area(1);
E(2,:) = multiplier(2) .* E(1,:);
E(3,:) = multiplier(3) .* E(1,:);
```

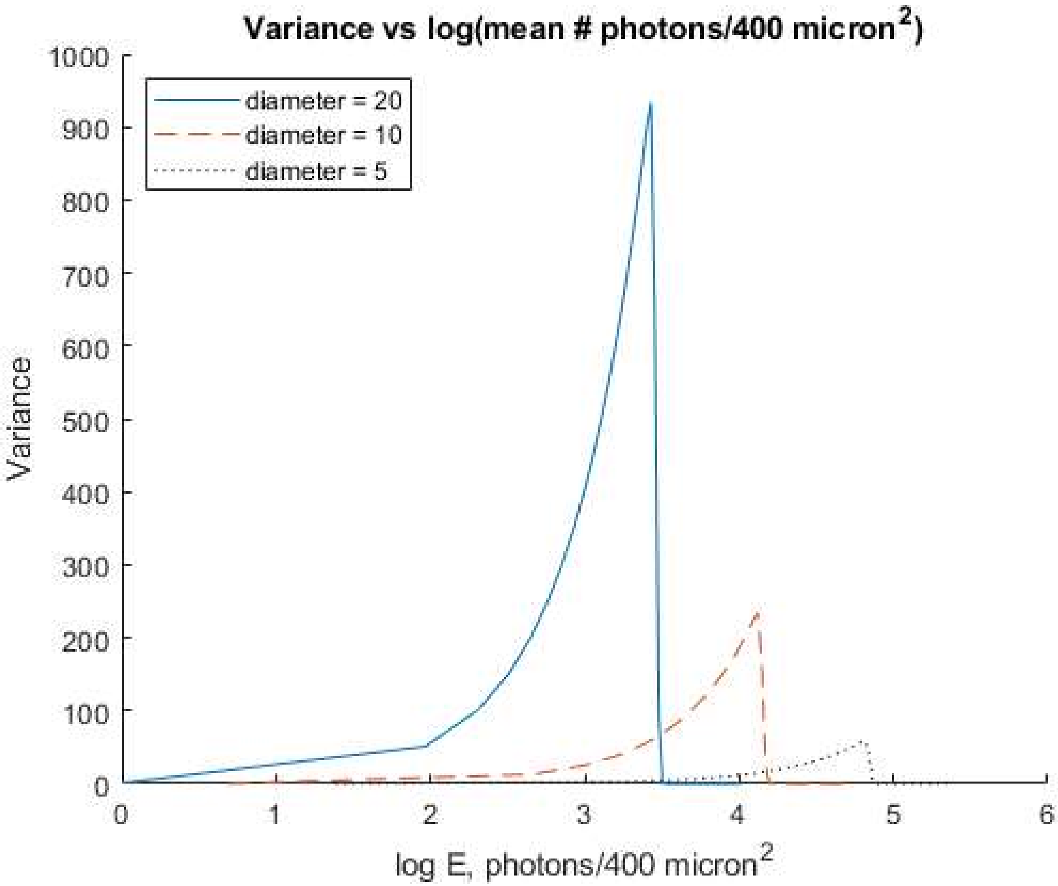
```
logE = log(E)./2;

Plot3(logE, l_norm,["diameter = 20", "diameter = 10", "diameter = 5"])
```



Task 4

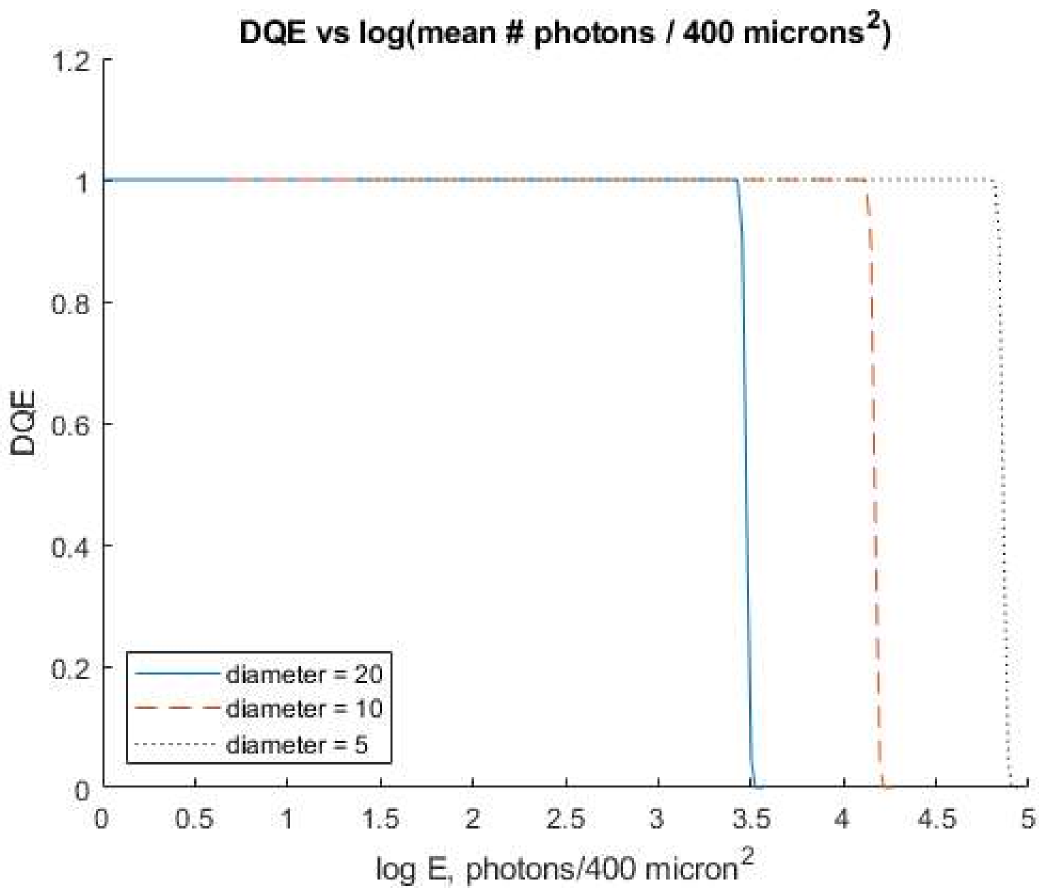
```
% Calculate variance for each area
variance = Variance(L, q);
variance = [variance; variance; variance];
variance = variance ./ multiplier';

Plot4_1(l_norm, variance,["diameter = 20", "diameter = 10", "diameter = 5"])
Plot4_2(logE, variance,["diameter = 20", "diameter = 10", "diameter = 5"])
```

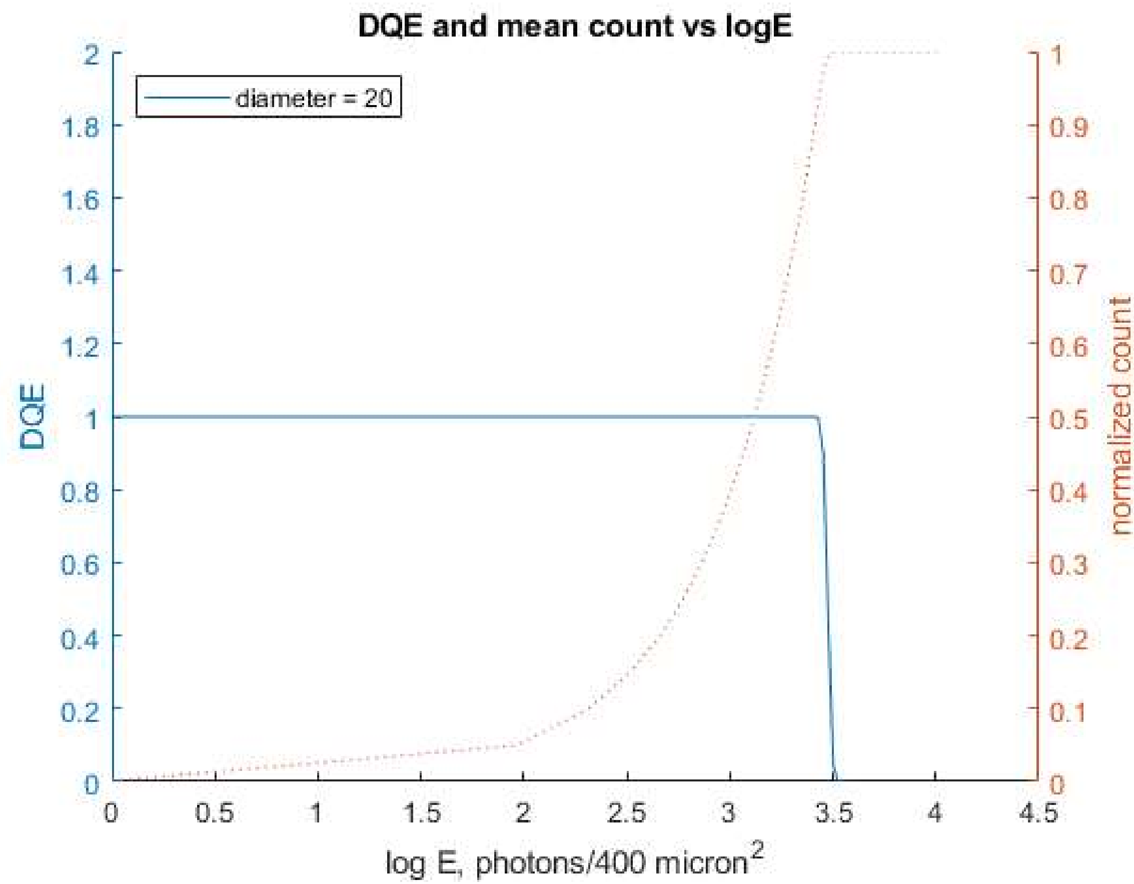

Variance vs normalized mean count level
diameter = 20
diameter = 10
diameter = 5
Variance
normalized mean couint level
0
100
200
300
400
500
600
700
800
900
1000
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1


Variance vs log(mean # photons/400 micron^2)
diameter = 20
diameter = 10
diameter = 5
Variance
log E, photons/400 micron^2
0
100
200
300
400
500
600
700
800
900
1000
1
2
3
4
5
6

Task 5

```
% Calculate DQE for each area
eta = 1;
dqe = DQE(L, q, eta, noise_AD, noise_read);

Plot5_1(logE, dqe, ["diameter = 20", "diameter = 10", "diameter = 5"])
Plot5_2(logE, dqe, l_norm, ["diameter = 20", "diameter = 10", "diameter = 5"])
```





Functions

```
% AD noise
function noise = NoiseAD(L, AD)
    noise = (L.^2)./(12.*2.^(2.*AD));
end

% Compute f1 (eq 6)
% Compute f2 (eq 9)
% Compute f3 (eq 16)
function f1 = F1(L,q)
    f1 = 0;
    for i = 0:L-1
        f1 = f1 + (1/L) * poisscdf(i,q);
    end
end
function f2 = F2(L,q)
    f2 = (1/L) * poisscdf(L-1,q);
end
function f3 = F3(L,q)
    f3 = 0;
    for i = 0:L-1
        f3 = f3 + ((1/(L*L)) * (2*i+1) * poisscdf(i,q));
    end
end

% DQE
function dqe = DQE(L, q, eta, noise_AD, noise_read)
    f1 = F1(L,q);
```

```
    f2 = F2(L,q);
    f3 = F3(L,q);

    % Calculate DQE(qN) (Eq 21)
    DQE_qN = (q.*f2.*f2.*L.^2)./(noise_AD + noise_read^2 + L.^2 *((1.-f3)-(1.-f1).^2));

    % Calculate DQE(q) (Eq 24)
    dqe = DQE_qN .* eta;
end
% Variance
function sig = Variance(L, q)
    f1 = F1(L,q);
    f3 = F3(L,q);
    sig = L^2 .* ((1-f3)-(1-f1).^2);
end
```

Plots

```
function Plot1(q_scaled, dqe)
    figure
    hold on
    plot(q_scaled(1,:), dqe(1,:), '-')
    plot(q_scaled(2,:), dqe(2,:), '--')
    plot(q_scaled(3,:), dqe(3,:), '-.')
    plot(q_scaled(4,:), dqe(4,:), ':k')
    xlim([0 10000])
    ylim([0 1.2])
    legend('eta = 1', 'eta = 0.5','eta = 0.25','eta = 0.125')
    title('DQE vs Mean # q')
    ylabel('DQE')
    xlabel('q, photons')
    hold off
end
function Plot2(q_scaled, dqe, leg)
    figure
    hold on
    plot(q_scaled, dqe(1,:), '-')
    plot(q_scaled, dqe(2,:), '--')
    plot(q_scaled, dqe(3,:), ':k')
    xlim([0 3000])
    ylim([0 0.6])
    legend(leg(1), leg(2), leg(3))
    title('DQE vs Mean # q')
    ylabel('DQE')
    xlabel('q, photons')
    hold off
end
function Plot3(q_scaled, LogE, leg)
    figure
    hold on
    plot(q_scaled(1,:), LogE, '-')
    plot(q_scaled(2,:), LogE, '--')
    plot(q_scaled(3,:), LogE, ':k')
    xlim([0 5])
    ylim([0 1])
    legend({leg(1), leg(2), leg(3)},'Location','northwest')
```

```
    title('normalized pix val vs log(mean # photons/400 microns^2')
    ylabel('l, normalized')
    xlabel('logE, photons/400 microns^2')
    hold off
end
function Plot4_1(a, b, leg)
    figure
    hold on
    plot(a, b(1,:), '-')
    plot(a, b(2,:), '--')
    plot(a, b(3,:), ':k')
    legend({leg(1), leg(2), leg(3)},'Location','northwest')
    title('Variance vs normalized mean count level')
    ylabel('Variance')
    xlabel('normalized mean couint level')
    hold off
end
function Plot4_2(a, b, leg)
    figure
    hold on
    plot(a(1,:), b(1,:), '-')
    plot(a(2,:), b(2,:), '--')
    plot(a(3,:), b(3,:), ':k')
    legend({leg(1), leg(2), leg(3)},'Location','northwest')
    title('Variance vs log(mean # photons/400 micron^2)')
    ylabel('Variance')
    xlabel('log E, photons/400 micron^2')
    hold off
end
function Plot5_1(a, b, leg)
    figure
    hold on
    plot(a(1,:), b, '-')
    plot(a(2,:), b, '--')
    plot(a(3,:), b, ':k')
    legend({leg(1), leg(2), leg(3)},'Location','southwest')
    title('DQE vs log(mean # photons / 400 microns^2)')
    ylabel('DQE')
    xlabel('log E, photons/400 micron^2')
    hold off
end
function Plot5_2(a, b, c, leg)
    figure
    hold on
    yyaxis left
    plot(a(1,:), b, '-')
    ylim([0 2])
    ylabel('DQE')
    yyaxis right
    ylabel('normalized count')
    plot(a(1,:), c, ':')
    ylim([0 1])
    legend({leg(1)},'Location','northwest')
    title('DQE and mean count vs logE')
    xlabel('log E, photons/400 micron^2')
    hold off
end
```

```
function Plot_extra()
    figure
    hold on
    title('Mean pix val vs mean # photons')
    ylabel('l')
    xlabel('q, photons')
    ylim([0 L])
    xlim([0 1.5*L])
    plot(q, L*(1-F1(L,q)))
    hold off
    xline(L, ':', {'L'});

    figure
    hold on
    title('gain vs mean # photons')
    ylabel('gain')
    xlabel('q, photons')
    plot(q, L*F2(L,q))
    xlim([0 1.5*L])
    hold off
    xline(L, ':', {'L'});
    yline(1);


    figure
    hold on
    title('Variance vs mean # photons')
    ylabel('variance')
    xlabel('q, photons')
    plot(q, Variance(L, F1(L,q), F3(L,q)))
    ylim([0 L])
    xlim([0 1.5*L])
    hold off
    xline(L, ':', {'L'});


    figure
    hold on
    title('DQE vs mean # photons')
    ylabel('DQE')
    xlabel('q, photons')
    plot(q, DQE(L, q, 1, noise_AD, noise_read))
    xlim([0 1.5*L])
    hold off
    xline(L, ':', {'L'});
    yline(1, ':', {'max dqe'});
end
```