Characterization of a novel detector using ROC

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New Ideas → Investigation → Clinical Practice

Investigating a novel detector using ROC Analysis

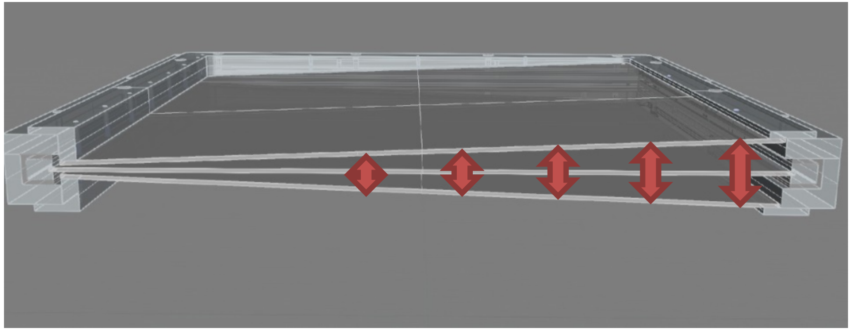
- Show how ROC analysis used as scientific tool to study new detectors
- Example of work with large area parallel plate ion chamber
- Discussion of how this can be generalized to other research

Evaluating Clinical Tools

- ROC Curves
  - Looks at how well a tool classifies both positives and negatives
    - Often, evaluations focus on catching errors without evaluating the false alarm rate
  - Flexibly compare multiple tools regardless of their metric
    - Just need to link to a binary output
  - Can *quantitatively* define a threshold for clinical use
    - Rather than using a “rule-of-thumb” approach

What is the IQM (Integrated Quality Monitor)?

- Purpose:
  - to perform real-time verification of treatment delivery
- Large area ion chamber with angled plates
  - Spatially dependent gradient along direction of MLC travel
  - Nearly unique signal from different collimation/fluence



iqm-system.com

What is the IQM (Integrated Quality Monitor)?

- Slides into head of linac
- Gives integrated counts as a function of control point
- Compares these integrated counts to a baseline measurement

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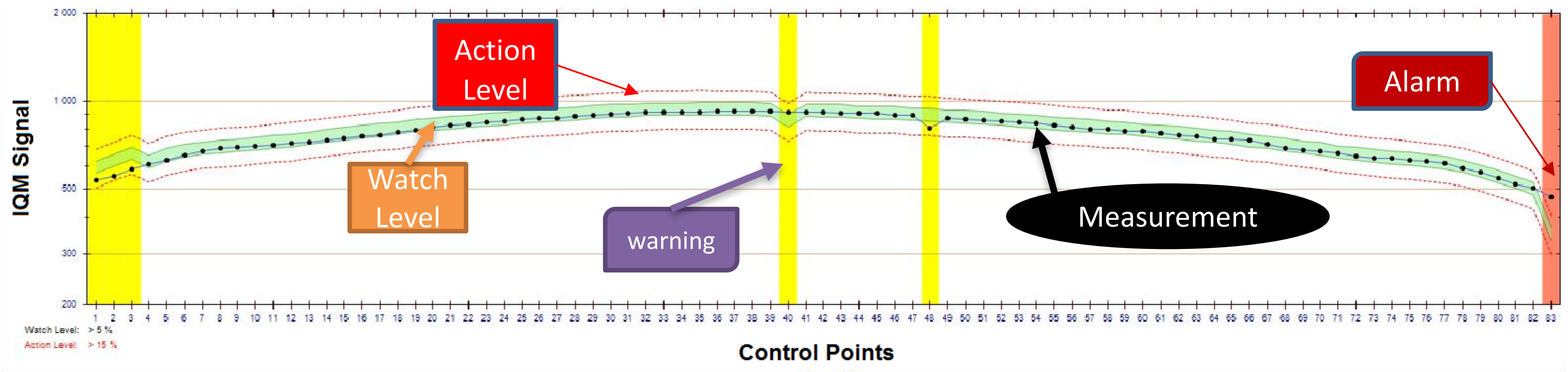
Using the IQM

- Computer in control room where therapists can monitor the IQM signal
- If IQM signal is more than tolerance value (in terms of ±percent difference from baseline), alarm will sound



Example screenshot of IQM Monitor software showing IQM counts as a function of control point

Some aspects of this device

- It is monitoring for a failure
  - Needs specific cutoff values
- It is checking for a (hopefully) rare situation
  - Needs to be evaluated in a way which is robust to skew in the data
  - Potentially more passing cases than failing cases

Dealing with Skew

- Rare errors
- ROC curves are insensitive to changes in class distribution
  - OK to have more passing cases than failing cases in your experiment
  - ROC is plot of true positive vs false positive

Assessing the Sensitivity and Specificity: Managing Alarm Fatigue

- Previous publications have investigated the IQM's sensitivity to MLC positioning errors, wrong energy, and wrong number of MUs
  - Islam et al (2009)
- In practice, need something that shows both good sensitivity and good specificity
  - Too many false alarms lead to **Alarm Fatigue**

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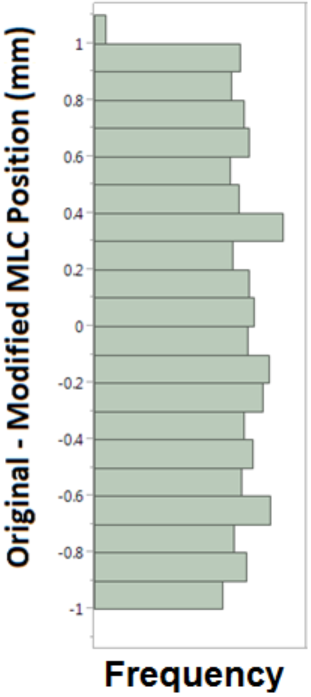
Assessing the Sensitivity and Specificity

- To assess sensitivity and specificity, used ROC
  - Response: percent difference from baseline of IQM integrated count per control point
  - Binary variable: does the delivery have an error or not?
- Need to know which plans truly have an error
  - Gold standard
  - Generate error plans

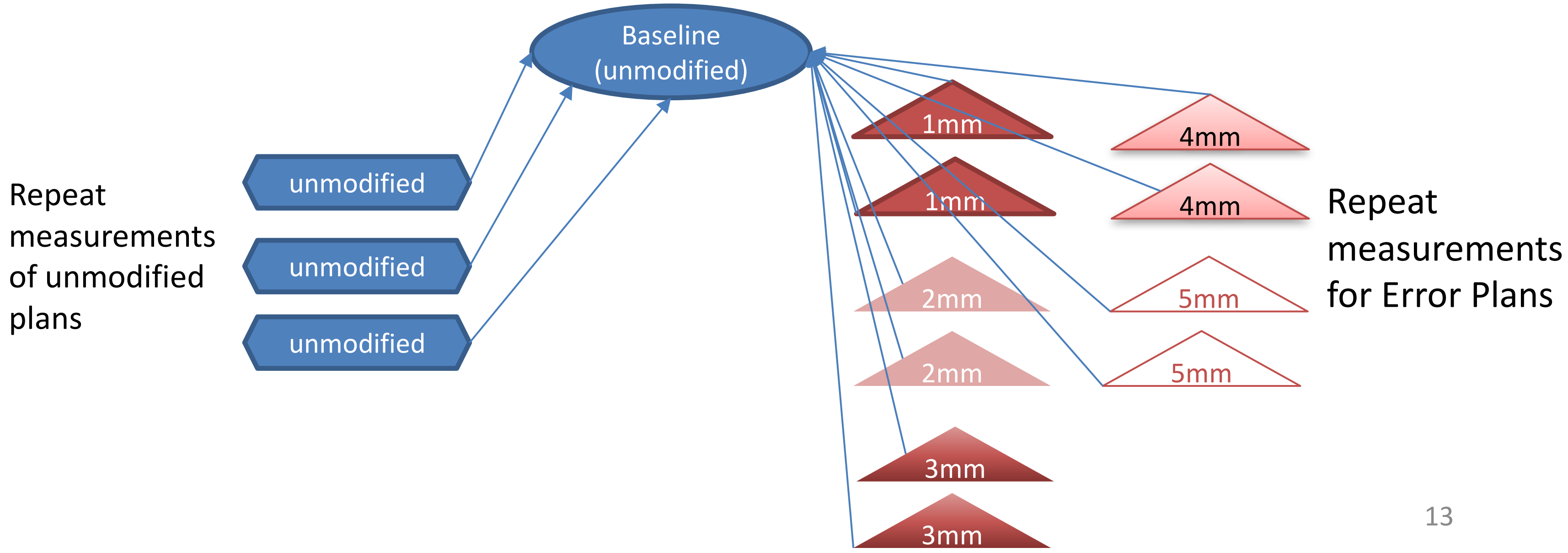
Assessing the Sensitivity and Specificity

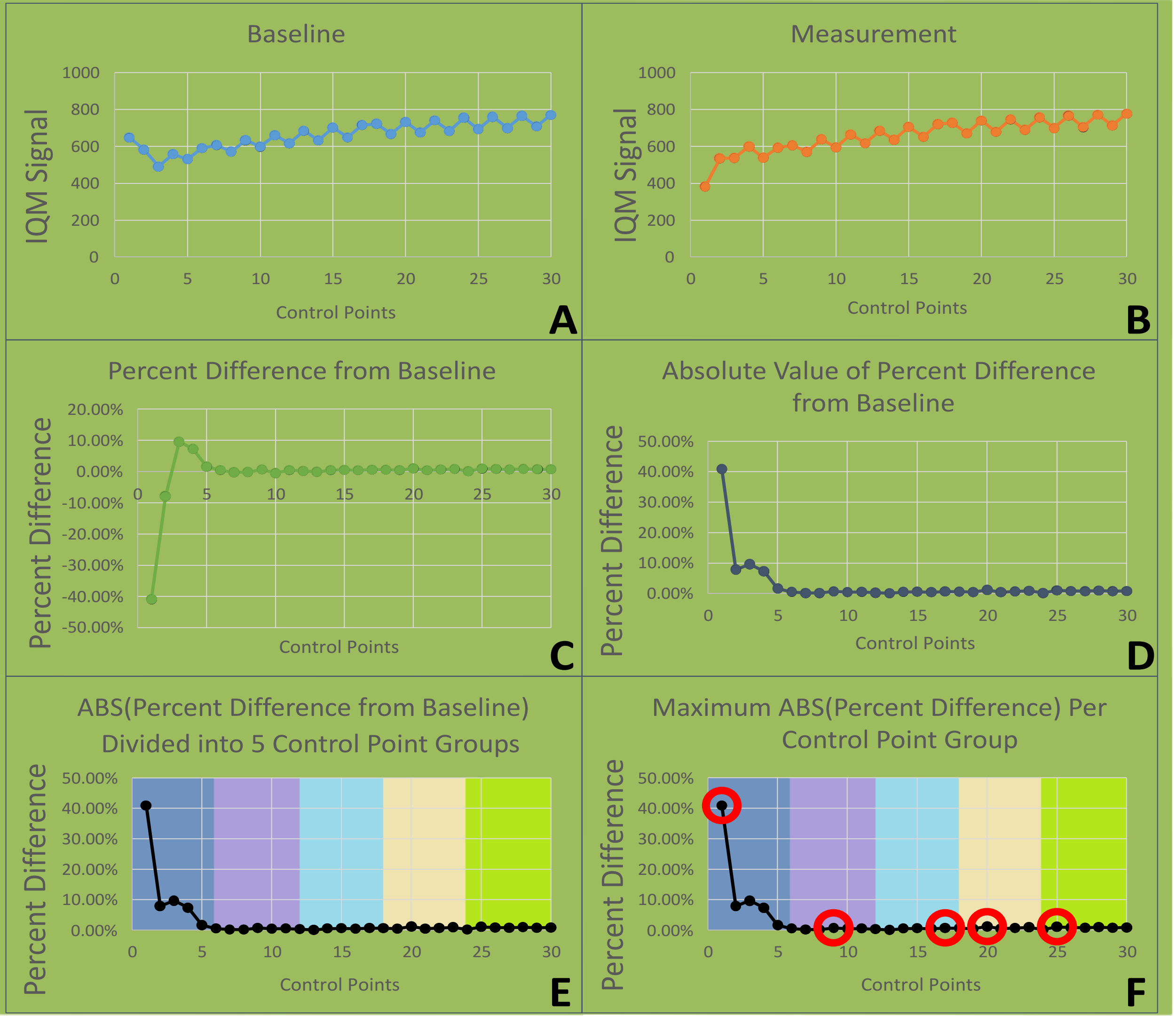
- To create error plans, used method of Steers et al 2016
  - Randomly perturb all in-field MLC positions by a distribution of errors ranging from ±1mm to ±5mm
  - For example, for the ±1mm error plan, the distribution of MLC errors per field will range from +1mm to -1mm



Assessing the Sensitivity and Specificity

- Used 5 original patient plans (3 brains, 1 liver, 1 lung)
- Created 5 additional MLC error plans per patient plan

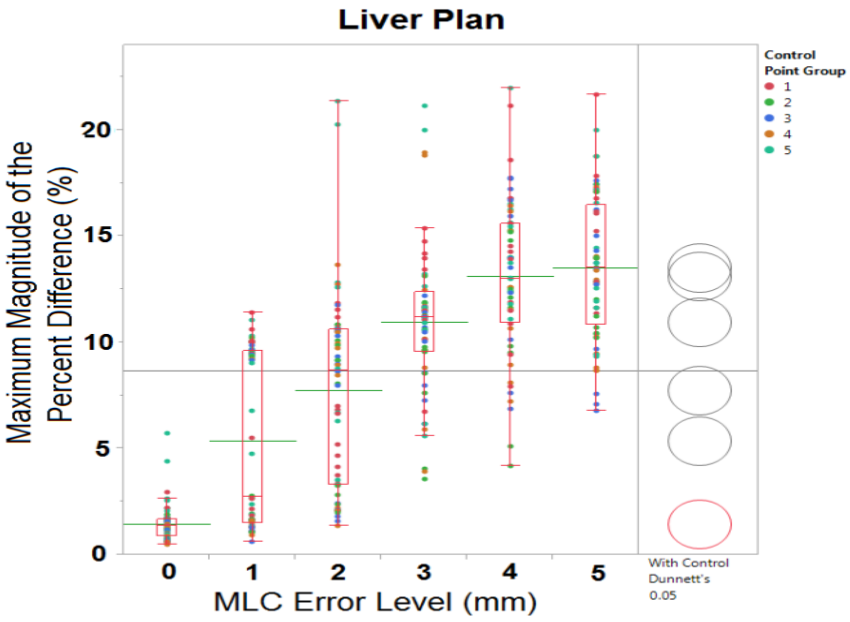


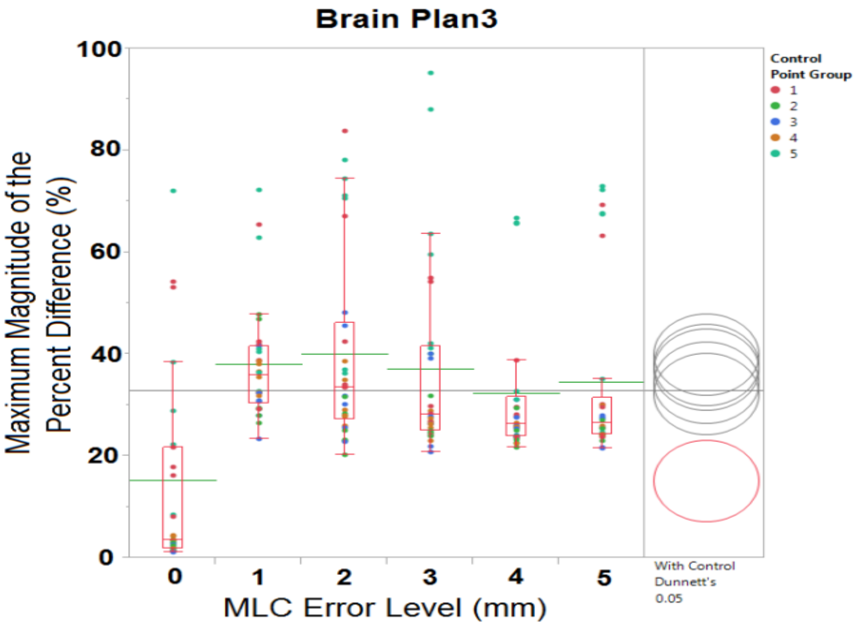


Assessing the Sensitivity and Specificity

- For the analysis we used maximum magnitude of the percent difference per control point group
- Due to distributed nature of MLC errors and relevance to clinic

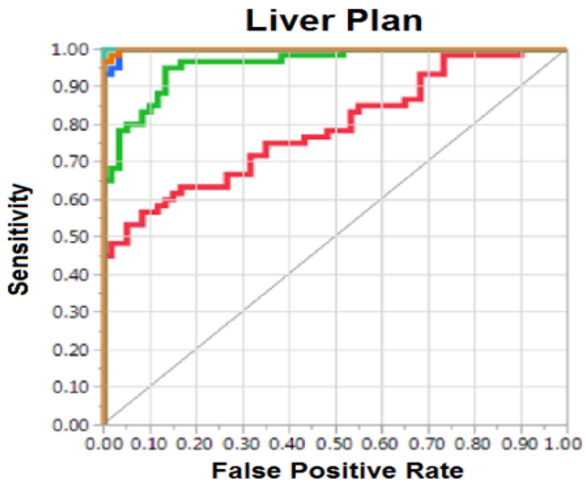
Distribution of percent differences & ROCs for good and less good plans

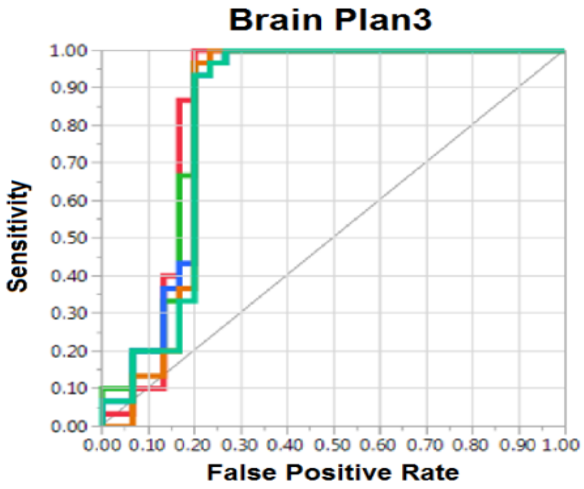




All of the MLC Error Levels (1mm to 5mm) were significantly different from their respective No-Error plans

Distribution of percent differences & ROCs for good and less good plans

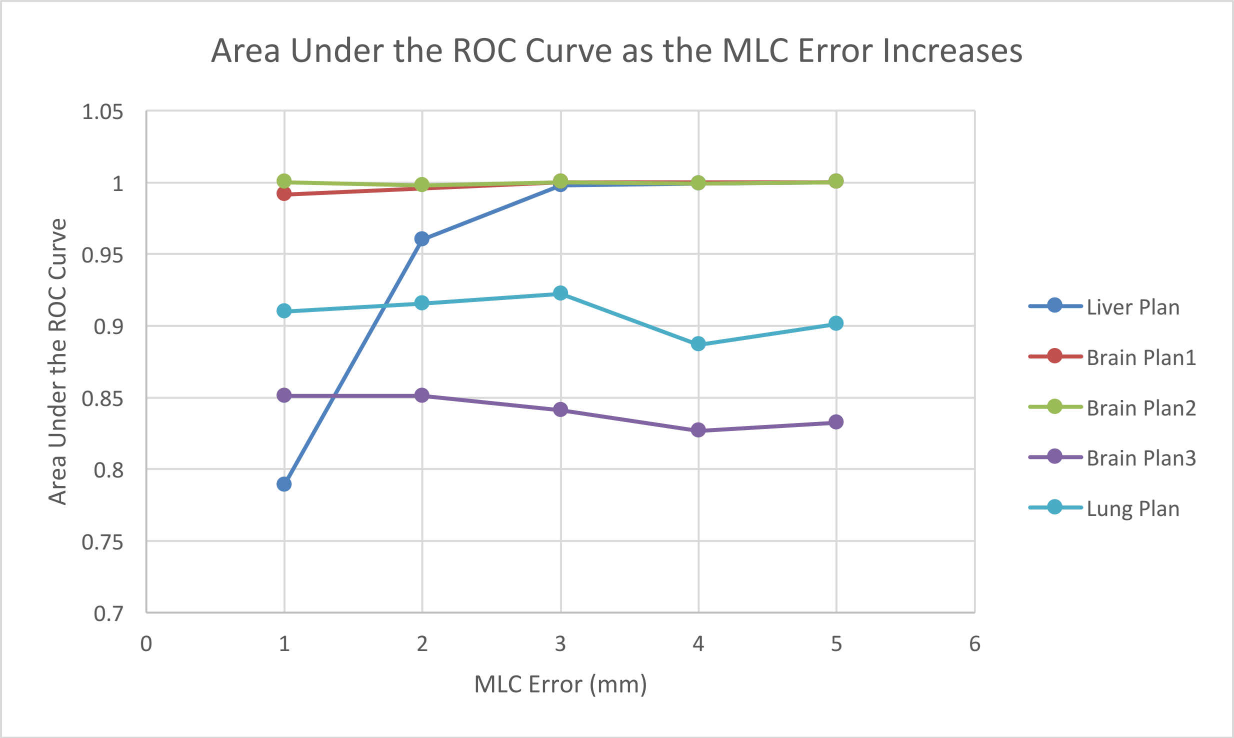




MLC Error Levels
- 1mm
- 2mm
- 3mm
- 4mm
- 5mm

All ROC curves showed good sensitivity and False Positive Rate

Area Under the Curve

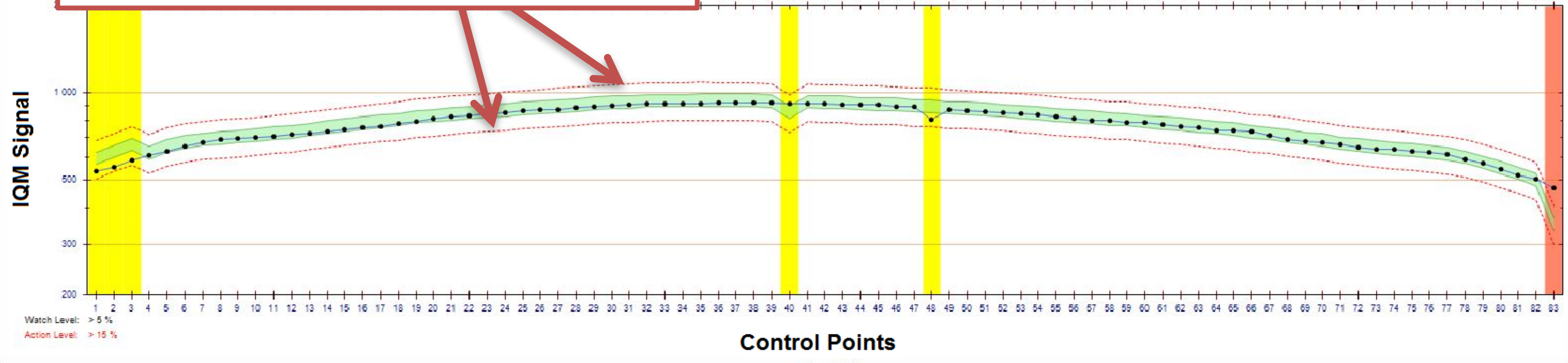


- AUC: Area under the ROC curve
- Gives an overall score for the classifier's sensitivity and specificity
  - Loses some information

Optimal Tolerances

- Recall how the IQM data is given to the user…

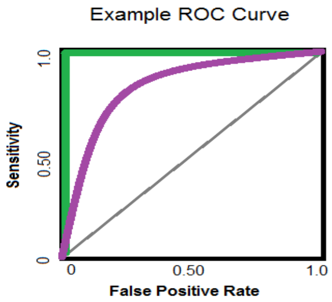
If the measurement's percent difference from baseline is greater than this → Alarm



Optimal Tolerances

Can find optimal tolerances from ROC curves, however due to inter-plan variation, more data needed to determine them

MLC Error (mm)	Liver Plan Optimal Cutoff (% from baseline)	Brain Plan1 Optimal Cutoff (% from baseline)	Brain Plan2 Optimal Cutoff (% from baseline)	Brain Plan3 Optimal Cutoff (% from baseline)	Lung Plan Optimal Cutoff (% from baseline)
1	2.6	10.8	11.0	23.3	22.0
2	2.0		10.8	22.9	21.1
3	3.5	17.4	11.5	20.8	16.3
4	6.9		12.1	21.8	21.9
5	6.8	14.7	12.4	21.6	16.4



Conclusions of Study

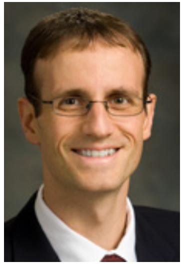
- IQM was able to tell the difference between plans with and without MLC errors (sensitivity <u>and</u> specificity)
- More work is needed to understand IQM response to different plan types in order to pick Optimal Tolerance values

Final Remarks

- ROC curves can be used to evaluate the sensitivity and specificity of emerging tools before becoming clinical
- They can be used to guide decisions on picking a relevant threshold
- They are flexible (only need binary outcome)

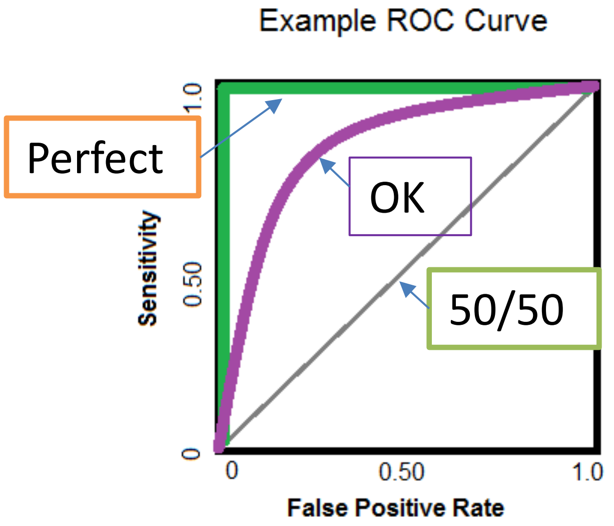
Acknowledgements

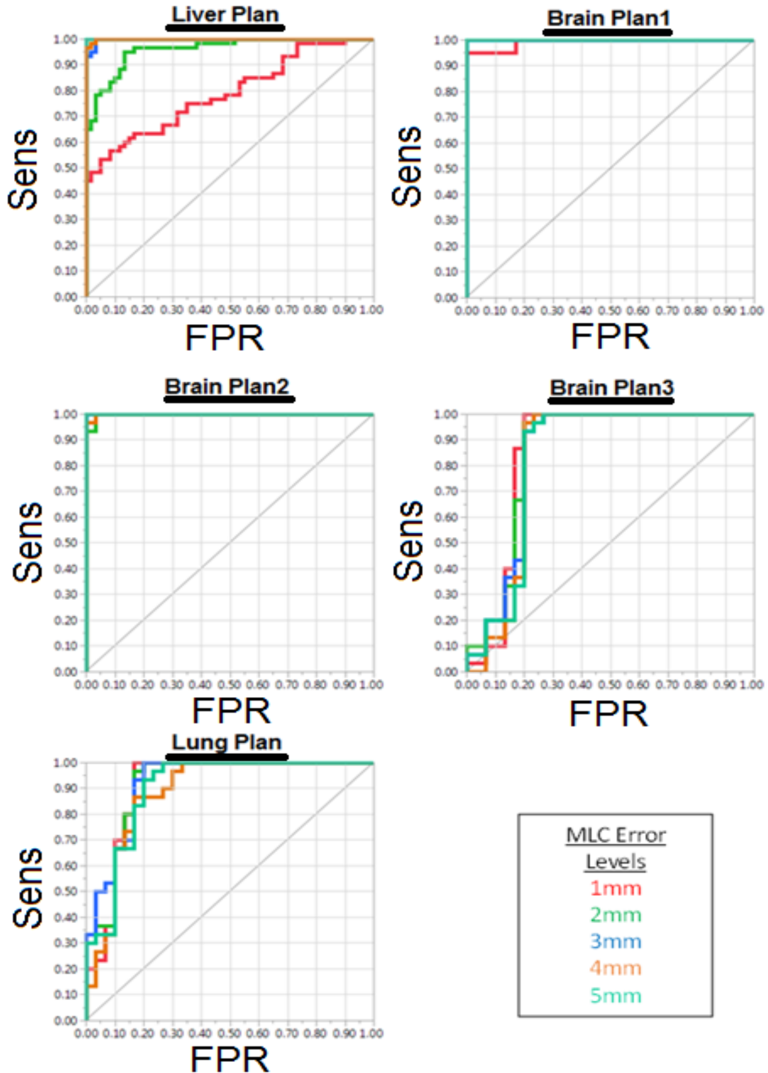
- Stephen Kry
- Benedick Fraass
- John Demarco
- Ke Sheng



Thank you

Receiver Operator Characteristic Curves





Different abilities to classify plans: possibly related to total MU (need more data to confirm)