

Knowledge Based Treatment Planning – Clinical Background and Application

Q. Jackie Wu, PHD FAAPM Professor

Department of Radiation Oncology Duke University Medical Center



Disclosure

- Research Grant: NIH/NCI
- Master Research Grant: Varian Medical Systems
- License Agreement: Varian Medical Systems
- Speaker Agreement: Varian Medical Systems



Acknowledgements

- John Kirkpatrick, MD/PHD (Duke University)
- Brian Czito, MD (Duke University)
- W. Robert Lee, MD (Duke University)
- Bridget Koontz, MD (Duke University)
- David Yoo, MD, PHD (Duke University)
- David Brizel, MD (Duke University)
- Chris Kelsey, MD (Duke University)
- Mark Dewhirst, DVM(Duke University)
- Radhe Mohan PHD (MD Anderson)
- Zhongxing Liao MD (MD Anderson)
- Jaques B. Bluett (MD Anderson)
- Xiaodong Zhang PHD (MD Anderson)
- Michael Gillin PHD (MD Anderson)

- 李英, 重庆医科大学第一附属医院
- 庞庭田,北京协和医院
- Lian, PHD (UNC)
- Sha Chang (UNC)
- Bhishamjit S. Chera, MD (UNC)
- Larry Marks, MD (UNC)
- Wilko Verbakel, PHD (Vu University)
- James Deye PHD (NCI)
- James Galvin PHD (RTOG)
- Ying Xiao PHD (RTOG)
- Kevin Moore PHD (UCSD)
- Charles Simone MD (U Penn)
- Liyong Lin PHD (U Penn)
- Jeffery D. Bradley MD (Wash U)







Overview

- How We Started ?
- The Initial Framework
- Going Back to Clinic
- What's next?



Building Planning Knowledge Models

How We Started ?

Learning Curve, Quality, Consistency

- > Standardization, Automation, Integration
- The Initial Framework
- Going Back to Clinic
- What's next?



Basics Of Knowledge-Based Planning (KBP)



truct	ures and Objectives		Exclude Structures (8)													4
Use	Normal Tissue Objectiv	•	Priority	. 80		Define Settings			100			Dase Vol	urse Histo	me Histogram		
8.	BOOY	Volume (cc)	13321	Points	131563	Resolution (mm):	4.50 .	1/								
1	Voo	er Vulume (%)	0.0	Dose [CGy]	5303.0	Priority	600			-						1111
	Brainstern	Volume [cc]	18	Pointe	545	Resolution (mm)	3.00		13.55		LL	3				
	Upp	pper Volume [%)	30.0	Dose (cGy)	113.0	Priority:	50		80							
	Upp	r .	30		193.0		70 =	76 E 76 [4] aurigon 60 50 [6] 76 - 40								
	Upp	r i	300	5 1	225.0		70									
	Upp	an)	10.0	5 J	1125.0	j j	100		60-			L	1		L.	
-	Vpp	·	0.0	1	2255.6	Lange and the second	200		1.4		1210					
E.	Cord+6	Votures [cc]	78	Pointer	2540	Resolution (mm)	3.00		-	M.	LL	L				
	Upp	er Volume (%)	60.0	Dose (cGy)	1687.0	त Priority त त	50									11
	Upp		50.0	3	1803.0		76		40							###
	Upp	ar i	300		2138.0		70									
	Upp	HT I	10.0	1	2363.0		100			L .		-	b bb	L .	¥ 4	4
	Voo	· · · · · · · · · · · · · · · · · · ·	0.0		2925.0		200									-
	Laryns	Velume [cc]	11	Pointa;	316	Resolution (nos)	3.00		20							##
	Upp	er Volume (%)	30.0	Dose (cGy]	1462.0	Priority:	50									
	Upp		60.0		1803.5		70						-	PP	PPF	M
	Upp	ar .	1 50.0		2025.6		90									14
	Upp	H .	30.0	1	2475.0		70		0		1000			-		NO.L
	Upp	4	10.0	3	3375.6		100		0		1000	2000	Dose (c	GYI	1000	2000
	Upp	9	0.0	1	4725.0	2	200 +	8			Some	structure	es are una	pproved or n	ejected	



Basics Of Knowledge-Based Planning (KBP)





Basics Of Knowledge-Based Planning (KBP)



truc	tures and Ob	jectives	[a		E	xclude Structures.	(8)
Us	e Normal Tissu	e Objective		Priority	80		Define Settings	
B	BODY		Volume [cc]:	13321	Points:	394878	Resolution [mm]:	4,50
		Upper	Volume [%]:	0.0	Dose [cGy]:	5300.0	Priority:	400
	Brainstem		Volume [cc]:	16	Points:	3597	Resolution (mm):	3.00
		Upper	Volume [%]:	80.0	Dose [cGy]:	113.0	Priority:	50
		Upper		50.0	i i	113.0	1	70
		Upper		30.0	l l	225.0	ſ	70
		Upper		10.0	l l	1125.0	ſ	100
		Upper		0.0	l l	2250.0	ſ	200
ſ	Cord+5		Volume [cc]:	70	Points:	15533	Resolution [mm]:	3.00
		Upper	Volume [%]:	60.0	Dose [cGy]:	1687.0	Priority:	50
		Upper		50.0	l l	1800.0	ſ	70
		Upper		30.0	i i	2138.0	ſ	70
		Upper		10.0	Ī	2363.0	ſ	100
		Upper		0.0	Í	2925.0		200
Ð	Larynx		Volume [cc]:	10	Points:	3222	Resolution (mm):	3.00
		Upper	Volume [%]:	80.0	Dose [cGy]:	1462.0	Priority:	50
		Upper		60.0	ſ	1800.0	ſ	70
		Upper		50.0	ſ	2025.0	ſ	90
		Upper		30.0	ſ	2475.0	ſ	70
		Upper		10.0	ſ	3375.0	l l	100
		Upper		0.0	ſ	4725.0	ſ	200 +



ъ

Basics Of Knowledge-Based Planning (KBP)



IMRT Constraints

	Patient Name				Patient	t ID		
	Treatment site	Rt pelvis						
	Imaging sets				Fusion	(Y/N)		
÷								
	Prescription							
	Target		Margin			Prescri	ption	
	PTV1					1.8 to 54	1Gy	

Constraints		
OARs	Dose	Volume (absolute or %)
ALARA for all		
No hot spots in bladder recturm, small bowel		
Don't push as much on femur- prefer to meet bowel/bladder		

Volume (%)



Building Planning Knowledge Models

How We Started ?

- The Initial Framework
 - Portable: Cases/Plans => Features
 - Systematic: Knowledge =>Machine Learning
- Going Back to Clinic
- What's next?







Building Knowledge Models

Platform Design







Building Knowledge Models

Feature Organization





statistics

Building Planning Knowledge Models

Systematic Modeling of Knowledge

Regression





Example of Bladder DVH Modeling





Building Planning Knowledge Models

- How We Started ?
- The Initial Framework
- Going Back to Clinic
 - Knowledge Model Guided Treatment Planning
- What's next?



1. Generate a new model

• Generate a new model in "Model Configuration"

+	<u></u>	🚰 📫 l			Anatomical	Site		
New	Open I	mport Export S	ave Close			Head/Neck		
					Struct	ures Thoray		
DVH Es	timation Model Prope	rties			×	THOTAX		
						Abdomen		
	Model ID					Dahria		
	Model Description					Feivis		
	model Description					Other		
					Structure Code Selection			
	Clinical Description	No clinical description attached			Structure			
	Technical December	No. to all all and all and all and all all all all all all all all all al			Structure ID			
	Technical Description	No tech Lai description attache	a		Label	ourucțure,	Scheme	
	Anatomical Site	Other	, i l					
						ame in th	10	
	Structures	Add Model Structure						
		Structure ID	Target Structure Course					
						nodel		
					Structure diction on			
					Filter Structure Codes	Codes found: 344		
						Codes Iodina. 344		
					Label	Code	Scheme	^
					Anal Canal	15703	FMA	
					Anal Sphincter External	21930	FMA	
					Anal Sphincter Internal	15/10 Id External Anal@abincta		
					Anta Anta	3734	FMA	
					Applicator	28999	RADLEX	
<u> </u>					Artifact	11296	RADIEX	
_				OK C	Attrium Left	7097	FMA	
				OK C	Attrium Left Attrium Right	7097 70 <u>96</u>	FMA	



2. Add plans to the model

Extract high quality plans into the model in "External Beam Planning"
 Add Plan C2 / Plan1 to DVH Estimation Model - 11886, Anon1370 (Duke-Prostate-001)



Add Plan C2 / Plan1 to DVH Est	imation Model - 11886, An	on1370 (Duke-Prosta	ate-001)									
Sort Order	Model ID	_										
DV/H Estimation Model	Duko Polyio		Dohrio	Man	day, May 05							
DVH Estimation Model	Duke-Pelvic		Pelvis	WOR	bay, may 05,							
Model Version Anatomical Region Trained Published Modified Description	Pelvis No No dukeuser2 Monday, f Prostate Low risk, high	elvis lo lo ukeuser2 Monday, May 05, 2014 7:11:43 PM rostate Low risk, high risk, anal rectal										
Plan Prescription	Clinical Description 54.000 Gy	Rx do	se									
Plan Structure ID (Codes) Type	Model St	ructure ID (Codes)									
Bladder ()	ORGAN	Bladder	(15900)	~								
BODY ()	EXTERN	IAL		*								
bowel region ()	ORGAN			•								
fiducials ()	ORGAN	Ma	tch org	on nó								
Lt Fem Head ()				an na								
Penile Bulb ()	ORGAN		h struct	hurog								
prostate ()	GTV	VVIII										
PTV54 ()	ΡΤ٧	PTV_Hi	gh (PTV_High)	Target 💌								
PTV76 ()	ΡΤ٧			-								
Rectum ()	ORGAN	Rectum	(14544)	•								
Rt Fem Head ()				•								
SV ()	сти			•								



3. Model training

• In "Model Configuration", select the plan to include in the training and then click "Train".

🏫 11886, Anon1370	Duke X	Q No Curr	rent Activity		Worklist 👻			Quicklinks 🔻			A		l	.ogout 👻	(
📑 🍊	5)		٠	7	X			Ť	*		?			
New Open			ave Cl	ose Dup				Publish			Н	elp			Exit
Model ID	Duke-ProAnal				•	Plans	of the DVH Esti	imation Model						Numb	er of Plans: 99
Model Version 13. Anatomical Region Pel	5.15 vis						Patient I	ID/Course ID/Plan	ID F	Plan Prescription		Structure Matching	Include	Extracted	In Model 🔶
Trained Yes Published No	3					0	Duke-Prostat	te-001/C1/1PTV54	4	54.000 Gy		Target: 1/1 Other: 4/4	V	Yes	13.5.15
Last Modified du	euser1 Tuesday, Ma	iy 06, 2014 12	2:41:48 AM			1	Duke-Prostat	te-001/C1/2PTV7	6	22.000 Gy		Target: 1/1 Other: 4/4	V		13.5.15
Description						2	Duke-Prostat	te-002/C1/1PTV5	4	54.000 Gy		Target: 1/1 Other: 4/4	V		13.5.15
						3	Duke-Prostat	te-002/C1/2PTV76	6	22.000 Gy		Target: 1/1 Other: 4/4	V		13.5.15
						4	Duke-Prostat	te-003/C1/IMRT:P	rimary	54.000 Gy		Target: 1/1 Other: 4/4	V		13.5.15
Clinical Description Publ	ishing Log			dit Model and S	tructures	5	Duke-Prostat	te-003/C1/IMRT:B	loost	22.000 Gy		Target: 1/1 Other: 4/4	V		13.5.15
Technical Description	ining Log					6	Duke-Prostat	te-004/C1/IMRT: F	Primary	54.000 Gy		Target: 1/1 Other: 4/4	V		13.5.15
						7	Duke-Prostat	te-004/C1/IMRT: E	Boost	22.000 Gy		Target: 1/1 Other: 4/4	V		13.5.15
Madel Olevelana and Oklastina						8	Duke-Prostat	te-006/C1/IMRT: F	Primary	54.000 Gy		Target: 1/1 Other: 4/4	V		13.5.15
Model Structures and Objectives						9	Duke-Prostat	te-006/C1/IMRT: E	Boost	20.000 Gy		Target: 1/1 Other: 4/4	V		13.5.15
Target ID		Vol [%]	Dose	Priority	gEUD a	10	Duke-Prostat	te-007/C1/IMRT:P	RI	54.000 Gy		Target: 1/1 Other: 4/4	V		13.5.15
Yes PTVp	(PTVp)					11	Duke-Prostat	te-007/C1/IMRT:B	OOST	22.000 Gy		Target: 1/1 Other: 4/4	V		13.5.15
Upper		0.0	105.0 %	Generated		12	Duke-Prostat	te-009/C1/IMRT:P	rimary1	54.000 Gy		Target: 1/1 Other: 4/4	V		13.5.15
Lower		100.0	99.0 %	Generated		13	Duke-Prostat	te-009/C1/IMRT:B	loost	20.000 Gy		Target: 1/1 Other: 4/4	V		13.5.15
Bladder	(15900)					14	Duko Drostoj	+= 010/01/IMDT- F	міло	E4 000 CV		Taraat: 1/1 Other: 4/4		Vaa	12 5 45
	()														



4. DVH Estimation

• In "Optimization" panel, "DVH Estimation" can be invoked to generate DVH estimates.

 114	🔶 🛛 Add gEUl) 🗸										
	Vol[cm ^s]	Vol [%]	Dose[Gv]	Actual	Priority	oFUD a	-			Dose [%]		0
	. e.[e]	101[10]	5000[0]]	Dose[Gy]		92000			0.0	37.0	74.1	U
PTV54	132.9											
Upper	2.7	2.0	54.00		120	x						
Upper	0.0	0.0	55.50		120	x		0.0				
Lower	131.6	99.0	53.00		120	x		0				
Lower	132.9	100.0	52.00		120	x	_	0.0				
Bladder	96.6							8				
Upper	64.1	66.4	8.42		70			0.0				
Upper	54.0	55.9	13.04		70			7				
Upper	44.2	45.8	20.57		70			0.				
Upper	0.0	0.0	54.01		90			60 60				
Upper	8.5	8.8	43.18		70	x		e [%	۵,			
Lt Fem Head	205.4							olum 50.				
Upper	0.0	0.0	22.76		70		=	> 0				
Rectum	92.2							40				
Upper	46.5	50.4	13.82		70			0				
Upper	34.1	37.0	23.44		70			30				
Upper	20.9	22.7	32.25		70			0			>	
Upper	0.0	0.0	52.01		90			20.				
Upper	2.5	2.7	44.55		70							
Rt Fem Head	204.3							10.	Teoľ	cted		
Upper	0.0	0.0	22.88		70			0				MAL I
BODY	16358.3							0			40.00	
bowel region	146.3		se 1	Volu	me	const	rg	iní	s and	Dose [Gy]		
fiducials	0.3								3D Dose Max			
Penile Bulb	4.6	nr	iori	ties	Car	he cu	ICT	3D	MAX for PTV5			
prostate	31.5	P						3D	MIN for PTV54			
PTV76	69.1						-		Elapsed Lime Iteration	s		



Knowledge Model-based HN Planning

٦	Dicom Data	Import	
🛃 gui_dvh_model			
Case Name	PTV Name	Dx (Gy)	
	PTV50	50	
	Dicom File Director	у	
	E:\r1_ui_DVH_model\eclip	se-export\	Select Directory
	Program Directory	,	
	E:\r1_ui_DVH_mod	del	Select Directory
	Get DVH Constrain	ıt	



Using IMRT Knowledge Model For VMAT





- Cross-institution Knowledge
 - If you believe best planning knowledge is shared among all planners
 - LUNG IMRT Pilot Study By RTOG/NRG
 - 71 Cases
 - 3 Institutions



	Mean	Median	Min	Max
Prescriptions (Gy)	67	64	40	74
		Institution 1	Institution 2	Institution 3
Volume (cm ³)	mean	421	595	512
	median	343	519	379
	min, max	62, 1132	76, 1132	175. 1161
Location (side)	Total	45	10	16
	Left/Left-Medial	18	4	5
	Right/Right-Medial	21	6	10
	Medial	6	0	1









Cross-Modality Knowledge Base

Cross-Modality Knowledge

 If you believe best planning knowledge is independent of treatment modality

Institution **B**

Institution A

7-8 min delivery time 7-8 min delivery time Delivery system: Varian IMRT Delivery system: Tomotherapy • Planning system: Tomotherapy Planning system: Eclipse Sequential Boost SIB 1 plan (one plan cover all PTVs with Multiple plans (one plan for 1 PTV) diff. daily doses) 40-50 Gy and 60-70 Gy 54.25 Gy and 70 Gy ~60 head-and-neck cases ~60 head-and-neck cases

Cross-Institution Knowledge Base



 In Spine SBRT, dose distributions in cord are highly correlated with tumor contour shapes



Contours

Dose



DUKE University Radiation Oncology

- Compute correlation between tumor contour shapes and cord dose distributions
- Use learned correlations to predict voxel-level dose distributions



Active Shape Model

 Align the reference tumor contours and all other contours using the iterative closest point (ICP) algorithm



Active shape models

PCA analysis of a set of aligned tumor contours



DUKE University Radiation Oncology

Optical Flow Dose Distribution Model

 measures dose variance between a reference image and any other images within the training dataset



Active optical flow dose distribution model

PCA analysis of a sequence of optical flow fields



DUKE University Radiation Oncology



DUKE University Radiation Oncology



DUKE University Radiation Oncology

Liu et al, PMB 60:N83-N92, 2015



- Rapid Learning Framework
- Multiple Knowledge Resources





Lung IMRT Model as A Rapid-learning Show Case

DVH Model + Beam Angle Model

- 100 Lung Cases
- All co-planar beams (best clinical knowledge)
- Ignore non-planar plans (clinical knowledge sparse)

Phase 1 : Class Solution

- Step1: Define distance between two beam bouquets
- Step2: Classify beam configuration using clustering analysis
- Step 3: Extract standard bouquets

Phase 1: Class Solution - Beam Bouquet Atlas



DUKE University Radiation Oncology





Clinical plan: solid

Beam Bouquet plan: dashed

Phase 1 : Class Solution Plans Using Beam Bouquets VS. Clinical Plans for 20 Validation cases



- Anatomy variation always happens in clinical treatment planning
- Reflects clinical application of knowledge
- Natural progression of knowledge application

 Correlation between the anatomical features and beam angle configurations learned by supervised classification method





Lung IMRT Model as A Rapid-learning Show Case

DVH Model + Beam Angle Model

- 100 Lung Cases
- All co-planar beams (best clinical knowledge)
- Ignore non-planar plans (clinical knowledge sparse)
- Extend Knowledge Models to Other Thorax Cases (large esophageal case)

- Example case: esophagus tumor extending from neck to abdomen
- Separate fields, even isocenters, may be needed to treat different parts of the tumor in superior-inferior direction
- Multiple beam configurations in one plan



DUKE University Radiation Oncology

Axial CT Slices









Z=-4



Z=-13



Z=-10

Z=2



Z=5







Z=11



Z=13





Radiation oncology





Clinical Plan

Model Plan



DUKE University Radiation Oncology



DUKE University Radiation Oncology



DUKE University Radiation Oncology



Lung IMRT Model as A Rapid-learning Show Case

DVH Model + Beam Angle Model

- 100 Lung Cases
- All co-planar beams (best clinical knowledge)
- Ignore non-planar plans (clinical knowledge sparse)
- Extend Knowledge Models to Other Thorax Cases
- Extend Knowledge Models to Non-coplanar Cases
 - Clinical knowledge about non-coplanar beam angles is sparse, immature
 - Extend the knowledge learned from co-planar beam to non-coplanar beam

Phase 3: Progressive Modeling - From Coplanar to Non-coplanar Beams



Phase 3: Progressive Modeling - From Coplanar to Non-coplanar Beams

Clinical Plan

Model Plan



DUKE University Radiation Oncology

Phase 3: Progressive Modeling - From Coplanar to Non-coplanar Beams

Clinical Plan

Model Plan



DUKE University Radiation Oncology

Summary

Benefits of Knowledge Modeling: Clinical

- Learning Curve, Quality, Consistency
- Standardization, Automation, Integration

Benefits of Knowledge Modeling: Institutional

- > Systematic, Objective
- Integrated Refinement and Evolution
- Benefits of Knowledge Modeling: Future
 - Feature Based Knowledge for Big Data Research
 - Standardization (Evidence-based) and Optimization (Personalized)

Treatment planning knowledge models are:

- 3% a. Confined to a single institution
- 90% b. Applicable to multiple modalities
- 6% C. Useful for only IMRT
- 1% d. Physician Specific
- 0% e. Useable only with Monte Carlo-based dose calculation algorithms



1. Treatment planning knowledge models are:

- a. Confined to a single institution
- b. Applicable to multiple modalities
- c. Useful for only IMRT
- d. Physician Specific
- e. Useable only with Monte Carlo-based dose calculation algorithms
- Answer: b
- Reference:
 - Lian et al, Modeling the dosimetry of organ-at-risk in head and neck IMRT planning: An inter-technique and inter-institutional study, Medical Physics 2013, 40(12)



The treatment planning knowledge that we can model include

- 0% a. incident beam angle selection
- 1% b. multiple OAR structures
- 0% C. multiple PTV prescriptions
- 1% d. DVHs of OARs

97% e. All the above



2. The treatment planning knowledge that we can model include

- a. incident beam angle selection
- b. multiple OAR structures
- c. multiple PTV prescriptions
- d. DVHs of OARs
- e. All the above
- Answer: e
- Reference:
 - Yuan L, Wu QJ, Yin F, Li Y, Sheng Y, Kelsey CR, Ge Y. Standardized beam bouquets for lung imrt planning. *Physics in medicine and biology* 2015;60:1831-1843.
 - Liu J, Wu QJ, Kirkpatrick JP, Yin FF, Yuan L, Ge Y. From active shape model to active optical flow model: A shape-based approach to predicting voxel-level dose distributions in spine sbrt. *Physics in medicine and biology* 2015;60:N83-N92.
 - Yuan L, Ge Y, Lee WR, Yin FF, Kirkpatrick JP, Wu QJ. Quantitative analysis of the factors which affect the interpatient organ-at-risk dose sparing variation in imrt plans. Med Phys 2012;39:6868-6878.



The organ sparing capability predicted by the knowledge model is

- 13% a. The average value of the sparing in the database
- **15% b.** Interpolated among a few similar cases
- 6% C. Independent of prescription dose
- 1% d. Only valid for maximum dose
- 65% C. Patient specific, based his/her anatomy and physician's prescription



• 3. The organ sparing capability predicted by the knowledge model is

- a. The average value of the sparing in the database
- b. Interpolated among a few similar cases
- c. Independent of prescription dose
- d. Only valid for maximum dose
- e. Patient specific, based his/her anatomy and physician's prescription

- Answer: e
- Reference:
 - Yuan L, Ge Y, Lee WR, Yin FF, Kirkpatrick JP, Wu QJ. Quantitative analysis of the factors which affect the interpatient organ-at-risk dose sparing variation in imrt plans. *Med Phys* 2012;39:6868-6878.



Thank you

