Obstacles and advances in IMRT treatment planning

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Where we need to go: IMRT software design goals

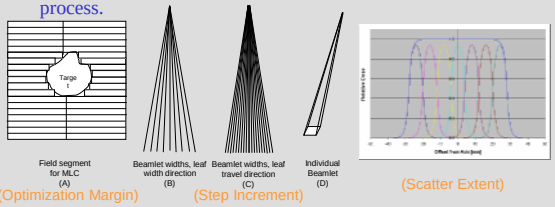
1. **Time Efficient**, to either save money or allow more options to be explored
2. Dosimetrically **reliable**, to insure that what you see (plan) is what you get (delivered)
3. **Clinically relevant**, so that *the priorities of the physician are respected* (if possible!).

Outline

- The current IMRT treatment planning paradigm
- Problems with the paradigm
- Advances
  - Plan evaluation tools (WUSTL)
  - Prioritized optimization (WUSTL and U Mich)
  - Interactive plan selection (Bortfeld, MGH)
  - Robust optimization (Eva Lee, Ga Tech)
  - 4D optimization (Eva Lee, Ga Tech)
  - Fast adaptive replanning (Dempsey, U of F)

Beamlets

- Beamlets represent dose in the patient as defined by small, discretized, MLC configurations of a beam.
- In inverse planning, an optimizer adjusts beamlet "weights" from several beams to achieve an optimal dose according to some cost function.
- We may use thousands of beamlets in the optimization process.



Basic IMRTP approaches

Optimize beamlet fluences

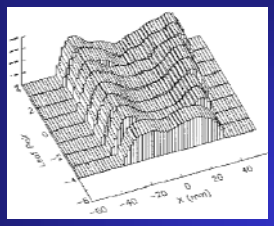
Derive collimator sequences

Select starting apertures, then modify them

(most common by far)

Optimization of beamlet fluence weights results in a 'fluence map' for each treatment head position

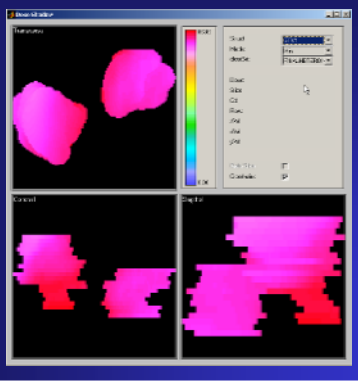
Fluence map example
(a map of the beamlet weights)



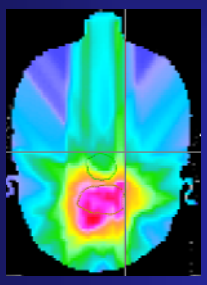
(From: Chui *et al., Medical Physics* (2001) **28**:2441-2449.)

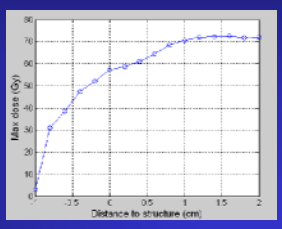
IMRT treatment plan review tools

Dose-shadow displays (Wiesmeyer et al.)



What kind of setup errors are dangerous?: Dose-distance plot for the ROI





Problems with the current optimization paradigm

IMRTP: the 'state of the art'

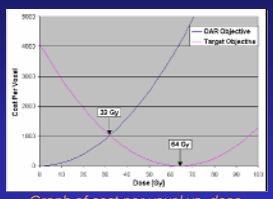
- Some mathematical statements should always hold
  - e.g., "No more than 45 Gy to the spinal cord"
  - These statements are 'constraints'
- Some mathematical functions should be made as small (or large) as possible
  - e.g., "the average square difference between the prescription target dose and the computed dose should be as small as possible."
  - Such statements are part of the 'objective function'

The 'objective function'

- Typically, the objective function is a sum of terms, some of which represent normal tissue structures and one or more terms represents the target.
  - This is called a 'linear sum objective function'
  - The different terms have different multiplying weights (constants) in front, representing relative importance

Linearly weighted objective functions

- Individual terms (or goal functions) are added to comprise the objective function.
- Typically, each anatomy structure of importance has one or more goal terms.
- Goals are evaluated for each voxel contained in a structure.



Graph of cost per voxel vs. dose

$$F \quad w_{\text{OAR}} \sum_{i\ 1}^{n} (D_i \quad 0)^2 \quad w_{\text{Target}} \sum_{j\ 1}^{m} (D_j \quad 64)^2$$

Objective for an OAR of n voxels

Objective for a target of m voxels

A 'state of the art' IMRT treatment planning system...

- Accepts constraints
  - Max dose
  - Min dose
  - Dose-volume constraints: no more than x% of an organ can receive y% dose (e.g., "V20 can be no larger than...").
- Tries to match or exceed goal DVH parameters
  - for target volumes
  - for normal tissues

The weight paradox: hard-to-control tradeoffs and the lack of clear priorities

- Normal tissue weights should be large enough so the mathematical engine tries to reduce dose to those structures
- Target weights should be much larger than normal tissue weights so that good target coverage is not compromised...but...
- There is no perfect compromise
  - Very high target weights: engine neglects normal tissues
  - Not very high target weights: engine does not preserve target dose characteristics

The input parameter "guessing game"

- Typical: Use the same DVH goals that worked (near the solution) last time ("Class solution")
  - often works for prostate (patients often look similar)
  - typically fails for H&N (geometry varies more)

State-of-the-art workflow: "Are we finished?"

Physician: *"Here is what I'd like."*

Later....Dosimetrist: *"I tried it, and tried to fix it. Here it is."*

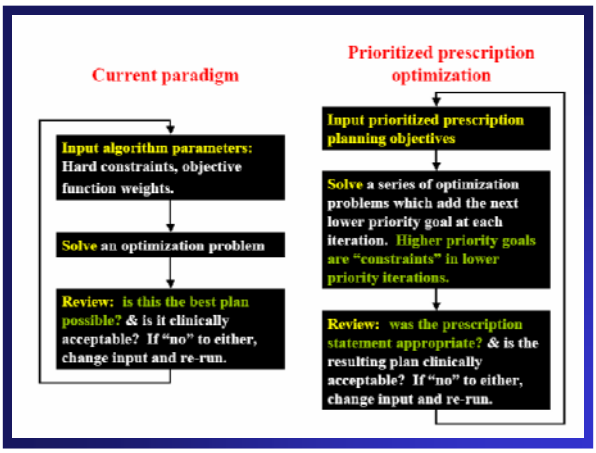
Physician thinks *"Is that the best they can do?"* Says: *"How busy are you? Can you try to improve this part?"*

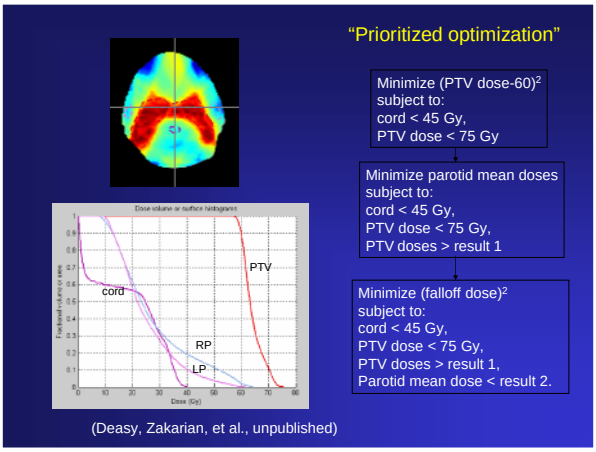
Dosimetrist: *"Pretty busy. But I'll try if you want me to."*

Interim conclusion

- The efficient control and use of linearly weighted objective functions is problematic
- We need a new paradigm with more control over tradeoffs…

http://www.isye.gatech.edu/nci-nsf.orart.2002/





Multicriteria IMRT optimization using a lexicographic method

Kyung-Wook Lee, Daniel L. McShan, and Benedict A. Fraass
University of Michigan

Lexicographic Ordering

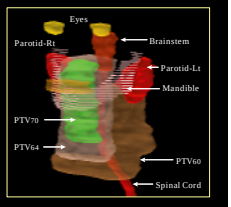
Multiple clinical objectives
↓
Prioritize objectives & Formulate multiple opt. problems
↓
Solve a sequence of opt. problems while preceding levels constrained (in order of priority level)
↓
Evaluate the resulting plan

Find $x \in \mathbf{R}^n$ that minimizes $f_i(x)$
subject to
$f_j(x) \le f_j(x_j^*)$
where $j = 1,2,\ldots,i-1; i > 1$ and $i = 1,2,\ldots,k$

- Reduce # of repeats
- Intuitive articulation of clinical preferences
- Avoid unnecessary tradeoffs
- Feasible space reduction strategy

Head & Neck Case (Parotid Sparing Protocol)

- 3 planning target volumes, critical organs, normal tissues.
- 5 axial beams and 6 MV energy
- 1023 beamlets
- 29172 dose points
- ~26 clinical objectives and goals



3 levels of optimization priority

Multiple Planning Goals

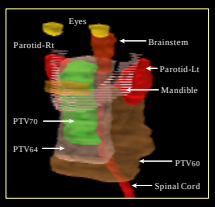
Planning Directives

1. Dose to Primary Tumor > 70 Gy
2. Dose to Nodal Volumes > 60, 64 Gy
3. Dose Uniformity < 110%
4. Max Dose to Spinal Cord < 45 Gy
5. Max Dose to Brainstem < 54 Gy
6. Max Dose to Optic Structures < 50 Gy
7. Mean Dose to Parotids < 26 Gy
8. …

…

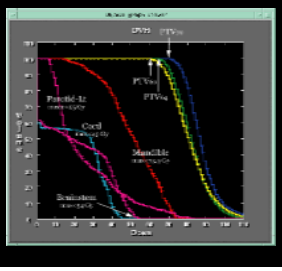
26. Minimize Dose to Normal Tissues

Head & Neck Case



Level 1 (high priorities)

- Prevent under-dosing to the target volumes
- Prevent over-dosing to the critical organs
- Spare the contralateral parotid

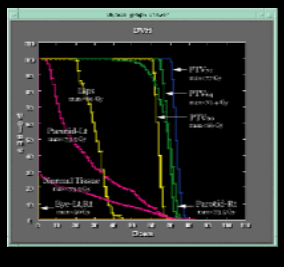


Algorithmic Performance

# of obj. function	1
# of constraints	0
major iterations	37
function calls	43
single function calc. time	~240 ms
single constraint calc. time	~310 ms
Total time	36 s

Level 2

- Achieve doses to the targets as uniform as possible
- Limit the max doses to normal structures

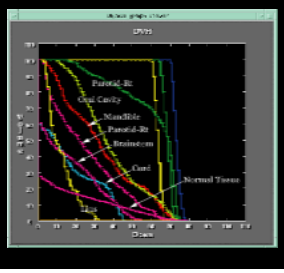


Algorithmic Performance

# of obj. function	1
# of constraints	7
major iterations	49
function calls	69
single function calc. time	~400 ms
single constraint calc. time	~970 ms
Total time	198 s

Level 3 (low priorities)

- Minimize doses to all non-target structures



Algorithmic Performance

# of obj. function	1
# of constraints	16
major iterations	107
function calls	214
single function calc. time	~410 ms
single constraint calc. time	~1.3 s
Total time	574 s

Preemptive Goal Programming

(Optimization strategies to implement soft-constraints with lexicographic ordering)

Based on inequality & equality operators (<, >, =)
e.g., PTV Min Dose > 70 Gy

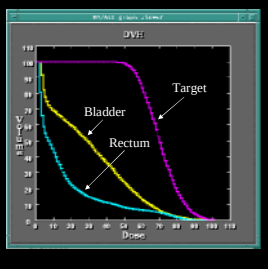
- Hard Constraints : Find a *feasible* solution or *fail.*
- Soft Constraints : Find a *feasible* solution, if not, find the *most* achievable solution.

NTCP-Constrained Dose Escalation Script for Prostate Planning

	General Planning Goals	GP with realistic goal levels
Level 1:	NTCP for rectum & bladder should be as low as possible.	$NTCP_{rectum} < 0.1\%$ $NTCP_{bladder} < 0.001\%$
Level 2:	Dose to target should be as uniform as possible.	$Uniformity_{target} < \pm 10\%$
Level 3:	Dose to target should be as high as possible.	$MeanDose_{target} > 100$ Gy

Level 1 (protect critical organs)

$NTCP_{rectum} < 0.1\%$
$NTCP_{bladder} < 0.001\%$



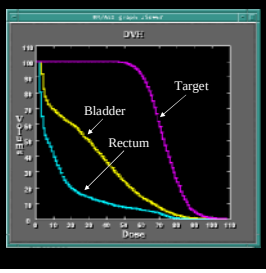
- Prostate case with 4 fields
- A total of 573, 0.5cm-beamlets
- Search began with random beamlet intensities.
- Search found a feasible solution.

Resulting $NTCP_{rectum}$ (~0.0%) < 0.1%
$NTCP_{bladder}$ (~0.0%) < 0.01%

- A total of ~10 iterations

Level 2 (achieve uniform target dose)

$Uniformity_{target}$ < ±10%



- Search began with random beamlet intensities.
- Search found a feasible solution.

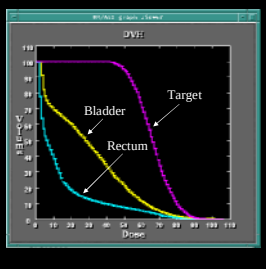
  Resulting Uniformity (~ ±10) < ±10

  keeping Level 1 goals unchanged:
  $NTCP_{rectum}$ (~0.1%) < 0.1%
  $NTCP_{bladder}$ (~0.0%) < 0.01%

- A total of ~12 iterations

Level 3 (escalate target dose)

$MeanDose_{target}$ > 100 Gy



- Search began with random beamlet intensities.
- Search failed to find a feasible solution, but gave the most achievable result.

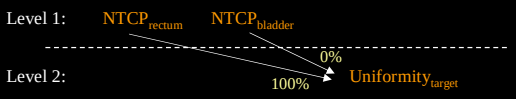
  Resulting MeanDose (74.6 Gy)

  keeping Level 1&2 goals unchanged:
  $NTCP_{rectum}$ (~0.1%) < 0.1%
  $NTCP_{bladder}$ (~0.0%) < 0.01%
  $Uniformity_{target}$ (~ ±10) < ±10

- A total of ~36 iterations

Post-optimal Sensitivity Analysis

Sensitivity (Lagrangian multiplier) tells how hard the objective function at the present solution is "pushing" or "pulling" against the particular constraint at the upper level.



Post-optimal Sensitivity Analysis

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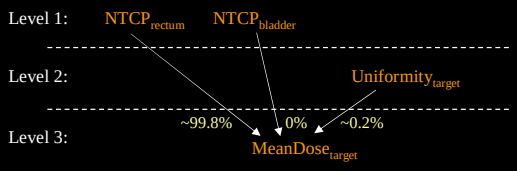
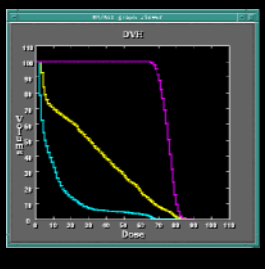


The analysis shows the NTCP constraint for rectum dominates the rest of the planning goals. It would be sensible to relax the rectum constraint if a higher mean target dose is necessary.

$NTCP_{rectum} < 0.1\% \rightarrow NTCP_{rectum} < 1\%$



- Search reinitiated looking for a solution with a higher mean target dose.
- MeanDose was further escalated: 74.6 Gy → 89.6 Gy

Prioritized treatment goals

- Prioritization of the prescription goals
  - Avoids tradeoffs among objectives which are difficult to control and sometimes clinically undesirable
  - Avoids fixing hard constraints to be more restrictive than necessary
  - Allows for more factors to be included in the prescription goals without degrading the most important goals.
  - More certainty that better plans are unobtainable.

Another approach: interactive exploration of the 'Pareto frontier'

Generalized Equivalent Uniform Dose

EUD_a is a power-law average over the dose distribution:

$$EUD_a(d) = \left(\frac{1}{n}\sum_{i=1}^{n} d_i^{\,a}\right)^{1/a}$$

EUD_a is equivalent to the dose-volume histogram reduction scheme in the Lyman-Kutcher-Burman NTCP model: n in that model has the role of $1/a$ in EUD_a.

Generalized Equivalent Uniform Dose

$$\mathrm{EUD}(\bar{\mathbf{d}};a)=\left(\frac{1}{N}\sum_{i\ 1}^{N}d_i^{a}\right)^{1/a},$$

a 0 $\Rightarrow$ EUD min. dose (targets)

a 1 $\Rightarrow$ EUD max. dose ('serial structures')

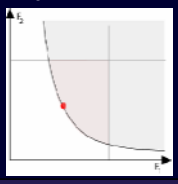
a 1 $\Rightarrow$ EUD mean dose ('parallel structures')

Pareto optimization

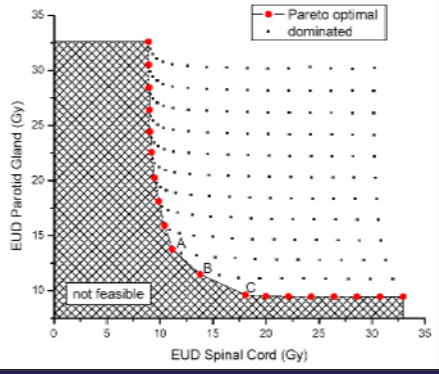
Vilfredo Pareto, 1848-1923

Italian-Swiss socio-economist

Pareto-optimality, "efficient":
You cannot make anybody better off without making someone else worse off.



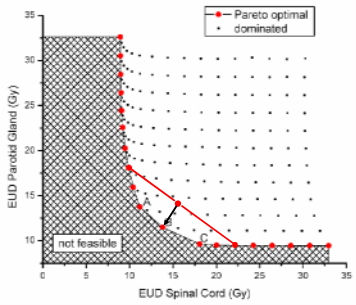
- A Pareto-optimal or "efficient" treatment plan is a plan in which we cannot improve one aspect (e.g., reduce the dose in one OAR) without compromising at least one other aspect (e.g., reduce the target dose)



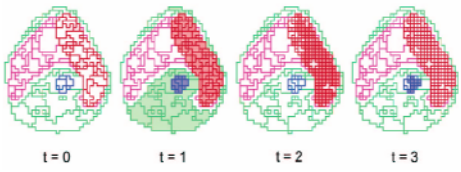
How to make it interactive?

- Pre-calculate 100-1000 Pareto optimal plans, store in database, interactive database navigation
- Online interpolation and optimzation
- Hierarchical voxel merging and local refinement for highly efficient calculations

Online interpolation and optimization

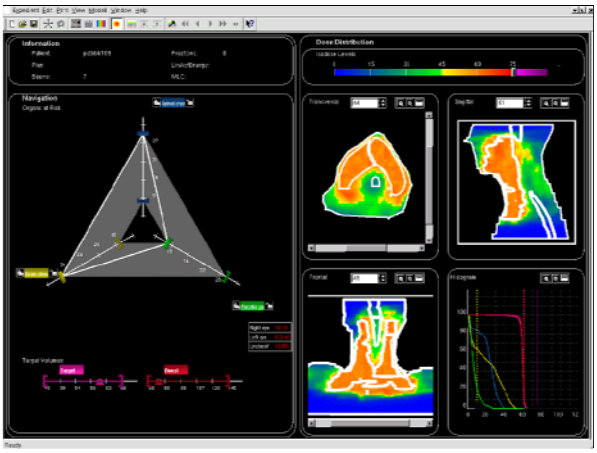


Example: local refinement



Entity	$\lvert\mathcal{A}^{(0)}\rvert$	$\lvert\mathcal{A}^{(1)}\rvert$	$\lvert\mathcal{A}^{(2)}\rvert$	$\lvert\mathcal{A}^{(3)}\rvert$
Boost	294	1333	4551	4551
Target	1337	1337	1337	1337
Myelon	73	228	228	467
Brain stem	38	44	44	44
Right parotis	101	104	104	104
Right eye	16	16	16	16
Left eye	9	9	9	9
Unclassified tissue	672	888	888	888
Whole volume	2540	3959	7177	7416

Original:
153349 voxels



Approaches to optimization in the presence of breathing

- Expand the GTV from some image set to form the PTV
- Combine CTVs from different breathing phases (ITV concept)
- Optimize using all phases explicitly but without synchronizing to breathing (multi-stage)

Multistage Treatment Planning Optimization For Management of Organ Motion in Radiotherapy Planning

Eva K. Lee[1,2], KyungDuck Cha[1], Thomas Bortfeld[3], Joe Deasy[4], Tsung-Lin Wu[1]

[1]Center for Operations Research in Medicine, Industrial & Systems Engineering, Georgia Institute of Technology [2]Winship Cancer Institute, Emory University School of Medicine; [3]Radiation Oncology, Massachusettes General Hospital; [4]Radiation Oncology, Washington University St Louis

Motivation of Study

- **Purpose:** To address some technical issues related to breathing registered IMRT treatment planning
- **Approach:** Track each voxel from each phase within the breathing cycle and develop treatment planning using all voxel information over multiple phases
- **Evaluation:** Observe robustness of approach, resulting plan quality and possible clinical significance

Methods to Handle Respiratory Effect and Control Comparison

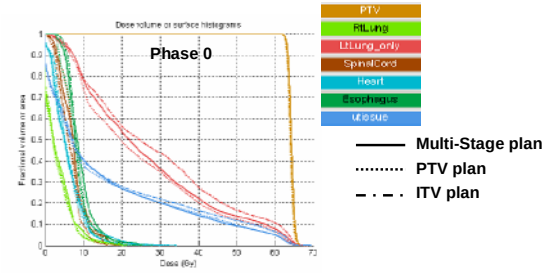
- **Patient data:** 4D CT scans of lung/liver cancer patients
- **Methods:**
  - 1) standard static PTV (control)
  - 2) ITV (defined as the union of CTVs in all breathing phases)
  - 3) multistage planning – use voxels over multiple phases for planning
- **CERR:** use for generation of beam angles (72 - 144 possible directions), and influence matrix

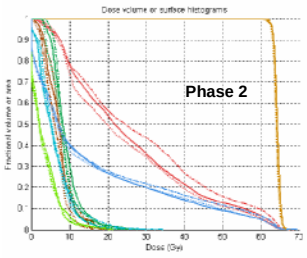
Treatment Planning Models

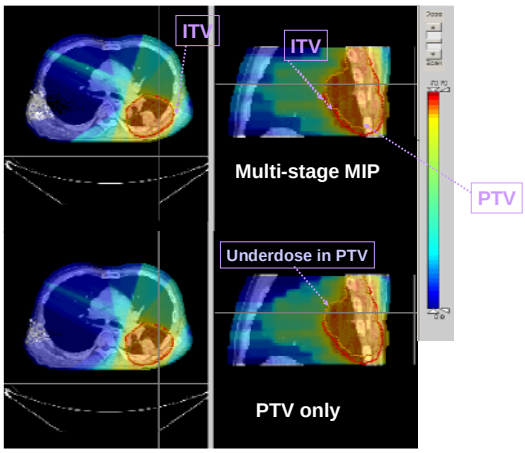
- **Approach:** large-scale mixed integer programming (mathematical models with continuous and discrete decision variables)
- **Features:**
  - 1) PTV coverage, homogeneity, underdose
  - 2) upper/lower dose bounds for OARs
  - 3) DVHs for OARs
  - 4) Number of beam angles allowed
  - 5) Objective: NTCP-driven

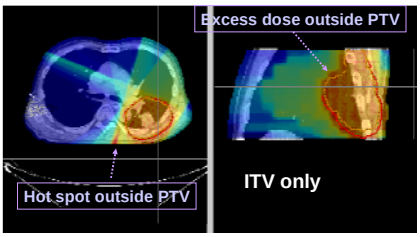
A Lung Cancer Case

- **Prescribed dose:** 63 Gy or higher to 95% of PTV
- **DVHs:**
  - 1) Tumor underdose <= 10% prescribed dose
  - 2) Spinal cord <= 45Gy
  - 3) V_{20} of lung <= 10% (ideal case)
    V_{10} of lung <= 20% (ideal case)
  - 4) Heart and esophagus, as low mean dose as possible (in vicinity of tumor)









Dose Wash Comparison

•Target underdose in PTV-plan vs Multistage MIP and ITV plans
•Improved conformity in Multistage MIP plan vs ITV plan
•Good coverage in both ITV and multistage plan

EK Lee, AAPM 2005

Observations in the Lung Cases

Simultaneous improvement in both target dose and dose to OARs

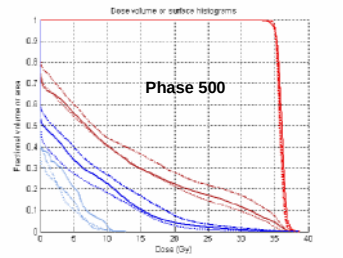
- Multistage MIP offers high homogeneity, and dramatically improves underdose of target compared to PTV plan
- Comparing multistage MIP plans vs ITV plans
  - Reduce 20% of mean dose to normal left lung tissue
  - Reduce 20% of mean dose to the heart (close to tumor)
  - Reduce drastically max-dose to esophagus and heart
  - Compromise with slight increase in mean dose to spinal cord (from 6.8 Gy to 7.3 Gy), and right lung (from 3.2 Gy to 3.4 Gy)

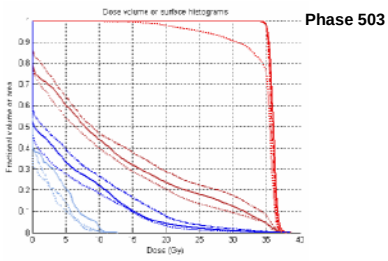
EK Lee, AAPM 2005

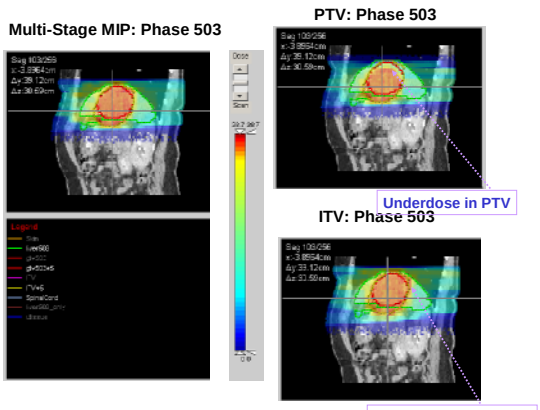
A Liver Cancer Case

- **Prescribed dose:** 35 Gy or higher to 95% of PTV
- **DVHs:**
  - 1) Tumor underdose <= 10% prescribed dose
  - 2) OAR: Spinal cord <= 40Gy
  - 3) V_{24} of lung <= 30% (ideal case)
    V_{10} of lung <= 20% (ideal case)
  - 4) OAR: Normal Liver <= 30 Gy (ideal case)
  - 5) OAR: Normal liver as low mean dose as possible

EK Lee, AAPM 2005







Observations in the Liver Cases

Simultaneous improvement in both target dose and dose to OARs

- Multistage MIP offers high homogeneity, and drastically improves underdose of target compared to PTV plan
- Comparing multistage MIP plans vs ITV plans
  - Improve PTV conformity by 10%, worsen homogeneity by 8% (redirect dose to tumor and spare healthy liver tissue)
  - Reduce 15% of mean dose to normal liver tissue
  - Reduce 20% of mean dose to the normal tissue
  - Compromise with slight increase in mean dose to spinal cord (from 1.5 Gy to 2.1 Gy).

Challenges

- Multistage MIP plans improve upon ITV approaches (and certainly upon static PTV approaches).
- Treatment plans are very complex and large-scale
- Computationally very challenging
- Clinical study to be conducted to observe possible clinical outcome improvement

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Robustness of treatment plans against systematic setup errors

- U Michigan (multiple instance planning)
- Ga Tech/WUSTL/MGH collaboration (Eva Lee, poster at this meeting)

Washington University in St. Louis School of Medicine

Motivation of Study

- **Purpose:** To develop and utilize innovative robust treatment planning techniques to make treatment plans resistant to the minor planning and delivery errors that may be present in 4D IMRT treatment planning and delivery.
- **Approach:** we investigate the concept of *robust objective functions* to manage systematic errors
- **Evaluation:** Observe robustness of approach, resulting plan quality and possible clinical significance

Methods to Handle Systematic Errors and Control Comparison

- **Patient data:** 4D CT scans of lung/liver cancer patients
- **Methods:**
  - 1) Standard static PTV (control)
  - 2) ITV (defined as the union of CTVs in all breathing phases)
  - 3) Robust planning – using underdose probability of tumor voxels (to achieve good tumor coverage) to compensate systematic errors during planning and delivery
- **CERR:** use for generation of beam angles (72 - 144 possible directions), and influence matrix

Under-Dose Probability (per voxel)

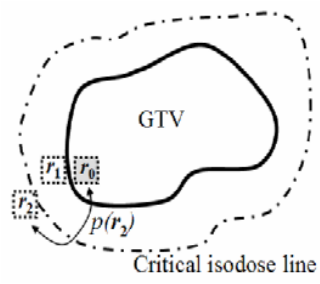


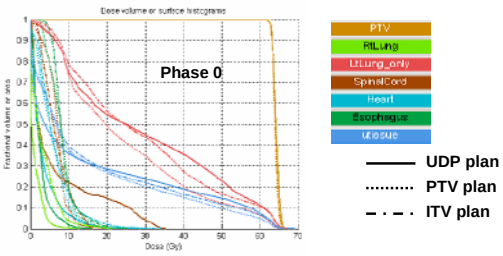
Figure UDP: This figure demonstrates the basic idea behind the probability of under-dose robust planning objective function. Each possible shift, with probabilities known from other studies, results in a sampling in a local neighborhood of potential dose values. Possible shifts of a given voxel (dashed box) are classified either as those resulting in under-dose (crossing the dashed critical iso-dose line) or not. Taking the worst case, the maximum probability of under-dose, per unit volume, is derived and used as an added term in the overall IMRT objective function.

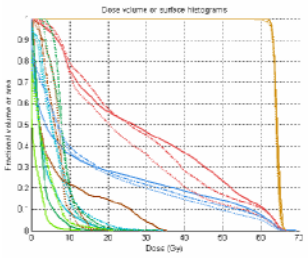
Treatment Planning Models

- **Model:** large-scale quadratic mixed integer programming (mathematical models with continuous and discrete decision variables)
- **Features:**
  - 1) PTV coverage, homogeneity, underdose
  - 2) upper/lower dose bounds for OARs
  - 3) DVHs for OARs
  - 4) Number of beam angles allowed
  - 5) Objective: **NTCP-driven and UDP of PTV**

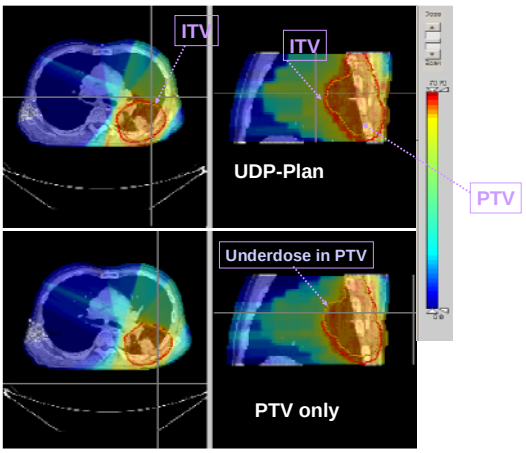
A Lung Cancer Case

- **Prescribed dose:** 63 Gy or higher to 95% of PTV
- **DVHs:**
  - 1) Tumor underdose <= 10% prescribed dose
  - 2) Spinal cord <= 45Gy
  - 3) V_{20} of lung <= 10% (ideal case)
    V_{10} of lung <= 20% (ideal case)
  - 4) Heart and esophagus, as low mean dose as possible (in vicinity of tumor)





Phase 4



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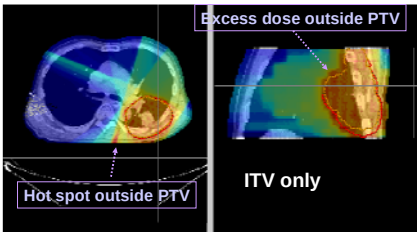

Dose Wash Comparison

- Target underdose in PTV-plan vs UDP-MIP and ITV plans
- Slight improved conformity in UDP-MIP plan vs ITV plan
- Good coverage in both ITV and UDP-plan

EK Lee, AAPM 2005

Observations in the Lung Cases

Simultaneous improvement in both target dose and dose to OARs

- UDP-MIP approach offers high homogeneity, and drastically improves underdose of target compared to PTV plan
- Comparing UDP-MIP plans vs ITV plans
  - Reduce 69% of mean dose to esophagus
  - Reduce 47% of mean dose to the heart
  - Reduce max-dose to esophagus and heart (by 35% and 13% respectively)
  - Compromise with slight increase in mean dose to spinal cord (from 6.8 Gy to 6.9 Gy), normal left lung (from 2.8 Gy to 2.9 Gy), and higher max-dose to spinal cord (35.4Gy).

EK Lee, AAPM 2005

Challenges

- UDP-MIP plans improve upon ITV approaches (and certainly upon static PTV approaches).
- The probability distribution of each voxel displacement can be difficult to determine
- Quadratic MIP can be computationally very challenging
- Further tests on other tumor sites are needed to validate its usefulness
- Clinical study to be conducted to observe possible clinical outcome improvement

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Robustness methods

- Development of robust objective functions (considering possible systematic setup errors) may be generally useful in treatment planning.

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What about very fast solution methods?

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Fast fluence map optimization for adaptive therapy

James F. Dempsey[1], Daniel Glaser[2], Jonathan Li[1], and H. Edwin Romeijn[3]

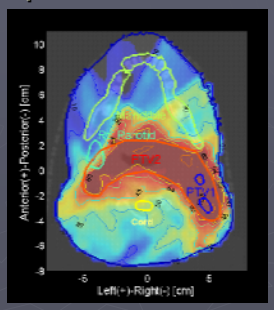
1) Department of Radiation Oncology, University of Florida, USA
2) Division of Optimization and Systems Theory, Department of Mathematics, Royal Institute of Technology, Sweden
3) Department of Industrial and Systems Engineering, University of Florida, USA

De Novo Optimization

- Just do it again
- No approximations
- Must be extremely fast method
- Algorithms for solving large-scale convex programming models are fast enough to just completely resolve the problem
  - Interior point methods
    - see e.g. Romeijn *et al.* PMB 48(21) (2003) 3521-3542
  - Limited Memory BFGS
    - see Lahanas *et al.* PMB 48(17) (2003) 2843-2871.

The Demands Adaptive IMRT Fluence Map Optimization

- To make use of IMRT optimization on a daily basis solutions must be:
  - Accurate ® Resolution
  - Robust ® Model
  - Fast ® Algorithm
- Patient should not wait more than a few minutes on the table
- Real-time optimization is the eventual goal
- Dealing with organ motion outweighs other refinements



The Model

- Fast analytic convex programming model
  - Convex voxel-based penalty functions are used to penalize deviations of a prescription dose for all voxels contained in target volumes, and surpluses of a tolerance dose for all voxels contained in critical structures
  - Partial-volume constraints that bound tail averages of the differential dose volume histograms are not used.
- See:
  - HE Romeijn, RK Ahuja, JF Dempsey, A Kumar, JG Li, A novel linear programming approach to fluence map optimization for intensity modulated radiation therapy treatment planning. Phys Med Biol. 2003 Nov 7;48(21):3521-42.

Fast Convex IMRT FMO Algorithms

- Primal-dual interior-point log barrier for LP formulations
  - CPLEX
  - 7 beam H&N solved in 71-280 seconds
- Primal-dual interior-point log barrier for QP formulations
  - CPLEX
  - 7 beam H&N solved in 45-145 seconds
- Primal-dual interior-point log barrier for general CP formulations Matlab UF & KTH
  - 7 beam H&N solved in 240-720 seconds
- Projected Gradient Method for general CP formulations
  - Matlab UF, KTH, & Catholic University Korea
  - 7 beam H&N solved in 25-133 seconds
- All times on a 1.7 GHz centrino w/ 1GB RAM

Projected Gradient Steepest Descent: The Most Obvious Algorithm!?

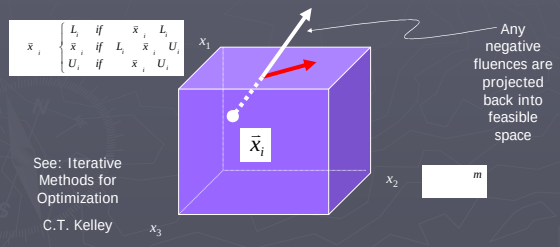
- Projected gradient allows simple bounds required for beam fluence
  - Negative fluence is not physical & removes dose
- Steepest descent + Armijo line search
  - Iteration is fast
  - Solution is robust
- In theory, FMO is poorly conditioned & SD should converge too slowly
- In practice, converges the fastest of all CP algorithms tested!!!
- Allows warm start!!!

Projected Gradient for Simple Bounds and Armijo Line Search

- Consider a 3D problem...

$$\bar{x}_{i+1} \quad \bar{x}_i \quad f(\bar{x}_i)$$

$$\bar{x}_i \quad \begin{cases} L_i & \text{if } \bar{x}_i \le L_i \\ \bar{x}_i & \text{if } L_i < \bar{x}_i < U_i \\ U_i & \text{if } \bar{x}_i \ge U_i \end{cases}$$



Any negative fluences are projected back into feasible space

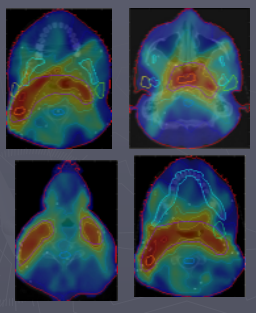
See: Iterative Methods for Optimization

C.T. Kelley

Results: Run Times 1.7 GHz Centrino

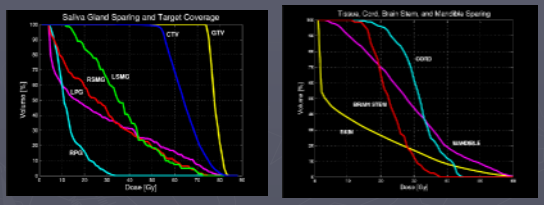
Beamlets	Voxels	Iterations	Times (s)
1,153	18,375	24	25.5
1,400	22,123	49	67.4
1,856	37,722	29	58.2
2,056	39,152	42	91.7
1,289	17,485	24	24.5
980	15,507	29	25.7
1,449	23,867	28	43.2
1,388	20,608	37	48.2
780	16,536	54	55.6
2,382	31,694	59	132.9
1,400	22,123	35	47.2

FMO IMRT Results



- High quality optimization enables daily IMRT optimization
  - 25-133 seconds to optimize on single PC
- 7 beam plan
- Targets to 73.8 and 54 Gy
- Spare tissue, saliva glands, cord, brain stem, and mandible

DVH IMRT Example



- Targets w/ >95% Vol. coverage
- <12% hot spot for high dose target
- Sparing for 3 out of 4 saliva glands <50% vol. @ 30 Gy
- <3% Tissue > 50 Gy
- Cord, brain stem, and mandible below tolerance

Conclusions

- Optimization times are already fast enough for daily IMRT optimization
- Convex programming models and the projection gradient algorithm provides a robust and efficient approach for *de novo* FMO
- Parallel implementations will be explored

Summary

- The current IMRT treatment planning paradigm
- Problems with the paradigm
- Advances
  - Plan evaluation tools (WUSTL)
  - Prioritized optimization (WUSTL and U Mich)
  - Interactive plan selection (Bortfeld, MGH)
  - Robust optimization (Eva Lee, Ga Tech)
  - 4D optimization (Eva Lee, Ga Tech)
  - Fast adaptive replanning (Dempsey, U of F)

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