

Plan

- · Introduction
- Uses of ROC analysis for QA
 - Compare plan quality metrics
 - Quantify detector performance
 - Improve IMRT/VMAT pre-treatment QA
- Bringing ROC analysis in the clinical routine?

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QA: pre-treatment / end-to-end / ...

- · When performing QA:
 - Multiple detectors can be chosen
 - Diode, ion chambers, films, EPID, gels
 - 1D, 2D, 3D
 - Multiple tests
 - Gamma implementation
 - 2D, 3D
 - Multiple definitions of pass/fail

A large amount of possible combinations, each can yield quite different results

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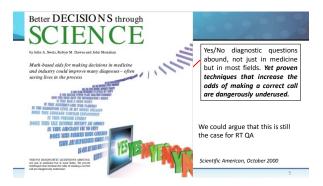
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Context

- Is an IBA MatriXX better at catching a single bad MLC leaf using my homemade gamma software with 3 %/ 3 mm than an EPID with a commercial gamma calculation using 2 %/ 2 mm?
- What detector should I use to catch a problem with the penumbra beam model in Eclipse?

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QA: pre-treatment / end-to-end / ...

- · Task of QA: find an error
 - Binary result: is there an error or ne
 - This is a signal detection problem
 - The error is the signal



Systems do not detect errors with the same accuracy

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Error	doto	ection
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- A given detection system:
 - Detector, test, pass/fail threshold
- · Capacity to detect error can be characterized
 - Sensitivity: fraction of time a positive result is 'real'

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

- Specificity: fraction of time a negative result is 'real'

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

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Why bring ROC curves to RT QA?

- · QA methods often have 'knobs' to adjust
 - For example, when using a simple 2D gamma test:
 - Which pixel to consider (e.g. % of prescribed dose)
 - % dose difference (%DD), distance to agreement (DTA)
 - % of pixels that must fail to consider an error
- Different systems have different optimum choices
 - It is unfair to compare different systems using the same %DD, DTA and pass rate
 - Each should use its optimum parameters

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Why bring ROC curves to RT QA?

- We believe ROC curves are the answer:
 - Offers an objective framework to compare QA systems
 - Account for detector, test, threshold
 - Easily and visually compare systems independently of the 'knobs' settings
 - Assess how a QA system perform for specific type of error

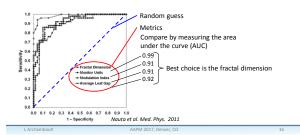
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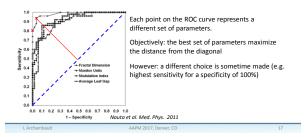
Uses of ROC analysis in the literature	
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ROC for QA in the literature	
 ROC formalism to improve RT QA is still in its early stage First use (to my knowledge) in 2005 	
Childress et al. Detection of IMRT delivery errors using a quantitative 2D	
dosimetric verification system, Med. Phys. 2005 - Since then: about a dozen papers on the topic	
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How has ROC been used in RT	
Main applications: Compare plan quality matrics	
 Compare plan quality metrics Plan quality, robustness, complexity 	
 Quantify detector performance Improve IMRT/VMAT pre-treatment QA 	
 Assess the capacity of QA to detect specific type of errors Find the optimal parameters of a test 	
Compare tests	

Uses of ROC analysis in the literature	
Comparing plan quality metric	
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Plan quality metrics	
A number (metric) extracted from the plan that is an indicator of the plan complexity and/or quality From TG-119: "the level of complexity of individual plans is"	
related to the delivery accuracy" • Questions	
 How does different metrics compare to one another? Do metrics predict plan quality? 	
ROC analysis	
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Some examples	
Nauta et al. Med. Phys. 2011	
 Mertric: fractal dimension Test: Identify plans with high/low fluence smoothing 	
 McNiven et al. Med. Phys. 2010: Metric: Modulation complexity score (MCS) 	
 Test: pass/fail of pre-tx QA Garcia-Romero et al. Med. Phys. 2016 	
Metric: DVH based, robustness, changes in TCP/NTCP Test: Dose difference compared to a reference calculation	

Predicting high/low modulation



Predicting high/low modulation



Importance of a common ground

	McNiven et al.	Nauta et al.
Other metrics	Total MU	Total MU, avg. leaf gaps, mod. index

A common ground would let us compare studies
 In this case: how MCS compares to fractal dimension

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Some observations	
 Designing metrics is easy, designing good metrics is challenging ROC: easily sorts through potential candidates ROC curves can be used to optimize the parameters of a test or classifier 	
However, the range of the parameters must be properly chosen	
"it is possible to use the AUC coming from the ROC analysis to determine the best set for these parameters, <u>provided that the range of the parameters is properly chosen."</u> - Garcia-Romero et al. Med. Phys. 2016	
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Uses of ROC analysis in the literature Quantifying detector performance	
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Quantifying detector performance	
A large diversity of QA detectors exists	
 Is a given detector better at catching some type of errors than other 	
Aside from improved ease of use, is there a point in designing new QA detectors?	
 How does a new system compare to older ones? Well demonstrated by the previous presentation 	
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Quantifying detector performance

• Example of a new detector:

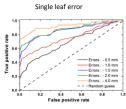


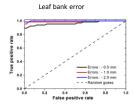
- A plane of 781 scintillating fibers
 Near-perfect water equivalence
- Near-perfect water equivalence everywhere
- Currently a bit impractical to use

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Quantifying detector performance





Guillot et al. Med. Phys. 2013

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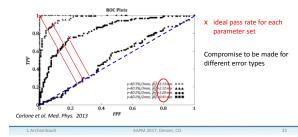
Optimizing detector performance

- For a given detector used for y evaluation: find the optimal parameters
 - %DD, DTA, threshold
- Example: the MapCHECK
 - Carlone et al. Med. Phys. 2013
 - Sensitivity to leaf errors
 - 17 IMRT plans without error
 - 17 plans with random errors

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Optimizing detector performance



Detection of specific errors

- Childress et al. Med. Phys. 2005
 - Dose calculation with and without errors
 - Wrong energy, wrong patient, collimator/gantry offset, missing beam, MU offset
 - Gamma based analysis
 - 5 % / 3 mm, 3 % / 2 mm
 - Normalized agreement test (NAT), NAT normalized to average PTV dose, γ pass rate \dots

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Detection of specific errors

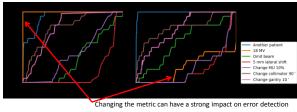


Data shamelessly extracted from Childress et al., Med. Phys. 2005

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Detection of specific errors

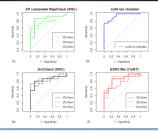


Data shamelessly extracted from Childress et al., Med. Phys. 2005

QA performance assessment

- Other groups have done similar work
 - McKenzie et al. Med. Phys. 2014
 - Extensive study of multiple detectors, %DD/DTA, anatomical site
 - · In-house phantom as the reference
 - Sjölin et al. Phys. Medica. 2016
 - · Detection incorrect dosimetric leaf gap
 - Bojechko et al. Med. Phys. 2015
 - In vivo EPID
 - MU scaling, MLC noise (random and systematic), patient shift

QA performance assessment



Comparing 'gold standard' in house QA system with various commercial solutions

McKenzie et al. Med. Phys. 2013

Importance of a common ground (2) McKenzie et al. No specific errors Compare measurements Gamma pass rate, 5 % / 3 mm lress et al. Specific errors Compare dose calculation Gamma NAT, 5% / 3 mm Data shamelessly extracted from Childress et al., Med. Phys. 2005 and McKenzie et al., Med. Phys. 2014 Uses of ROC analysis in the literature Improving pre-treatment QA Critique of current pre-tx approaches • There are numerous critique of gamma based QA: - "gamma scores could not reliably identify a plan with poor dosimetric accuracy" Kruse et al. 2010 - "planar IMRT QA passing rates do not predict clinically relevant patient dose errors" · Nelms et al. Med. Phys. 2011 "For the same pass-rate criteria, different devices and software combinations exhibit varying levels of agreement" Hussein et al. Radiother. Oncol. 2013

Pre-tx QA vs external verification

- Kry et al. (IJROBP 2014) looked at pre-tx QA versus IROC-Houston phantom results
- · ROC analysis for 3 type of detectors:
 - MapCHECK, Film: γ 3 % / 3 mm
 - lon chamber: dose difference
- Does the pre-tx QA predict the phantom results?

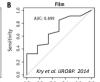
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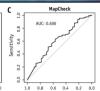
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Pre-tx QA vs external verification







- · Results are slightly better than a random guess
 - QA processes with larger AUC are needed

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Toward better and more useful QA

- No matter what the future of pre-tx QA is, it is important to have quantitative assessment of QA systems
 - Large AUC
 - Sensitivity/specificity
 - For different type of errors
 - Optimum parameters

"only once [the errors] are detected can they be properly diagnosed and rooted out of the system"

- Nelms et al. Med. Phys. 2013

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Bringing ROC in the clinical routine?	
	
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ROC analysis for better QA	
Nobody likes doing useless work	
 Nevertheless, there is increasing evidence that QA may not always provide adequate information 	
 ROC may address some of these problems Reduce heterogeneity in QA performance 	
Between equipment, institutions Move toward 'evidence based' QA procedures	
Improve the performance (and usefulness) of QA	
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How to (as a single institution)?	
An overview of the workflow	
 Plan list (w/ and w/o errors) Measurements with a given QA system 	
Sweep parameters (pass rate, %DD/DTA,) Classify each plan according to these sets of parameters	
4. Plot ROC curves	
5. Compute AUCPerformance of the system VS others	
Determine the best set of parameters	

How to (as a single institution)?	
While apparently simple, rigorous ROC analysis can be	
demanding - Better results with lots of plans with and without errors	
- better results with lots of plans with and without errors	
 Possible solutions Retrospective analysis 	
But be careful about the reference Scripts/automation to plan and deliver erroneous dose	-
distribution LArchambault AAPM 2017, Denver, CO 40	
LACCHIRTOGRIL ANAMA 2011, Deriver, CO 40	
How to (as a profession)?	
Establish common ground for comparison	
- What should we use as the reference? • Planned dose distribution	
Measured plan without errors Results from a given QA system	
 Should we define specific sets of errors to test? If so, which errors? 	
Having the same framework will simplify comparison	
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How to (as a profession)?	
Publish results	
- The more data out there the better	
 Provide tools/datasets to ease implementation Script that add errors in DICOM-RT plans 	

Easily done in python

Linac automation to run batches of testsOpen datasets of plans with and without errors?

Next steps	
In my opinion, the next steps should be:	
Try define a common ground Get more papers/data out	
Make informed decision based on quantitative assessment	
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and more distant future	
 Pre-tx is essentially a classification task Is the plan good or bad? 	
 A single passing rate threshold is rather simplistic 	
 Machine learning proposes several 'classifiers' that could be trained on our data ROC analysis is the tool of choice to compare classifiers 	
T. Fawcett, "An introduction to ROC analysis", Pattern Recognition Letters, 2006 **Telephone Telephone T	
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Last words	
We don't have all the answers yet, but hopefully you	
are now somewhat convinced of the benefits of ROC analysis to improve our QA	
• Lets discuss	
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