Advances in Treatment Planning and Applications to Pediatric Radiotherapy

Mahesh Gopalakrishnan
Northwestern Memorial Hospital
Chicago

Disclosures

- none

Outline of talk

- Cardiac Sparing whole lung IMRT (CS-WL-IMRT)
  - Rationale
  - Initial results and data from R21
- CS-WL-IMRT with thyroid, breast-sparing combined with addition of flank or whole abdomen field (Modified CS-WL-IMRT)
- Comparison of DVH's
- Adaptive planning- DIR, auto contouring and re-planning
- AI in Radiation Oncology

Cardiac sparing whole lung IMRT (CS-WL-IMRT)

- Whole lung Irradiation (WLI) has been widely used in the management of lung metastases for Wilms tumor, Ewing Sarcoma and rhabdomyosarcoma.
- Cardiac failure is an important late effect observed in childhood cancer survivors after WLI and doxorubicin.
- Rationale
  - Prove superior dosimetric coverage for WLI
  - Spare heart from high doses of radiation

CT Simulation

- Vac-loc with arms up or down for immobilization
- Neck rest or aquaplast mask
- Anesthesia administered (<= 4years of age)
- First CT was a non-contrast scan (2-3mm slices)
- Second CT was a contrast scan
  - Help delineate cardiac anatomy
- All patients underwent 4D CT simulation

Target and OAR definition

- CTV = Maximum Lung Expansion (MLE) in 4D scan
- MLE-CTV = CTV+ 5mm
- PTV = MLE-CTV + 5mm
  - Expanded to include entire vertebrae and mediastinum LNs

- OAR
  - Heart and chambers
  - Breast tissue
  - Thyroid
  - kidneys

Treatment Planning

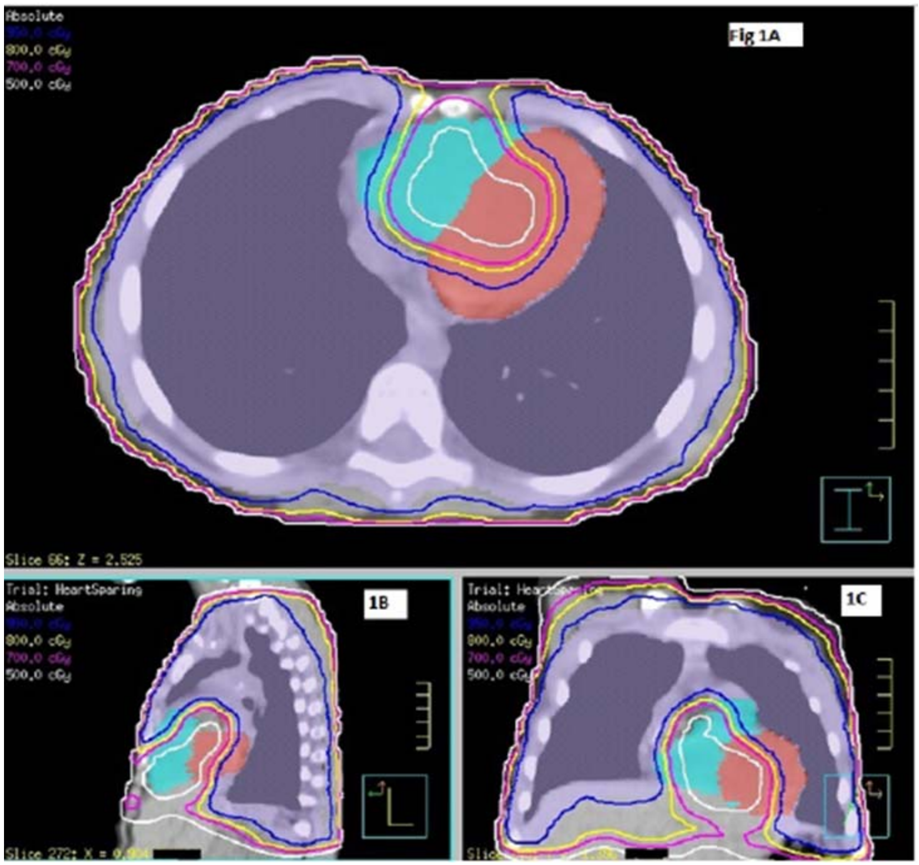
- Prescription
  - 12Gy/1.5Gy – Wilms
  - 15gy/1.5Gy – others

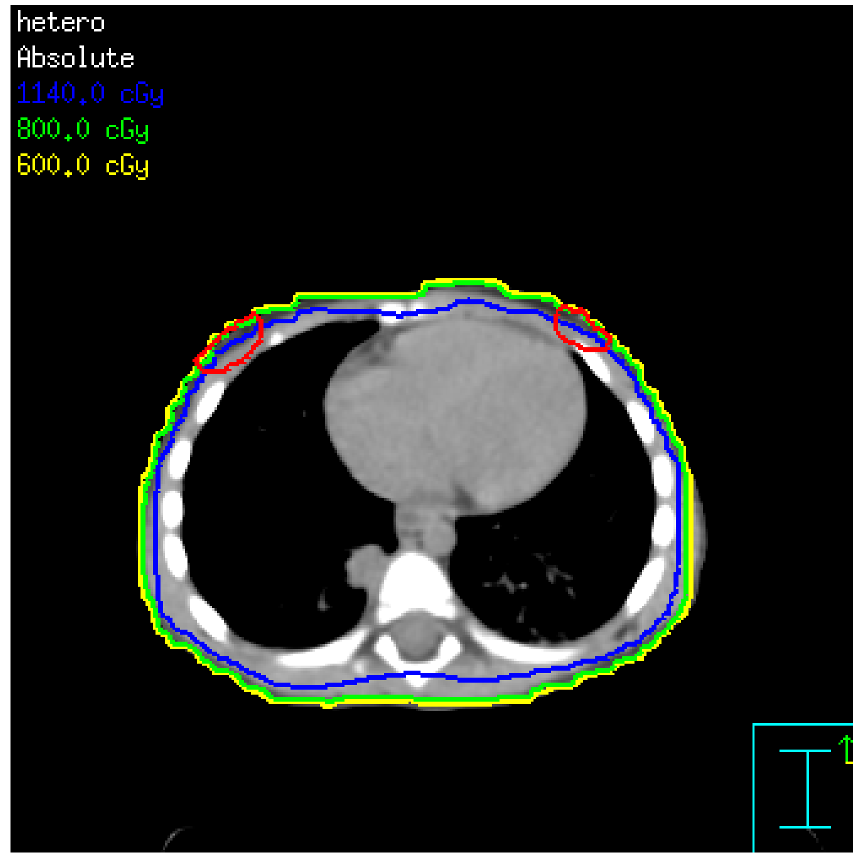
- Target coverage
  - 95% of PTV to receive 95% of prescription dose (~1000- 5000cc)
  - 105% of prescription dose <=2% of PTV volume
  - 110% of prescription dose <= 1% of PTV volume

  - Max dose
    - Cord - <107%
    - Heart, liver - <110%

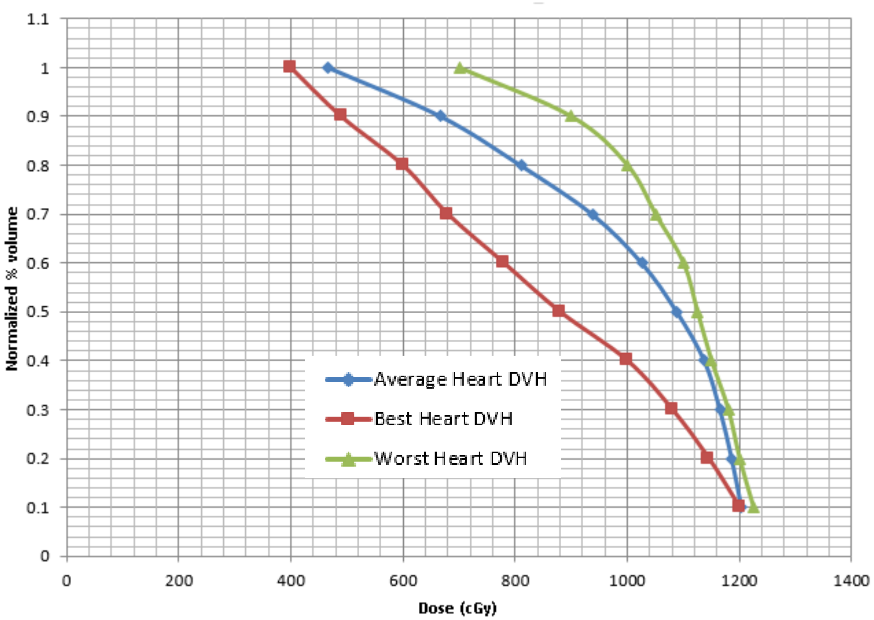
  - Beams
    - Step and Shoot or Sliding window
      - 9 beams – equally spaced
    - VMAT

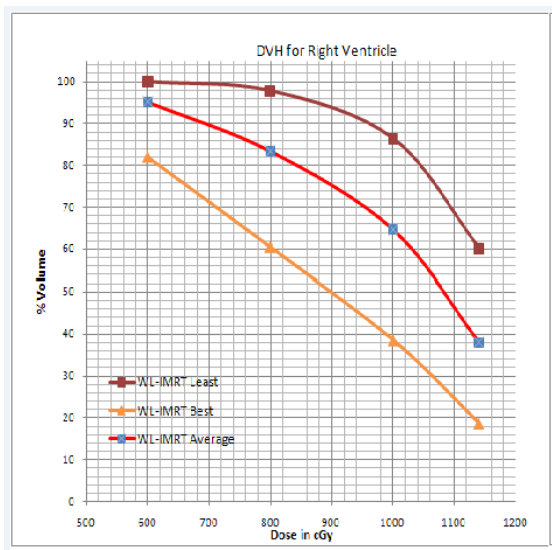
CS-IMRT v/s AP-PA

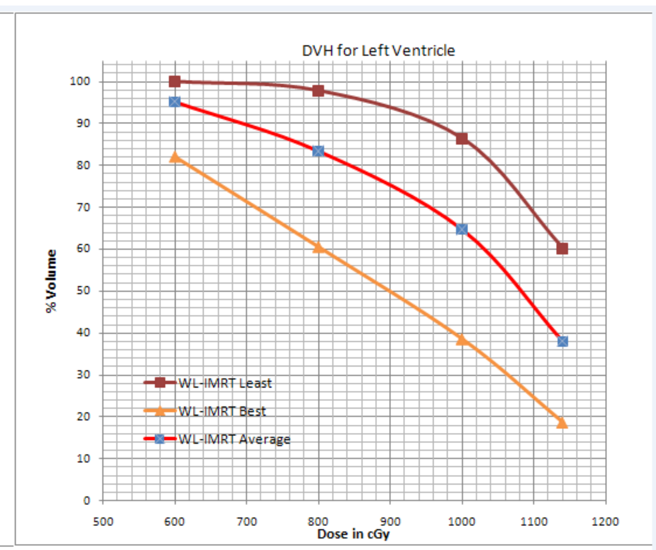




DVH for Heart, RV and LV

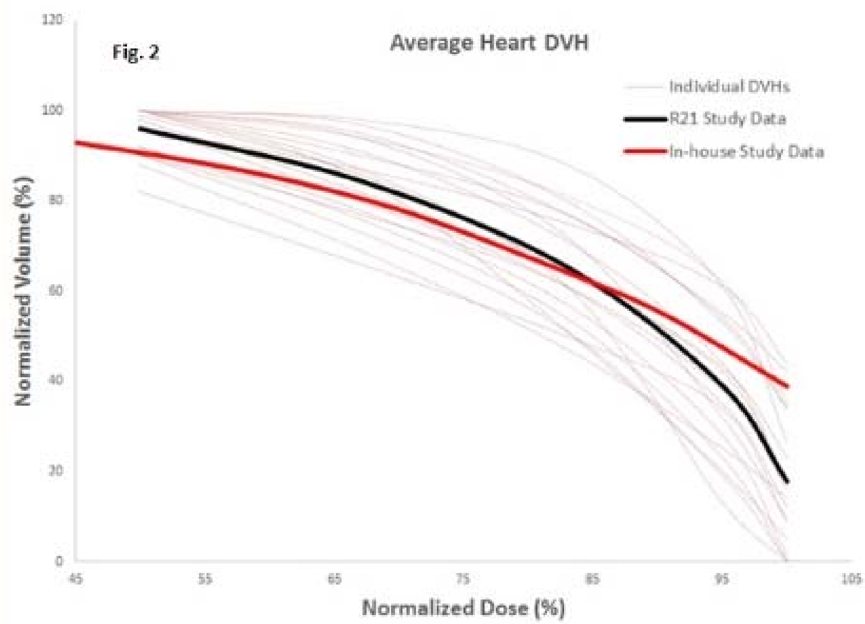


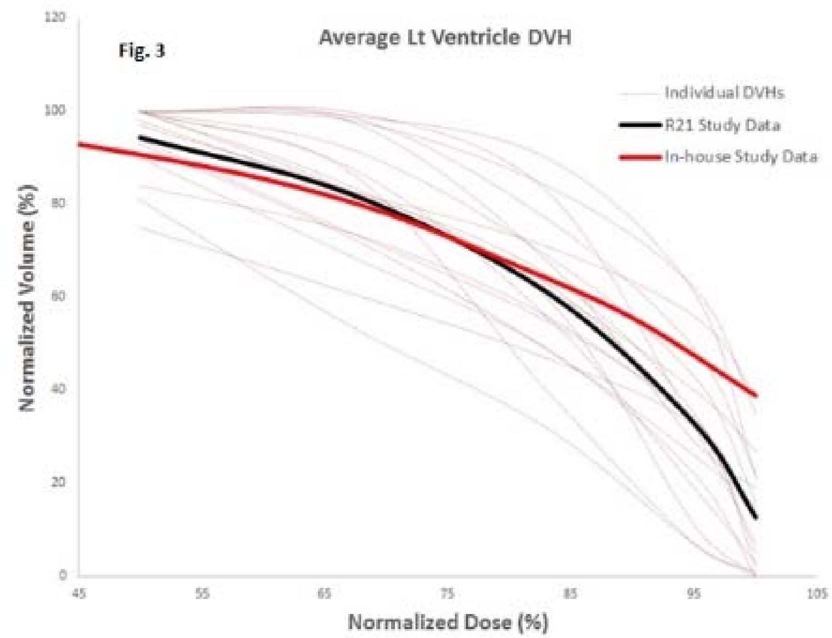




Average Dvh data from **in-house** study for 20 patients

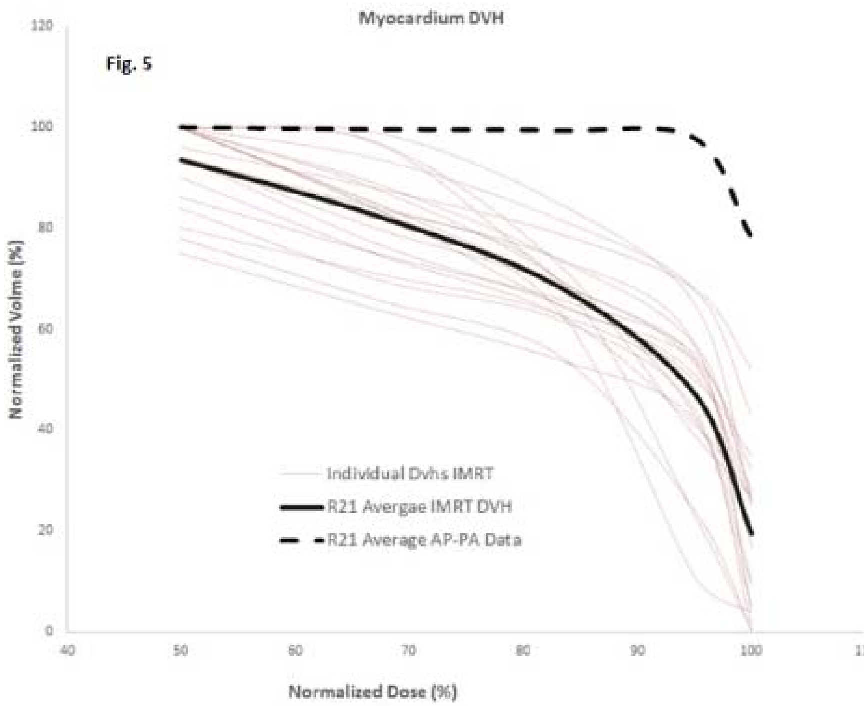
DVH Heart and Left Ventricle, Myocardium and RV

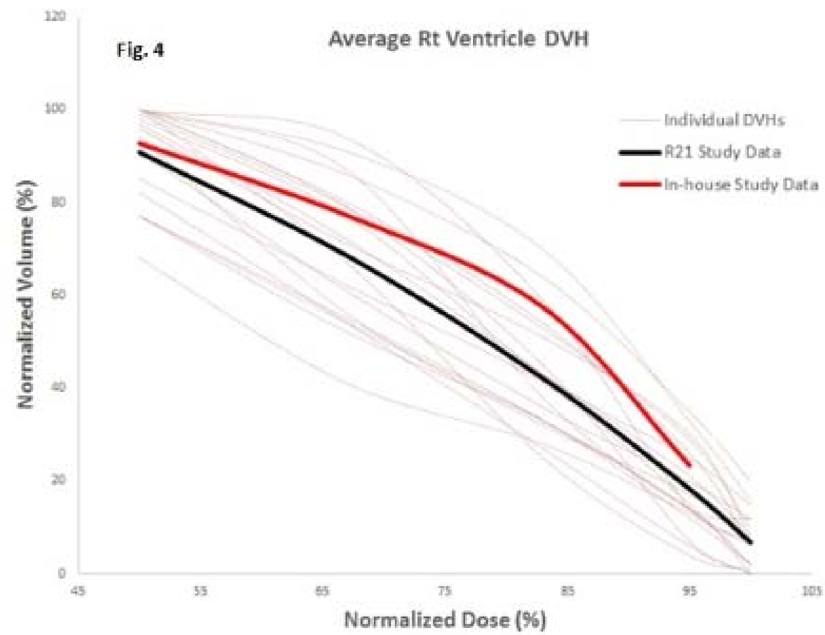




20 patients; multiple institutions- R21 Study

DVH for Myocardium and Right Ventricle





20 patients; multiple institutions- R21 Study

Table 1.

Comparison of 4-dimensional cardian sparing IMRT and 3-dimensional standard whole lung irradiation to the Heart, Ventricles, Atria, Liver, Thyroid, Coronaries and Myocardium

Normal tissue		V50			V67			V83			V95		
		IMRT	AP-PA	*P-value*	IMRT	AP-PA	*P-value*	IMRT	AP-PA	*P-value*	IMRT	AP-PA	*P-value*
Heart	Mean	96% **(92)**	100.00%	0.0083	85% ***(80)***	100%	<.0001	65% ***(64)***	100%	<.0001	39% ***(40)***	97	<.0001
	SD	5.4	0.8		9.5	1.3		12.1	2.2		15.5	6.7	
LV	Mean	95% ***(95)***	100%	0.006	82% ***(83)***	100%	<.0001	61% ***(65)***	100%	<.0001	33% ***(38)***	99%	<.0001
	SD	7.8	0		13.5	0.2		15.2	0.5		15.9	2.7	
RV	Mean	91% ***(81)***	100%	0.002	69% ***(58)***	99%	<.0001	42% ***(37)***	99%	<.0001	18% ***(17)***	97%	<.0001
	SD	10.8	1.6		15.2	2.6		12.7	4		8.9	8.2	
LA	Mean	99% ***(100)***	100%	0.36	98% ***(100)***	100%	0.036	87% ***(88)***	100%	0.0002	55% ***(60)***	94	<.0001
	SD	0.4	0.2		3.8	1.1		12.3	2.5		22.3	15.4	
RA	Mean	99% ***(100)***	99%	0.78	97% ***(98)***	100%	0.009	86% ***(86)***	100%	<.0001	57% ***(60)***	97%	<.0001
	SD	0.4	0.7		3.3	1.3		10.5	2		22.5	11.1	
LCA	Mean	99%	100%	0.33	98%	100%	0.051	91%	100%	0.0008	66%	100%	<.0001
	SD	1.1	0		4.5	0		9.5	0		25.1	0	
RCA	Mean	100%	100%	NA	98%	100%	0.025	88%	99%	<.0001	53%	96	<.0001
	SD	0	0		3.5	1.3		9.9	3.1		20.9	12.8	
Liver	Mean	55% ***(56)***	54%	0.88	48% ***(47)***	51%	0.47	39% ***(31)***	48%	0.025	27% ***(17)***	37	0.008
	SD	11.4	14		11.2	14		10.5	14		9.7	13.6	
Thyroid	Mean	44% ***(50)***	33%	0.27	33% ***(37)***	28%	0.61	20% ***(26)***	23%	0.72	6% ***(17)***	16%	0.1
	SD	32.5	33.1		31	31.3		24.4	29.8		8.5	26.2	
Myocardium	Mean	94% ***(97)***	100%	0.05	80% ***(85)***	100%	<.0001	59% ***(73)***	100%	<.0001	32% ***(54)***	99%	<.0001
	SD	7.4	0		12.4	0.2		16.3	0.7		20.6	2.7	

*** Data in paranthesis indicate the values from our initial in-house study****

Mod-CS-IMRT+Whole Abdomen v/s CS-IMRT

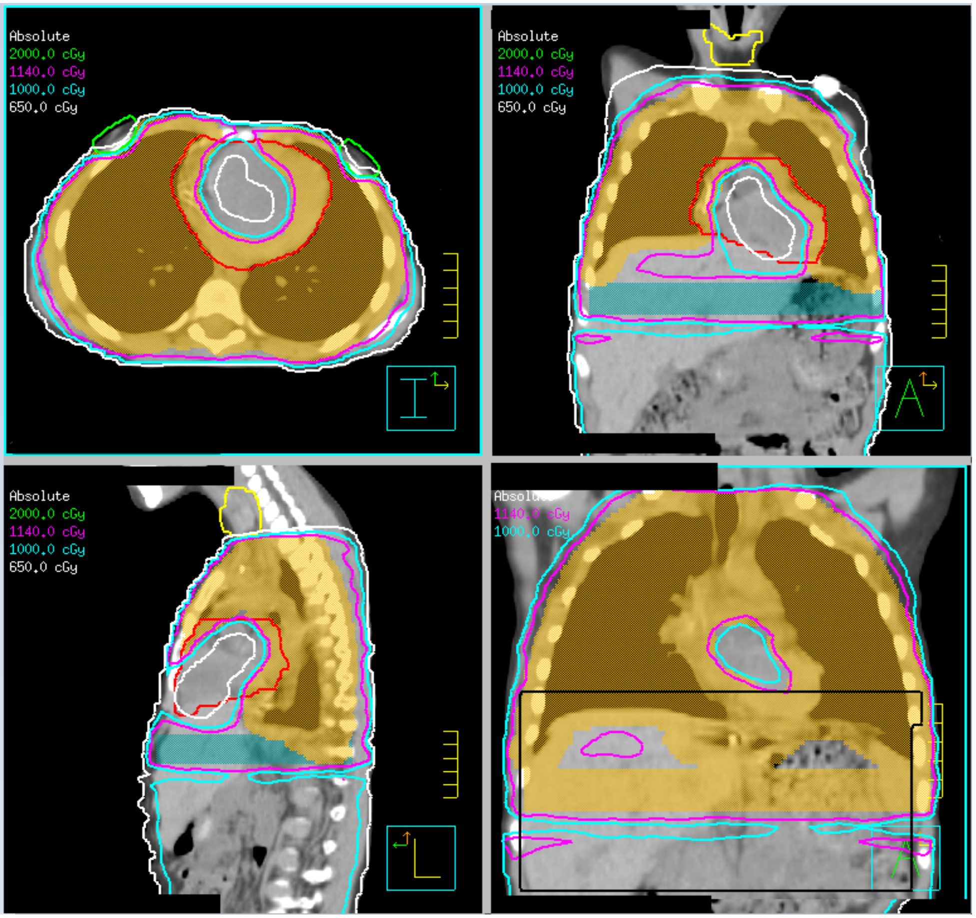
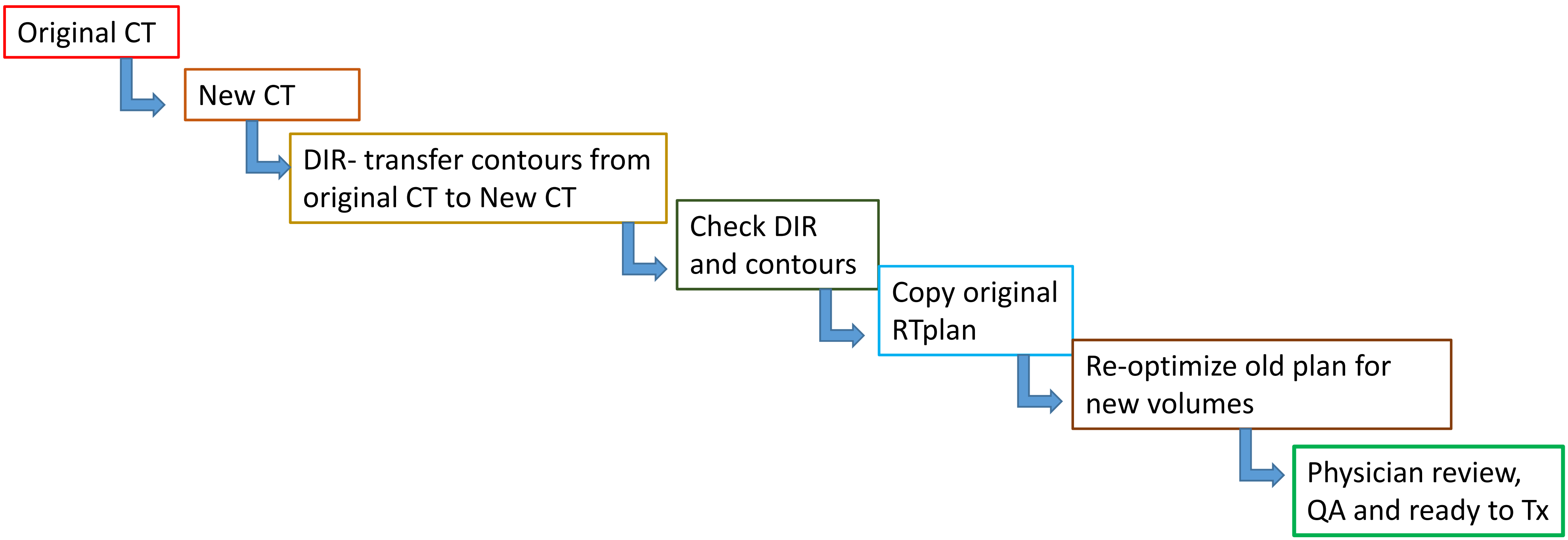


Table 2. **Comparison of CS-IMRT and Modified CS-IMRT+WA for Heart, Ventricles, Atria, Thyroid, Coronaries, Breast and Myocardium**

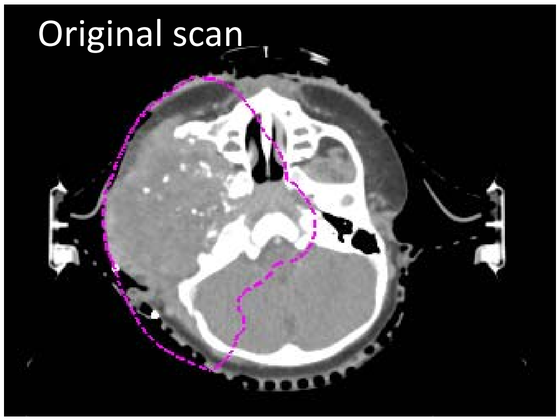
Normal tissue		V50			V67			V83			V95		
		CS-IMRT	Mod-CSIMRT+WA	*P-value*	CS-IMRT	Mod-CSIMRT+WA	*P-value*	CS-IMRT	Mod-CSIMRT+WA	*P-value*	CS-IMRT	Mod-CSIMRT+WA	*P-value*
Heart	Mean	93%	98%	0.17	83%	86%	0.55	65%	68%	0.33	35%	43%	0.03
	SD	7.95	5.04		12	10		9.4	10		8.14	8.3	
LV	Mean	92%	97%	0.26	82%	85%	0.5	63%	67%	0.4	36%	44%	0.1
	SD	9.1	5.20		13.3	11.0		11	12		10.4	12	
RV	Mean	87%	99%	0.26	72%	78%	0.6	42%	47%	0.36	15%	21%	0.08
	SD	16.7	0.28		24.2	20		16.4	17		11	13	
LA	Mean	99%	99%	0.35	96%	97%	0.62	86%	88%	0.57	39%	40%	0.2
	SD	1.2	0.51		5.57	3.5		13.5	11		18.2	19	
RA	Mean	99%	99%	0.3	97%	98%	0.87	88%	89%	0.82	53%	57%	0.06
	SD	0.71	1.8		4	3.1		9.7	8.7		10.5	20	
LCA	Mean	96%	99%	0.16	93%	94%	0.79	79%	81%	0.65	57%	61%	0.5
	SD	9.6	2.1		11.3	9.5		12.8	13		14	11	
RCA	Mean	99%	99%	0.63	97%	97%	0.63	88%	89%	0.45	49%	51%	0.5
	SD	1.79	1.4		5.3	4.8		8.7	9.4		16	16	
Myocardium	Mean	93%	97%	0.23	84%	86%	0.5	67%	71%	0.29	46%	56%	0.04
	SD	8.5	4.6		10.2	8.6		7.5	8		8.8	12	

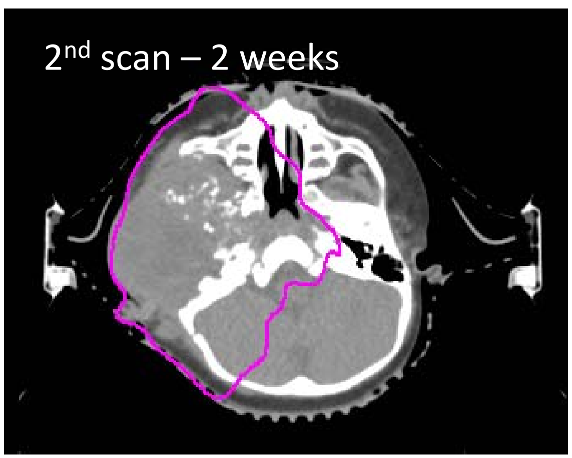
	Gy	CS-IMRT	Mod-CSIMRT+WA	*P-value*
Breast	Mean	10	5	0.0002
	SD	1.1	1.1	
Thyroid	Mean	5	2	0.006
	SD	2.6	1.5	

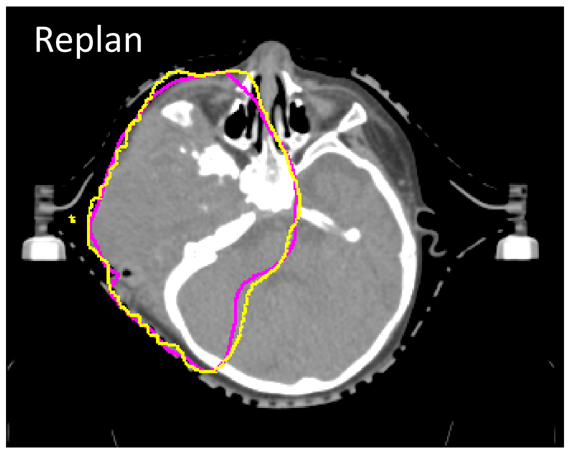
Adaptive Re-plan Off-line Workflow



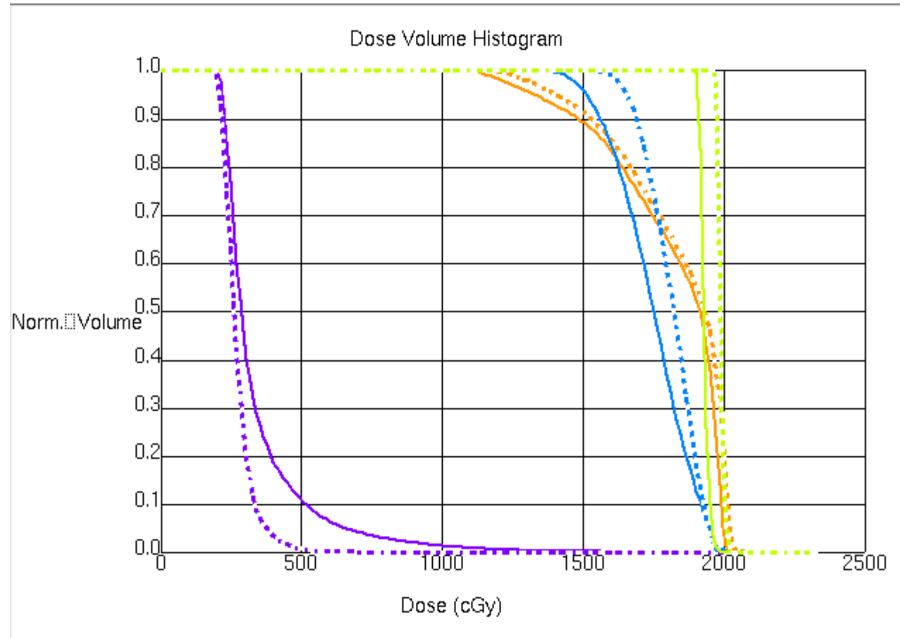
Adaptive Re-plan Off-line







DIR – 5 minutes
Dose re-optimization- 10 minutes
Plan Eval – 5 minutes



ROI Statistics

Line Type	ROI	Trial or Record	Min.	Max.	Mean	Std. Dev.
	Brain stem	Original Ct and plan	1000.4	2034.9	1808.8	217.1
	Brain stem	New CT and plan	1103.2	2074.2	1837.7	203.5
	Lt parotid	Original Ct and plan	194.4	1572.5	338.5	160.1
	Lt parotid	New CT and plan	187.6	682.4	270.9	54.5
	Chiasm	Original Ct and plan	1327.7	1985.1	1741.7	132.2
	Chiasm	New CT and plan	1486.1	2005.8	1813.1	91.0
	Rt optic	Original Ct and plan	1899.4	1991.2	1929.4	15.0
	Rt optic	New CT and plan	1958.3	2021.8	1988.7	10.3

Adaptive Replan- Conclusions

- Improves throughput
- Improves efficiency and safety
- Still requires time commitment from staff (Physicians and Physics)

- Limitations
  - Limited soft tissue details from CBCT
  - GPU based calculation could help with calculation time
  - Currently true "ON-LINE" adaptive only done with MR-Linac

AI In Radiation Oncology

- Image segmentation -Contouring – OAR and PTV
- Dose optimization
- Clinical decision making
- Outcome prediction

Segmentation methods (Auto contouring)

- Prior knowledge
  - Atlas based segmentation
    - Single or multi-atlas
  - Model based segmentation
    - Statistical shape models (SSM) or Statistical appearance models (SAM)
  - Machine learning based segmentation
    - Automatic detection and classification of tissues
    - Great for classification, detection and pattern recognition
    - Often combined with Atlas based or shape model segmentation

- Non- prior knowledge
  - Segmentation based on image voxel intensities (Lung, bone etc)

Sharp et al. Medical Physics, Vol. 41, No. 5, 2014

TABLE II. Commercial software tools for automated medical image segmentation (F = female; H and N = head and neck; M = male TPS = treatment planning system).

Supplier	Product name	Method	Included atlases	Integrated with TPS	Reference
Accuray	MultiPlan 5.0	Atlas-based model-based	Brain, M pelvis	Yes	Reference 101
BrainLab	iPlan	Atlas-based	Brain, H and N,M pelvis, spine, thorax	Yes	Reference 102
Dosisoft	IMAgo	Atlas-based	Brain, H and N	Yes	Reference 103
Elekta	ABAS 2.01	Atlas-based model-based	H And N, M pelvis	No	Reference 14
MIM software	MIM Maestro 6+	Atlas-based	H and N	No	Reference 104
Mirada	RTx 1.4, Workflow box	Atlas-based	Ano-rectal, Breast, H and N, F pelvis, M pelvis, thorax	No	Reference 105
OSL	OnQ RTS	Altas-based	H and N, M pelvis, thorax	No	Reference 106
Philips	SPICE 9.8	Atlas-based model-based	Abdomen, H and N, pelvis, Thorax	Yes	Reference 13
RaySearch	RayStation 4.0	Atlas-based model-based	Abdomen, H and N, F pelvis, M pelvis, thorax	Yes	Reference 107
Varian	Smart Segmentation	Atlas-based	H and N, M Pelvis, thorax	Yes	Reference 108
Velocity	VelocityAI 3.0.1	Atlas-based	Brain, H and N, F pelvis, M pelvis	No	Reference 58

Table 1. Relevant publications on machine learning approaches to radiotherapy target delineation. Abbreviations: organ at risk (OAR), computed tomography (CT), Dice similarity coefficient (DSC), magnetic resonance imaging (MRI), clinical target volume (CTV).

Publication	Cancer Site	Machine Learning Method	Target Volume Delineation	Radiotherapy Planning Modality	Number of Patients	Validation	Outcome and Important Features
Nikolov S [32]	Head and neck	Deep Learning	OAR	CT	663	Compared against manual contours by senior radiographers adjudicated by senior consultant clinical oncologist	19 out of 21 OAR surface DSC scores less than 5% deviation when compared to clinician manual contours. Did not achieved target for brainstem and right lens
Li Q [37]	Head and neck	Deep Learning	Tumour	MRI	29	Compared against manual contours by consultant clinical oncologists	Mean DSC 0.89. Good agreement when compared to manual contours
Cardenas CE [38]	Head and neck	Deep Learning	High risk CTV	CT	52	Compared against manual contours by clinicians	Median DSC 0.81. Good agreement when compared to manual contours by clinicians with only minor or no change
McCarroll R [39]	Head and neck	Machine Learning	OAR	CT	128	Compared against manual contours by consultant clinical oncologist	Mean DSC 0.78. Once validated was used in clinical setting and prospectively tested with accuracy of 63%. 50% of auto-contours were used without changes
Speight R [40]	Head and neck	Machine Learning	CTV	CT	15	Auto-contours edited by clinicians compared against manual contours by clinician	Edited CTV DSC 0.87. Mean clinician time saved by 112 min per plan when compared to manual contours
Martin S [41]	Prostate	Machine Learning	Tumour	MRI	15	Compared against manual contours by 5 clinicians of varying experience	3 phases of trial. Mean DSC 0.89. Good agreement with clinician contours requiring minimal changes. Time saved in all cases
Lustberg T [42]	Lung	Deep Learning	OAR	CT	20	Compared against manual contours by a single radiotherapy technician	Median DSC 0.57 and median time saved by 79%. Saved time in lung and spinal cord contouring but not for left lung and oesophagus
Bell LR [43]	Breast	Machine Learning	Tumour	CT	28	Compared against manual contours by 8 clinicians	DSC more than 0.70. Good agreement with clinician manual contours. Coverage agreement poorest towards heart border structures

Assessing the Role of Artificial Intelligence (AI) in Clinical Oncology: Utility of Machine Learning in Radiotherapy Target Volume Delineation

Ian S. Boon [1,*], Tracy P. T. Au Yong [2] and Cheng S. Boon [3]

Challenges

- Heterogeneous data sets
- Image quality (Lack of soft tissue information, Resolution, slice thickness, FOV, low SNR)
- Organ motion/ filling
- Change in organ due to tumor burden (use prior dataset info)
- Multiple image acquisition parameters (MRI)

- Solutions
  - Consensus definition of anatomical structure boundaries (RTOG 0522- 111 patients)
  - Train algorithm on RTOG consensus data set to develop multi-atlas algorithms

Auto segmentation- Conclusions

- Shows promise in automated contour generation
- Need to improve on accuracy, multiple sites, robustness and reproducibility
- Need well curated data sets to train AI
- Develop quality metrics to assess validity

Automated planning

- AutoPlan
- Knowledge based planning
- Multicriteria Optimization

Treatment Planning - Deep Learning

Automatic treatment planning based on three-dimensional dose distribution predicted from deep learning technique

Jiawei Fan* and Jiazhou Wang*
Department of Radiation Oncology, Fudan University Shanghai Cancer Center, Shanghai 200032, China
Department of Oncology, Shanghai Medical College Fudan University, Shanghai 200032, China

Zhi Chen*
Department of Radiation Oncology, Fudan University Shanghai Cancer Center, Shanghai 200032, China
Department of Oncology, Shanghai Medical College Fudan University, Shanghai 200032, China
Department of Medical Physics, Shanghai Proton and Heavy Ion Center, Shanghai 201321, China

Chaosu Hu, Zhen Zhang, and Weigang Hu[a)]
Department of Radiation Oncology, Fudan University S
Department of Oncology, Shanghai Medical College Fu

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A feasibility study for predicting optimal radiation therapy dose distributions of prostate cancer patients from patient anatomy using deep learning

Dan Nguyen, Troy Long, Xun Jia, Weiguo Lu, Xuejun Gu, Zohaib Iqbal & Steve Jiang

- AI in Radiation Oncology has great potential in
  - Auto segmentation
  - Treatment Planning
  - Adaptive treatment planning