Perception Metrics in Medical Imaging

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Abstract

Detection of anomalies is one of the main aims in medical imaging. The degree to which the image achieves this purpose directly influences physicians’ diagnostic decisions. The analysis of image perception is also an important aspect of evaluating the performance of medical imaging devices. This thesis traces the development of perception metrics in medical imaging. A series of fundamental concepts and theories behind medical image perception are explained associated with the review and a structure of medical imaging concepts is derived. This structure makes readers appreciate the unity of medical imaging science and understand these fundamental concepts as part of the whole, rather than as unrelated and isolated elements. In addition, a lab exercise based on Rose model is designed to help students have a better understanding of image perception.
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List of Abbreviations

- MTF – Modulation Transfer Function
- CNR – Contrast to Noise Ratio
- ER – Effective Spatial Resolution
- FWHM – Full-Width-at-Half-Maximum
- PSF – Point Spread Function
- ACF – Autocorrelation Function
- NPS – Noise Power Spectrum
- TP – Test Patterns
- SNR – Signal to Noise Ratio
- ROC – Receiver Operating Characteristic
- C-D – Contrast-Detail
- CTF – Contrast Threshold Function
- CSF – Contrast Sensitivity Function
- MTFA – Modulation Transfer Function Area
- NEQ – Noise-Equivalent Quanta
- HVS – Human Visual Systems
- AUC – Area Under ROC Curve
- TP – True Positive
- FP – False Positive
- FN – False Negative
- TN – True Negative
- TPF – True-Positive Fraction
- FPF – False-Positive Fraction
- TNF – True-Negative Fraction
1 Introduction

1.1 Background
Detection of anomalies is one of the main aims in medical imaging. The necessary conditions are: (1) the clinical information required is contained in the image; (2) it can be interpreted by the physicians.

The degree to which the image achieves the purpose in (1) directly influences physicians’ diagnostic analysis. Only when what is contained in an image is a faithful and adequate representation of the actual content, the physicians can possibly make diagnostic decisions with a reasonable degree of certainty. However, another issue is put forward by factor (2): the physicians’ performance should be considered as well because large differences in performance have been found between different observers.

Usually physicians’ performance is not perfect and their errors can affect patient care and treatment. In order to figure out why these errors occur and what steps can be taken to reduce them, understanding the capabilities of the human visual system with respect to medical imaging is necessary. Since 1940s, various techniques of medical image perception have been developed along with the transition from the traditional film-based display to soft-copy monitor viewing of medical images, acting as an important role of assessing the performance of medical imaging devices[1][2]. The individual research fields range over mathematics, physics, physiology and psychology, including physical characteristics of imaging quality, analysis of the anatomy of the human visual system, evaluation medical imaging using observer performance, etc.

1.2 Motivation
Several articles have given introductions of medical image perception and all of them stress the importance of perception research [2-6]. However, there are two inadequacies I found in these reviews: (i) generally these articles do not contain basic objective parameters assessing image quality, which, to my best knowledge, is an essential part in perception metrics; (ii) relationships between various image quality concepts and comparisons between different perception theories are seldom discussed in these reviews. In order to improve the two shortages, I intended to trace the development of perception metrics in medical imaging using a way that readers can more easily understand. Besides the literature overview, designing a lab exercise as an aided tool can help students have a better understanding of image perception. With these intentions, I write this thesis and hope it could be useful for medical imaging study.
1.3 Thesis Outline

First, the development of perception metrics in medical imaging in the past decades is reviewed and summarized in a systematic manner. Corresponding to the two processes mentioned in Section 1.1, the review is divided into two sections: (1) Chapter 2 presents an overview of fundamental concepts which can be unified and regarded as the physical and objective parameters assessing the quality of an image. (2) In Chapter 3, the comprehensive perception models and method linking the image quality with observers’ performance are introduced; discussions about the connections and differences between each method are included.

Second, a lab exercise based on Rose Model, one of the early perception theories, is designed to help students have a better understanding of image perception (Chapter 4). With the help of my supervisor, the lab exercise was finally applied to the teaching and worked well.

In the end, Chapter 5 states the conclusion. (Figure 1-1)
2 Objective Descriptions of Image Quality

In radiology, the outmost measure of the quality of a radiologic image is its usefulness in determining an accurate diagnosis. Since the image is ultimately to be viewed by human beings, it can be stated that the only “correct” method of quantifying image quality is through subjective evaluation which is not standarizable. Developing objective image quality evaluation is therefore desirable. It provides the basis for intersystem comparisons and the repeatability lacking in subjective processes.

This chapter discusses about the fundamental objective parameters of medical image quality. Figure 2-1 illustrates the terminology used to describe image quality. The three basic components are indicated in blue ellipses: contrast, spatial resolution and noise. Then intermediate linking concepts of Modulation Transfer Function (MTF), Contrast-to-Noise Ratio (CNR), Effective spatial Resolution (ER) are indicated in the areas bridging pairs of basic concepts. Definitions and relationships between each will be explained. Readers can understand these concepts as part of the whole, rather than as unrelated and isolated elements. And there is no a hierarchy in Figure 2-1 that one imaging concept somehow is superior to another. It is the integration of them that provides an objective description of image quality.
2.1 Three basic quantities

2.1.1 Contrast

Contrast (C) is defined as the difference between the mean photon fluence in the image of the subject (\(\Phi_{OB}\)) and that outside this image (\(\Phi_{BG}\)) divided by \(\Phi_{BG}\). (Figure 2-2)

\[
C = \frac{\Phi_{OB} - \Phi_{BG}}{\Phi_{BG}}
\]  

(Figure 2-2) A model to illustrate the contrast of the subject (the light-colored circle)

In medical imaging, the contrast in an image depends on both tissues characteristics as well as different steps in the imaging processes. Figure 2-3 lists components of image contrast in different imaging systems and the relative factors.

![Figure 2-3 Components of Image Contrast](image)

1. Subject Contrast
   - 1. Attenuation Coefficient
   - 2. Subject thickness
   - 3. Incident photon spectrum

2. Detector Contrast
   - 1. Detector Type
   - 2. Film Characteristic Curve
   - 3. Spatial Response of Detector

3. Display Contrast
   - Window and level settings in electronic image display
2.1.2 Spatial Resolution
Spatial resolution refers to the size of the smallest possible detail in an image. The common way to measure spatial resolution is by the Full-Width-at-Half-Maximum (FWHM) value of the Point Spread Function (PSF). PSF is defined as the response of the system to an input of point source. It describes the blurring properties of an imaging system in the spatial domain. FWHM of PSF is the distance between the points where the intensity is half of the maximum one, quantifying the degree of blurring of the point object. The smaller FWHM is, the better resolution the imaging system has.

Figure 2-4(a) A blurred image of a point source (b) A PSF curve (red) and its FWHM.[7]

2.1.3 Noise
Following Bushberg et al. [8], the concept of noise is illustrated using isometric display (Figure 2-5). It relates to the uncertainty or the imprecision during a signal’s recording.

Figure 2-5 A low noise image is shown on the left, with increasing amounts of noise added to the “image” toward the right. [8]
Noise sources in medical imaging:

- Quantum noises (fundamental and unavoidable)
  - Factor: statistical fluctuations in the number of photons emitted from a source; the random nature of x-ray attenuation and detection processes

- Film and screen grain noise
  - Factor: non-uniform distribution and density of grains

- Amplification noise
  - Factor: generated in the transistors, or integrated circuits of an amplifier.

- Thermal noise
  - Factor: presents in electronic circuits as a result of the thermal agitation of the charges in conductor

- Quantization noise
  - Factor: in analog-to-digital conversion, the difference between the actual analog value and quantized digital value due to rounding or truncation.

Noise measure (1): Standard deviation

One measure of noise is in terms of standard deviation. For example, in an experimental setting, a noisy signal can be measured as many times as possible. After a large number of measurements, we calculate the mean and the standard deviation using the formula below.

\[
\bar{x} = \frac{1}{N} \sum_{i=1}^{N} x_i
\]

\[
\sigma^2 = \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \bar{x})^2
\]

where \(x_i\) are individual measurements; \(N\) is the number of measurements; \(\bar{x}\) is the sample mean and \(\sigma^2\) is variance; \(\sigma\) is the standard deviation, which is used to quantify noise measurement.

However, characterizing noise by the standard deviation is of limited use in medical imaging, as it does not take into account the spatial distribution of the noise variations. For example, see figure below, the histograms of the two samples result in the same mean and standard deviation, but the noise profiles are vastly different.[9]
Figure 2-6 Two samples and corresponding histograms of the intensity fluctuation distribution. \( I(x) \) is the intensity fluctuation value at point \( x \). [9]

**Noise measure (2): Autocorrelation function & Noise power spectrum**

The statistic diagram contains no information about a possible spatial correlation between the pixels. The extent of such correlation can be specified by means of the *autocorrelation function* (ACF), see Equation (2-4)

\[
ACF(\alpha, \beta) = \lim_{X,Y \to \infty} \frac{1}{2X2Y} \int_{-X}^{X} \int_{-Y}^{Y} I(x, y) I(x + \alpha, y + \beta) \, dx \, dy 
\]  

(2-4)

where \( I(x + \alpha, y + \beta) \) is the intensity fluctuation measured at a point displaced from the point \( (x, y) \) by a distance \( \alpha \) along the x-axis and a distance \( \beta \) along the y-axis. Over long distances, the autocorrelation function tends to zero. The different ACFs of the two noisy profiles in Figure 2-6 are shown in Figure 2-7. Hence, ACF provides a more complete description of the noise.
Noise power spectrum (NPS) or Wiener spectrum is a measure to specify the spatial frequency content of the noise and equals to the ensemble average of the Fourier transform squared of the intensity fluctuations, defined by:

\[
NPS(u, v) = \lim_{X,Y \to \infty} \left\{ \frac{1}{2X2Y} \int_{-X}^{X} \int_{-Y}^{Y} I(x, y) e^{-2\pi i (ux + vy)} dx dy \right\}^2
\]  \quad (2-5)

It describes the variance in amplitude as a function of the frequency components of the noise. (Figure 2-8)
A theorem relating ACF and NPS is found from the Wiener-Khintchine Theorem. [11] This theorem states that spectrum and the autocorrelation function form a Fourier transform pair:

\[ \text{NPS}(u, v) = \int_{-X}^{X} \int_{-Y}^{Y} \text{ACF}(x, y) e^{-j2\pi(ux+vy)} \, dx \, dy \quad (2-6) \]

\[ \text{ACF}(x, y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \text{NPS}(u, v) e^{-j2\pi(ux+vy)} \, du \, dv \quad (2-7) \]

The theorem tells that the power spectrum can be obtained from the autocorrelation function, an alternative method for noise power spectrum estimation.

### 2.2 Intermediate linking descriptors

Although noise, spatial resolution and contrast are the three fundamental concepts of image quality, it is obviously insufficient if an imaging device could be described and evaluated in terms of only one of the three factors. Several intermediate linking concepts are used to tie together the simple three.

#### 2.2.1 Contrast & Resolution

Resolution provides an objective measure of a system’s resolving power to details. Edge contrast determines the sharpness in the resolved detail. They aren’t good measures of image quality if taken separately (Figure 2-9).
2.2.1.1 **Linking descriptor: MTF**

A metric of image quality linking contrast and resolution is Modulation Transfer Function (MTF).

MTF is a measure of the ability of the system to reproduce image contrast at various spatial frequencies. Spatial frequencies correspond to image detail. High spatial frequency means fine image detail. Therefore, MTF combines contrast and resolution together.

For example, a phantom is composed of alternating black and white lines (line pairs) which are progressively finer. Even though those lines are still resolved through the imaging system, they progressively deteriorate in both edge clarity and contrast as they become finer (Figure 2-10). MTF quantifies how much contrast remains between white and black lines through the imaging system as a function of the spatial frequency of the object.

Assuming that:

\[ I_{\text{max}} \] is the maximum luminance for white areas; \[ I_{\text{min}} \] is the minimum luminance for black areas;
\[ C = \frac{(I_{\text{max}} - I_{\text{min}})}{(I_{\text{max}} + I_{\text{min}})} \]  

Contrast(C) is the difference in darkness between the black and the white lines;

\[ C(0) \] is the “0” frequency contrast; \( C(f) \) is the contrast at spatial frequency \( f \).

\[ \text{MTF}(f) = \frac{C(f)}{C(0)} \]

An MTF of 1.0 represents perfect contrast preservation, while values less than this mean more and more contrast is being lost — until an MTF of 0, where line pairs can no longer be distinguished regarded as the resolution limit. (Figure 2-11)

![MTF Curve](image)

**Figure 2-11 The example illustrates an MTF curve [13]**

A comparison of MTF curves from three systems is shown in the figure below.

![MTF Comparison](image)

**Figure 2-12 A comparison of 3 MTF curves: case (a) represents a system with high contrast at low frequencies but it quickly falls by increasing the frequency; In case (b), the resolution is better than (a) but the contrast is worse for low frequencies; In case (c), the system provides high contrast in different frequency and high resolution as well.**
2.2.2 Contrast & Noise
Contrast itself is not precise enough to assess the quality of a medical image, because in a noisy image the visibility of the tissue will decrease even though the true tissue contrast keeps the same.

2.2.2.1 Linking descriptor: CNR
Contrast to Noise Ratio (CNR), the name obviously tells us the role it plays: linking contrast and noise.

According to Smith & Webb’s book[14], CNR is defined by:

\[ \text{CNR}_{AB} = \frac{c_{AB}}{\sigma_N} = \frac{|S_A - S_B|}{\sigma_N} \]  

(2-8)

where \(S_A\) and \(S_B\) are signal intensities for signal producing structures A and B in the region of interest and \(\sigma_N\) is the standard deviation representing the image noise.

In Figure 2-13, different levels of noise are added to the original image. The high level of noise corresponds to a low CNR. Take the red circle area as an example, although the original contrast between the two grids does not change, high noise level leads to hardly distinguishing them. Therefore combing contrast with noise, CNR gives a better objective measure of image quality.

![](image)

(a) Original image

(b) Noise level: high(low CNR)  
(c) Noise level: middle(middle CNR)  
(d) Noise level: low(high CNR)

Figure 2-13 Visual impact of different noise levels [15].

2.2.3 Noise & Resolution
The interaction between noise and resolution exists as well.
2.2.3.1 Linking descriptor: ER

In Rudin’s book[16], spatial resolution are divided into “nominal spatial resolution” and “effective spatial resolution”. Nominal spatial resolution (i.e. dimension of the pixel) is given by the ratio of field-of-view divided by the number of voxels in each dimension; Effective spatial Resolution (ER) is defined as the smallest structure that can be detected under the specific circumstances which is influenced by the noise level.

Look at the figures below, the nominal resolution is identical for all images displayed while the effective resolution increases with enhancing noise level. Small structures (the red circle area) are difficult to detect.

![Image of three images showing the influence of noise on effective spatial resolution](image_url)

- Figure 2-14 Influence of noise to the effective spatial resolution (Figure 1.2 in Reference 16)

![Graph showing the relationship between ER and noise level](image_url)

- Figure 2-15 Effective spatial resolution, as a function of noise level.
3 Perception Methods

As mentioned in Chapter 1, besides objective process, subjective diagnosis of the physician plays an important role in medical image perception as well. There are several methods investigating the relationship between the physical characteristics of image quality and the observer’s performance, which is called psychophysical methods. In the following overview, they are divided into two major classes: (i) TP methods (ii) ROC method. See figure below.

![Diagram showing the relationship between image quality, observer's performance, and psychophysical methods.]

**Figure 3-1** Psychophysical methods linking image quality and observer’s performance

**TP** is the abbreviation of Test Pattern. TP methods mean the measurements of perception depending on test patterns. Two detection models of TP methods will be introduced.

**ROC** is the abbreviation of Receiver Operating Characteristic. It can be applied to a practical diagnostic task directly, independent of test patterns.

### 3.1 Detection models based on test patterns (TP)

#### 3.1.1 Rose Model

**3.1.1.1 Theory**

Early psychophysicists found that the quantum nature of light limits the human visual system performance. In 1932, Barns and Czerny [17] explored the influence of statistical fluctuations in photon arrival on the human visual perception. In 1942, Hecht, Shlaer and Pirenne designed an experiment to measure the minimum number of photons detectable by the retina. De Vries[18] estimated influence of light-quanta on visual acuity and contrast sensitivity. In 1946, Blackwell[19] suggested that visual contrast thresholds of the normal human observer were determined for a wide range of field brightness through a set of experiments (Figure 3-2).
Figure 3-2 Minimum contrast needed to detect a circular signal of diameter 18.2 min of arc as a function of background brightness Adapted from Fig. 10 of Reference 19

Based on Blackwell’s research, Albert Rose [20] was the first to set up an absolute scale in terms of the performance of an imaging device, which is widely known as the “Rose model” or “Rose criterion”. The absolute scale is Signal to Noise Ratio (SNR), defined as $SNR_{Rose} = C \sqrt{A \Phi_{BG}}$ (Mathematic analysis can be found in Appendix). Using the test pattern in Figure 3-3 Rose found that for reliable detection of an object, $SNR_{Rose}$ should exceed a constant $k$ value which would be expected to be approximately 5. His theory led to the general expectation that lesion detectibility should be proportional to object contrast ($C$) and to the square root of object area ($A$) and photon fluence ($\Phi_{BG}$).

To be notable, there were many important assumptions to Rose model, including:

- **Uniform Object**
- **Uniform Background**
- **Poisson-distributed noise**: The noise is the standard deviation in the number of quanta
- **Low-contrast**: Rose model neglects the fact that noise in the potential signal location has unequal variances for the signal-present and signal-absent cases and made an approximation that $\Phi_{OB} \approx \Phi_{BG}$, which limits his theory to be valid only in low-contrast signals.
3.1.1.2 Application of Rose Model

Rose model captures the trade-off between noise, object size and contrast, pointing out the effects of photon fluctuations on both human vision and electronic imaging systems. Rose’s idea was immediately applied in the medical imaging field. In 1949, Sturm and Morgan described the effect of noise on the threshold visibility of details in radiographic images using Rose’s concepts. Until now Rose model has been used as the foundation to predict the detectability of abnormalities in clinical examinations. One remarkable application, contrast detail curve analysis, is introduced below:

Contrast detail curve analysis

A number of investigators were interested in the test pattern in Rose’s paper (Figure 3-3) and developed it to evaluate object detectability at the threshold of human visibility in medical images, called the Contrast-Detail curve (C-D curve) analysis. In this method, the image of a phantom which contains disks with various diameters and thickness, similar to Figure 3-3, is observed by the radiologist then a C-D curve is generated. C-D curve is a graphical representation in which the disk thickness and diameter are plotted for each contrast-detail combination detected in the radiographic image of the phantom. (Figure 3-4)
Figure 3-4 *Left:* A contrast-detail phantom and an image of the C-D phantom. Objects that are small and have low contrast will be hard to see (lower left of C-D image), and objects that are large and have high contrast will be easy to see (upper right). The white line is the demarcation line between the circular test objects that can and can’t be seen. *Right:* System A has higher spatial resolution but lower contrast resolution, compared to system B. [8]

The right picture in Figure 3-4 shows that C-D curve analysis can be used to compare imaging systems. This method derives a set of Radiographic Contrast/Detail Phantoms which provide a quick mean for monitoring performance of the system and come into widespread clinical use, see Figure 3-5 and 3-6.

*Figure 3-5* Radiographic Contrast/Detail Phantom: *Gammex 1151* produced by Gammex Inc.[31]
3.1.2 Channel Models

The measurements based on spatial frequency analysis, another main approach of image perception, were collectively called Channel Models in this thesis. They are divided into three sections to introduce: (i) Human visual system’s sensitivity to different frequencies of patterns; (ii) Imaging system’s sensitivity to different frequencies of signals; (iii) SNR optimization using frequency domain analysis.

3.1.2.1 Frequency sensitivity of the visual system

In 1948, O.H. Schade, Rose’s contemporary and colleague, proposed the basic idea of decomposing visual images into sinusoidally modulated luminance grating[33]. In this case, the contrast threshold for detecting the sine-wave test pattern is found to be a function of the spatial frequency of the sine wave pattern (the number of cycles/light and dark bars in one degree of visual angle), called Contrast Threshold Function (CTF). The inverse of the contrast threshold (1/contrast threshold) is defined as the contrast sensitivity. A plot of the contrast sensitivity as a function of spatial frequency is known as the Contrast Sensitivity Function (CSF), first measured by Shade in 1956[34]. Based on Shade’s method, a series of papers from Cambridge (Campbell and Robson 1968[35]; Blakemore and Campbell 1969[36]; Campbell et al 1970[37]) lead to the concept of spatial-frequency channels, suggesting that visual system may contain many separated “channels”, each selectively sensitive to limited ranges of spatial frequencies, see Figure 3-7.
Figure 3-7(a) The test image produced by Campbell and Robson (Reference 38)

Figure 3-7(b) The thick curve represents the contrast sensitivity of the human visual system to a sinusoidal grating, plotted against spatial frequency. The shaded area remains invisible to us unless the spatial frequency content of the images is shifted into the visible domain. The thinner curves represent channels sensitive to a narrow range of spatial frequencies. (Figure 1 in Reference 38)
3.1.2.2 Frequency sensitivity of the imaging system

To investigate the contrast performance of an imaging system over a spatial frequency range, a familiar concept is applied: MTF, which has been introduced in Section 2.2.1.1. MTF measures the ability of the system to reproduce image contrast at various spatial frequencies.

MTFA: MTF & CTF

Conceptually, CTF and MTF are similar because they both deal with the contrast performance limitations through spatial frequency-dependent analysis. When MTF of the imaging system and CTF of the human version are plotted together (Figure 3-8), the crossover point defines the highest spatial frequency that can be detected (limiting resolution). The area on the graph between the two curves is referred to as the Modulation Transfer Function Area (MTFA) [39], which represents the amount of image information that is conveyed to the viewer. Theoretically, the greater the MTFA, the greater the information perceived by the eye. Through an intelligent way MTFA relates the purely physical parameter MTF with the observer CTF.

![Figure 3-8 MTFA (Figure 5.8 in Reference39)](image)

3.1.2.3 SNR optimization

With the development of Fourier analysis in medical imaging, a number of investigators tried to bridge the seemingly distinct Rose model based particle approach and the Fourier-based wave approach. Rose model describes noise in terms of the statistical variance in a number of photon quanta, which is inadequate (see Noise measure in Section 2.1.3). To optimize
SNR, scientists [40] suggested the Fourier-based description of SNR at a specified exposure level. Signal is described as the modulation of a sinusoidal signal and noise is expressed in terms NPS, see below:

\[ SNR^2(q, u) = \frac{\tilde{d}^2 \text{MTF}^2(u)}{NPS_d(u)} = NEQ(q, u) \]  

\[ SNR = \sqrt{NEQ(q, u)} \]  

where \( q \) is the average number of input quanta per unit area, \( \tilde{d} \) is the average number of output quanta per unit area, \( NPS_d(u) \) is the output NPS and \( \text{NEQ} \) is the Noise-Equivalent number of Quanta.

Although optimizing the description of SNR, this method kept Rose’s idea that using SNR to evaluate the performance of the imaging system.

3.1.3 Application of Channel Models

During the 1960s, Rossmann and co-workers adapted Fourier-transform & linear-system theory for use by the medical imaging community, enabling a quantitative description of signal-transfer relationships [41-46]. Specific applications of linear-systems analysis to radiographic imaging has been described by various authors [47-49]. Barrett & Swidndell [50] made a more extensive use of this approach: they applied linear-system theory to describing fundamental principles and characteristics of various imaging systems in radiography, CT, nuclear medicine, ultrasound and other areas. One application developed from the test pattern of channel models is introduced below:

Radiographic phantom

Following the examples of experiment phantoms used in Channel models (Figure 3-7), a set of test patterns for X-Ray resolution have been designed to evaluate film screen systems and magnification techniques, see Figure 3-9.
Figure 3-9 X-ray test patterns used for spatial resolution measurements [51,52]

Like the test patterns introduced in Section 3.1.1.2, these phantoms enable easy and quick quality checks of X-ray imaging chains. Rectangular, circular and high resolution line group tests with various spatial frequency ranges are available [51].

3.2 ROC method

3.2.1 Introduction

In 1960, based on statistical-decision-theory approach, Lusted [53] introduced Receiver Operating Characteristic (ROC) analysis into medical diagnostic tests. The method requires the observer not only to make yes-or-no response about the presence of pathology in an image but also to give a confidence level (test value) about each decision.

The figure below shows the number of patients with and without a disease arranged according to the value of a diagnostic test. The overlap area indicates where the test cannot distinguish the normal from disease with 100% accuracy. Then according to a cut-point (indicated by the vertical black line), above which we consider the test to be abnormal and below which we consider the test to be normal, the diagnosis results are divided into four cases, see Table 3-1.
The position of the cut-point will determine the number of true positive, true negatives, false positives and false negatives.

From the values of the different fractions, a set of statistics can be defined.

The true-positive fraction (TPF):

$$TPF = \frac{TP}{TP + FN}$$

It is also known as Sensitivity, which means probability that a test result will be positive when the disease is present, i.e. the hit rate.

The false-positive fraction (FPF):

$$FPF = \frac{FP}{TN + FP}$$

also called the false alarm rate which means a test result will be positive when the disease is not present.
The true-negative fraction (TNF):

\[ TNF = \frac{TN}{TN + FP} \]

It is also known as Specificity, which means the probability that a test result will be negative when the disease is not present.

**ROC curve**

A ROC curve is generated when Sensitivity is plotted in function of (1-specificity) for different cut-off points (or decision threshold). As the separation between normal and abnormal cases increases, the corresponding ROC curves approach the upper left corner (Example in Figure 3-11). Thus a ROC curve closed to the upper left corner corresponds to a high test accuracy.

![ROC curves](image)

*Figure 3-11 Different ROC curves corresponding to various degrees of overlap. d’ represents the degree of overlap. The smaller it is, the larger the overlap is. ROC curve labeled d’=3 shows a situation where there is large overlap between normal and abnormal cases. On contrast, the curve labeled d’=1 shows a relatively good separation between the abnormal and the normal. [55]*

**AUC in ROC curve**

The total Area Under ROC Curve (AUC) indicates the performance a diagnostic test (Figure 3-11). Larger AUC means the test with a better accuracy at various diagnostic thresholds used to discriminate cases and non-cases of disease. Equal AUCs of two tests represents similar overall performance of tests but it does not necessarily mean that the two curves are
identical. Figure 3-12 has hypothetical ROC curves of two medical tests A (red line) and B (black line) applied on the same subjects to assess the same disease. Test A and B have nearly equal area but cross each other. Comparison of the two tests’ performance depends upon specific clinical setting. For example, high sensitivity of the test is needed in diagnosing serious disease like cancer in a high risk group. In that case, test A performs better than test B. On the other hand, when diagnosing in a low risk group, the false positive rate should be low so that patients do not unnecessarily suffers pain and pays price. Therefore test B performs better than A.

![Figure 3-12 Two ROC curves crossing each other but with nearly same area: A performs better than B when high sensitivity is required while B performs better than A when low false positive rate is needed.](image)

3.2.2 Application of ROC

As each point on the ROC curve corresponds to a different criterion level, ROC is a criterion-free method and independent of the bias produced by the variation of decision criteria by the observers. This makes it easier to compare the diagnostic performance of different imaging modalities (e.g., MRI versus CT) [56]. ROC method was also used to study the effect on diagnostic accuracy of reducing patient dose[57]. Some scientists[58,59] extended the traditional two-dimensional (2D) ROC analysis by including a threshold parameter in a third dimension resulting from soft decisions (SD) and introduced its application to magnetic resonance (MR) image classification.

Excellent reviews of the ROC techniques used in medical image perception research can be found in Krupinski and Jiang (2008)[60], Hillis (2010)[61], and Tourassi (2010)[62].
3.3 Discussion

3.3.1 Rose model and Channel models

Rose model explores the relationship between the number of image quanta and perception of detail, while Channel models investigate the influence of the signal's spatial frequency over perceived image quality. Their analysis methods are quite different. However there are also connections between them.

- **Test pattern:** From the classification of this chapter, readers can find that both of these two models are depended on test patterns.

- **Threshold contrast:** Curves in Figure 3-4 and Figure 3-7 (b) show that both of the two models measure the threshold contrast for a wide and representative range of signals with the help of test patterns.

- **Human Visual System (HVS):** Furthermore, the two measurement methods both attempt to incorporate HVS characteristics with perceptual quality measures. Figure 3-13 used by Rose demonstrates the maximum amount of information that can be conveyed by various known numbers of photons. Figure 3-14 shows how different frequency bands influence the information acquired by the observer. The two sets of figures reflect the properties of HVS that the human eye's sensitivity to luminance variations depends on several factors including light level and spatial frequency [63].

- **Synthetically quantitative description of image quality:** Compared with the basic objective concepts of image quality in Section2, Rose model and Channel models combining image contrast, resolution and noise together, which can be found in the expression of $\text{SNR}_{\text{Rose}}$ and optimized SNR in Channel models.
Figure 3-13 The picture used by Rose [64], a woman with flowers, to demonstrate the maximum amount of information which can be represented with varying numbers of photons: A, $3 \times 10^3$; B, $1.2 \times 10^4$; C, $9.3 \times 10^5$; D, $7.6 \times 10^5$; E, $3.6 \times 10^5$; F, $2.8 \times 10^7$. The inherent statistical fluctuations in photon density limit one’s ability to detect features in the original scene.

Figure 3-14 Filtering by spatial frequency channels [65]
3.3.2 TP methods vs. ROC method

As psychophysical perception methods, TP and ROC both relate physical properties to observer response making subjective sensation measurable and are used to evaluate different imaging devices.

In TP methods, although the measurements consider about the subjective performance of the observer, they still apply a standard to evaluation, the *contrast threshold*. The limitation is the criterion of the threshold may vary from measurement to measurement and from observer to observer. If observers do not use a strict decision criterion and report any possible stimulus as being the signal, then they are using a lower value for the threshold than if they adopted a strict criterion and only reported that a signal was present when they were absolutely certain that they were correct. Lopez et al [66] used test patterns designed to measure contrast threshold for ultrasound images and found greater variability overall than is usually found for x-ray images. In contrast, ROC is a criterion-free method as each point on the ROC curve corresponds to a different criterion level. Using different cut-points for different clinical situations can help to minimize one of the erroneous types of test results. However, TP methods also have advantages in practical applications. The comparisons between TP and ROC are shown below:

<table>
<thead>
<tr>
<th></th>
<th>TP</th>
<th>ROC</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Advantages</strong></td>
<td>• Providing quick and convenient measurements for intersystem comparisons, evaluation of performance;</td>
<td>• Using more rigorous way to measure the detectability;</td>
</tr>
<tr>
<td></td>
<td>• No special analysis tools required, preferred for clinical application</td>
<td>• Results are more reliable and not influenced by observer’s subjective decision criterion, preferred for experimental work</td>
</tr>
<tr>
<td><strong>Disadvantages</strong></td>
<td>Measurement of contrast threshold depends on the observer’s subjective decision criterion</td>
<td>The evaluation is inconvenient, time-consuming and expensive</td>
</tr>
<tr>
<td><strong>Common</strong></td>
<td>• Both TP and ROC take into account the physical properties of the display and the psychophysical aspects of the observer;</td>
<td>• Although ROC graphs do not use noise, contrast, or resolution as dependent or independent variables, outcomes are dependent on all of these factors, the same as TP methods.</td>
</tr>
</tbody>
</table>

Table 3-2 A comparison between TP methods and ROC method
Modern medical imaging techniques rely on computer manipulation to create the final image so radiologists are viewing filmless images and more factors influence the clinical reading environment, such as optimal monitor luminance, the linearity of the display system and tone scale[67-70]. Although developed when film imaging were popular in clinics, the two groups of perception methods were still widely used nowadays according to introduction of their applications. In the next chapter, we will test Rose model in digital imaging environment, where you can see its validity when conditions are well controlled.
4 Lab Design of Rose Model

4.1 Motivation
The impression made by reading is surely not to be compared to that given by doing an experiment. Moreover, experimental teaching is an important step during the whole teaching process. An idea of applying a lab exercise of image perception to teaching activities is put forward.

As the first one to introduce an absolute scale in terms of the detective quantum-efficiency metric, Rose model has had a long history of application in both human vision and evaluation of imaging system components [72]. In this way, a lab exercise based on Rose model is performed as an introductory of medical image perception metrics for the students.

The lab exercise gives an understanding of how the Rose model can effectively be used when all the conditions and assumptions are satisfied. Students will test and discuss if the threshold of detectability introduced by Rose is consistent for different contrast and sizes of objects.

4.2 Design of the Phantom
As the key of the whole lab exercise, the design of the phantom will be introduced.

4.2.1 Requirements
From $K = SNR_{Rose} = C \cdot \sqrt{A \cdot \Phi_{BG}}$, we want to test the influence of $C$, $A$ and $\Phi_{BG}$ respectively on the $K$ value thus various sizes of targets are needed. In addition, the acquired $K$ values should range from less than 5 to more than 5 so that students could identify the Rose model threshold. Furthermore, Section 3.1.1.1 lists important assumptions in Rose model which the design should follow as well.

4.2.2 Material of the phantom

4.2.2.1 Material
Among the assumptions in Rose model, low-contrast situation is particularly important because it affects the selection of the phantom’s material.

Contrast can be expressed as:

\[ C = 1 - \exp(-\mu \cdot \Delta x) \]

where $\mu$ is the attenuation coefficient of the phantom, $\Delta x$ is the difference in thickness between the target and background.
Either high $\mu$ with small $\Delta x$ or low $\mu$ with large $\Delta x$ can obtain small $C$. However, when $\mu$ is too high, $\Delta x$ need to be quite small, which is not easy to manufacture in practice. In addition, high $\mu$ leads to a low photon fluence passing through the target in unit time, which means long acquisition time is required in order to get enough photons in the image. This is not applicable in a time-limited lab exercise. Therefore, material with low attenuation coefficient is preferred. In this lab, the *aluminum* is chosen to product the phantom due to its relatively small $\mu$ for specific energy.

### 4.2.2.2 Problem: Attenuation coefficient

In the lab, the radiation source is $^{57}$Co, which produces gamma ray with photo peak $=122$keV. Theoretically, there should be no difficulties acquiring the attenuation coefficient of aluminum from *Tables of X-Ray Mass Attenuation Coefficients offered by NIST* (National Institute of Standards and Technology). However, the practical situation is different and the value from NIST can not be applied directly. A set of experiments below are performed to prove that.

**Three experiments to test the attenuation of aluminum:**

Firstly, a flood image is acquired with $t=600\,\text{s}$; a region with area of $15\times15\,\text{pixel}$ is chosen to calculate the average photon number $\Phi_0$. (Figure 4-1(a)) Secondly, three aluminum plates with the thickness of 5mm, 10mm, and 15mm were put on the detector respectively to acquire three images ($t=600\,\text{s}$); in each image, the new average photon number $\Phi$ in the same selected region is recorded (Figure 4-1(b)(c)(d)).
Then according to $\Phi(r) = \Phi_0(r) \cdot \exp(-\mu \cdot x)$, where $x$ is thickness, the attenuation coefficients in different cases are calculated. The results are listed below:

<table>
<thead>
<tr>
<th>Thickness of the objects (mm)</th>
<th>5</th>
<th>10</th>
<th>15</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu$ (cm$^{-1}$)</td>
<td>0.245</td>
<td>0.2463</td>
<td>0.26</td>
</tr>
</tbody>
</table>

Table 4-1 Attenuation coefficients in different cases

According to the table, $\mu$ is around 0.25 cm$^{-1}$. In contrast, from NIST, the attenuation coefficient of aluminum at 122 keV is 0.421 cm$^{-1}$. The measured results are all smaller than that in NIST.

Reason analysis:

The process of attenuation involves a number of interactions, including the photo-electric effect in which the photon is effectively stopped and Compton scattering in which the photon is deflected with loss of energy. The normal attenuation coefficient, often referred to as the narrow beam attenuation coefficient, is used to estimate the loss of primary photons whether scattered or completely stopped. In practice, some of the scattered
photons are still detected within the photo-peak energy window [71] (Figure 4-2). A narrow energy window on the gamma camera can reduce the number of these scattered events that are detected. Besides, when the transmitted beam is collimated properly, the scattered photons are also prevented from reaching the detector and so are not measured. However, in this lab the collimator has been removed, which means the detector is exposed more to the scattered radiations (Figure 4-3). In that case, if the energy window width increases, more scattered radiations reach the detector. Thus, along with the unattenuated photons the scattered photons are also measured and these can lead to a smaller measured attenuation coefficient. Next, a set of experiments are conducted to test the effects of energy window width on measurements of attenuation coefficient.

![Figure 4-2 Compton scattered photons lose energy as a result of the deflection but, due to the limited energy resolution of the gamma camera the scattered photons may still be detected in the photopeak. (Figure1, Reference 71)](image)

![Figure 4-3 Scatter Radiation](image)

**Verifying experiments:**

Test attenuation coefficient when energy window width: 26%, 15% and 5%.

(Note: For width = 5%, the acquisition time is prolonged due to the reducing of the photon density.)
Here is the result:

<table>
<thead>
<tr>
<th>Width</th>
<th>26%</th>
<th>15%</th>
<th>5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>t(s)</td>
<td>600</td>
<td>600</td>
<td>1000</td>
</tr>
<tr>
<td>(\mu) (cm(^{-1}))</td>
<td>0.22-0.23</td>
<td>0.25-0.26</td>
<td>0.45-0.48</td>
</tr>
</tbody>
</table>

Table 4-2: The results of attenuation coefficient

**Comment:** When the energy window width is just 5%, the measured value is closed to the value from NIST. Thus a relatively narrow energy window helps to reduce the scattered radiation. But it does not imply the window width can be narrowed as much as possible due to the severe degradation in uniformity. In the following experiments, 15% as the window width is applied and the corresponding attenuation coefficient is 0.258 cm\(^{-1}\) on average.

### 4.2.3 Size design of the phantom

Aluminum is used to build both targets and background. An aluminum plate of thickness 5mm is regarded as the background. Nine aluminum blocks of different sizes are the targets to produce square signals with a range of sizes and contrasts (Figure 4-4).

![Figure 4-4(a) Sketch drawing of the background](image)

<table>
<thead>
<tr>
<th>No.</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>a(mm)</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>20</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>b(mm)</td>
<td>7</td>
<td>7</td>
<td>7</td>
<td>7</td>
<td>14</td>
<td>14</td>
<td>14</td>
<td>7</td>
<td></td>
</tr>
<tr>
<td>c(mm)</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>3</td>
<td></td>
</tr>
</tbody>
</table>

(c is the thickness of the objects; the dimensional accuracy of the objects is ±0.1mm)

![Figure 4-4(b) Sketch drawing of the target and the list of the sizes](image)
Figure 4-5 shows the phantom in real.

Figure 4-5 The testing pattern: an aluminum plate as the background and part of the targets

4.3 Design of the Test Procedure

Four groups of experiments are conducted to test the phantom.

$k$ can be calculated through the equation below:

$$k = C \sqrt{A \cdot \Phi_{BG}} = [1 - \exp(-\mu \cdot x_2)] \cdot \sqrt{A \cdot \Phi_0 \cdot x_1}$$  \hspace{1cm} (4-1)

where $\Phi_0$ is the fluence in the air, $x_1$ is the thickness of the background and $x_2$ is the thickness of the target.

Contrast(C) dependence in the $k = C \cdot \sqrt{A \cdot \Phi_{BG}}$

Experiment 1: Targets with the same area (A) but different thicknesses($x_2$) so they will have different contrasts after the same acquisition time.

Acquisition time $t = 180s$ ($\Phi_0 = 85$ counts/pixel). Parameter values in the equation and the calculation results are shown below:
Table 4-3 The results of different $k$ values

**Experiment 2:** Change the targets with bigger $A$.

Acquisition time $t = 180$ s ($\Phi_0 = 85$ counts/pixel).

<table>
<thead>
<tr>
<th>No.</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu$ (cm$^{-1}$)</td>
<td>0.258</td>
<td>0.258</td>
<td>0.258</td>
<td>0.258</td>
</tr>
<tr>
<td>$\Phi_0$(c/p)</td>
<td>85</td>
<td>85</td>
<td>85</td>
<td>85</td>
</tr>
<tr>
<td>$A$(mm$^2$)</td>
<td>70</td>
<td>70</td>
<td>70</td>
<td>70</td>
</tr>
<tr>
<td>$x_1$(mm)</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>$x_2$(mm)</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>$k$</td>
<td>3.6</td>
<td>5.4</td>
<td>7.1</td>
<td>8.8</td>
</tr>
</tbody>
</table>

Note: c/p is count/pixel for short.

Table 4-4 The result of different $k$ values

**Experiment 3:** Targets with different sizes but the same thickness

Acquisition time $t = 180$ s ($\Phi_0 = 85$ counts/pixel).
<table>
<thead>
<tr>
<th>No.</th>
<th>2</th>
<th>6</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu$ (cm$^{-1}$)</td>
<td>0.258</td>
<td>0.258</td>
<td>0.258</td>
<td>0.258</td>
</tr>
<tr>
<td>$\Phi_0$ (c/p)</td>
<td>85</td>
<td>85</td>
<td>85</td>
<td>85</td>
</tr>
<tr>
<td>A (mm$^2$)</td>
<td>70</td>
<td>140</td>
<td>280</td>
<td>35</td>
</tr>
<tr>
<td>$x_1$ (mm)</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>$x_2$ (mm)</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>$k$</td>
<td>5.4</td>
<td>7.6</td>
<td>10.8</td>
<td>3.8</td>
</tr>
</tbody>
</table>

Table 4-5 The result of different $k$ values

Dependence of $\Phi_{BG}$ in the $K = C \cdot \sqrt{A \cdot \Phi_{BG}}$

**Experiment4:** Try longer acquisition time in order to get bigger $\Phi_{BG}$

Acquisition time $t = 540s$ ($\Phi_0 = 265$ counts/pixel).

<table>
<thead>
<tr>
<th>No.</th>
<th>1</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu$ (cm$^{-1}$)</td>
<td>0.258</td>
<td>0.258</td>
</tr>
<tr>
<td>$\Phi_0$ (c/p)</td>
<td>265</td>
<td>265</td>
</tr>
<tr>
<td>A (mm$^2$)</td>
<td>70</td>
<td>70</td>
</tr>
<tr>
<td>$x_1$ (mm)</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>$x_2$ (mm)</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>$k$</td>
<td>6.4</td>
<td>9.5</td>
</tr>
</tbody>
</table>

Table 4-6 The result of different $k$ values

**Comment**

Through controlling different variables, the four groups of experiment test the visual threshold $\text{SNR}_{\text{Rose}}$, and shows the trade-off between noise, object size and contrast described by Rose model. They are the main experiment procedure in the student lab exercise.
4.4 Lab instructions
The structure of the instruction is shown below. The formal lab instruction is provided in Appendix 1.

4.5 Summary
In this chapter, the lab design process for Rose model is stated. In the ensuing lab exercise, the results consist with Rose’s theory. Although more than 60 years have passed, the detective quantum efficiency metric introduced by Rose is still valid when conditions are well controlled. Like Burgess mentioned in his paper[72], “Those of us who work in imaging owe a great deal to these publications(Rose), which were the product of a brilliant mind and an unerring intuition.” During this process, new findings were acquired, including the attenuation coefficient discussion.
5 Conclusion

In the wake of the development of medical imaging devices, the significance of perception research remains vital. It is the source of more efficient procedures to evaluate the new diagnostic imaging systems.

This thesis traces the development of perception metrics in medical imaging from fundamental objective parameters assessing image quality to comprehensive perception methods. Relationships between various image quality concepts and comparisons between different perception theories are discussed. The lab exercise based on Rose model acts as tool assisting students to have a better understanding of image perception. With the help of my supervisor, the lab exercise was finally applied to teaching.

It is hoped that this thesis could make students appreciate the unity of medical imaging science. They can understand these trivia concepts and theories as part of the whole, rather than as isolated elements, the same is true on other studies.
6 Reference

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http://www.svi.nl/HalfIntensityWidth Last access: 24th May, 2012


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Appendix

Lab Instruction of Rose Model (My supervisor did the actual writing)
Photon counting, SNR and the Rose model

Part I

Theoretical background

1 Introduction

A very nice introduction to the Rose model is given by Jack L. Lancaster in his hand-outs for his course Physics of Diagnostic Imaging II, available at this web address1 and it’s reported in the following for your convenience:

The Rose model named after its formulator Albert Rose, was employed in order to account for the quantized nature of X-rays or Gamma rays. It is to help determine the detectability or visibility of an object within a radioautograph.

Dr. Rose was a scientist at the Radio Corporation of America (RCA) investigating the basic operating parameters of television in the 1940’s and 1950’s. In particular, he was trying to relate levels of contrast, resolution, and noise. Isaac Newton once said, “To see over the horizon, you must stand on the shoulders of giants”. In much the same way, Rose built his model of human visual perception on the painstaking data of Richard Blackwell, a scientist who worked on visual perception studies for the United States Navy during World War II. At that time, the Navy was interested in what level of light and how large an object was required by a sailor to spot an enemy vessel at night. It is obvious that a large light is easier to see than a smaller light, and that a bright light is easier to see than a dim light. But is a large dim light easier to see than a small bright light? The Navy wanted to know the answer to this question, and provided Blackwell with funds to conduct this research.

The by-gone days of governmental largess for research are apparent in the study that Blackwell performed. For his work, he hired 20 young women and kept them housed and fed in a dormitory built close to his laboratory. For two years he had the women observe simple images of gray circles on plain backgrounds. During each observation, each woman reported whether or not she saw the circle, and in which quadrant of the projection screen it was located. They performed thousands of observation studies, and slowly out of this painstaking work emerged a pattern which related the size of the target and the contrast level between the target and background, to the level of illumination (or noise level) of the scene. The results published in graphical form by Blackwell formed the basis for the more theoretical work by Rose. The theory, outlined by Rose, basically is a probabilistic model of low-contrast threshold detection.

1If your reading a paper version of this instructions the web address is:
2 Basic definitions

Before going into a further presentation of Rose model, let me refresh some basic definitions that will be used in the following.

2.1 Photon fluence

X-ray or gamma-ray fluence $\Phi(r)$ is defined as the number of photons passing through a unit area a distance $r$ from the radiation source (see figure 1). In this lab we have an uncollimated point-like source of gammarays and therefore we have a contribution to the dependence of the fluence from source distance that is simply $\propto \frac{1}{r}$. The other important factor is what radiation has gone through. We are going to work in the approximation described in figure 1, that is $r \gg x$ so that in the case depicted in figure 1 one can write:

$$\Phi(r) = \Phi(x_0)e^{-\mu x}$$

where $\mu$ is the linear absorption coefficient of the material of thickness $x$. It is evident that the difference between $\Phi(r)$ and $\Phi(x_0)$ depends on both $x$ and $\mu$ but not, in principle, on $x_0$ (within reasonable limits).

Figure 1: A schematic view of our set up.

2.2 Contrast

Let us define (object) contrast, $C$, as:

$$C = \frac{\Phi_{DB} - \Phi_{BG}}{\Phi_{BG}}$$

where $\Phi_{DB}$ is the fluence through an object at a given distance from the source (usually at the detector) and $\Phi_{BG}$ is the fluence through the background at the same distance. The labeling object/background is arbitrary, of course. Contrast is a simple measure of how much the object sticks out of the background. In principle one could think that any finite value of $C$ would correspond to a detectable object in a given background but life is more complex than that and in the next subsections we will discuss other important parameters.

Let me point out here that contrast is a much more complex quantity than the simple definition given here might suggest. A more complete presentation of the subject can be found here²

Figure 2: Simple model for contrast definition.

2.3 Stochastic phenomena and the Poisson distribution

Emission, transport and the detection of radiation are stochastic phenomena. Radiation detection (that is a combined event involving emission, transport and interaction at the detector) obeys the

---

²If your reading a paper version of this instructions the web address is: http://nc.uthscsa.edu/personalpages/lancaster/DL.II.Chapters/DL_chap4.pdf
2.3 Stochastic phenomena and the Poisson distribution

Poisson distribution. Let me first give a standard definition of the Poisson distribution (stolen from wikipedia):

If the expected number of occurrences in a given interval is \( \lambda \), then the probability that there are exactly \( k \) occurrences (\( k \) being a non-negative integer, \( k = 0, 1, 2, \ldots \)) is equal to:

\[
f(k; \lambda) = \frac{\lambda^k e^{-\lambda}}{k!}
\]

This might not tell you so much but have a look at Poisson distributions for different values of \( \lambda \) that are plotted in figure 3.

The main properties of the Poisson distribution for our purposes are the following:

- \( \lambda \) is the expected number of occurrences (the mean)
- \( \lambda \) is also the variance of the distribution (\( \sigma^2 \))

larger \( \lambda \)  means larger variance but smaller relative spread \( \propto \frac{\sigma}{\lambda} = \frac{1}{\sqrt{\lambda}} \)

All the above features can be appreciated in the following plots:

![Poisson PDF](image.png)

Figure 3: Poisson distribution for different values of the distribution mean.
2.4 Quantum noise

In order to illustrate the concept of quantum noise in a simple manner let us make a practical example from figure 3 above: if you expect to detect 25 photons/s in a detector in correspondence to your object and 35 photons/s in correspondence to the background, you must consider that around 70% of your measurements (mean ±σ) will return a count rate in the interval 20-30 photons/s for the object and 29-41 photons/s for the background. A single measurement giving a count rate of 29 or 30 can therefore not be associated univocally with the object nor the background. If you wanted to extend you confidence interval to 95% (mean ±2σ) then you will have to consider possible values between 15 and 35 photons/s for the object and between 23 and 47 photons/s for the background. This variation in the number of counts around the expected value is intrinsic to the physics of radiation emission, transport and detection and can therefore never be eliminated.

Note that quantum noise will not give any trouble if you wanted to distinguish between λ = 5 and λ = 35 in figure 3.

2.5 Noise

On top of the quantum noise there will always be noise that comes from irregularities in the object and the background, noise in the electronics of our detecting device, oscillations in the x-ray tube kV and mA, presence of background radiation ...

Any medical imaging measurements will be affected by both quantum noise and noise.

2.6 Signal to noise ratio

From the discussion above one might intuitively understand that the visibility of an object depends on the relationship between C' and noise. What is needed is that the signal (in our example above proportional to the contrast, see section 3.1 for details) is, to some extent, above the variations due to noise. Defining precisely what to some extent means is very difficult and is the object of Rose’s research that led to the formulation of his criterium, but a starting point is to define the parameter signal-to-noise ratio SNR:

\[
\text{SNR} = \frac{\text{signal}}{\text{noise}}
\]

3 Rose model

The visibility of an object in a background is a complex phenomenon involving not only strictly technical questions but even subjective matters (e. g. visual perception) and A. Rose succeeded in capturing all of these with a very simple criterium:

if SNR ≥ 5 ⇒ object is visible.

Rose's criterium is not a water-proof law and is valid only in the low contrast regime as we shall soon see, but it is nevertheless an outstanding achievement to have been able to capture such a complex problem with such a simple equation.

3.1 A simple analysis of SNR in Rose model

In Rose original paper the SNR is indicated with the letter k and we shall retain this convention in the following. What does SNR or k depend on? From our definition of contrast one sees that C' is independent on the object size, on the other hand it is intuitive to think that the visibility of an
object is strongly dependent on the size of the object. Let us express $k$ in terms of $\Phi_{BG}$, $C$ and the size of the object $A$ in the following in order to elucidate the dependence of visibility from these 3 parameters. We refer to the case in figures 1 and 2.

Our signal will be the difference in photons counted in correspondence of the object, $N_{OB}$, and the photons counted in correspondence of the background, $N_{BG}$:

$$signal \equiv N_{OB} - N_{BG} = A(\Phi_{OB} - \Phi_{BG}) = CA \Phi_{BG}$$

where the definitions of fluence and contrast have been used to obtain the right hand side expression. The (quantum) noise is $\sqrt{N_{OB}} = \sqrt{A \Phi_{OB}}$ (overline indicates expected or mean value) and, in the case of low contrast regime (that is $\Phi_{OB} \approx \Phi_{BG}$) it can be approximated with $\sqrt{A \Phi_{BG}}$.

With the above approximation (let me repeat, valid only when the counting difference between background and object is small) the parameter $k$ (i.e. the SNR) can be expressed as:

$$k \equiv \frac{signal}{\sigma} \approx C \sqrt{A \Phi_{BG}} = Cs$$

According to the Rose model an object, in the low contrast regime, is visible if $k \geq 5$.

In this laboratory exercise you will investigate the validity of Rose criterium by varying the 3 parameters $C$, $A$ and $\Phi_{BG}$ independently from each other.

## Part II

### Laboratory exercise instructions

#### 4 Introduction

In this laboratory you will use a SPECT camera (GE Neurocam) but please keep in mind that you will be performing a transmission experiment. The radiation source is outside the object that is imaged and the collimator will be removed from the Neurocam head that's been used so that it will work in a similar way as a flat panel detector in x-ray radiography.

The camera head has a scintillator crystal that is NaI and photomultiplier tubes matrix with Anger logic circuit for events positioning. Let me repeat that in this case, since we are doing a transmission experiment, the direction of the gamma rays is known and no collimator is used at the scope. The field of view at the camera head is divided in $256 \times 256$ px.

In the instructions you will find questions that are highlighted by being in **red and boldface**, those questions must be answered in your laboratory rapport. Your report should also contain a description of the experiment performed and a brief description of the Rose model. Include even the images taken. There are even preparatory questions that you should try to answer before you perform the experiment. Those are highlighted by being in **blue and boldface** and by means of a bookmark on the side margin like the one on the right here.

#### 5 Correction matrix

Ideally we should perform this experiment with a flood source providing a uniform fluence all over the detector. Of practical reason are we forced to use instead a point source that is going to be placed
at a relatively large distance so that the flux can be, in first approximation, considered to be uniform. It is clear, however, that the flux is not going to be perfectly uniform: can you list all of the reasons why that is so?

In order to regain uniformity you are going to generate a correction matrix, that is a matrix that corrects for the fact that your detector response to a uniform radiation field is not uniform. Start your experiment by positioning NeuroCam's head 3, without collimator, perfectly horizontal in the bottom position. Put then the source holder in position (see figure) and place the 57Co-source inside the holder.

In order to obtain an intrinsic flood image and calculate the uniformity correction matrix do the following (Refer to Appendix A: how to use the Neurocam for issuing indicated commands):

1. With the source located at the fixed position (see fig. 4) wait for 1 minute in monitor mode. Is the image forming on the monitor uniform. (Use the Tab-key to show head 3)?

2. You might have an explanation for the relatively higher brightness in the center of the image but why are the edges of the image even brighter than the centre?

3. Press F4 and choose protocol #8: "Static", 2Dgammas.

4. Set patient name and number.

5. Go to spectrum mode with F2 and check that width and position of the energy window are ok.

6. Set the flag "yes" on discrimination mask and see how the edges are cut off the image.

7. Set "Termination" to 600 seconds (this is the image acquisition time)

8. Start acquisition with F5, wait for the spectrum to stabilise and press F5 again

9. Choose "yes" on the "correction mask"

10. Choose acquisition time 600 seconds and start acquisition. When the acquisition terminates press F7 to store the image.

---preparatory question #1

---warm up & calibration

---Figure 4: Positioning of the source holder for determining correction matrix.

---option in order to cut off the edges.

---Let me point out once more that, in this case, we will correct both for the non-uniformity of the detector response and for the non uniformity of the radiation field.
11. Transfer data from the Neurocam computer to a PC. (see Appendix A & B for detailed instructions)

12. Use this image and the matlab code (BildHcr.m) provided in Appendix C to build a correction matrix.

13. Check this matrix both visually by plotting the image and by looking at the different weight value of each pixel.

14. Describe the correction matrix and its function

6 Compare images with or without correction.

1. With the same set up as before acquire an image with acquisition time 300 s.

2. Transfer image file to PC and use codes in Appendix D (noHcr.m & testMODEL.m) to visualise the image with and without uniformity correction. Set “Jet” in “Colormap” to see the difference more clearly.

3. Describe the differences in the images and comment on that.

4. Note the average pixel count for 300 s acquisition and estimate Ψ_{1/2} per pixel per s.

7 Poisson distribution

1. Acquire a flood image as in previous steps with at least 1800 s acquisition time. During those 1800 s start dealing with next step 2.

2. Open the MATLAB program called poisson(Appendix E) on the PC. Look at the code and try to understand what it does. Discuss it within the group and with your lab-assistant. If you still have a lot of time to go for the acquisition to be ready, start doing point 1 in section 8.1 “Contrast dependence”.

3. Transfer the data from Neurocam to the PC.

4. Run the program (type in your data file name!) and you will get two plots. What do you learn from these plots?
Chapter 8: Checking Rose model (at last!)

You will be using nine Aluminium blocks (dimensions specified in Table 1) and one 5 mm-thick Aluminium plate to be used as substrate for this part of the laboratory. Assume a linear attenuation coefficient of 0.2 cm\(^{-1}\) for those objects.

<table>
<thead>
<tr>
<th>object #</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>a (mm)</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>20</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>b (mm)</td>
<td>7</td>
<td>7</td>
<td>7</td>
<td>7</td>
<td>14</td>
<td>14</td>
<td>14</td>
<td>14</td>
<td>7</td>
</tr>
<tr>
<td>c (mm)</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>3</td>
<td>3</td>
</tr>
</tbody>
</table>

Table 1: Al-blocks dimensions. What is referred to as “thickness” in the instruction is indicated with c in this table. The dimensions are given with accuracy ±0.1 mm.

Calculate the contrast of objects 1-9 when they are placed on the platform. (The contrast object-platform).

8.1 Contrast dependence

Object thickness is changed, object area and acquisition time are kept constant \(\Rightarrow\), \(C\) (contrast) changes, \(A\) and \(\Phi_{BG}\) remain the same.

1. calculate \(C\) and \(k\) for objects 1-7, assuming an acquisition time of 300 s
2. put objects 1, 2, 3 and 4 on the substrate and on head 3.
3. set acquisition time to 300 s and acquire an image
4. transfer image file to PC and read it in Matlab (see Appendix B and Appendix D -testMODEL.m)
5. note which of the objects are visible
6. is the experimental result consistent with Rose model?
7. repeat points 2-6 with objects 5, 6 and 7

Comment on the results of this test.

8.2 Size (area) dependence

1. calculate \(C\) and \(k\) for objects 2, 6, 8 and 9 assuming an acquisition time of 300 s
2. put objects 2, 6, 8 and 9 on the substrate and on head 3.
3. set acquisition time to 300 s and acquire an image
4. transfer image file to PC and read it in Matlab
5. note which of the objects are visible
6. is the experimental result consistent with Rose model?

Comment on the results of this test.
8.3 Dependence on the number of counts ($\Phi_{BG}$)

1. calculate $C$ and $k$ for objects 1 and 2 assuming an acquisition time of 600 s
2. put objects 1 and 2 on the substrate and on head 3.
3. set acquisition time to 600 s and acquire an image
4. transfer image file to PC and read it in Matlab
5. note which of the objects are visible
6. is the experimental result consistent with Rose model?

Comment on the results of this test. Summarise the results of the 3 sets of experiments, what is the visibility of an object depending on? With which parameters can you play when doing clinical examinations?
A  Operating Neurocam

A.1  Switch on

1. Switch on the gantry power
2. Switch on the monitor and the Neurocam computer
3. The data acquisition program starts automatically. To start the program from DOS prompt type **bits** (for example after you have exit the acquisition program for transferring files to PC).

A.2  Switch off

1. Access the main menu by pressing ESC as many times as needed
2. Press **F10** – Mainten.
3. Press **F10** – Shutdown (it means only quit the program!)
4. Press **F7** – Confirm
5. Now you should be at DOS prompt and you can switch off the computer, monitor and gantry.

A.3  Load and execute 2DGammacameraresolut protocol

1. Go to the main menu by pressing ESC as many times as needed
2. Press **F6** – Protocol
3. Select protocol **2DGammacameraresolut** from the list and press Enter
4. Press **F4** – P. Execute
5. Type the patient id (any characters) and patient name
6. Choose yes in the correction mask option
7. Set the acquisition time to desired value
8. Press **F5** – Continue
9. Press **F5** – Start
10. At the end of the acquisition, press **F10** - Mainten and **F10** - Shutdown. The image data will be stored on hard-disk.
11. If you want to transfer data to PC press **F7** - Confirm and follow the instructions in Appendix B

A.4  Energy window settings

The energy window size and offset can be changed by typing in actual numbers or by going into the spectrum display mode **F2-Spc-Img** and window setting **F3-Window**. With the up/down arrow keys the window size can be changed. The **CTRL + left/right arrow keys** set the offset of the window.
B  Transfer files between GE Neurocam SPECT computer and another PC via serial port

The Neurocam computer will be in the following called simply Neurocam, the computer (OS Windows) to transfer data to will be called just PC.

1. Connect the Neurocam computer and the PC with null modem cable (plug the cable into the RS232 connectors of the computers).
2. Start both the Neurocam computer and the PC.
3. Start the hyperterminal program in the PC. (Start menu > Accessories > Communications > Hyper Terminal).
4. Open the “Lab.h” preset in the hyperterminal (File > Open).
5. Start the term90.exe in the Neurocam computer. It is located in the C:\NC folder.
6. Enter the following commands in the DOS command prompt:

```c:
cd \NC
term90```

7. Press the ALT+F buttons in the Neurocam computer. This opens the File menu of the term90 program.
8. Select the “Upload” menu item and the “ZMODE” protocol.
9. Select the file in the file selection window what you would like to transfer. The transfer starts automatically after the file selection. The program transfers only one file per time.
10. Press ALT+F to enter the menu and choose the “Exit” item to leave the data transfer program. The PC stores receives data files in a predefined folder (Desktop\Received). Note that the Neurocam stores the data files in the directory D:\. This is the current directory in the file selection window. The name of the data files starts with “DS00” followed by a four digit number. The highest number contains the last data of the last acquisition. The extension is .001 or .002 or a three digit number between 001 and 999.
11. If you need to go back to 2DGammacameraresolution protocol after transferring the data, press the ALT+X buttons in the Neurocam computer, choose yes to exit the program. Then enter the following commands in the DOS command prompt:

```cd ..
bts```
C  Build a correction matrix

(All the programs below are in the following directory:

C:\Users\Lab\Desktop\NeurocamData)

Build1cr.m

% Correction matrix with T=600s
clear;
close all;
%read the file which is obtained without objects
filename='DS003062_001'; %for 600s
fid=fopen(filename,'r');
for y=1:256
for x=1:256
C20(x,y)=fread(fid,1,'uint16');
end
end
%build the Correction Matrix
avg=sum(sum(C20))/(200*172); % get the average value of the matrix
for i=1:256
for j=1:256
if C20(i,j)>0.01
Hcr(i,j)=avg./C20(i,j);
else
Hcr(i,j)=1; % the correction matrix does not do any change to the elements whose value in the original matrix is zero
end
end
end
end
D Read files without and with correction matrix

noHcr.m

```matlab
% read the data file without the correction matrix
clear;
filename='DS00###.###'; % input the filename
fid=fopen(filename,'r');
for y=1:256 % number of projection pixels in y
  for x=1:256 % number of projection pixels in x
    C(x,y)=fread(fid,1,'uint16');
  end
end
figure,imagesc(C),colormap(gray);
```

testMODEL.m (read the file with Hcr)

```matlab
% Correction matrix with T=600s
clear;
close all;
% read the file which is obtained without objects
filename='DS00###.###'; % for 600s
fid=fopen(filename,'r');
for y=1:256
  for x=1:256
    C20(x,y)=fread(fid,1,'uint16');
  end
end
% build the Correction Matrix
avg=sum(sum(C20))/(200*172); % get the average value of the matrix
for i=1:256
  for j=1:256
    if C20(i,j)>0.01
      Hcr(i,j)=avg./C20(i,j);
    else
      Hcr(i,j)=1; % the correction matrix does not do any change to the elements whose value in the original matrix is zero
    end
  end
end
% read the file with Hcr
filename='DS00###.###'; % input the filename
fid=fopen(filename,'r');
for y=1:256
  for x=1:256
    C(x,y)=fread(fid,1,'uint16'); % matrix C keeps the initial data of the image
```
end
end

Crl=Hcr, 'C;
figure, imagesc(Crl), colormap(gray);
avg2=sum(sum(Crl))/(200*172);
E Poisson distribution

poisson.m

% test whether the photon distribution is corresponding to Poisson
% distribution
clear;
close all;

filename='DS003072.001'; % input the image used to build the correction matrix
(t=200s)
for y=1:256
for x=1:256
C20(x,y)=fread(fid,1,'uint16');
end
end
% build the Correction Matrix
avg1=sum(sum(C20))/(200*172); % get the average value of the matrix
for i=1:256
for j=1:256
if C20(i,j)>0.01
Hcr(i,j)=avg1./C20(i,j);
else
Hcr(i,j)=1; % the correction matrix does not do any change to the elements
whose value in the original matrix is zero
end
end

filename='DS00###.###'; % input the filename which you test
fid=fopen(filename,'r');
for y=1:256
for x=1:256
C(x,y)=fread(fid,1,'uint16');
end
end

Crl=Hcr.*C; %Crl=C;
figure,imagesc(Crl),colormap(gray);
C2=Crl(108:147,108:147); % choose a square of the image to test the poisson
distribution
CC=reshape(C2,1,40*40);

Avg=sum(CC)/1600 % get the average value
AvgPoi=poissfit(CC) % returns the maximum likelihood estimate of the parameter
of the Poisson distribution
sigma=std(CC) % get the standard deviation

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