

# Application of Robust Optimization in Lung Cancer Treatment

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Joint with

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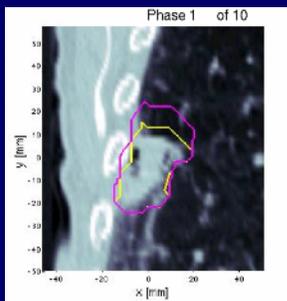
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## Outline

- Motion uncertainty
- Relationship between motion and probability density functions
- Robust optimization (Goldilocks approach)
- Comparison of approaches

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## How do we ensure that we generate "good" plans in the face of uncertainty?

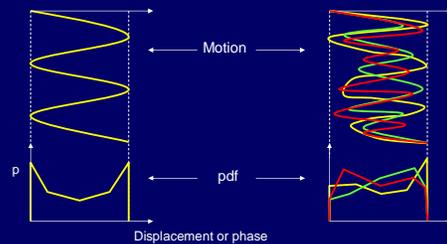


- What exactly is the uncertainty here?
- Not just the motion, but the possible *irregularities in the motion* itself.
- A "good" plan guarantees tumor coverage while minimizing healthy tissue dose

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## Existence of probabilities doesn't necessarily imply uncertainty

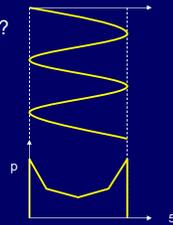
- Could be a natural expression of physical phenomena: regular motion leads to a pdf
- However, uncertain motion may lead to many pdfs



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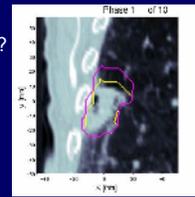
## 4D optimization approach

- Construct an intensity map that takes into account (de-convolution) one pdf associated with the motion. This undoes the blurring effect of motion.
- What does the 4D approach assume?
- Assumptions:
  - Reproducibility/stability of motion
  - Takes into account EXACTLY ONE pdf
  - “Best case”



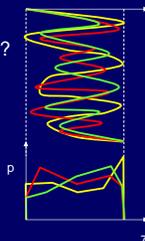
## ITV-like approach

- Construct an intensity map that achieves ITV coverage
- We say it is “ITV-like”, since we consider anatomical voxels, and not geometric voxels
- What does the ITV approach assume?
- Assumptions:
  - Totally unstable motion
  - Takes into account ALL pdfs
  - “Worst case”

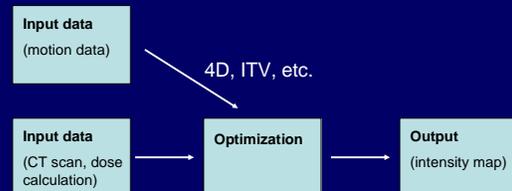


## Robust (Goldilocks) approach

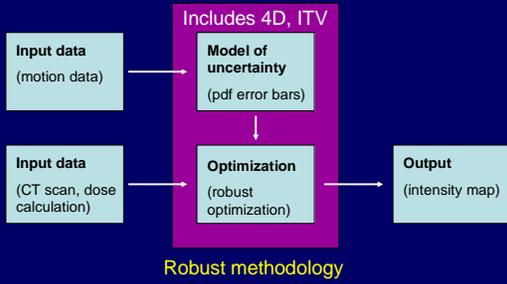
- Construct an intensity map that takes into account some amount of motion uncertainty (some family of pdfs), but not all pdfs.
- What does the robust approach assume?
- Assumptions:
  - Motion pdf within some error bounds
  - Takes into account SOME pdfs
  - “Not too hot, not too cold”



## Sketch of traditional approach



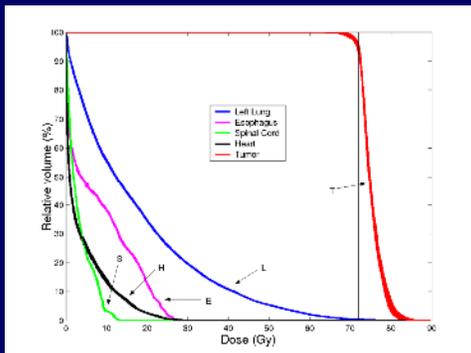
## Sketch of robust approach



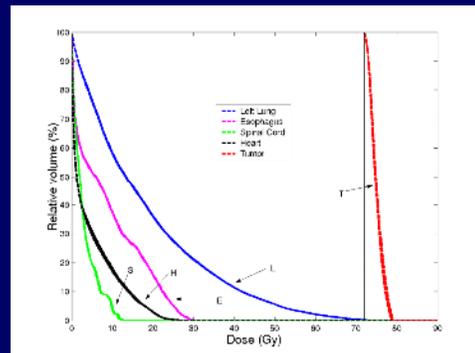
## Lung Case

- Tumor in left lung
  - Critical structures: left lung, esophagus, spinal cord, heart
  - Approx. 100,000 voxels, 1600 beamlets
  - Minimize dose to healthy tissue
  - Lower bound and upper bound on dose to tumor
  - Simulate delivery of optimal solution with 52 "realized pdfs"
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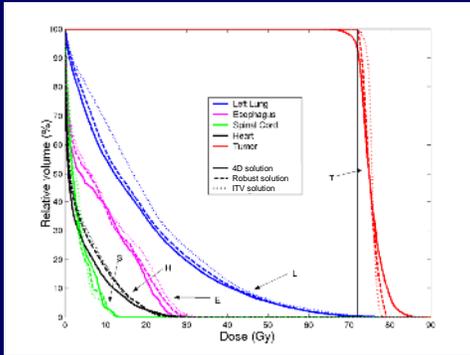
## 4D (one pdf) DVH



## Robust DVH



## Comparison of approaches



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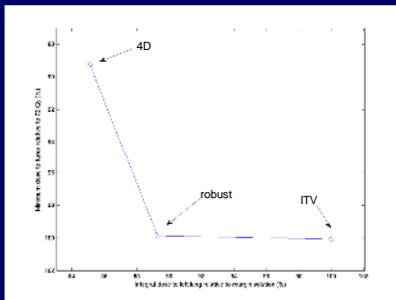
## Numerical results

|                         | 4D<br>(one pdf) | Robust<br>(some pdfs) | ITV<br>(all pdfs) |
|-------------------------|-----------------|-----------------------|-------------------|
| Minimum dose in tumor*  | 89.25 %         | 99.87 %               | 100.07 %          |
| Total dose to left lung | 85.11 %         | 89.27 %               | 100.00 %          |

\* Relative to minimum dose requirement

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## A multi-objective perspective



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## Continuum of Robustness

4D (one pdf)      Robust (some pdfs)      ITV (all pdfs)

No Uncertainty      Some Uncertainty      Complete Uncertainty

- Can prove this mathematically
- Flexible tool allowing planner to modulate his/her degree of conservatism based on the case at hand

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## Takeaways

- Not just breathing motion, but *breathing motion uncertainty*
- Robust optimization gives us a continuum of options to deal with various levels of uncertainty
- Patient belongs somewhere in this continuum
- Model the patient, and the robust framework comes up with the right treatment in the continuum

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## Some future directions for Robust Optimization

- Experiments with linac and detector array
  - SU-FF-T-224
- Use in conjunction with other strategies
  - SU-DD-A3-6
- Application to uncertainties in IMPT
  - MO-D-M100J-3
- Individualization, adaptation, other sites
  - This session!

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