Model Observers for the Objective Quality Assessment of Medical Images

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VQEG
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UMR 6164

Images of interest

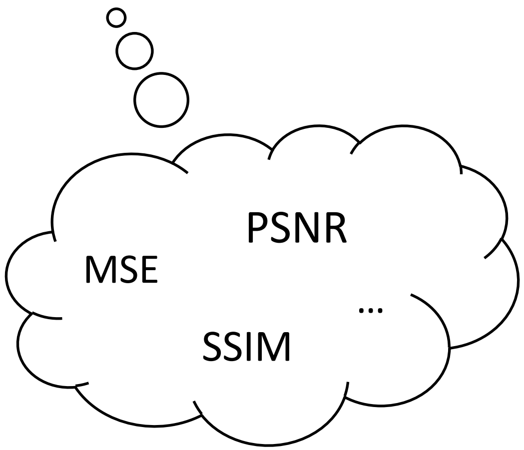
- **Still radiographic images** acquired from the acquisition systems of varied imaging modalities:
  - CT (Computed tomography),
  - MRI (Magnetic Resonance Imaging),
  - ultrasound,
  - PET (Positron Emission Tomography),
  - SPECT (Single Photon Emission Computed Tomography)...

- **End-Users**: radiologist, physician, practitioner…

Why do we assess medical image quality ?

Diagnostic task-based assessment

There is a need for good measurements of medical image quality.



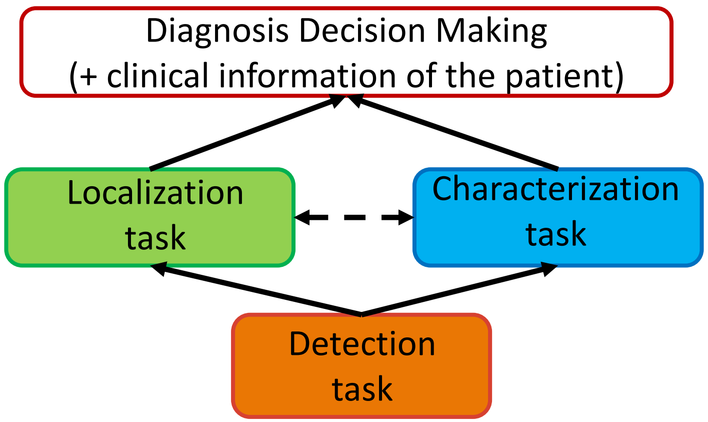
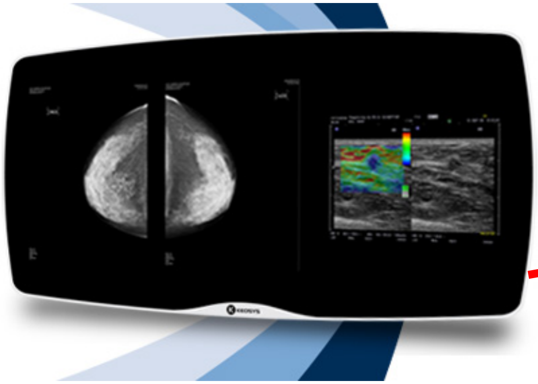


Image quality metrics → Task-based approach

Medical image quality ?

A diagnostic accuracy & efficacy matter

Task-based approach using human observers

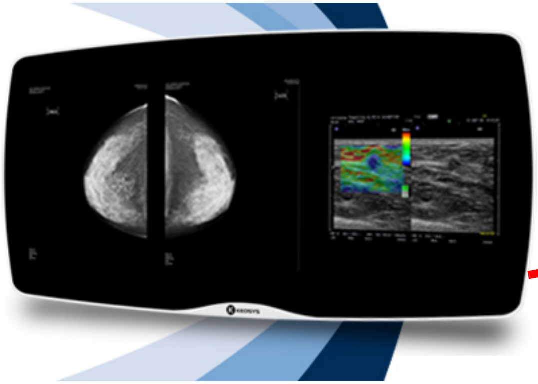


Task performance 1

Task performance 2

- Time-consuming, expensive efforts
- Variance exists between and within radiologists' responses

Task-based approach using model observers



Model

Observer

(MO)

Task performance 1

Task performance 2

- Much easier, faster and cheaper to carry out
- No variance within its responses

Agenda

1. Model observer tasks:
   (1) Detection of one single signal on 2D images
   (2) Detection-Localization of one single signal on 2D images
   (3) Detection-Localization of multiple signals on 2D images
   (4) Detection-Localization of multiple signals on 3D images

2. Validation & performance
   (1) Figure of merit: ROC & Variants of ROC
   (2) Experiments using human observers

3. MO approximation using ANN

4. Conclusions and future works

Detection of one single signal on 2D images

- **Detection of a signal (*x*) on a noisy background (*b*)**:

$$\boxed{\mathcal{H}_h : \; \boldsymbol{g} = h\boldsymbol{x} + \boldsymbol{b}, \; h = 0, 1}$$

$\mathcal{H}_0$: signal-absent

$\mathcal{H}_1$: signal-present

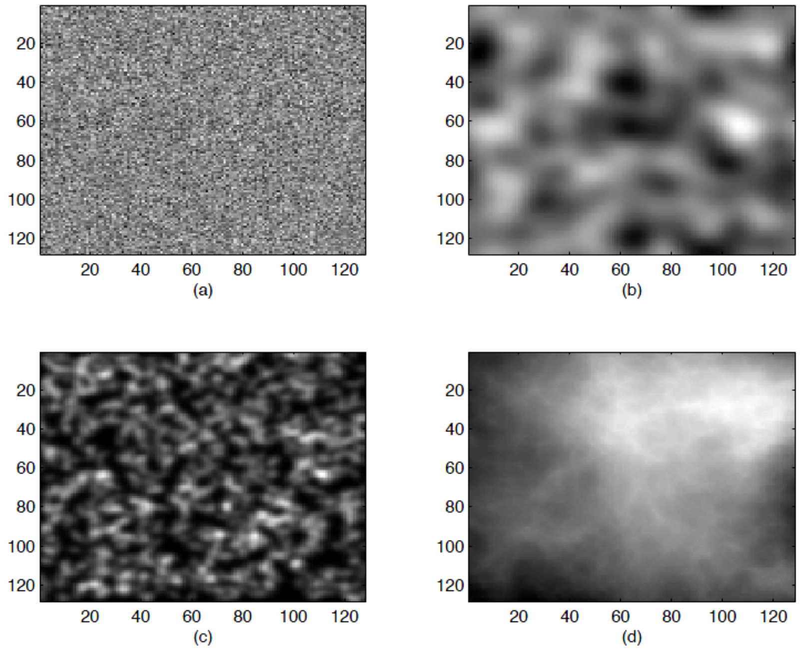
$\boldsymbol{g}$: M $\times$ 1 column vector (through vertical concatenation)

- In general, MO computes a scalar test statistic λ(**g**) via a discriminant function of the image and they differ by their discriminant functions.

Decision rule:

$$\lambda(\boldsymbol{g}) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \lambda_c$$

Background model



- Simulated backgrounds:

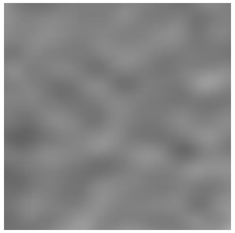
(a) **White Gaussian background (WGB)**

(b) **Correlated Gaussian background (CGB)**

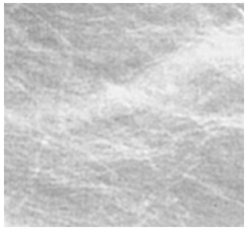
(c) **Lumpy background (LB)**

(d) **Clustered lumpy background (CLB)**

- Real backgrounds (small homogeneous regions):



MR Image



Mammogram Image

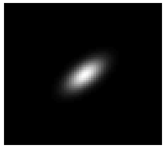
One context of the task: Modality

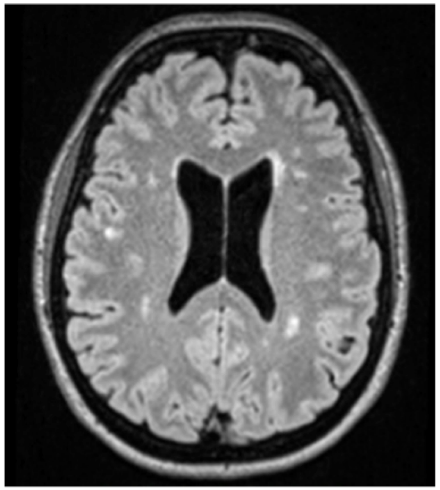
- One example: 2D elliptical Gaussian function

  -> to simulate Multiple Sclerosis (MS) lesion

$$[\boldsymbol{x}]_{\boldsymbol{p}} = a \, \exp\left(-\frac{1}{2}\left(\boldsymbol{p}-\boldsymbol{q}\right)^{\mathrm{t}} \mathbf{B}^{\mathrm{t}}\mathbf{D}^{-1}\mathbf{B}\left(\boldsymbol{p}-\boldsymbol{q}\right)\right)$$

$$\mathbf{D} = \begin{bmatrix} b\sigma^2 & 0 \\ 0 & \sigma^2 \end{bmatrix} \qquad \mathbf{B} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}$$





Multiple Sclerosis (MS)

Another context of the task: Pathology

MOs → Signal Known Exactly (SKE)

MOs → Signal Known Statistically (SKS)

Signal parameters

$$\boxed{\alpha = [a, \theta, b, \sigma, \boldsymbol{q}]}$$

SKE MOs

	Ideal Observer (IO)	Hotelling Observer (HO)	Channelized HO (CHO)
Input data	Full knowledge of the PDFs of the image for each hypothesis $P(\boldsymbol{g}\,\vert\,\mathcal{H}_0)$ and $P(\boldsymbol{g}\,\vert\,\mathcal{H}_1)$	First- and second- order statistics of the image for each hypothesis	First- and second- order statistics of the channelized image for each hypothesis
Output (test statistic)	likelihood-ratio $\lambda_{\mathrm{IO}}(\boldsymbol{g}) = \frac{P(\boldsymbol{g}\vert\mathcal{H}_1)}{P(\boldsymbol{g}\vert\mathcal{H}_0)}$, or log-likelihood-ratio $\ln \lambda_{\mathrm{IO}}(\boldsymbol{g}) = \ln \frac{P(\boldsymbol{g}\vert\mathcal{H}_1)}{P(\boldsymbol{g}\vert\mathcal{H}_0)}$	$\lambda_{\mathrm{HO}}(\mathbf{g}) = \mathbf{w}_{\mathrm{HO}}^t \mathbf{g}$ where $\mathbf{w}_{\mathrm{HO}} = \mathbf{S}_2^{-1}(\langle \boldsymbol{g}\,\vert\,\mathcal{H}_1\rangle - \langle \boldsymbol{g}\,\vert\,\mathcal{H}_0\rangle)$, $\mathbf{S}_2 = 1/2(\mathbf{K}_0 + \mathbf{K}_1)$, $\mathbf{K}_0$ and $\mathbf{K}_1$ are the ensemble covariance matrices of the image data, without and with signal respectively.	$\lambda_{\mathrm{CHO}} = \boldsymbol{w}_{\mathrm{CHO}}^{\mathrm{t}} \boldsymbol{g}'$ where $\boldsymbol{g}' = \mathbf{U}^{\mathrm{t}} \boldsymbol{g}$, $\boldsymbol{w}_{\mathrm{CHO}} = \widehat{\Sigma'}^{-1} \widehat{\boldsymbol{x}'}$, $\widehat{\boldsymbol{x}'} = \langle \boldsymbol{g}'\,\vert\,\mathcal{H}_1\rangle - \langle \boldsymbol{g}'\,\vert\,\mathcal{H}_0\rangle$, $\widehat{\Sigma'} = 1/2(\mathbf{K'}_0 + \mathbf{K'}_1)$, $\mathbf{K}_0$ and $\mathbf{K}_1$ are the ensemble covariance matrices of the channelized image data, without and with signal.
Discriminant function linearity	Nonlinear	Linear	Linear
Optimality	Optimal (maximum AUC among all MOs)	Optimal (maximum *detectability index d′* among all linear MOs)	Optimal or anthropomorphic (depending on channel profile)
Calculability	High-dimentional PDFs are difficult to compute for real clinical data sets, except for simple cases	High-dimentional ensemble covariance matrices of the image are difficult to be inverted.	Dimensionality, resulting in the calculation burden, is reduced by the channelization technique.

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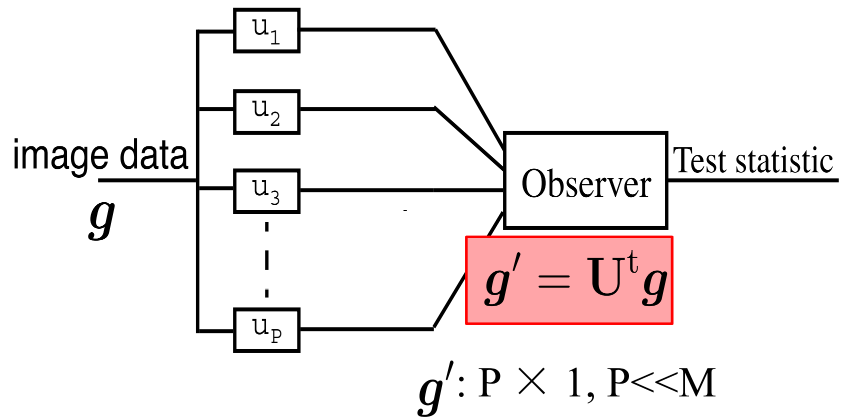
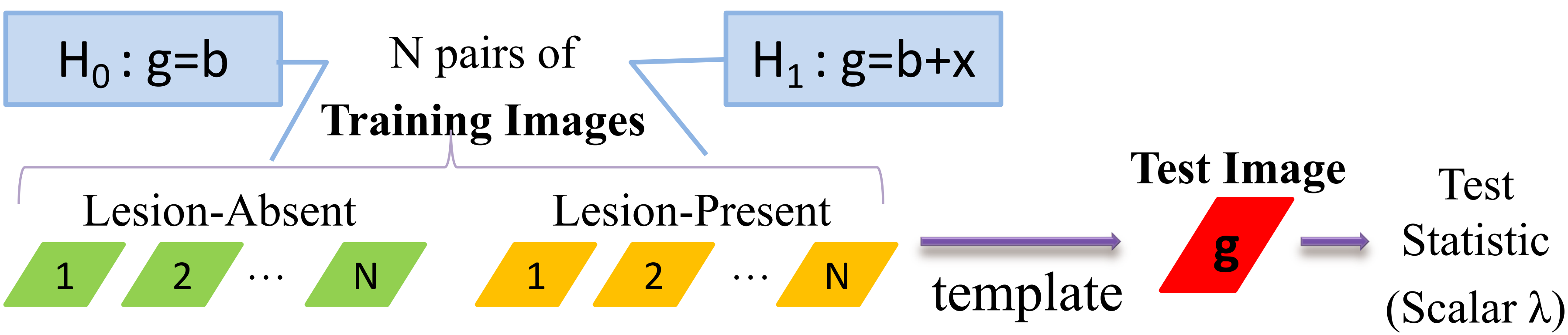
SKE MO: Channelized Hotelling Observer (CHO)

- Channelization:



- Practical Implementation:



SKS MOs

Authors [ref.]	Diagnostic task	Unknown parameters	# signals per image	Brief description of method
Eckstein *et al.* [15, 16, 17]	detection	size and shape	one	A different template is built for every combination of signal parameters and the optimal template response (in a maximum likelihood sense) is output as the final test statistic.
Park's *et al.* [5]	localization	position	one	A scanning CHO scans the image exhaustively, and the location that gives the largest test statistic is chosen as the tentative location while that test statistic is the final test statistic.
Gifford *et al.* [24, 25, 26]	localization	position	one	A visual-search (VS) model firstly identifies some candidate blobs guided by features of the test image, then applies a scanning CHO on each candidate blob.
Clarkson [27, 28]	estimation	all possible parameters	one	A theoretical framework of an ideal Estimation ROC (EROC) observer (cf. [27, 28]), whose EROC curve lies above those of all other observers for the given joint detection-estimation task, was proposed.
Whitaker *et al.* [29]	estimation	amplitude, size and location	one	A scanning-linear estimator performs a global-extremum search to maximize a linear metric.
Goossens *et al.* [30]	detection & estimation	orientation	one	Parameters estimates and detection decision are chosen jointly to maximize the joint posterior probability $P(\alpha, \mathcal{H}_h \mid \boldsymbol{g})$. Steerable channels are used to estimate the orientation.
Zhang *et al.* [31]	detection & estimation	amplitude, orientation, scale	one	Channelized detection-estimation Joint Observer (CJO) extended the model proposed by Goossens *et al.* to estimate scale and orientation at the same time.

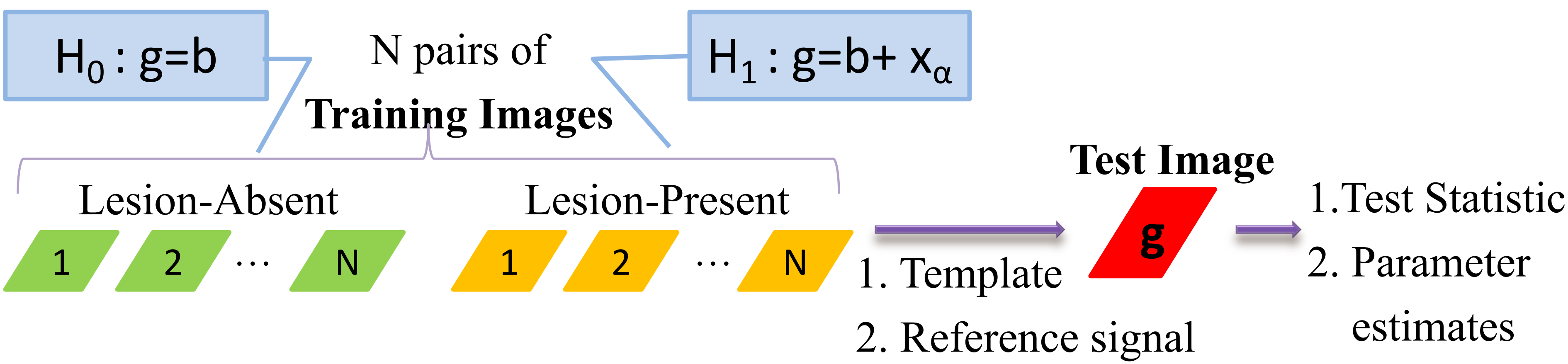
SKS MO: CJO (Channelized Joint Observer)

Validation of a hypothesis $\mathcal{H}_h$ is accompanied by the maximum a posteriori probability (MAP) estimation of unknown signal parameters:

$$\widehat{(\alpha, \mathcal{H}_h)} = \underset{\alpha, \mathcal{H}_h}{\arg\max}\, P(\alpha, \mathcal{H}_h \,|\, \boldsymbol{g})$$

CJO[1]: unknown signal amplitude, orientation and size

- Practical Implementation:



[1]L. Zhang, B. Goossens, C. Cavaro-Menard and P. Le Callet, "A model observer for the detection and estimation of signals with unknown amplitude, orientation and size", JOSA A, 2013.

Agenda

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   (1) Figure of merit: ROC & Variants of ROC
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3. MO approximation using ANN

4. Conclusions and future works

Position unknown SKS MOs

Authors	Diagnostic task	Unknown parameters	# signals per image	Brief description of method
Park's *et al.*	localization	location	one	A scanning CHO scans the image exhaustively, and the location that gives the largest test statistic is chosen as the tentative location while that test statistic is the final test statistic.
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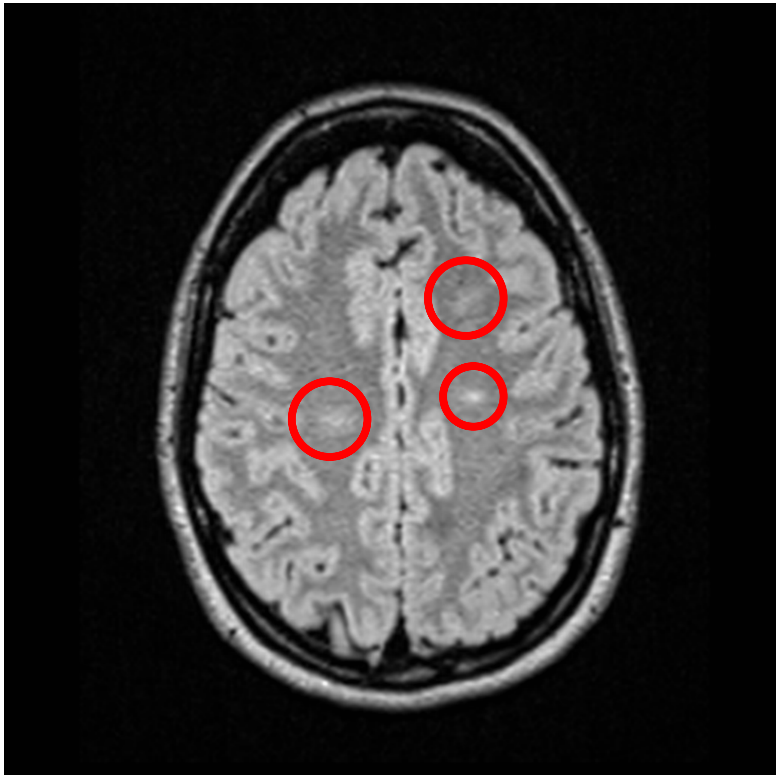
- Scanning-MO



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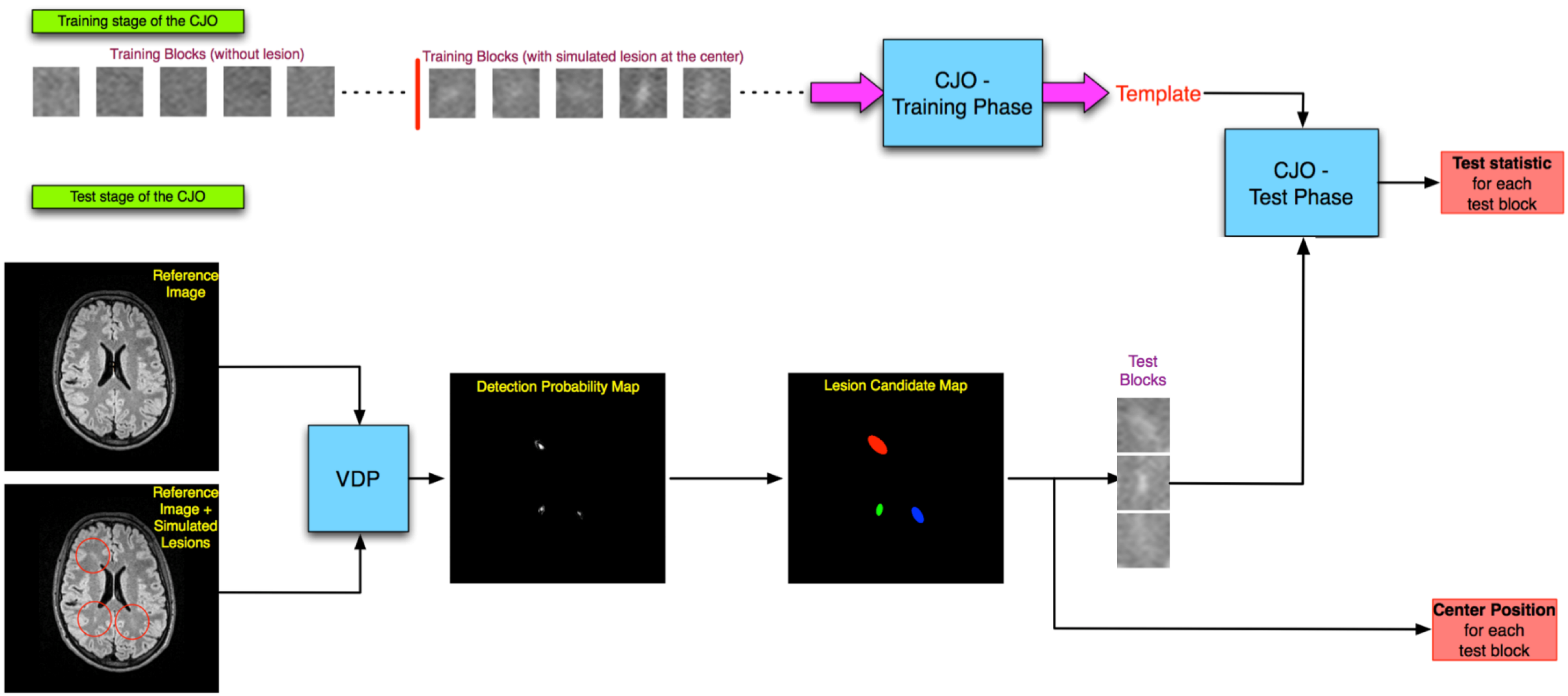
PCJO² (Perceptually relevant CJO)



- Address the difficulty of multiple-signal localization using a HVS model to select candidate blocks.
- PCJO greatly extends the range of variable signal parameters

[2]*L. Zhang, C. Cavaro-Menard, P. Le Callet, et J.-Y. Tanguy, "A Perceptually Relevant Channelized Joint Observer (PCJO) for the Detection-Localization of Parametric Signals", IEEE Transactions on Medical Imaging, oct. 2012*

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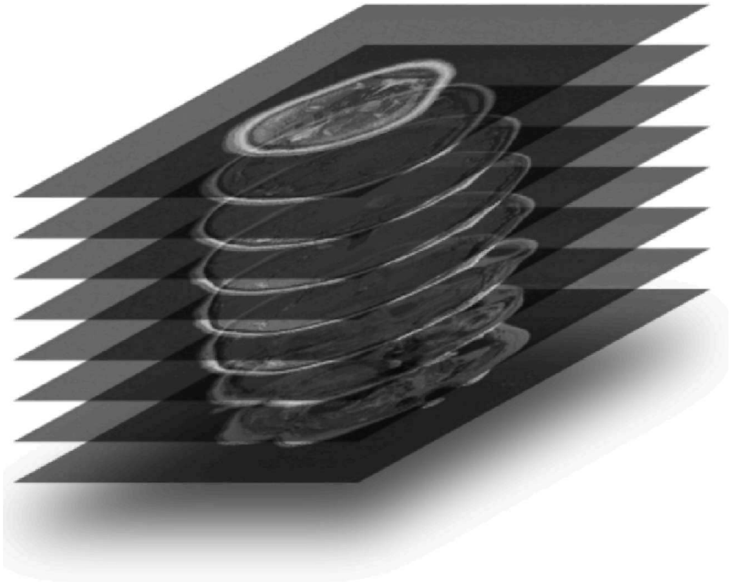
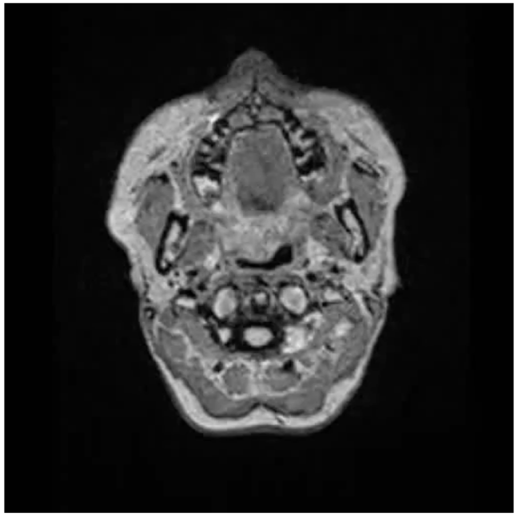
Multi-slice/Volumetric images

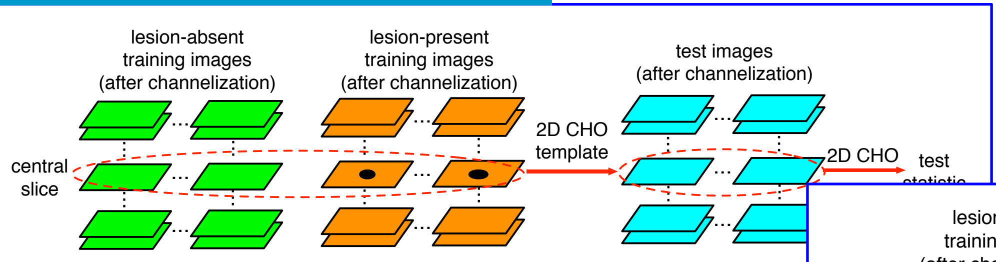




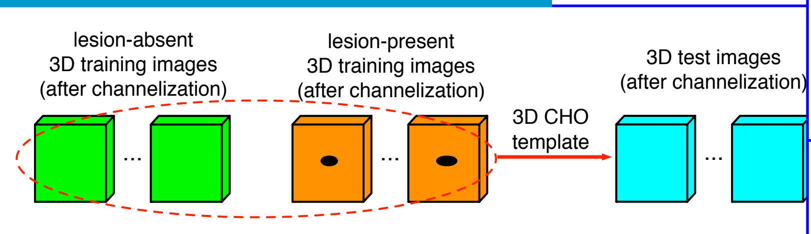
Volumetric image provides more anatomical information, which allows for a better distinction between true lesions and noise or background structure.

Multi-slice/Volumetric Model Observers

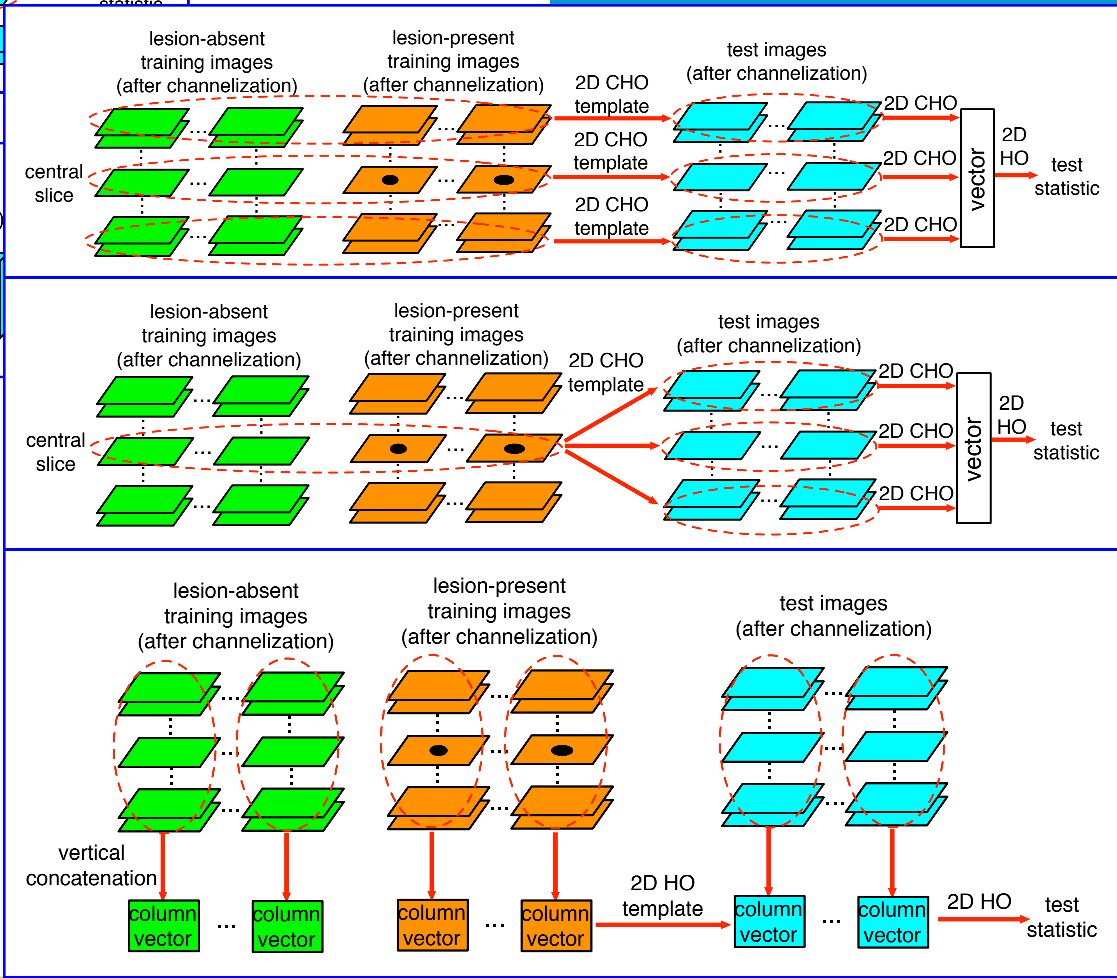
Single-slice CHO (ssCHO)



Volumetric CHO (vCHO)



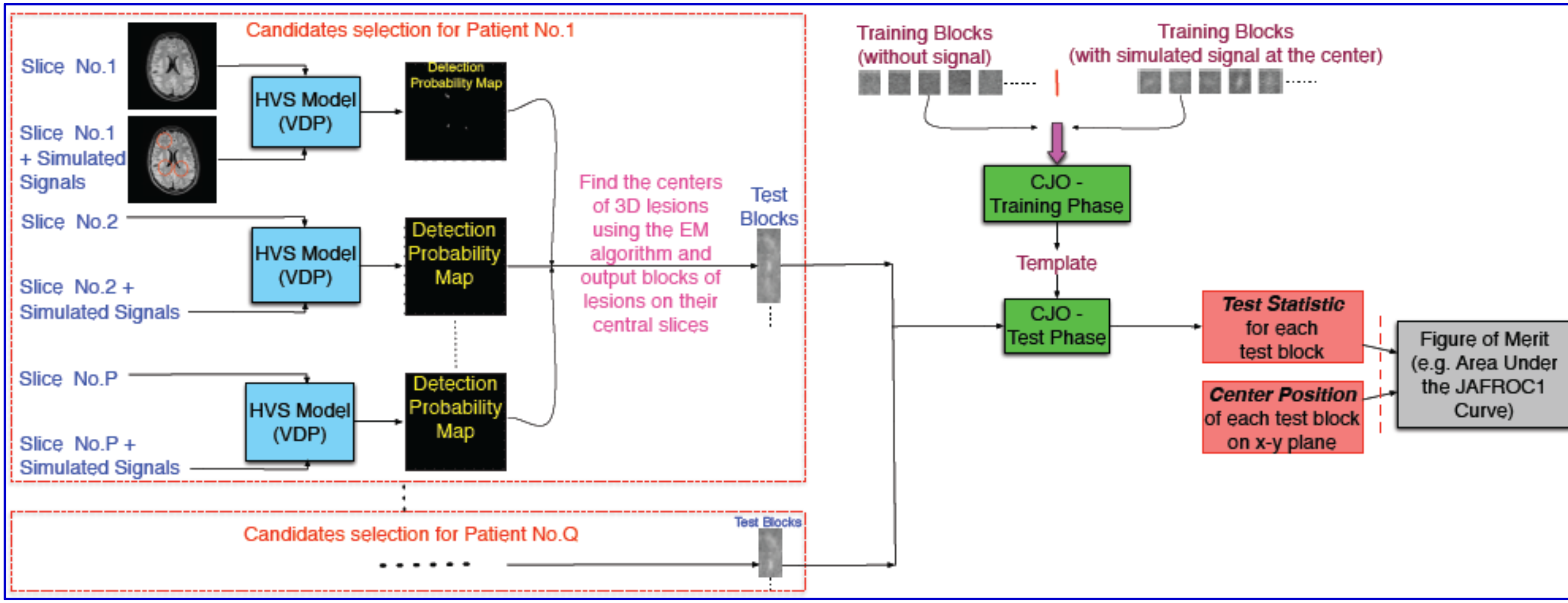
Multi-slice CHO (msCHO)



- perform only SKE detection task
- detect only symmetrical signal
- the signal is located at the center

msPCJO[3]

introduced the asymmetrical signal and the SKS task into the multi-slice numerical observer, capable of estimating signal parameters (location, amplitude, orientation and size).



[3]L. Zhang, C. Cavaro-Ménard, P. Le Callet, "A multi-slice model observer for medical image quality assessment". ICASSP, April 2015, Brisbane, Australia.

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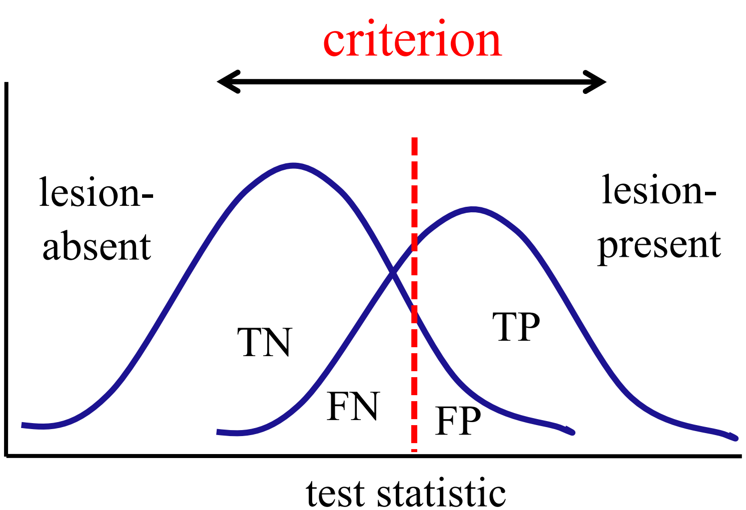
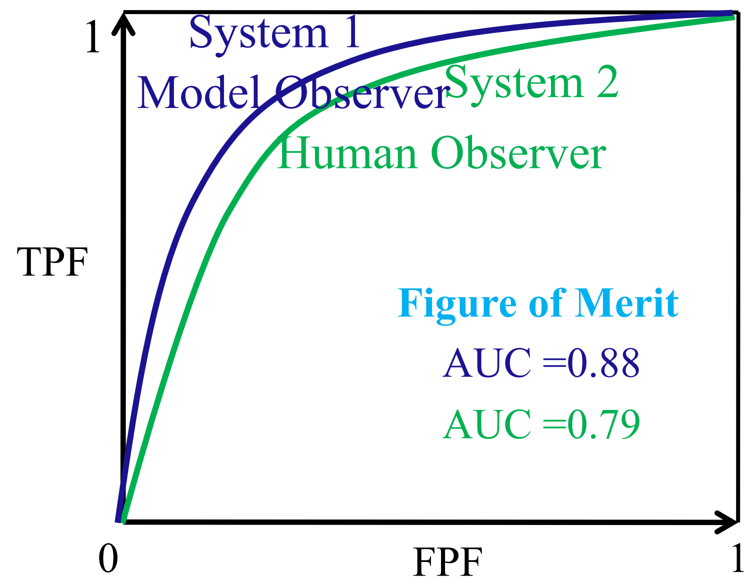
ROC (Receiver Operating Characteristics)

To characterize the performance of detection task of one single signal on 2D images:

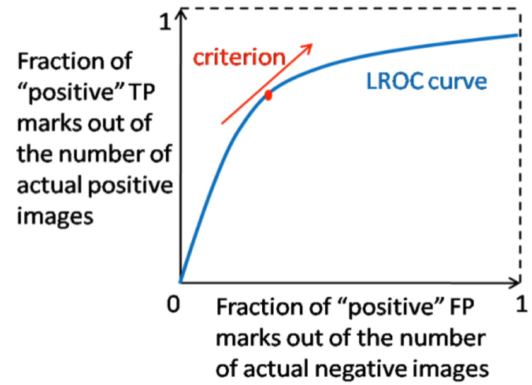
		Gold standard	
		lesion-present	**lesion-absent**
Observer's response	**positive**	TP	FP
	negative	FN	TN

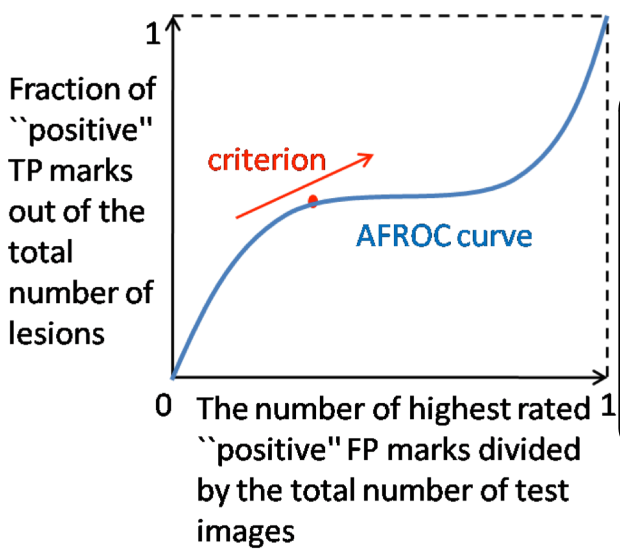




Detection-localization tasks

- Marked coordinates (? distance < acceptance radius)
  - TP
  - FP
- Marked rate (? rate > decision criterion)
  - "positive"
  - "negative"





JAFROC1:

www.devchakraborty.com

Highest statistical power for detection-localization task

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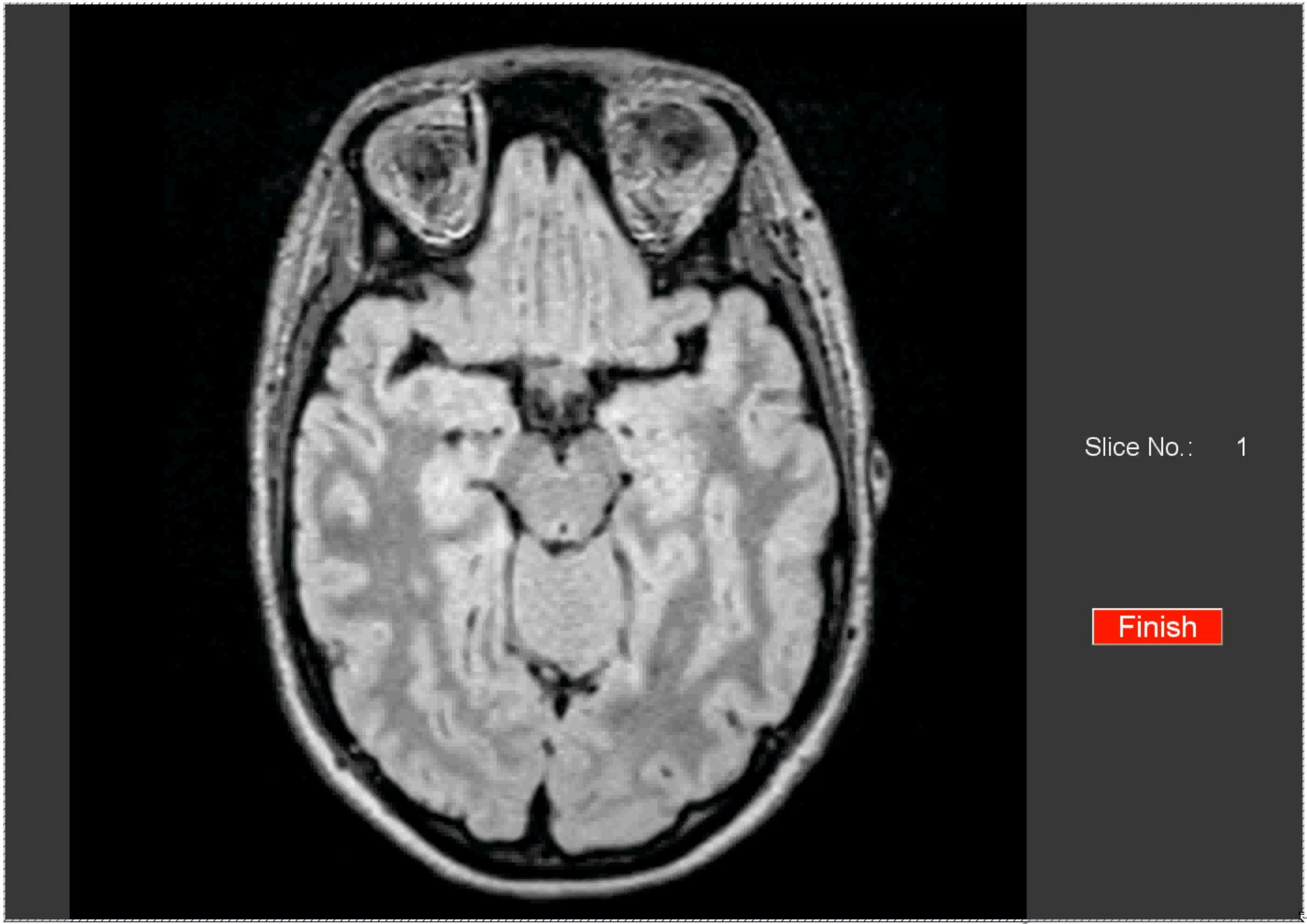
Validation study on 2D images

Validation study on 3D images



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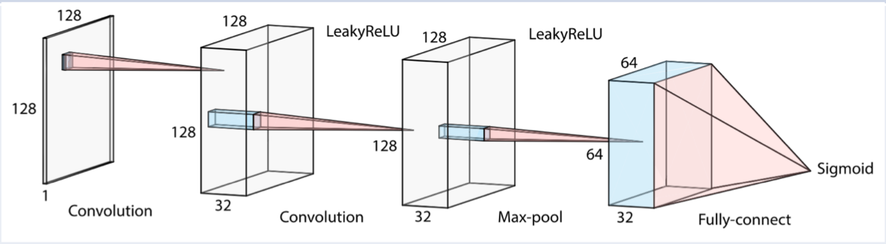
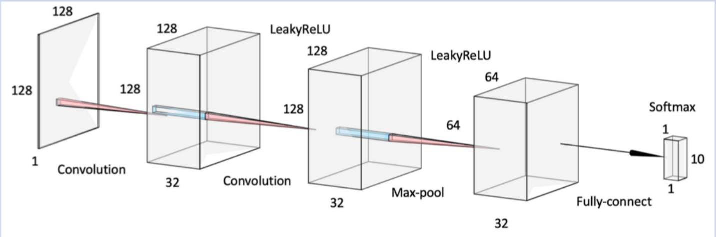
MO approximation using ANN

Authors	Year	Task	ANN
Kupinski *et al.* [1]	2001	Detection	A neural network with an input layer, a single hidden layer and a single output node
Zhou *et al.* [2]	2019	Detection	
Zhou *et al.* [3]	2020	Detection and Localization	

[1] Kupinski, Matthew A., et al. "Ideal observer approximation using Bayesian classification neural networks." IEEE transactions on medical imaging 20.9 (2001): 886-899.

[2] Zhou, Weimin, Hua Li, and Mark A. Anastasio. "Approximating the Ideal Observer and Hotelling Observer for binary signal detection tasks by use of supervised learning methods." IEEE transactions on medical imaging 38.10 (2019): 2456-2468.

[3] Zhou, Weimin, Hua Li, and Mark A. Anastasio. "Approximating the Ideal Observer for joint signal detection and localization tasks by use of supervised learning methods." IEEE transactions on medical imaging 39.12 (2020): 3992-4000.

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MO approximation using ANN

- General idea:
  - Learn the empirical estimate of the Hotelling template
  - Solve the high-dimentionality problem
  - Localization task is addressed by scanning observer paradigm

- Open questions:
  - No comparison between CHO and ANN approximated HO
  - Only tested on simulated images

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Conclusions

- Model observers have been proposed:
  - not to substitute medical experts
  - but to predict medical experts' performance
  - quantify/evaluate medical imaging systems
- MO study should have some relevance for clinical tasks of interest.
- Use medical experts for the validation.
- Important “context” impact factors:
  - Pathology type:
    - Characteristics of lesion
    - Number of lesions…
  - Modality
  - Expertise …

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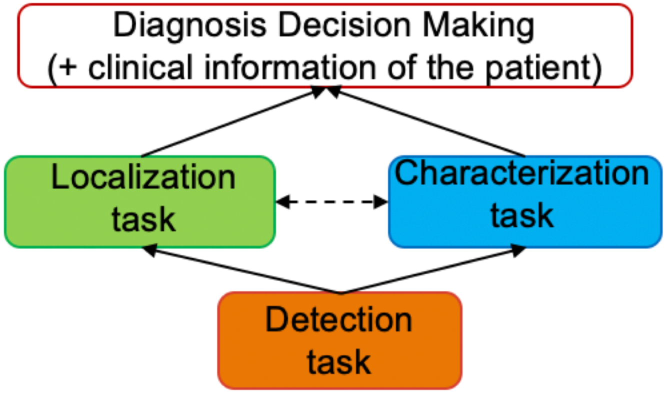
Future works?

- More applications of the model observers
- More modalities ?
  - More background models
  - Color…
- More tasks?

  - Characterization task

  - Segmentation task

  - Surgery task…



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16th December 2021

Thank you for your attention!

QAH working group
Quality Assessment for Health Applications

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