Detector DQE and Task-Based Observer Performance

R.M. Gagne, A. Badano, J.S. Boswell, B.D. Gallas, R.J. Jennings, K.J. Myers, P.W. Quinn
Office of Science and Engineering Laboratories
FDA/CDRH

Outline

• Framework for task-based assessment
• Object models
– SKE/BKE imaging tasks and beyond
• Descriptions of imaging performance (DQE)
• Connection of DQE/NEQ to task-based assessment
• Examples of quantitative assessment
• Conclusion

Quantitative assessment of image quality must consider:

- Object models
- Imaging hardware \( H \)
- Noise (quantum noise, electronic noise, ...)

Ideal Observer
- Computes test statistic, \( t(g) \)
- Given, \( g \), makes inference about object, \( f \)
- Determines FOM from statistics of \( t(g) \)

Imaging task
- Detection, localization, characterization, estimation

What are useful models of objects for quantitative system evaluation?

Objects: \( f = f_s + f_b \)
Data: \( g = H f + n \)

SKE/BKE Imaging Tasks

Objects: \( f = f_s + f_b \)
- Signal with known size, shape, amplitude and location
Data: \( g = \Delta s + b + n \)
- Uniform and statistically known background
Data: \( g = b + n \)
SKE and BKE and reality!

Objects: \( f = f_s + f_b \)

- Signal location and amplitude uncertainty
- Anatomical structures (lumpy backgrounds)

MIB Simulation

Background Known Statistically (BKS)

Lumpy background

\( f(r) = \sum_{i=1}^{n} f_i(r - r_i) \)

Clustered lumpy background

\( f(r) = \sum_{i=1}^{n} \sum_{j=1}^{k} f_j(r - r_{ij} - R_{ij}) \)

MIB Imaging Phantoms

- Experimental set-up for collecting signal data
- Experimental setup for collecting non-uniform random background data

MIB

High-resolution images of actual objects

High-resolution images of the thorax and the frequency components in signals

Christoph.hoeschen@medizin.uni-magdeburg.de

Outline

- Framework for task-based assessment
- Object models
  - SKE/BKE imaging tasks and beyond
- Descriptions of imaging performance (DQE)
  - Connection of DQE/NEQ to task-based assessment
  - Examples of quantitative assessment
- Conclusion

What are meaningful metrics for the CD mapping model (very fine pixels)?

- Detective Quantum Efficiency (DQE) as summary measure
  - spatial frequency domain
  - assumptions (LSIV and stationarity)
- Gray scale transfer, resolution, noise and cost (patient dose or imaging time)
- Grounded in statistical decision theory (SDT)
  - task based
Detective Quantum Efficiency
Transfer of information in terms of SNR

\[ \text{DQE}(v) = \frac{\text{SNR}_{\text{out}}^2(v)}{\text{SNR}_{\text{in}}^2(v)} \]

Noise Equivalent Quanta

\[ \text{NEQ}(v) = G' \text{MTF}^2(v) / \text{NPS}(v) \]

- G, gray-scale transfer
- MTF(v), resolution
- NPS(v), noise
- Q, input quanta (cost)

Outline
- Framework for task-based assessment
- Object models
  - SKE/BKE imaging tasks and beyond
- Descriptions of imaging performance (DQE)
- Connection of DQE/NEQ to task-based assessment
- Examples of quantitative assessment
- Conclusion

Ideal Observer
1. Given image data, \( g \).
2. Decide which hypothesis (\( H_1 \) or \( H_2 \)).
3. Use Bayes theorem to form likelihood ratio, \( L \), as optimal decision scalar.
   \[ L = \frac{p(g|H_2)}{p(g|H_1)} \]
   - linear, shift invariant imaging system
   - signal and background known exactly (SKE/BKE)
   - additive, zero-mean, Gaussian distributed noise
   - low-contrast signal

Ideal Observer’s FOM for SKE/BKE tasks in Gaussian noise

\[ \text{SNR}_{\text{r}}^2 = \Delta s' K_n^{-1} \Delta s \]

Upper bound for human and machine performance!!!

Origin of NEQ/DQE approach!!!

Connection to DQE/NEQ
Spatial Domain:
\[ \Delta s = H f_s \]

- \( f_s \), Expected Input Signal
- \( H \), System Transfer Function

\[ \text{SNR}_{\text{i}}^2 = f_s' (H' K_n^{1/2} H) f_s \]

Image noise referred to object domain\(^1\) \( = \text{NEQ}(v) \)

Spatial Frequency Domain (previous assumptions, stationary noise and continuous mathematics!)

\[ \text{SNR}_{\text{i}}^2 = G' \int |F_s(v)|^2 \text{MTF}^2(v) dv \]

- \( G' \text{MTF}^2 \), Image noise referred to object domain \( = \text{NEQ}(v) \)

"Our old friend the prewhitening matched filter"

Exposure at detector close to optimum for film-screen (11 mR)

Image of spiculated mass at center of breast

- G, gray-scale transfer
- MTF(v), resolution
- NPS(v), noise
- Q, input quanta (cost)
Outline

• Framework for task-based assessment
• Object models
  – SKE/BKE imaging tasks and beyond
• Descriptions of imaging performance (DQE)
• Connection of DQE/NEQ to task-based assessment
• Examples of quantitative assessment
• Conclusion

Examples of quantitative assessment

• Basis for observer SNR
  – wholly on empirically determined parameters
  – simulated image formation with validation of end results
• Spatial or spatial frequency domains
  – assumptions
• Connection to DQE/NEQ

SKE/BKE Imaging Tasks – Digital Mammography

Approach (15 images, total mAs = 1569)

• Estimate a row of covariance matrix from the image data ($K_n$)
  – several hundred samples per image
• Estimate expected difference signal ($\Delta s$) from the image data
  – one sample per image
• Calculate SNR using “bootstrapping” techniques
  $$SNR^2 = \Delta s^4 K_n^{-1} \Delta s$$

Approach (GE 2000D)

• SNR, as a function of mAs for all specks in group 4 (0.24 mm) of ACR/MAP
  – range of about 7 to 2
• Difference of 30 % between specks within a group
  – overlap between groups (not shown)

SKE/BKE Imaging Tasks – Digital Fluoroscopy

Approach

• Estimate observer SNRs using spatial-temporal noise power spectrum (NPS)
  – noise stationarity assumption
• Calculate unbiased SNR
  $$SNR = \sqrt{\frac{\bar{N}(i) MTF^2}{\overline{W}(i)}}$$

SKE/BKE Imaging Tasks (Thomson FPI)

Approach

• Estimate a row of covariance matrix from the image data ($K_n$)
  – several hundred samples per image
• Estimate expected difference signal ($\Delta s$) from the image data
  – one sample per image
• Calculate SNR using “bootstrapping” techniques
  $$SNR^2 = \Delta s^4 K_n^{-1} \Delta s$$

Impact of signal size, location, and pixel fill-factor on detectability?\textsuperscript{18}

- Simulation of image formation
  - depth dependent PSFs (GdOS) using Monte Carlo for light transport within phosphor\textsuperscript{20}
  - Set of noise and signal plus noise images
    - signals: spherical calcifications (50µm - 400 µm dia)

- Fill-factor: \(\text{photo-sensitive area} / \text{pixel area}\)

Simulation of Image Formation

- A. Incident x rays (polychromatic)
- B. Depth of Interaction
- C. Amplification
- D. Optical scatter and escape
- E. Detection by pixels

Fill Factor Efficiency

- 75 µm spherical calcification
  - 25 positions (red)
- Efficiency as \(\text{SNR}^2 / <\text{SNR}^2(100\% \text{ fill}) \rangle\) versus fill factor (DQE?)

Shift Variant Imaging\textsuperscript{21-25}

- Observer SNR
  - ideal, if possible, or ideal linear (Hotelling)\textsuperscript{26-28} as next best thing
- Signal and/or background only known statistically (not exactly)\textsuperscript{29-31}
  - clustered lumpy background
  - Hotelling observer

Beyond SKE/BKE imaging tasks!

- Observer SNR
  - ideal, if possible, or ideal linear (Hotelling)\textsuperscript{26-28} as next best thing
- Signal and/or background only known statistically (not exactly)\textsuperscript{29-31}
  - clustered lumpy background
  - Hotelling observer

Spatial Domain

\[\Delta S' = H \cdot K_b \cdot H + K_s \cdot \Delta S\]

- \(K_b\): Background structure noise

Spatial Frequency Domain

\[G(x) / \int MTF(x) \cdot W_b(x) \cdot W_s(x) \, dx\]

- \(W_b(x)\): Background Structure

Conclusions

- Quantitative approaches available particularly for DR/DF/CT and SKE/BKE imaging tasks
- Observer FOM provides means for system performance assessment and optimization
  - bounds on human performance
- Connection to DQE/NEQ
- Lots to be done to move away from SKE/BKE imaging tasks
References:

6. Christoph.hoeschen@medizin.uni-magdeburg.de

References:


References:


References: