Does software make me more efficient?

Mark J. Gooding, Ph.D.
Chief scientist
Mirada Medical
Presentation structure

• A bit about me

• A bit about the topic of discussion

• A look at efficiency in three clinical tasks
  – Auto-contouring
  – Multi-modal target contouring
  – Adaptive therapy

Very High Energy Electrons (>100 Mev) in Radiation Therapy

Colleen DesRosiers, PhD, DABR
But first…. Let’s get interactive

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But first…. Let’s get interactive

What shape is a football?

http://aamd2017.participoll.com
But first.... Let’s get interactive

What shape is a football?

A

B

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Why should you bother listening to me?

- 9 years in academic medical imaging research
- 8 years in commercial medical imaging research
- Chief Scientist
Introduction to the question

*Does software make me more efficient?*
Introduction to the question

*Does software make me more efficient?*

**How do you feel about your workflow?**

A. Software is key to our efficient workflow

B. Our workflow is efficient despite the software

C. Workflow could be improved, but the software is not the main problem

D. Software hinders our workflow most

Introduction to the question

Does software make me more efficient?

Technology Adoption Curve

EVERETT ROGERS - DIFFUSION OF INNOVATIONS 1962

- 2.5% Innovators
- 13.5% Early Adopters
- 34% Early Majority Adopters
- 34% Late Majority Adopters
- 16% Laggards
Introduction to the question

*Does software make me more efficient?*

Over enthusiastic marketing
Auto-contouring
Atlas-based auto-contouring
Atlas-based auto-contouring

Deformable registration

Atlas (contoured CT) → Current case
Atlas based auto-contouring

Single-atlas auto-contouring
- DIR and contour warping
- Contour consensus
- Patient image

Multi-atlas auto-contouring
- DIR, contour warping
- Patient image

Selection of single atlas
- DIR and contour warping
- Contour consensus
- Patient image

Selection of multiple atlases
- DIR, contour warping
- Contour consensus
- Patient image
Where are we on the adoption curve?

Does your institution **have** an auto-contouring system?

A  Yes
B  No
C  Don’t know

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Where are we on the adoption curve?

Auto-contouring

- Reasonably good workflow integration
- Performance standardising
- Vendors competing on price / workflow integration

INNOVATORS: 2.5%
EARLY ADOPTERS: 13.5%
EARLY MAJORITY ADOPTERS: 34%
LATE MAJORITY ADOPTERS: 34%
LAGGARDS: 16%
Does it do it’s job?

Does your institution **routinely use** an auto-contouring system?

A  Yes
B  No
C  Don’t know

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Disappointed?

The auto-contouring marketing promise:

England will win the next Football World Cup

The product will select the most similar atlas
You will save more time
Atlas based auto-contouring

Single-atlas auto-contouring

- DIR and contour warping
- Patient image

Multi-atlas auto-contouring

- DIR, contour warping
- Contour consensus
- Patient image

Selection of single atlas

- DIR and contour warping
- Patient image

Selection of multiple atlases

- DIR, contour warping
- Contour consensus
- Patient image
Can atlas selection make results better?

Hypothesis 1: Using an atlas more similar to the patient will have a better contouring performance compared to the use of a randomly chosen atlas.

But how much better?

316 Head & Neck
Contours + Image

Contour propagation
Image registration

Patient image
Contours

Original contours

Evaluate performance
- Dice Similarity Coefficient (DSC)
- Hausdorff Distance (HD)
- Average Distance (AD)
- Root Mean Square Distance (RMSD)

99540 atlas-patient pairs
Extreme Value Theory

An example from Oxford – Once-in-a-hundred-year flooding:
Extreme Value Theory

- Fit GPD model to extreme cases

- Estimate the magnitude *expected* of one-in-a-hundred-years rainfall: 194 mm

- Estimate the achievable auto-contouring performance for a database of 5000 atlases
Multi-atlas results

- Estimated *expected* performance assuming an atlas database of 5000 atlases
- Contour fusion results assumes 10 best

<table>
<thead>
<tr>
<th>Structure</th>
<th>Single Atlas - DSC</th>
<th>Contour Fusion - DSC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brain</td>
<td>0.988</td>
<td>0.996</td>
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<tr>
<td>Brainstem</td>
<td>0.903</td>
<td>0.943</td>
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<tr>
<td>Oral Cavity</td>
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<tr>
<td>Parotid L</td>
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<td>Parotid R</td>
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<td>Spinal cord</td>
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<td>Submandibular gl. L</td>
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<tr>
<td>Submandibular gl. R</td>
<td>0.863</td>
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<table>
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<tr>
<th>Metric</th>
<th>Single Atlas</th>
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<tr>
<td>HD (mm)</td>
<td>4.54</td>
<td>4.61</td>
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<tr>
<td>AD (mm)</td>
<td>0.97</td>
<td>0.98</td>
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<tr>
<td>RMSD (mm)</td>
<td>1.28</td>
<td>1.29</td>
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</table>
Good news!

With the most similar atlas
You will save more time
The auto-contouring will be better
The problem

Estimates the *potential* performance for a very large atlas database...

...assuming *perfect atlas selection* by an oracle with fore-knowledge of the output performance
Can we select the best atlas?

Hypothesis 2: Using an atlas with an image more similar to the patient image will have a better contouring performance compared to the use of a randomly chosen atlas.

Extensive comparison of methods in the literature and commercially available

- Local and global descriptors
- Direct atlas search and template-based search
- 154 selection methods were implemented
Performance analysis: Atlas selection

Results

Brainstem: DICE

Right Parotid: DICE

Online atlas selection methods
34 out of 154 shown
Performance analysis: Atlas selection

Results

Box plots of results on the Right Parotid
Why doesn’t atlas selection work?
Why doesn’t atlas selection work?

- Poor correlation of similarity measures to **meaningful** image differences
- Poor correlation image differences to **meaningful** contour differences
- Image measures can’t account for **Contouring variability**
The end result

Over enthusiastic marketing
Untested assumptions

The product will select the most similar atlas
You will save more time

Expectation ≠ Reality
But the literature shows it saves time....

<table>
<thead>
<tr>
<th>Reference</th>
<th>Anatomy</th>
<th>No. of Patients</th>
<th>No. of Atlases</th>
<th>Time saved (mins)</th>
<th>Time saved (%)</th>
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<td>mastication) structures in the head and neck.&quot; *International Journal</td>
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<td>Young, Amy V., et al. &quot;Atlas-based segmentation improves consistency</td>
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<td>and decreases time required for contouring postoperative endometrial</td>
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<td>cancer nodal volumes.&quot; <em>International Journal of Radiation Oncology</em></td>
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<td>Gambacorta, Maria Antonietta, et al. &quot;Clinical validation of atlas-based</td>
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<td>using auto-segmentation computed system.&quot; <em>Acta Oncologica</em> 52.8 (2013):</td>
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<td>in the clinical workflow.&quot; <em>International Journal of Radiation Oncology</em></td>
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<td>Langmack, K. A., et al. &quot;The utility of atlas-assisted segmentation in</td>
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<td>atlas-based organ-at-risk auto-segmentation-assisted radiation planning</td>
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Take home messages – Part 1

⚠️ Question the assumption made in marketing

⚠️ Consider the workflow impact
Multi-modal target contouring
Multi-modal target contouring
Multi-modal target contouring

Image registration
Where are we on the adoption curve?

Does your institution **routinely use** multi-modal target contouring?

A. Yes – PET/CT only
B. Yes – MRI only
C. Yes – PET/CT and MRI
D. No
E. Don’t know

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Where are we on the adoption curve?

Multi-modal target contouring

- Wide range of solutions
- Clinical use standardising
- Vendors competing on features / quality

2.5% INNOVATORS
13.5% EARLY ADOPTERS
34% EARLY MAJORITY ADOPTERS
34% LATE MAJORITY ADOPTERS
16% LAGGARDS
PET/CT

☑️ Shows metabolically active areas

⚠️ Not anatomical

⚠️ Low resolution
MRI

- Better soft tissue contrast
- Large range in acquisitions
- Often low res out of plane
- Limited field of view
- May be off-axis
- May have geometric distortion
How well integrated is it?

Where does your institution do multi-modal target contouring/registration?

A  Yes – all integrated on the TPS
B  Yes - 3rd Party
C  N/A – We don’t do it
D  Don’t know

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It’s about improving treatment

Multi-modal contouring will improve treatment
Work without Multi-modal target contouring

Simulation CT

Dosimetrist
- OAR contouring
- Planning

Rad Onc
- Target contouring
- Plan approval

Med Phys
- Plan Check

Treatment
So why can it feel painful?

Simulation
CT

Dosimetrist
Get MRI or PET
Registration
OAR contouring
Planning

Rad Onc

Target contouring
Plan approval

Med Phys
Registration
Registration QA
Plan check

Treatment
Let’s talk about efficiency

The ratio of the useful work performed by a machine or in a process to the total energy expended or heat taken in.

Photo: Raphael Matos, InsideTheRace.com
How is multi-modal target contouring increasing efficiency?

**Simulation CT**

**Get MRI or PET**

**Registration**

**OAR contouring**

**Planning**

**Dosimetrist**

**Rad Onc**

**Med Phys**

**Useful work + extra effort**

**Target contouring**

**Plan approval**

**Registration QA**

**Plan check**

**Treatment**
How do you do it?

How does your institution perform multi-modal target contouring?

- **A** Yes – Rigid registration only
- **B** Yes – Deformable registration
- **C** No – We still don’t use it!
- **D** Don’t know

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Image registration

- **Similarity measure**
  - Performs anatomical matching

- **Transformation model**
  - Constrains the solution

- **Regularization**
  - Prevents matching noise
## Common similarity measures

<table>
<thead>
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<th>Similarity measure</th>
<th>Assumption</th>
<th>PET/CT</th>
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<tr>
<td>Sum-Squared-difference (SSD)</td>
<td>Intensities in both images are the same</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correlation Coefficient</td>
<td>Intensities not the same, but have same order. i.e. brighter in one image = brighter in the other image</td>
<td></td>
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<tr>
<td>Modelled-SSD</td>
<td>Simple linear modelling can be used to map intensities. SSD performed on mapped intensities</td>
<td></td>
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<tr>
<td>Mutual Information (MI)</td>
<td>Some relationship between intensities in each image</td>
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</table>
## Common similarity measures

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</tbody>
</table>
Correlation

Intensity in 1st image vs. Intensity in 2nd image

- SSD
- CC

Intensity in 2nd image vs. Intensity in 1st image

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## Common similarity measures

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Modelled SSD

Intensity in 1st image

Intensity in 2nd image
# Common similarity measures

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Mutual Information

Intensity in 1st image

Intensity in 2nd image
## Common similarity measures

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<tr>
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<td>✓</td>
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Transformation models

Constrains the solution to a smaller range of possibilities
Rigid registration
Free-form deformable

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B-Splines
Radial Basis Functions
Transformation models

Constrains the solution to a smaller range of possibilities

- More constrained → Faster (potentially)
- More constrained → Smoother
- More constrained → Less accurate
Regularizers

Prevent the similarity measure over fitting to noise
Regularizers

Similarity of images

Smoothness of deformation
Regularizers

Prevent the similarity measure over fitting to noise

- More constrained  ➔  Faster (potentially)
- More constrained  ➔  Smoother
- More constrained  ➔  Less accurate
So what’s all this go to do with efficiency?

The ratio of the useful work performed by a machine or in a process to the total energy expended or heat taken in.

Photo: Raphael Matos, InsideTheRace.com
Reducing efficiency

Wrong similarity measure
Over constrained
Under constrained

Less useful work
Lower efficiency
Using the registration

⚠️ Resampling loses information
Using the registration
Efficiency choice

- Harder to integrate
  - Contouring → Resample contour
- Loss of accuracy
  - Resample image → Contouring
- Easier to integrate
  - Target contoured → Registration
- Maintains accuracy
  - Contouring → Resample image

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Take home messages – part 2

⚠️ No gain without pain!

⚠️ Be wary of resampling the image
Adaptive Therapy

Acquiring a new planning CT mid-treatment to account for changes in patient anatomy / response to treatment
Where are we on the adoption curve?

What percentage of your patients do you routinely consider adaptive therapy for?

A. None
B. 1 – 10 %
C. 10 – 30 %
D. 30 – 50 %
E. 50 – 100 %

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Where are we on the adoption curve?

What percentage of your patients do you routinely do adaptive therapy for?

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<td>A</td>
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<td>B</td>
<td>1 – 5 %</td>
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<td>C</td>
<td>5 – 10 %</td>
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<tr>
<td>D</td>
<td>10 – 20 %</td>
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<td>E</td>
<td>20 – 40 %</td>
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<tr>
<td>F</td>
<td>40+ %</td>
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Where are we on the adoption curve?

Adaptive therapy

2.5% INNOVATORS
13.5% EARLY ADOPTERS
34% EARLY MAJORITY ADOPTERS
34% LATE MAJORITY ADOPTERS
16% LAGGARDS
Where are we really on the adoption curve?

What does your institution do before deciding to adapt?

A Physical assessment of patient by the Rad Onc
B Visual assessment of CBCT
C Quantitative structure assessment on CBCT
D Quantitative dose assessment on CBCT without recalculation
E Quantitative dose assessment on CBCT with dose recalculation
F Quantitative dose assessment on re-planning CT

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Where are we really on the adoption curve?

What does your institution do for adaptive therapy?

A. Replan on new CT, without dose volume summation
B. Replan on new CT, using rigid dose from previous plan
C. Replan on new CT, using deformed dose from previous plan
D. Replan on new CT, using cumulative dose from previous plan across all CBCTs

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Where are we on the adoption curve?

Adaptive therapy

- Multiple components needed
- Clinical benefit being evaluated
- Vendors need to collaborate with Innovators and each other

Fully adaptive therapy

2.5% INNOVATORS

13.5% EARLY ADOPTERS

34% EARLY MAJORITY ADOPTERS

34% LATE MAJORITY ADOPTERS

16% LAGGARDS

Increasing effort
Adaptive Therapy – An efficiency choice

What would the increase in quality can I achieve if ...?  
How much time can I spend/tolerate?

Treatment quality  
Effort/time required
Adaptive therapy is a broad spectrum

We support adaptive therapy
You can improve quality
Take home message 3

⚠️ No gain without pain!

⚠️ Clinical evidence will drive efficiency

⚠️ Clinical evidence will drive software effort reduction
Take home messages – the summary

⚠️ Question the assumption made in marketing

⚠️ No gain without pain!

⚠️ Clinical evidence will drive software effort reduction