Robust Optimization accounting for Uncertainties

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Outline

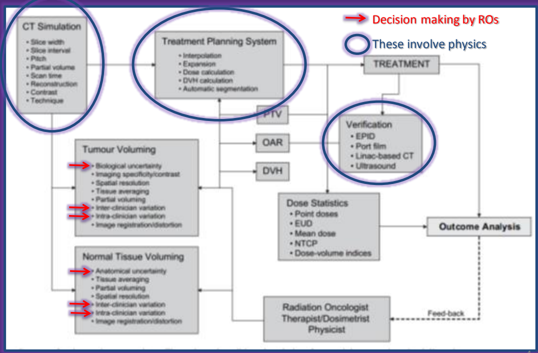
1. Optimality and uncertainty
2. Robust optimization: better than margins
3. What does all that mean in practice?

1. Optimality and Uncertainty

The dilemma:

- We want the optimal treatment plan for our patients!
- But, how can we design the optimal plan when the underlying parameters are uncertain?

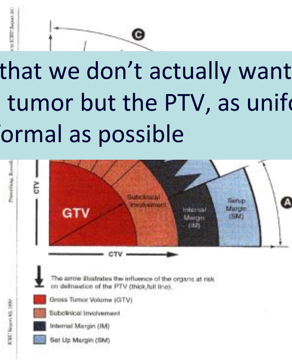
Factors involved in volumetric uncertainty in target volume delineation



Hamilton & Ebert, Clin. Oncol 17: 456-464; 2005

The “normal” way to deal with this: Use margins

- Pretend that we don’t actually want to treat the tumor but the PTV, as uniformly and conformal as possible



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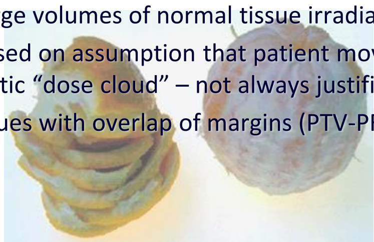
Margins to counteract uncertainties

- Large volumes of normal tissue irradiated
- Based on assumption that patient moves in a static “dose cloud” – not always justified
- Issues with overlap of margins (PTV-PRV)



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Robust optimization = a better way to deal with optimality under uncertainty

- We want to make a treatment plan as good as possible and at the same time protect it against uncertainties
- Robustness = immunity to uncertainty
- Robust optimization: bringing robustness and optimality together
- How can we do that?

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Robust optimization, the approach:

- Consider different **scenarios** of treatment delivery (instances of geometry of patient positions, organ motion, range over- or undershoot for protons, ..)

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THE ROLE OF UNCERTAINTY ANALYSIS IN TREATMENT PLANNING

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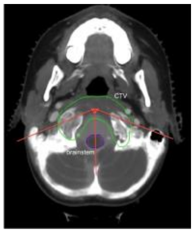
Photon Treatment Planning Collaborative Working Group. IJROBP 21:91-107; 1991

Para-aortic nodes – junction

Nominal | "Upper bound" Misregistered by 1 cm | "Lower bound" Misregistered by 1 cm

IMPT example: chordoma



29 different scenarios:

- Nominal scenario (1)
- 3 mm setup error ±x, ±y, ±z (6)
- 3 mm setup error (diagonal) (20)
- 5% range error, over- and undershoot (2)

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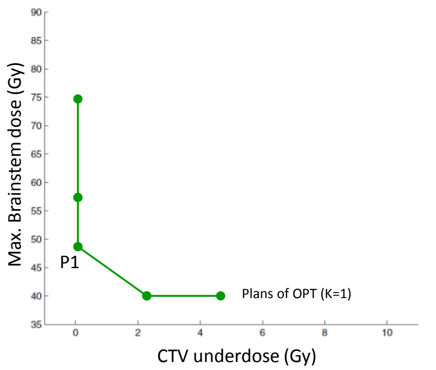
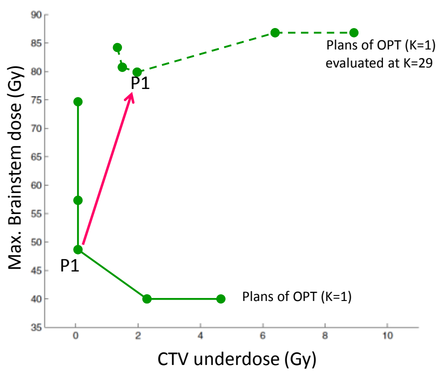
Planning tradeoff, nominal case



Plan degradation



Robust optimization, the approach:

- Consider different **scenarios** of treatment delivery (instances of geometry of patient positions, organ motion, range over- or undershoot for protons, ..)

1. **The worst case approach**: make sure that constraints are fulfilled in all scenarios, and that we obtain the best plan in the worst case ("minimax").

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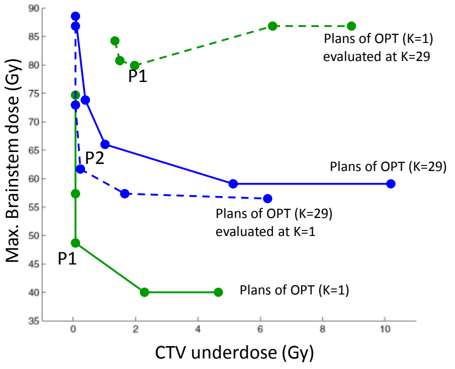
Robust solution (worst case, minimax)



Robust optimization, the approach:

- Consider different **scenarios** of treatment delivery (instances of geometry of patient positions, organ motion, range over- or undershoot for protons, ..)

1. **The worst case approach**: make sure that constraints are fulfilled in all scenarios, and that we obtain the best plan in the worst case ("minimax").
2. **"Stochastic programming"**: describe uncertainties with random variables, assume probability density functions (pdf), and optimize expected value of the objective function.

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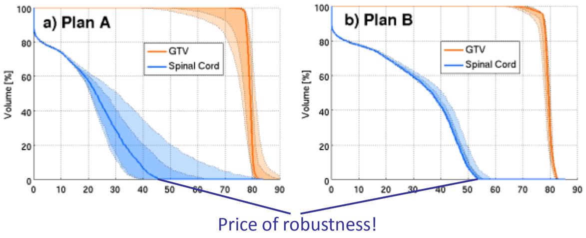
The price of robustness
non-robust (Plan A) and robust (Plan B)



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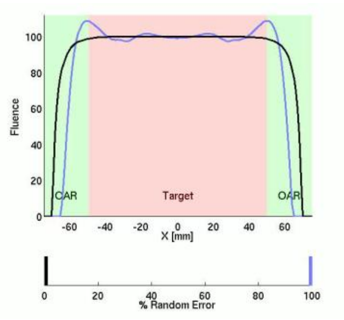
Example: setup error (1D)

- Error scenarios defined by shifting to the left or right in steps of 1mm.
- **Random error**: 32 random shifts (for 32 fractions) sampled from a Gaussian with a mean of zero and a set standard deviation σ_{Rand}
- **Systematic error:** single shift with standard deviation σ_{Sys} added to the random shift above

Example: setup error (1D)

(10 mm)^2

$$\sigma_{Tot}^2 = \sigma_{Rand}^2 + \sigma_{Sys}^2$$

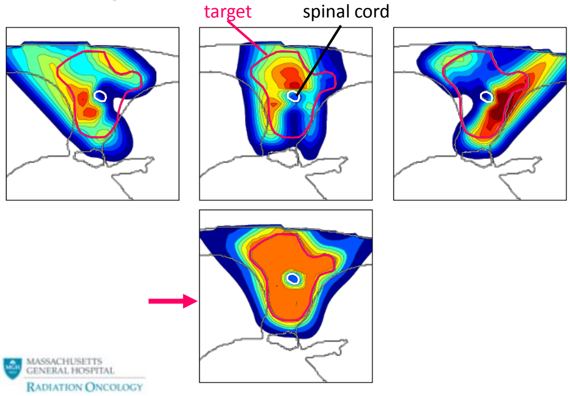


Observations random/systematic errors:

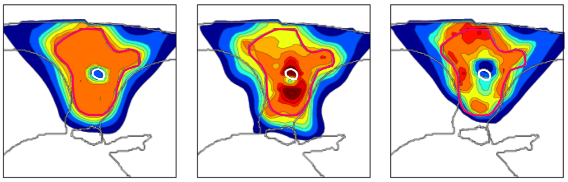
- Random errors require smaller margins than systematic errors -> van Herk margin recipes.
- Robust optimization leads to beam “horns” instead of margins.

IMPT plan, 3 fields

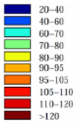
target
spinal cord



Sensitivity analysis



(a) Nominal dose (b) 5mm overshoot (c) 5mm undershoot



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Stochastic programming

$$\underset{x}{\text{minimize}} \quad \sum_s p_s \Bigg[\underbrace{w_T \sum_{i \in T} (d_i^s - D^{pres})^2}_{\text{Target dose deviation}} + \underbrace{w_{SC} \sum_{i \in SC} (d_i^s)^2}_{\text{Spinal cord dose}} \Bigg] + \underbrace{f_{HT}(d^1)}_{\text{healthy tissue dose}}$$

3 scenarios:

- *Scenario 1*: Nominal scenario, $p_1 = 0.5$
- *Scenario 2*: 5 mm range overshoot, $p_2 = 0.25$
- *Scenario 3*: 5 mm range undershoot, $p_3 = 0.25$

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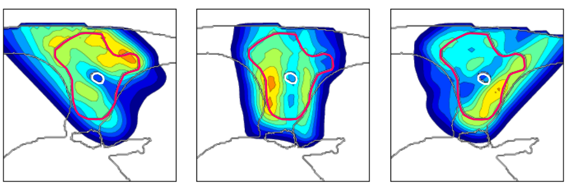
Robust IMPT plan



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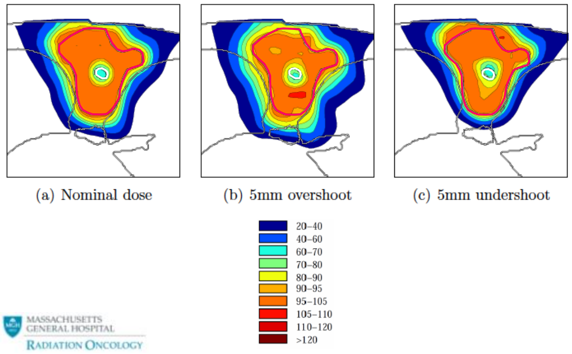
Sensitivity analysis II (robust plan)



(a) Nominal dose (b) 5mm overshoot (c) 5mm undershoot

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Observations protons:

- Proton range errors in IMPT cannot effectively be dealt with through margins.
- Here we absolutely need robust optimization.

- More on robust optimization for protons:
  - IMPT session, talk by Jan Unkelbach et al. Thursday, 7:30-9:30AM, Ballroom E

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Vision for the future

- No (PTV) margins in treatment planning
- Instead, quantify motion and uncertainties, and let the planning system find a robust solution. This may be a margin-like solution but could also be an advanced intensity-modulated solution (e.g., “horns”).

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3. **What does all that mean in practice?**

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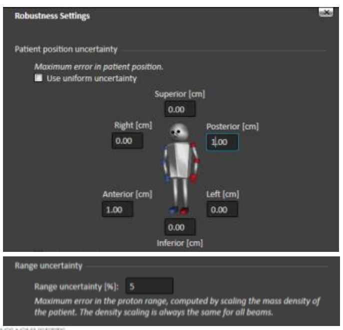
Implementation in RayStation 4.5



User interface

Setup uncertainty

Range uncertainty

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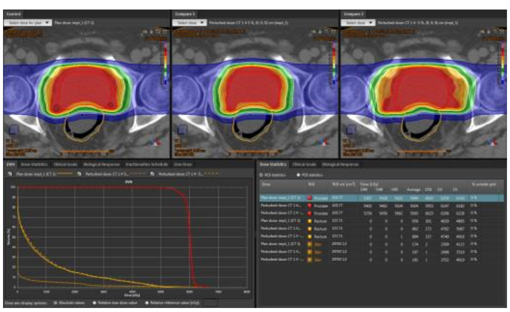

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Robust optimization
Take-home-messages:

- Uncertainty -> Different scenarios
- Robust optimization done in two ways:
  1. optimize worst scenario (minimax)
  2. stochastic programming (optimization of *expected* outcome)
- There is always a price of robustness.
- Robust optimization can lead to new types of fault-tolerant dose distributions, e.g. beam “horns” for motion, and robust proton dose distributions.
- Robust optimization is coming to you (i.e., to your planning system).

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Uncertainty analysis and robustness – 30 year old dreams come true…

Calculation of the uncertainty in the dose delivered during radiation therapy[a)]

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(Received 4 February 1985; accepted for publication 10 May 1985)

There is, inevitably, uncertainty in our knowledge of the dose at any point within an irradiated patient. A technique is presented for estimating this uncertainty by performing three parallel calculations, one using nominal values and the others extreme values of the parameters upon which the dose depends. Such calculations can be made with almost any algorithm for calculating dose. They result in an estimate, at some specified confidence level which is determined by the data used, of the range of dose likely at any point. Such calculations should help therapists to avert over- or underdosage which might not be evident in conventional calculations of the nominal dose.

Med Phys 12(5):608-612, 1985

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Planning objectives and constraints

Chordoma (Rx = 78 Gy)			
Structures	Type	Scenarios	Bound (in Gy)/Direction
Objectives			
CTV	Underdose ramp (d^{pres} = Rx)	All	Minimize
Brainstem, spinal cord	Max	All	Minimize
Constraints			
CTV	Min	Nominal	$\geqslant$ 60
CTV	Max	Nominal	$\leqslant$ 85.8
R/L cochlea	Max	9	$\leqslant$ 50
R/L parotid	Mean	9	$\leqslant$ 26

Learning objective

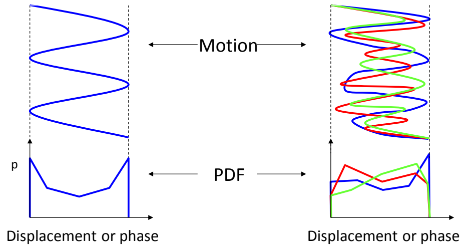
- To highlight the basic ideas and clinical potential of robust optimization procedures to generate optimal treatment plans that are not severely affected by uncertainties.

Uncertainty and Motion

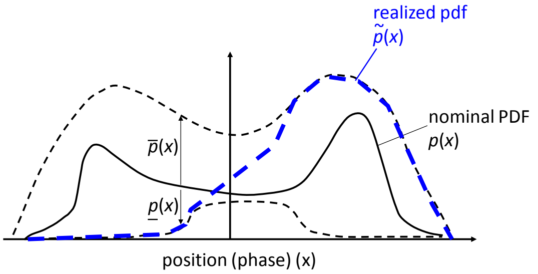
- Motion does not <u>necessarily</u> imply uncertainty
  - If motion is perfectly known, then there is no uncertainty. This case is "easy" to deal with.
- But, when there is motion (e.g., breathing), there are typically more potential sources of uncertainty:
  - Uncertainties in the motion characteristics such as frequency, amplitude, shape of trajectory, irregularity of the motion.

Uncertainty model for de-blurring method

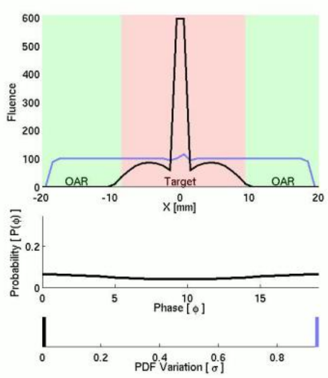
- PDF for regular breathing
- Uncertain motion may lead to many PDFs



Uncertainty set – PDF and "error bars"



Tim Chan et al: Phys Med Biol 51:2567 (2006)



Observations re. breathing motion:

- If we know nothing about the motion but the rough amplitude, adding margins is the best we can do.
- If we know more, such as the breathing PDF, we can do much better with robust optimization.

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