

IQmodelo: Statistical software for task-based image quality assessment with model observers

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- Public domain statistical analysis software for task-based image quality assessments with model observers
- Compatible with MATLAB® release R2007b and newer, some functions require Statistics Toolbox™
- <http://code.google.com/p/iqmodelo/>

The screenshot shows the Google Code project page for IQmodelo. The page has a blue header with the project name and a search bar. Below the header, there are tabs for Project Home, Wiki, Issues, and Source. The main content area is divided into two columns. The left column contains project information such as the code license (Other Open Source), labels (statistics, imaging, FDA, CDRH, FDA-CDRH, OSEL, DIAM, DIDS), members (adam.voun_@gmail.com), and external links (MFMG, assessment of classifiers). The right column contains a summary of the project, a link to the zip file of the full package, a direct access to the repository contents, and a section for software methods. The software methods are divided into Parametric Methods for Linear Observers and General Methods. The Parametric Methods include Channelized Hotelling Observers, Channelized Hotelling Observers with known difference of class means, Known-template linear observers, and Known-template linear observers with known difference of class means. The General Methods include Nonparametric ROC analysis for fixed readers, Nonparametric LROC and EROC analysis for fixed readers, Binomial proportions for fixed readers, and ANOVA-based multi-reader multi-case analysis for random readers. There is also a Demos section with a link to a list of demos.

iqmodelo
Statistical Software for Image Quality Assessment with Model Observers

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Code license
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See source for details

Labels
statistics, imaging, FDA, CDRH, FDA-CDRH, OSEL, DIAM, DIDS

Members
adam.voun_@gmail.com

Links

External links
[MFMG](#)
[assessment of classifiers](#)

Summary

The IQmodelo package consists of statistical software for task-based image quality assessments using mathematical model observers. All software is written for MATLAB. IQmodelo was developed at the U.S. Food and Drug Administration, Center for Devices and Radiological Health.

[Zip file of full package](#)
[Direct access to repository contents](#)

Software

Parametric Methods for Linear Observers

- [Channelized Hotelling Observers](#)
- [Channelized Hotelling Observers with known difference of class means](#)
- [Known-template linear observers](#)
- [Known-template linear observers with known difference of class means](#)

General Methods

- [Nonparametric ROC analysis for fixed readers](#)
- [Nonparametric LROC and EROC analysis for fixed readers](#)
- [Binomial proportions for fixed readers](#)
- [ANOVA-based multi-reader multi-case analysis for random readers](#)

Demos

- [List of demos](#)

Overview of Contents

- Parametric methods for linear observers
 - useful for ROC assessment of known-location detection/discrimination tasks
 - “exact” confidence intervals
 - channelized Hotelling observers
 - channelized Hotelling observers with known difference of class means
 - known-template linear observers
 - known-template linear observers with known difference of class means
- General methods
 - relaxed assumptions, approximate confidence intervals
 - nonparametric ROC, LROC, and EROC analysis for fixed readers
 - nonparametric analysis of binomial proportions for fixed readers
 - ANOVA-based multi-reader multi-case analysis for random readers
- Demos
- User manual – complete list of functions and references

Parametric Methods: channelized Hotelling observers

- each image multiplied with channel matrix to get channel output vector
- general case:
 - Wunderlich et al., IEEE Trans. Med. Imag., 2015
 - assumptions: channel outputs for signal absent and signal-present images follow multivariate normal distributions with common covariance matrix
 - typically satisfied for known-location signal detection/discrimination
- known difference of class means:
 - Wunderlich and Noo, IEEE Trans. Nucl. Sci., 2013
 - additional assumption: difference of means for signal-present and signal-absent channel outputs is known
 - reconstruction of high-dose data may yield accurate approximation

Parametric Methods: known-template linear observers

- ratings produced by taking inner product of template and image
- general case:
 - Wunderlich and Noo, Med. Phys., 2011
 - assumptions: ratings for signal absent and signal-present images are normally-distributed with common variance
 - typically satisfied for known-location signal detection/discrimination
- known difference of class means:
 - Wunderlich and Noo, IEEE Trans. Nucl. Sci., 2012
 - additional assumption: difference of means for signal-present and signal-absent ratings is known
 - reconstruction of high-dose data may yield accurate approximation

Nonparametric Methods: fixed observers

- ROC
 - Mann-Whitney (trapezoidal) AUC point estimates
 - variance/covariance analysis: DeLong et al., Biometrics, 1988
- LROC
 - generalization of Mann-Whitney and DeLong methods
 - Wunderlich and Noo, IEEE Trans. Med. Imag., 2012
- EROC
 - generalizes LROC to combined detection and estimation tasks
 - Wunderlich and Goossens, SPIE J. Med. Imag., 2014
- Binomial proportions
 - examples: probability of correct decision in MAFC task, probability of correct localization in LROC task
 - Noo et al., Proc. SPIE Med. Imag. Conf., 2013

- Obuchowski-Rockette method with Hillis' degrees of freedom (ORH method)

References:

Obuchowski and Rockette, Commun. Stat. Simulat. 1995

Hillis, Stat. Med. 2007, 2014

- applicable to any figure of merit
- requires fixed-reader covariance matrix that can be estimated with functions described previously for nonparametric ROC, LROC, EROC, and MAFC analysis

Confidence Interval Coverage Parameters

The analysis functions return $1 - \alpha$ confidence intervals, where

$$\alpha = \alpha_1 + \alpha_2$$

α_1 : controls lower bound

α_2 : controls upper bound

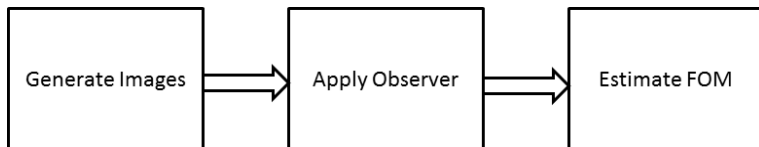
Examples:

- 2-sided 95% interval: $\alpha_1 = \alpha_2 = 0.025$
- 1-sided 95% interval: $\alpha_1 = 0.05, \alpha_2 = 0$

List of Demos

- known-location signal detection, ROC analysis
 - demo1a.m : one imaging scenario, 2-sided CIs
 - demo1b.m : same as demo1a, but with 1-sided CIs
 - demo2a.m : two imaging scenarios, 2-sided CIs
 - demo2b.m : same as demo2a, but with 1-sided CIs
- unknown-location signal detection, LROC analysis
 - demo3.m : one imaging scenario
 - demo4.m : two imaging scenarios

Demo Structure



Because each demo presents performance estimates obtained from a single random data set, the results

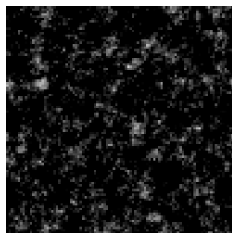
- are subject to statistical variations
- do not justify general conclusions

Demos 1 and 2: Setup

- **Task:** known-location signal detection
- **Observer:**
 - known-template linear observer
 - template: uniform disk roughly same size as signal
 - channelized Hotelling observer (CHO)
 - 3 DOG channels
 - 40 Gabor channels
- **Figure of merit:** area under ROC curve (AUC)

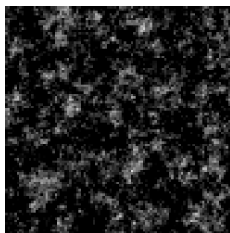
Demos 1 and 2: Images

- image size: 96×96
- colored gaussian noise background following power-law model
 - common noise component across imaging scenarios \Rightarrow correlation
- gaussian signal added at center
- specified set of seeds for random number generator \Rightarrow same results
- 150 signal-absent images, 150 signal-present images



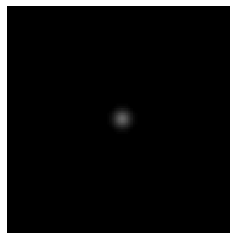
signal absent

grayscale: [0, 50]



signal present

grayscale: [0, 50]



signal

grayscale: [0, 25]

```

demo1a
----- demo 1a -----
computing lesion-absent images (m=150) ...
computing lesion-present images (n=150) ...

Displaying two-sided 95% confidence intervals for AUC:

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
fixed template linear observer:
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
2AFC estimates:

p =

    0.7933

p_CI =

    0.7208    0.8509

nonparametric (Mann-Whitney) estimates:

AUC =

    0.8068

AUC_CI =

    0.7532    0.8511

```

Demo 1a results

observer	method	point estimate	95% CI (2-sided)
disk-template	2AFC	0.793	[0.721, 0.851]
disk-template	Mann-Whitney-DeLong	0.807	[0.753, 0.851]
disk-template	parametric	0.805	[0.754, 0.850]
disk-template	parametric known-means	0.783	[0.765, 0.802]
CHO-DOG	parametric	0.810	[0.757, 0.853]
CHO-DOG	parametric known-means	0.794	[0.775, 0.813]
CHO-Gabor	parametric	0.890	[0.819, 0.907]
CHO-Gabor	parametric known-means	0.880	[0.860, 0.900]

Demo 1b results

observer	method	point estimate	95% CI (1-sided)
disk-template	2AFC	0.793	[0.734, 1]
disk-template	Mann-Whitney-DeLong	0.807	[0.763, 1]
disk-template	parametric	0.805	[0.763, 1]
disk-template	parametric known-means	0.783	[0.768, 1]
CHO-DOG	parametric	0.810	[0.766, 1]
CHO-DOG	parametric known-means	0.794	[0.778, 1]
CHO-Gabor	parametric	0.890	[0.827, 1]
CHO-Gabor	parametric known-means	0.880	[0.863, 1]

Demo 2

- Compare two fixed imaging scenarios with confidence interval for $AUC_B - AUC_A$
- Same signal and noise statistics for each scenario
- Common noise component across scenarios \Rightarrow correlated results
- For the parametric methods,
 - known-template, known difference of class means method provides accurate CI for AUC difference (assumes same correlation for signal-absent and signal-present ratings)
 - other parametric methods rely on Bonferroni inequality to obtain (overly) conservative confidence intervals (see appendix of manual)
- The nonparametric methods give accurate confidence intervals for AUC difference, but do not utilize known difference of class means

Common one-sided hypotheses

Non-inferiority test: ($\delta = \text{non-inferiority margin}$)

$$H_0: \text{AUC}_B - \text{AUC}_A \leq -\delta$$

inferiority

$$H_1: \text{AUC}_B - \text{AUC}_A > -\delta$$

non-inferiority

- used to assess “substantial equivalence”

Superiority test: ($\delta = 0$)

$$H_0: \text{AUC}_B - \text{AUC}_A \leq 0$$

non-superiority

$$H_1: \text{AUC}_B - \text{AUC}_A > 0$$

superiority

For either test:

- Can evaluate with one-sided $1 - \alpha$ intervals of the form $[\Delta\text{AUC}_L, 1]$ by setting $\alpha_1 = \alpha$, $\alpha_2 = 0$
- For a given α , one-sided intervals are more efficient than two-sided intervals

Demo 2a results

observer	method	\widehat{AUC}_A	\widehat{AUC}_B	95% CI (2-sided)
disk-template	2AFC	0.793	0.827	$[-0.054, 0.121]$
disk-template	Mann-Whitney-DeLong	0.807	0.791	$[-0.080, 0.049]$
disk-template	parametric	0.805	0.784	$[-0.134, 0.091]$
disk-template	parametric known-means	0.783	0.787	$[-0.022, 0.030]$
CHO-DOG	parametric	0.810	0.778	$[-0.147, 0.081]$
CHO-DOG	parametric known-means	0.794	0.789	$[-0.047, 0.038]$
CHO-Gabor	parametric	0.890	0.908	$[-0.072, 0.119]$
CHO-Gabor	parametric known-means	0.880	0.900	$[-0.025, 0.065]$

Demo 2b results

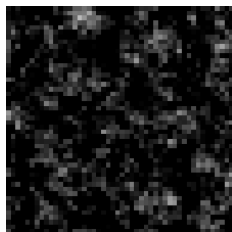
observer	method	\widehat{AUC}_A	\widehat{AUC}_B	95% CI (1-sided)
disk-template	2AFC	0.793	0.827	$[-0.040, 1]$
disk-template	Mann-Whitney-DeLong	0.807	0.791	$[-0.070, 1]$
disk-template	parametric	0.805	0.784	$[-0.120, 1]$
disk-template	parametric known-means	0.783	0.787	$[-0.018, 1]$
CHO-DOG	parametric	0.810	0.778	$[-0.133, 1]$
CHO-DOG	parametric known-means	0.794	0.789	$[-0.042, 1]$
CHO-Gabor	parametric	0.890	0.908	$[-0.060, 1]$
CHO-Gabor	parametric known-means	0.880	0.900	$[-0.020, 1]$

Demos 3 and 4: Setup

- **Task:** unknown-location signal detection
- **Observer:**
 - known-template scanning-linear observer
 - template: uniform disk roughly same size as signal
 - template scanned over all pixels
 - rating = maximum score
 - mark = location of maximum score
- **Figures of merit:**
 - probability of correct signal localization (P_{CL})
 - area under LROC curve (\mathcal{A}_L)

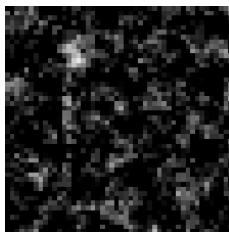
Demos 3 and 4: Images

- image size: 48×48
- colored gaussian noise background following power-law model
 - common noise component across imaging scenarios \Rightarrow correlation
- gaussian signal added at random location (uniformly distributed)
- specified set of seeds for random number generator \Rightarrow same results
- 150 signal-absent images, 150 signal-present images



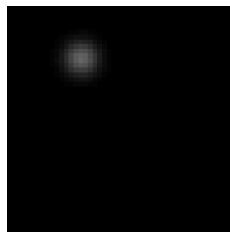
signal absent

grayscale: [0, 25]



signal present

grayscale: [0, 25]



signal

grayscale: [0, 25]

```
----- demo 3 -----  
computing lesion-absent images (m=150) ...  
computing lesion-present images (n=150) ...  
scanning linear observer:  
  
Displaying point estimates and two-sided 95% confidence intervals...  
  
Probability of correct localization:  
  
PCL =  
  
    0.5867  
  
PCL_CI =  
  
    0.5060    0.6629  
  
Area under LROC curve:  
  
AL =  
  
    0.4903  
  
AL_CI =  
  
    0.4167    0.5639
```

----- demo 4 -----

computing lesion-absent images (m=150) ...
computing lesion-present images (n=150) ...
scanning linear observer:

Displaying point estimates and two-sided 95% confidence intervals for performance differences...

Probability of correct localization:

PCL =

0.5867
0.6200

PCL_CI =

-0.0722 0.1389

Area under LROC curve:

AL =

0.4903
0.4742

AL_CI =

-0.1036 0.0714

Summary

- <http://code.google.com/p/iqmodelo/>
- See manual and demo code for details on function usage
- Always justify assumptions!
- Some approaches for efficiently utilizing sample images:
 - use observer models and estimators that don't require splitting images into separate training and testing sets
 - one-sided confidence intervals for one-sided hypotheses
 - obtain class mean difference and incorporate into performance estimation
 - more complex tasks, e.g., unknown-location signal detection