

# Optimization of Gamma Knife Radiosurgery

Michael Ferris

University of Wisconsin, Computer Sciences

Jin-Ho Lim, University of Houston

David Shepard

University of Maryland School of Medicine

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# Radiation Treatment Planning

- Cancer is the 2nd leading cause of death in U.S.
  - Only heart disease kills more
- Expected this year in the U.S. (American Cancer Society)
  - New cancer cases = 1.33 million (> 3,600/day)
  - Deaths from cancer = 556,500 (> 1,500/day)
  - New brain/nerv. sys. cancer cases > 18,300 (> 50/day)
- Cancer treatments: surgery, radiation therapy, chemotherapy, hormones, and immunotherapy

# Radiation As Cancer Treatment

- Interferes with growth of cancerous cells
- Also damages healthy cells, but these are more able to recover
- **Goal:** deliver specified dose to tumor while avoiding excess dose to healthy tissue and at-risk regions (organs)

# Commonalities

- Target (tumor)
- Regions at risk
- Maximize kill, minimize damage
- Homogeneity, conformality constraints
- Amount of data, or model complexity
- Mechanism to deliver dose

# Stereotactic radiosurgery?

- Stereotactic - originated from the Greek words stereo meaning three dimensional and tactos meaning touched
- Stereotactic - fixation system (Leksell, 1951)
  - Bite on dental plate to restrict head movement
  - Or screw helmet onto skull to fix head-frame in position
  - Treatment almost always to head (or neck)
- Multiple radiation fields from different locations
- Radiosurgery - one session treatment
  - High dose, single fraction (no movement errors!)

# Types

- Particle beam (proton)
  - Cyclotron (expensive, huge, limited availability)
- Cobalt60 based (photon)
  - Gamma Knife (focus of this talk)
- Linear accelerator (x-ray)
  - (Tumor size) cone (12.5mm - 40mm) placed in collimator
  - Arc delivery followed by rotation of couch (4 to 6 times)

# The Gamma Knife

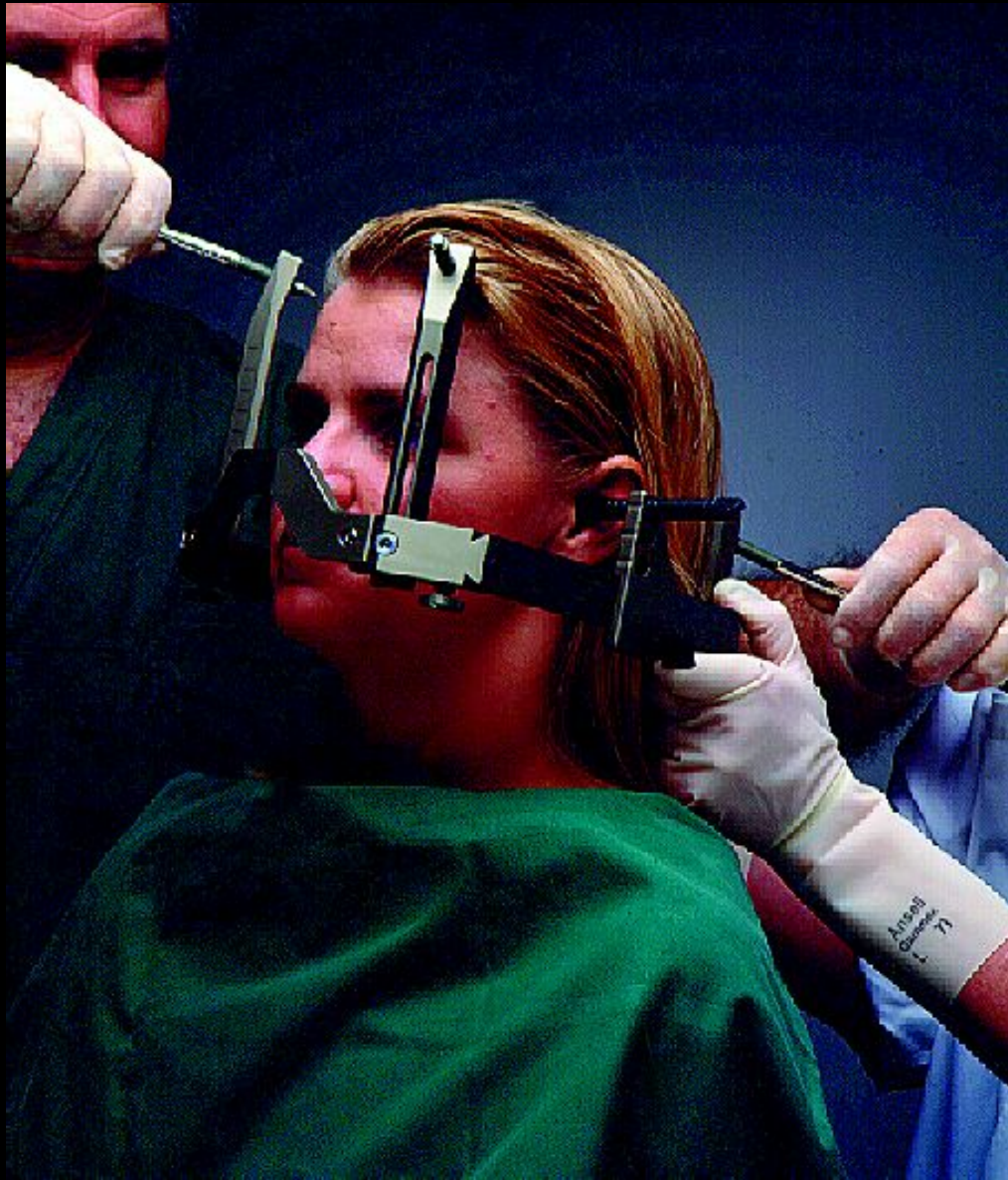




201 cobalt gamma ray beam sources are arrayed in a hemisphere and aimed through a collimator to a common focal point.

The patient's head is positioned within the Gamma Knife so that the tumor is in the focal point of the gamma rays.



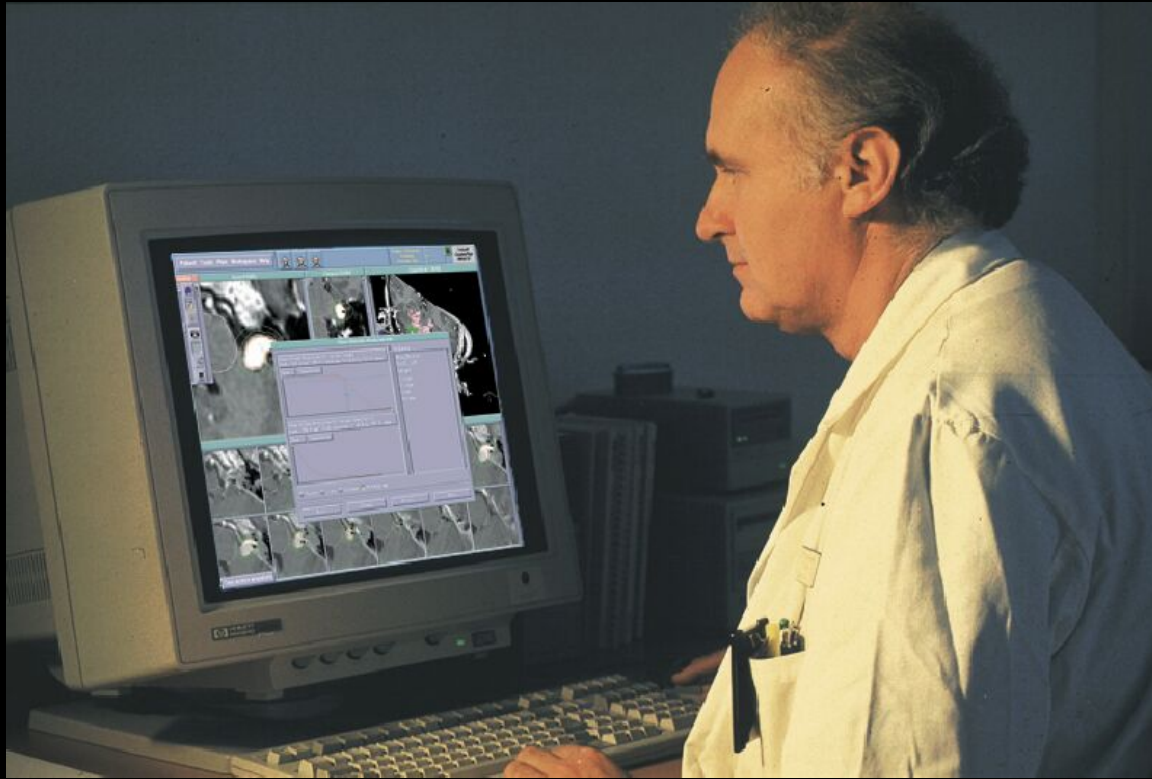


## How is Gamma Knife Surgery performed?

Step 1: A stereotactic head frame is attached to the head with local anesthesia.

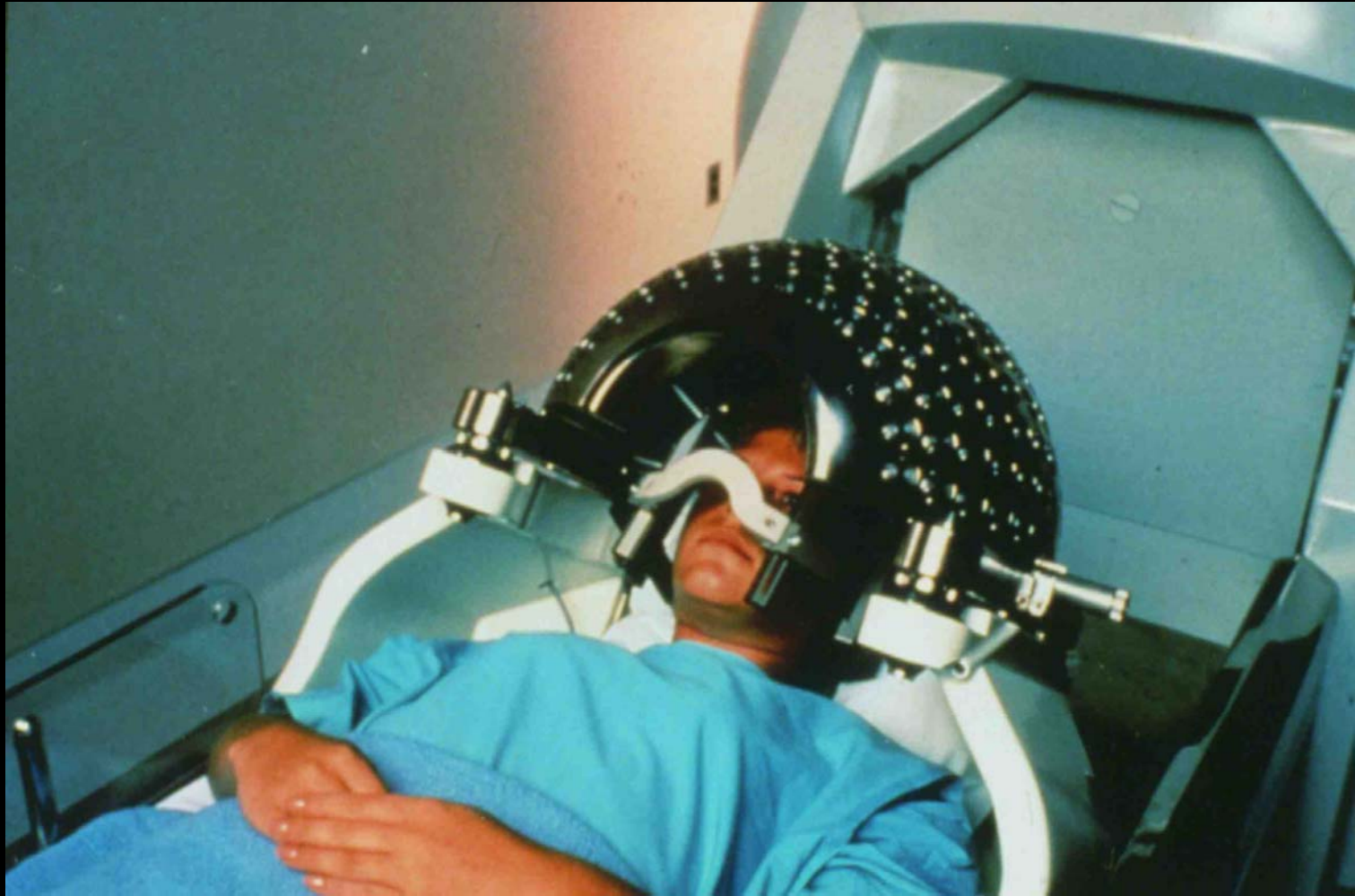


Step 2: The head is imaged using a MRI or CT scanner while the patient wears the stereotactic frame.

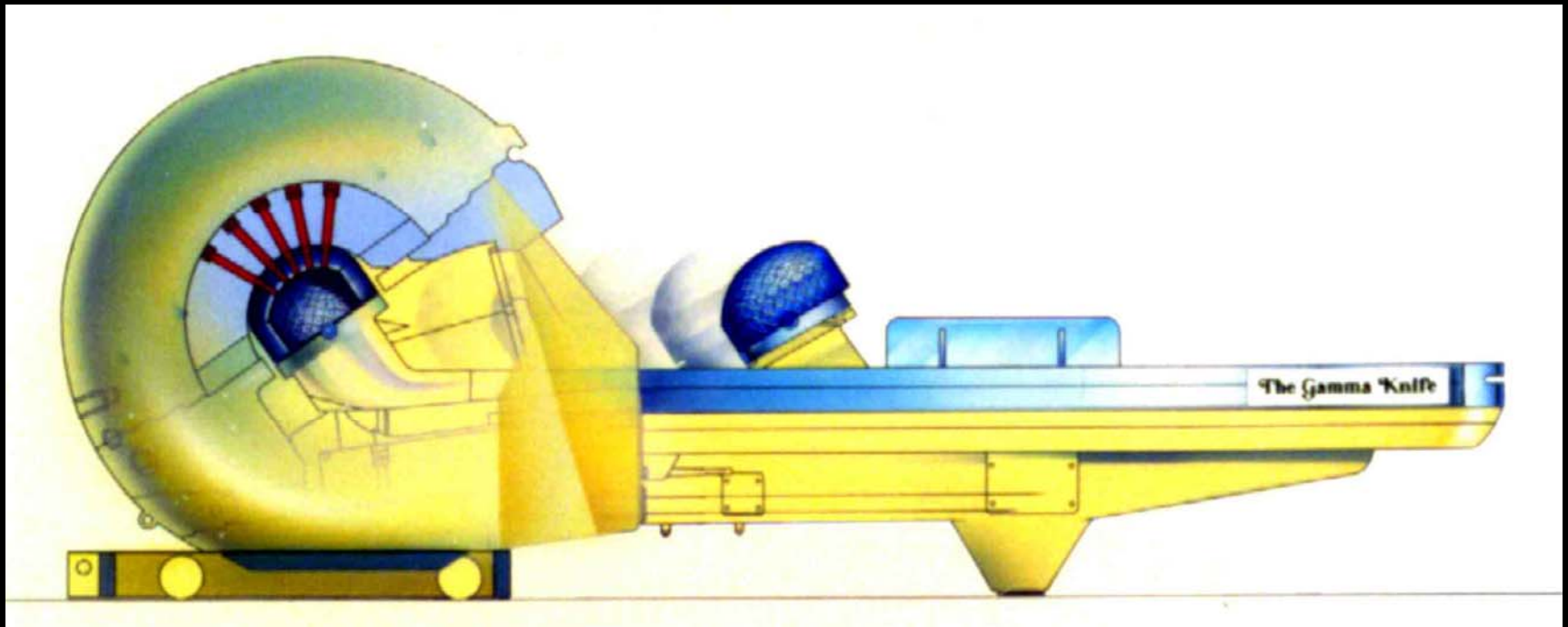


Step 3: A treatment plan is developed using the images. **Key point:** very accurate delivery possible.





Step 4: The patient lies on the treatment table of the Gamma Knife while the frame is affixed to the appropriate collimator.



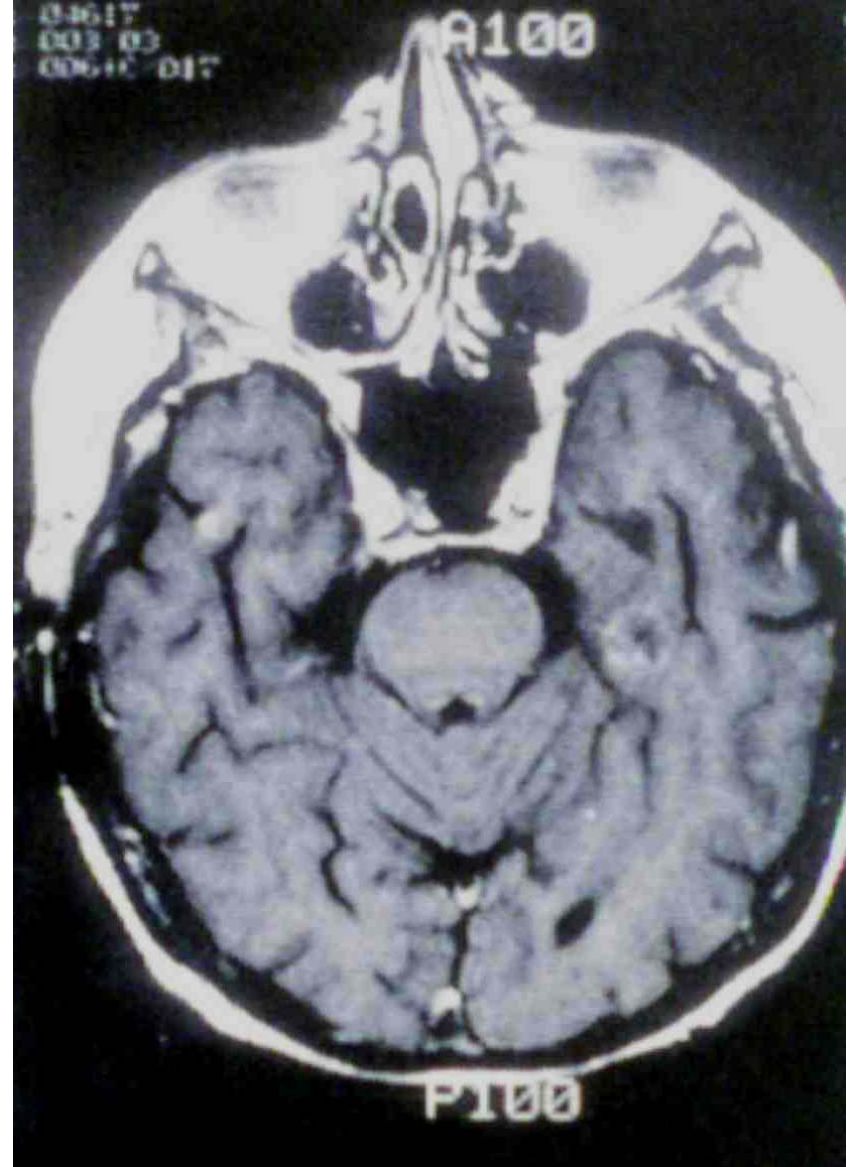
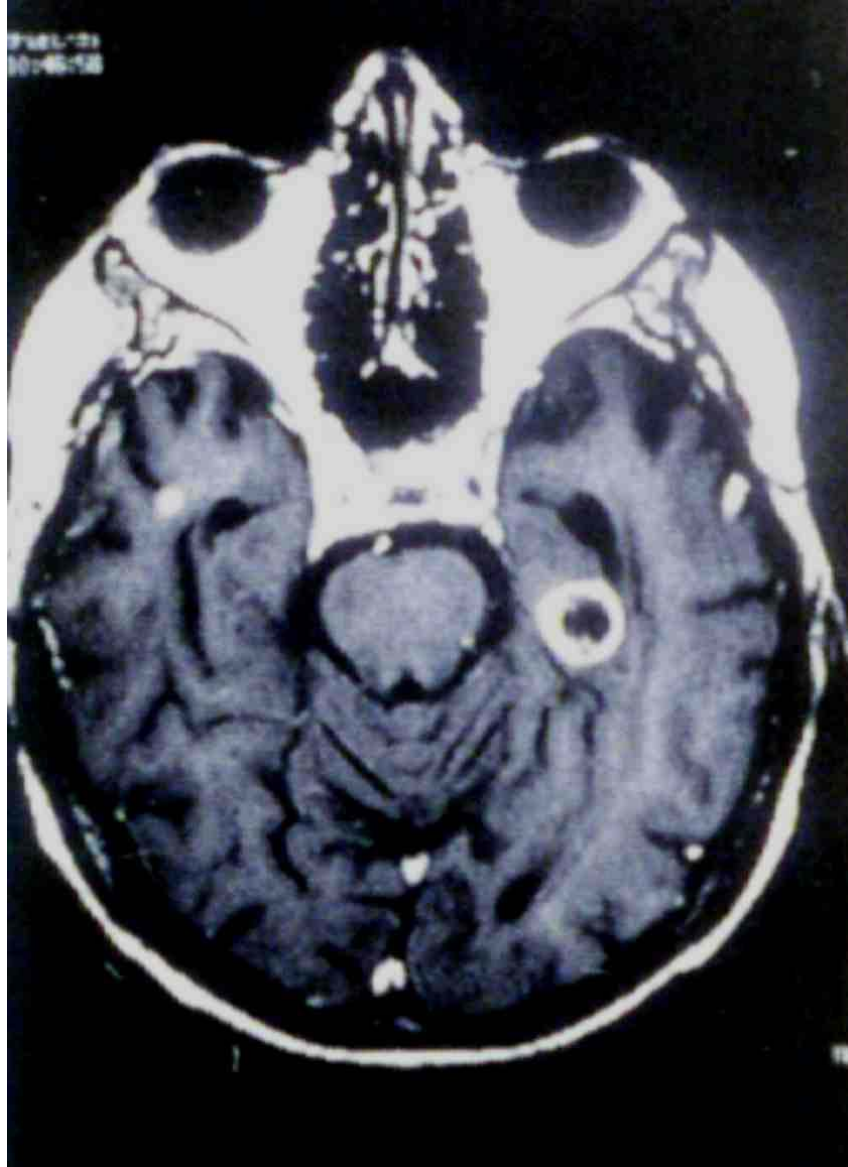
Step 5: The door to the treatment unit opens. The patient is advanced into the shielded treatment vault. The area where all of the beams intersect is treated with a high dose of radiation.

# Procedure

- Placement of head frame
- Imaging (establish coordinate frame)
- Treatment planning
- Treatment
  - Multiple arcs of radiation
  - Multiple shots from Gamma Knife
- Frame removal









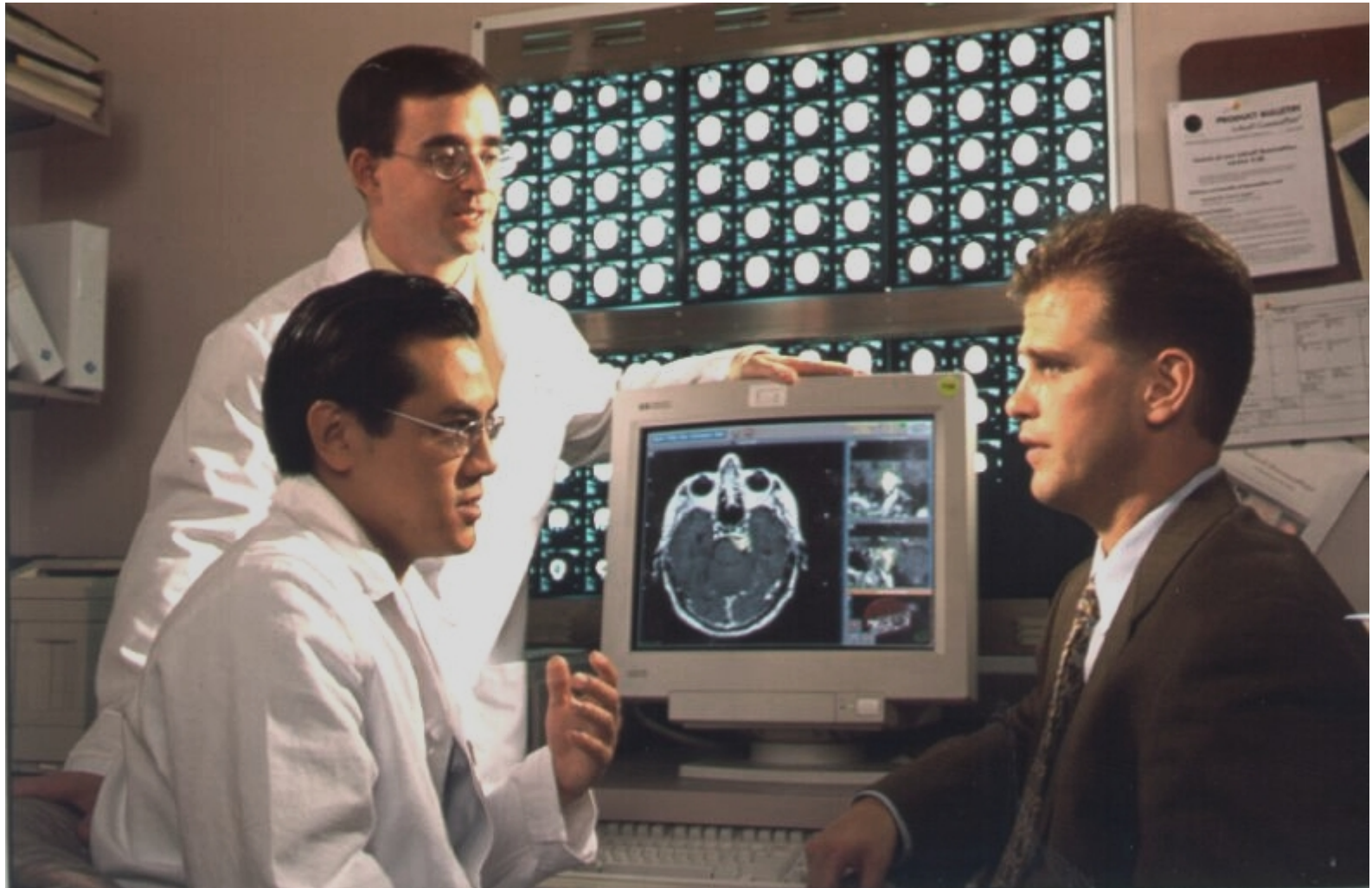
# What disorders can the Gamma Knife treat?

- Malignant brain tumors
- Benign tumors within the head
- Malignant tumors from elsewhere in the body
- Vascular malformations
- Functional disorders of the brain
  - Parkinson's disease

# Gamma Knife Statistics

- 120 Gamma Knife units worldwide
- Over 20,000 patients treated annually
- Accuracy of surgery without the cuts
- Same-day treatment
- Expensive instrument

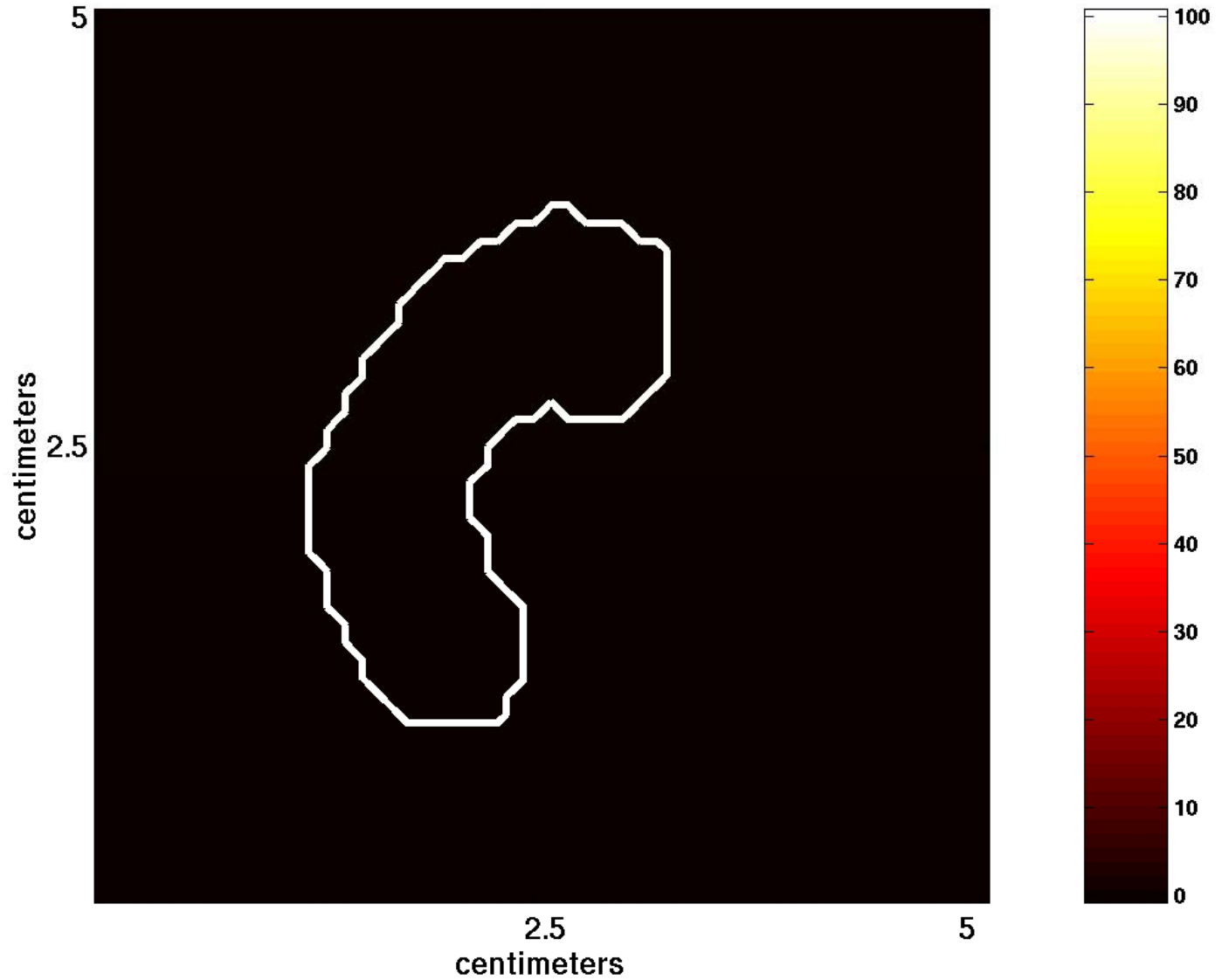
# Treatment Planning



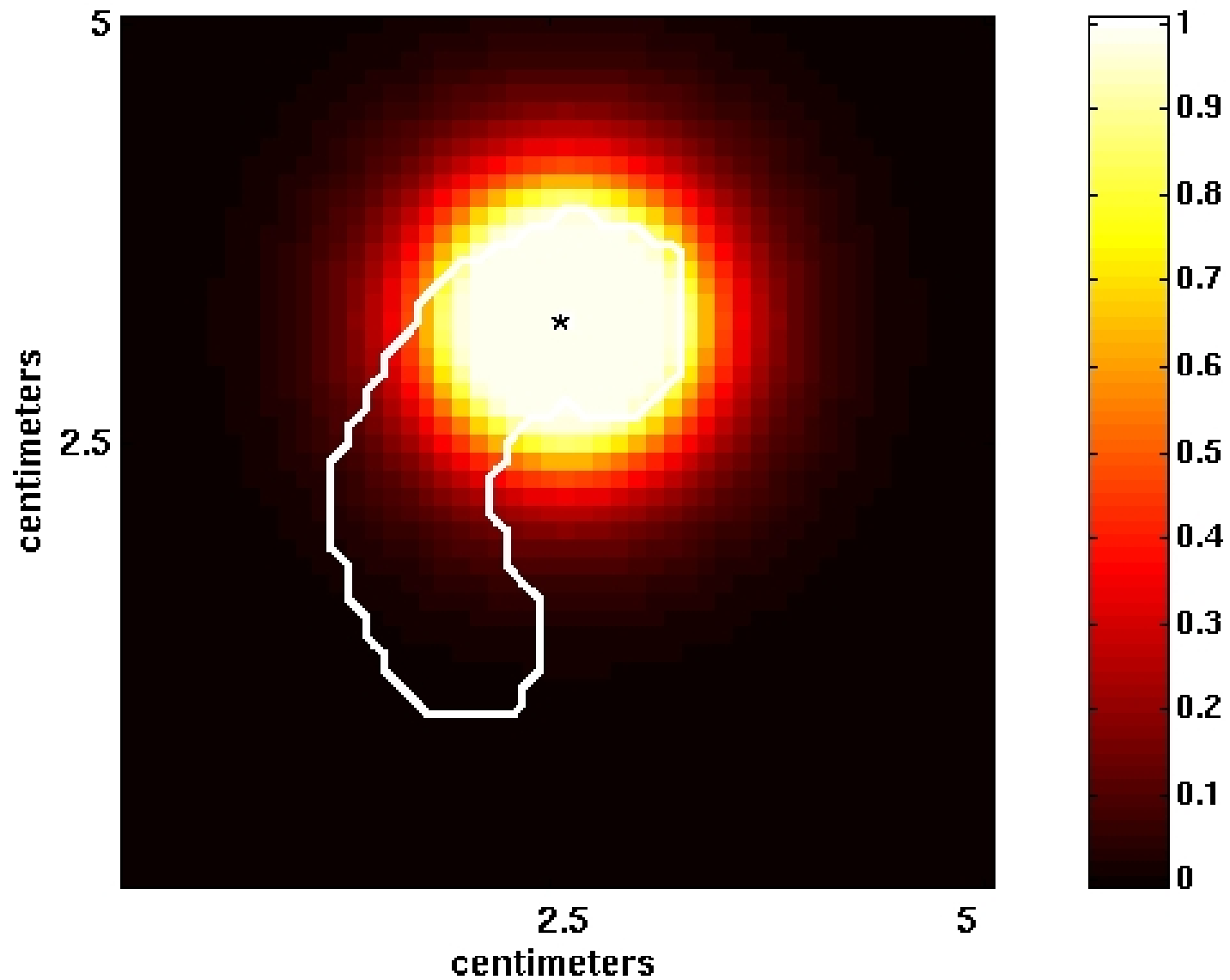
# Treatment Planning

- Through an iterative approach we determine:
  - the number of shots
  - the shot sizes
  - the shot locations
  - the shot weights
- The quality of the plan is dependent upon the patience and experience of the user

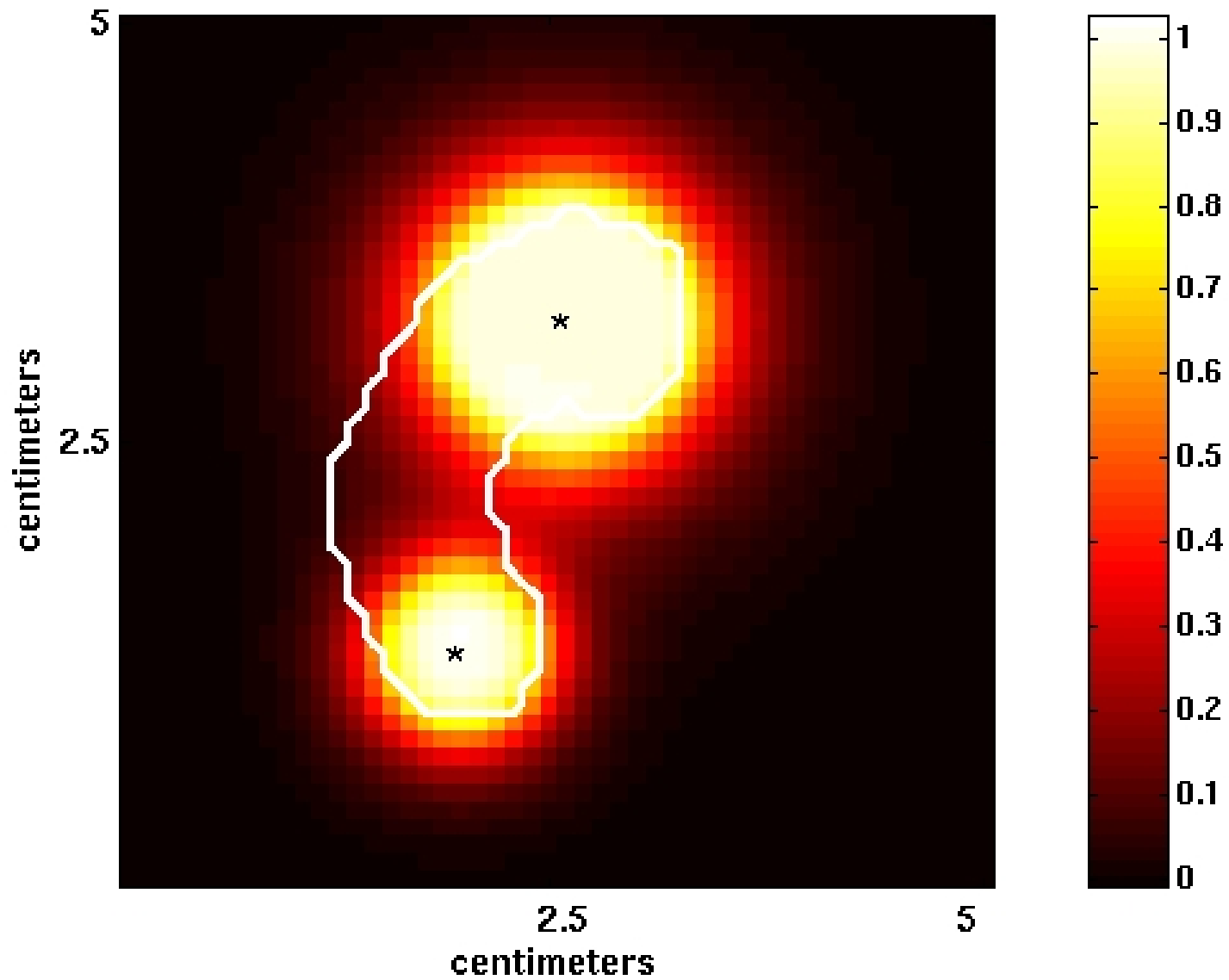
# Target



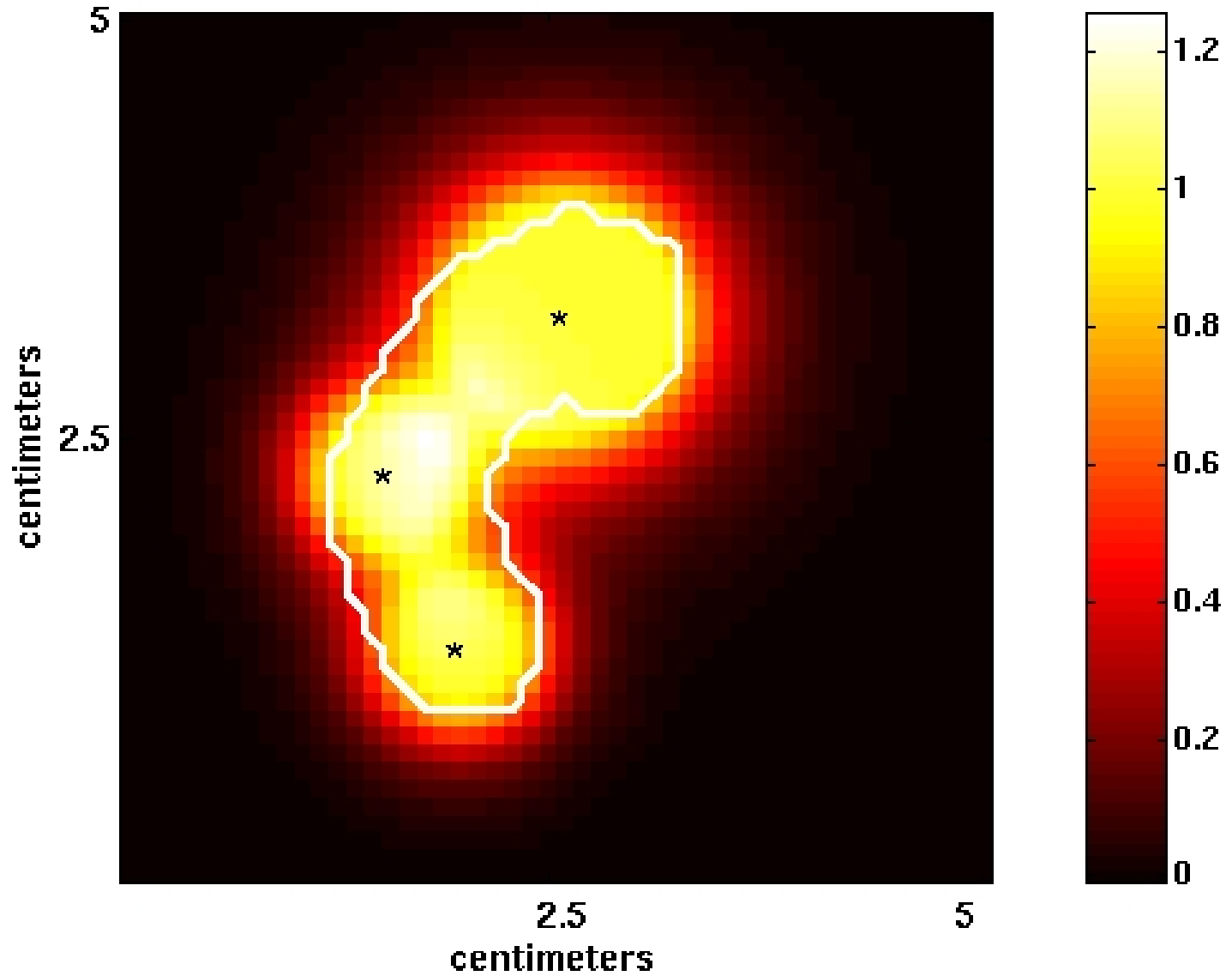
# 1 Shot



# 2 Shots

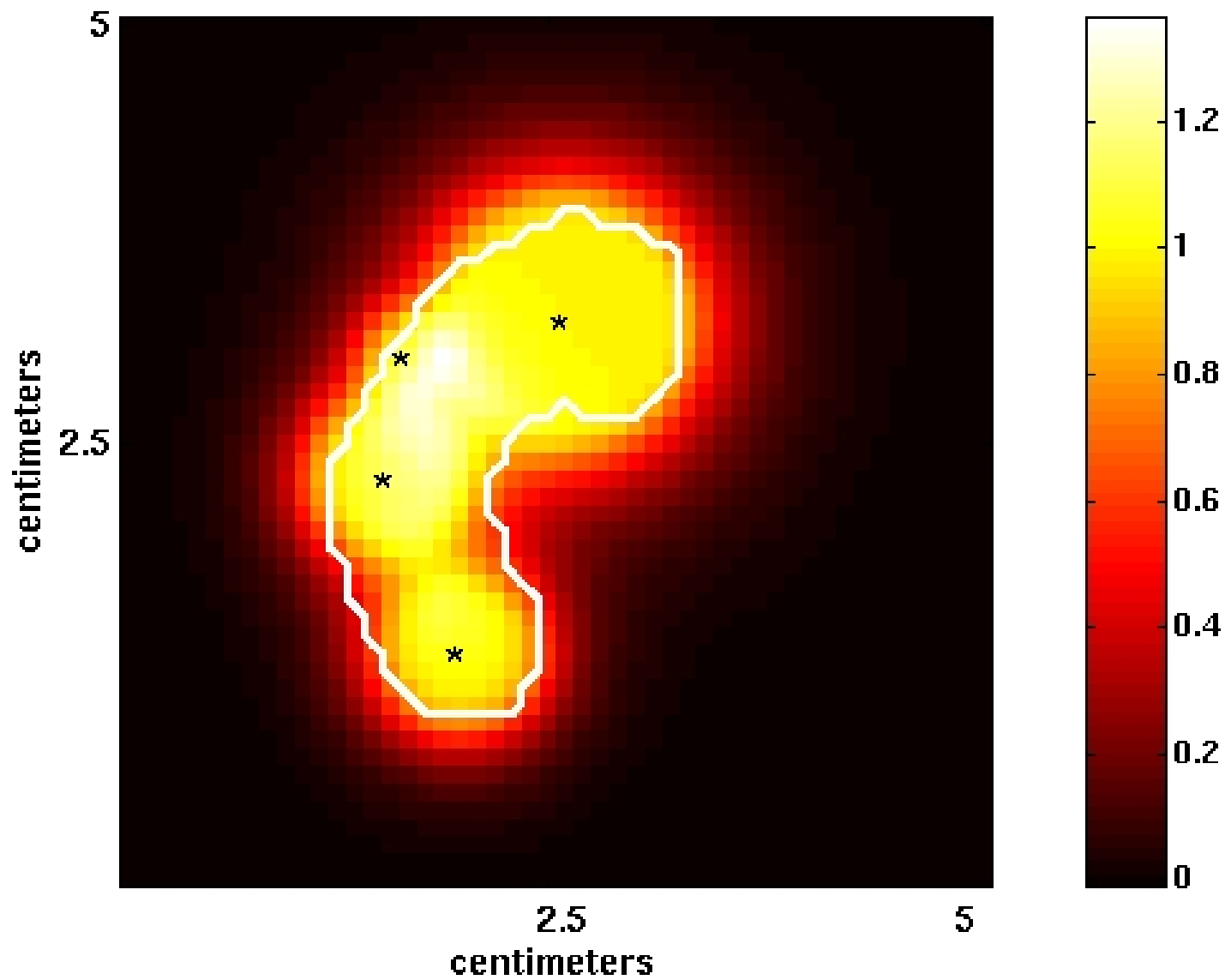


# 3 Shots

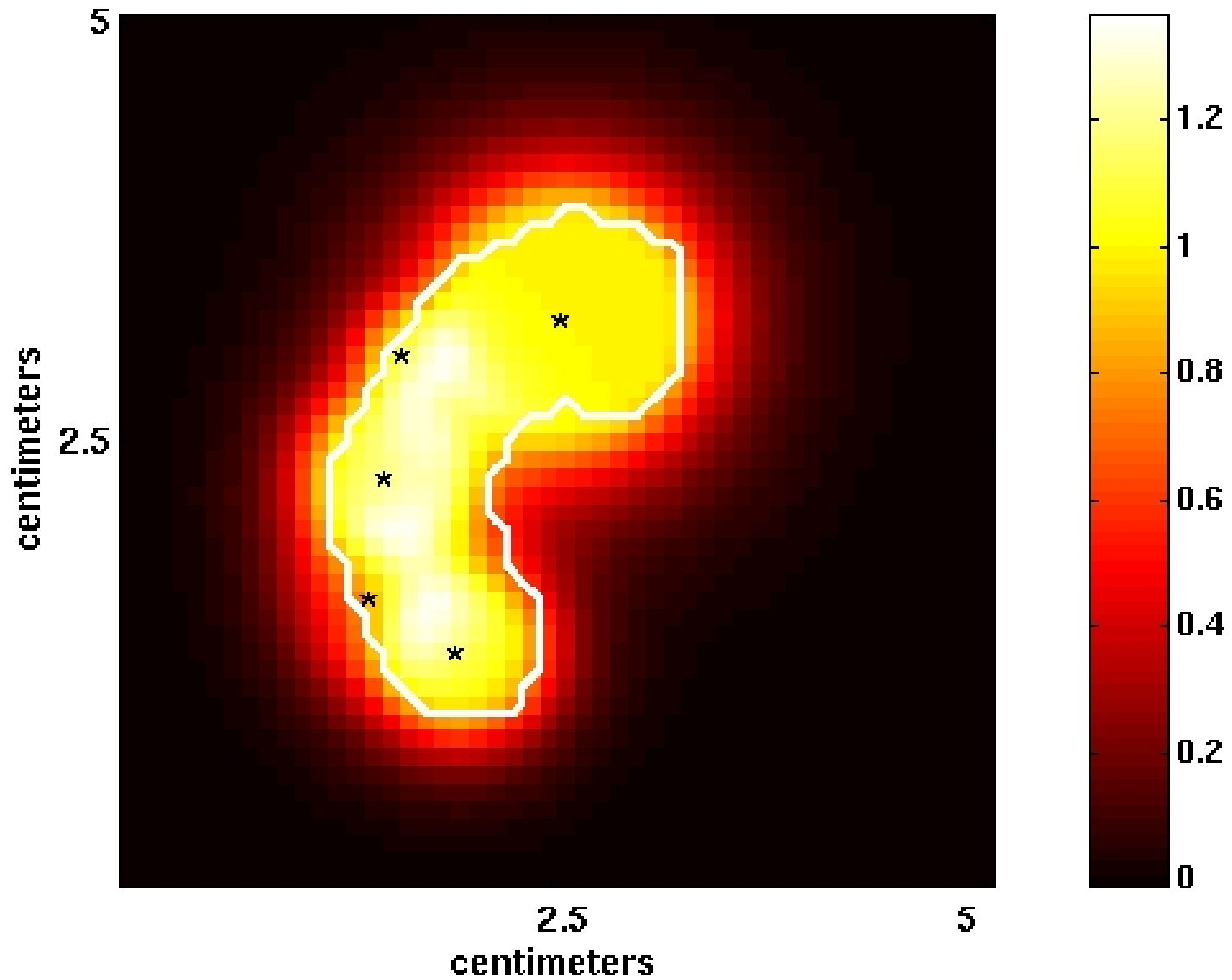




# 4 Shots



# 5 Shots



# Inverse Treatment Planning

- Develop a fully automated approach to (Gamma Knife) treatment planning
- A clinically useful technique will meet three criteria: robust, flexible, fast
- Benefits of computer generated plans
  - uniformity, quality, faster determination

# Computational Model

- Target volume (from MRI or CT)
- Maximum number of shots to use
  - Which size shots to use
  - Where to place shots
  - How long to deliver shot for
- Conform to Target (50% isodose curve)
- Real-time optimization

# Summary of techniques

Method	Advantage	Disadvantage
Sphere Packing	Easy concept	NP-hard Hard to enforce constraints
Dynamic Programming	Easy concept	Not flexible Not easy to implement Hard to enforce constraints
Simulated Annealing	Global solution (Probabilistic)	Long-run time Hard to enforce constraints
Mixed Integer Programming	Global solution (Deterministic)	Enormous amount of data Long-run time
Nonlinear Programming	Flexible	Local solution Initial solution required

# Ideal Optimization

$$\min_{t_{s,w}, x_s} \text{Dose}(\text{NonTarget})$$

subject to

$$\text{Dose}(i) = \sum_{s \in S, w \in W} t_{s,w} D_w(x_s, i)$$

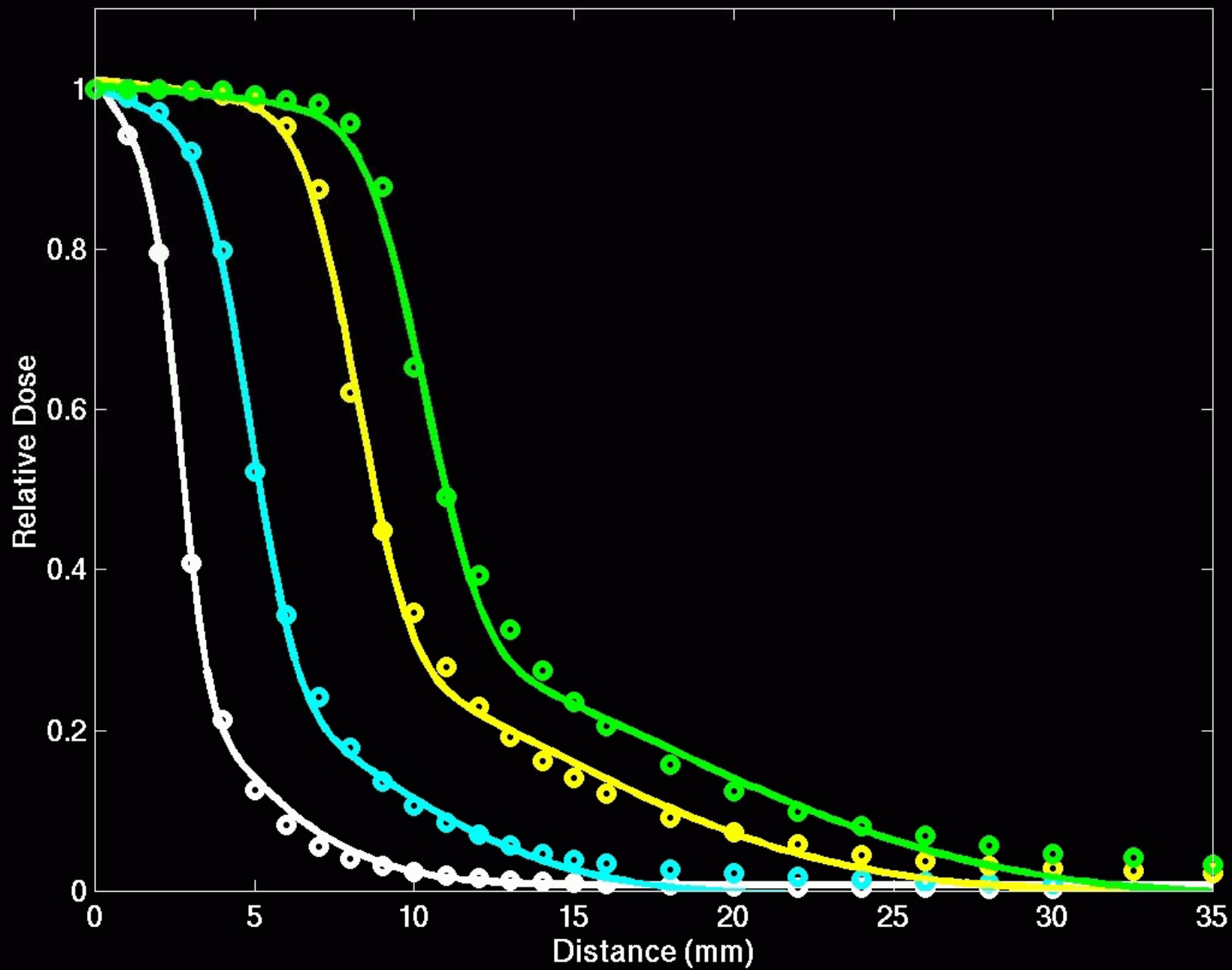
$$0.5 \leq \text{Dose}(\text{Target}) \leq 1$$

$$t_{s,w} \geq 0$$

$$|S| \leq N$$

# Solution methodology

- Detail dose distribution calculation
- Describe nonlinear approximation
- Outline iterative solution approach
- Starting point generation
- Modeling issues
- Examples of usage





# Dose calculation

- Measure dose at distance from shot center in 3 different axes
- Fit a nonlinear curve to these measurements (nonlinear least squares)
- Functional form from literature, 10 parameters to fit via least-squares

$$m_1 \operatorname{erf}\left(\frac{d_1(x)-r_1}{\sigma_1}\right) + m_2 \operatorname{erf}\left(\frac{d_2(x)-r_2}{\sigma_2}\right)$$

# Nonlinear Approach

Let  $x_s$  be the variable locations

$$s = 1, 2, \dots, N$$

$D_w(x_s, i)$  is nasty nonlinear function

What width shot to use at  $x_s$ ?

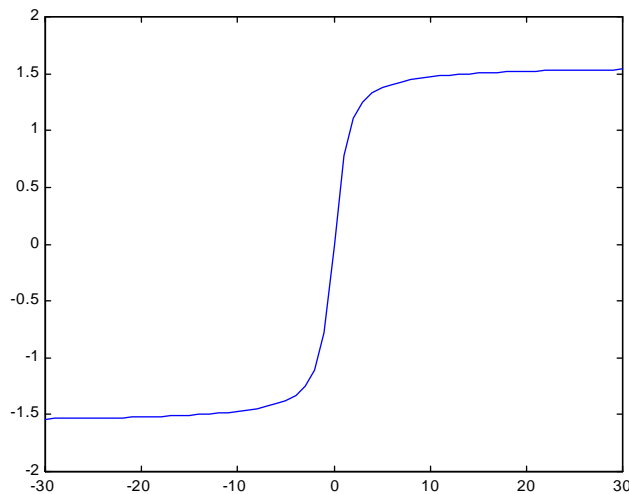
$$\psi_{s,w} = \begin{cases} 1 & \text{if shot } s \text{ is width } w \\ 0 & \text{else} \end{cases}$$

$$\underline{T}\psi_{s,w} \leq t_{s,w} \leq \overline{T}\psi_{s,w}$$

$$\sum_w \psi_{s,w} \leq 1$$

# Nonlinear approximation

- Approximate via "arctan"



$$\forall s \in S$$
$$\sum_w \arctan(t_{s,w}) \leq \frac{\pi}{2}$$

- First, solve with coarse approximation, then refine and reoptimize

# Difficulties

- Nonconvex optimization
  - speed
  - robustness
  - starting point
- Too many voxels outside target
- Too many voxels in the target (size)
- What does the neurosurgeon really want?

$$\min_{t_{s,w}, x_s} \text{Under}(Target)$$

$$\text{s.t. } Dose(i) = \sum_{s \in S, w \in W} t_{s,w} D_w(x_s, i)$$

$$0 \leq \text{Under}(i) \leq 1 - Dose(i)$$

$$Dose(Target) / \left( \sum_{s,w} t_{s,w} \overline{D_w} \right) \geq P$$

$$\sum_{s,w} \arctan(t_{s,w}) \leq N \pi / 2$$

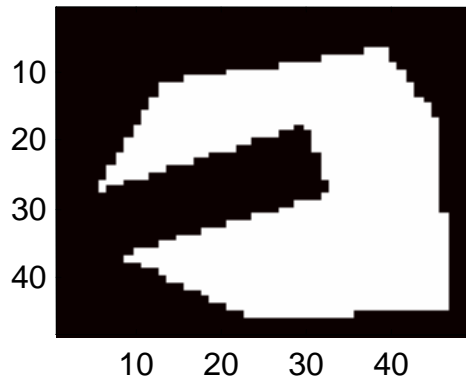
$$0 \leq Dose(i) \leq 1, \quad 0 \leq t_{s,w}$$

# Iterative Approach

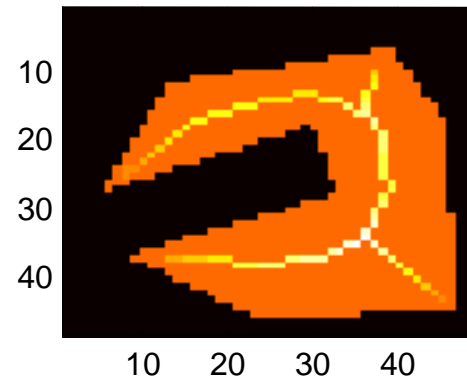
- Rotate data (prone/supine)
- Skeletonization starting point procedure
- Conformity subproblem (P)
- Coarse grid shot optimization
- Refine grid (add violated locations)
- Refine smoothing parameter
- Round and fix locations, solve MIP for exposure times

# Skeleton Starting Points

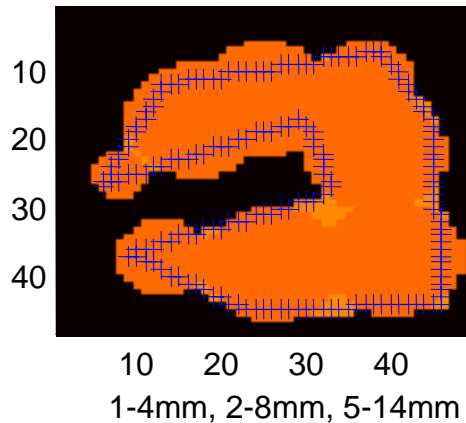
a. Target area



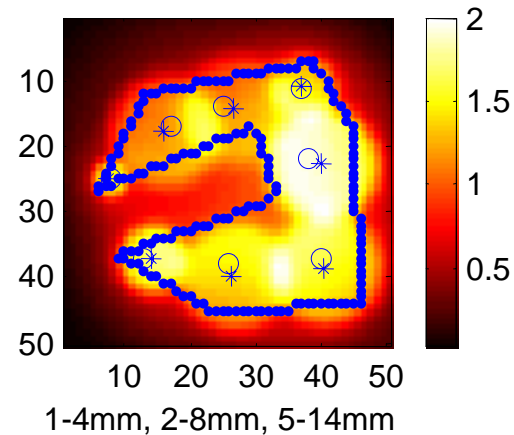
b. A single line skeleton of an image



c. 8 initial shots are identified



d. An optimal solution: 8 shots



# Run Time Comparison

Average Run Time	Size of Tumor		
	Small	Medium	Large
Random (Std. Dev)	2 min 33 sec (40 sec)	17 min 20 sec (3 min 48 sec)	373 min 2 sec (90 min 8 sec)
SLSD (Std. Dev)	1 min 2 sec (17 sec)	15 min 57 sec (3 min 12 sec)	23 min 54 sec (4 min 54 sec)



# MIP Approach

If we choose from set of shot locations

$$\psi_{s,w} = \begin{cases} 1 & \text{if use shot } s \text{ of width } w \\ 0 & \text{else} \end{cases}$$

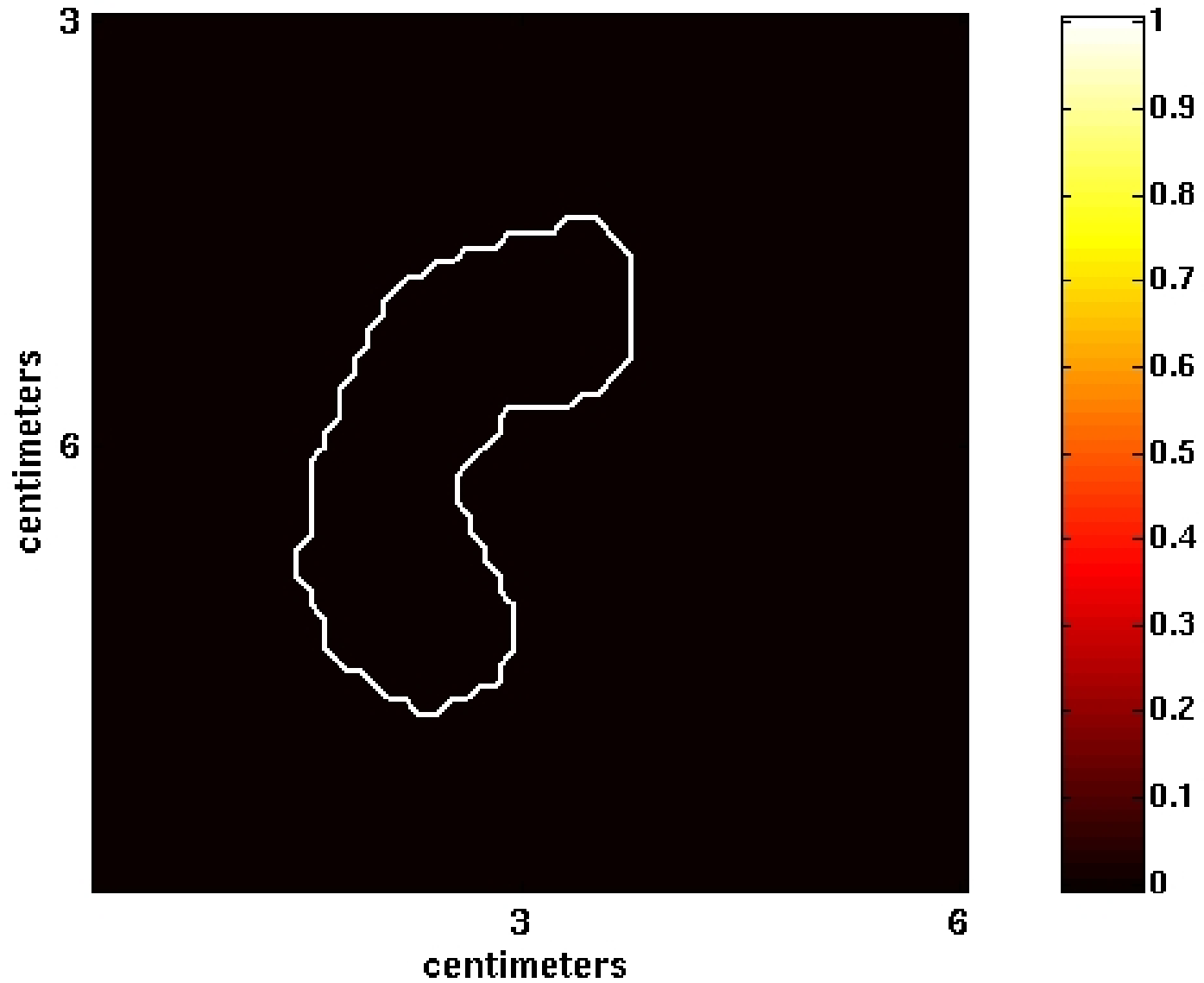
$$D_{s,w}(i) := D_w(x_s, i)$$

$$Dose(i) = \sum_{s \in S, w \in W} t_{s,w} D_{s,w}(i)$$

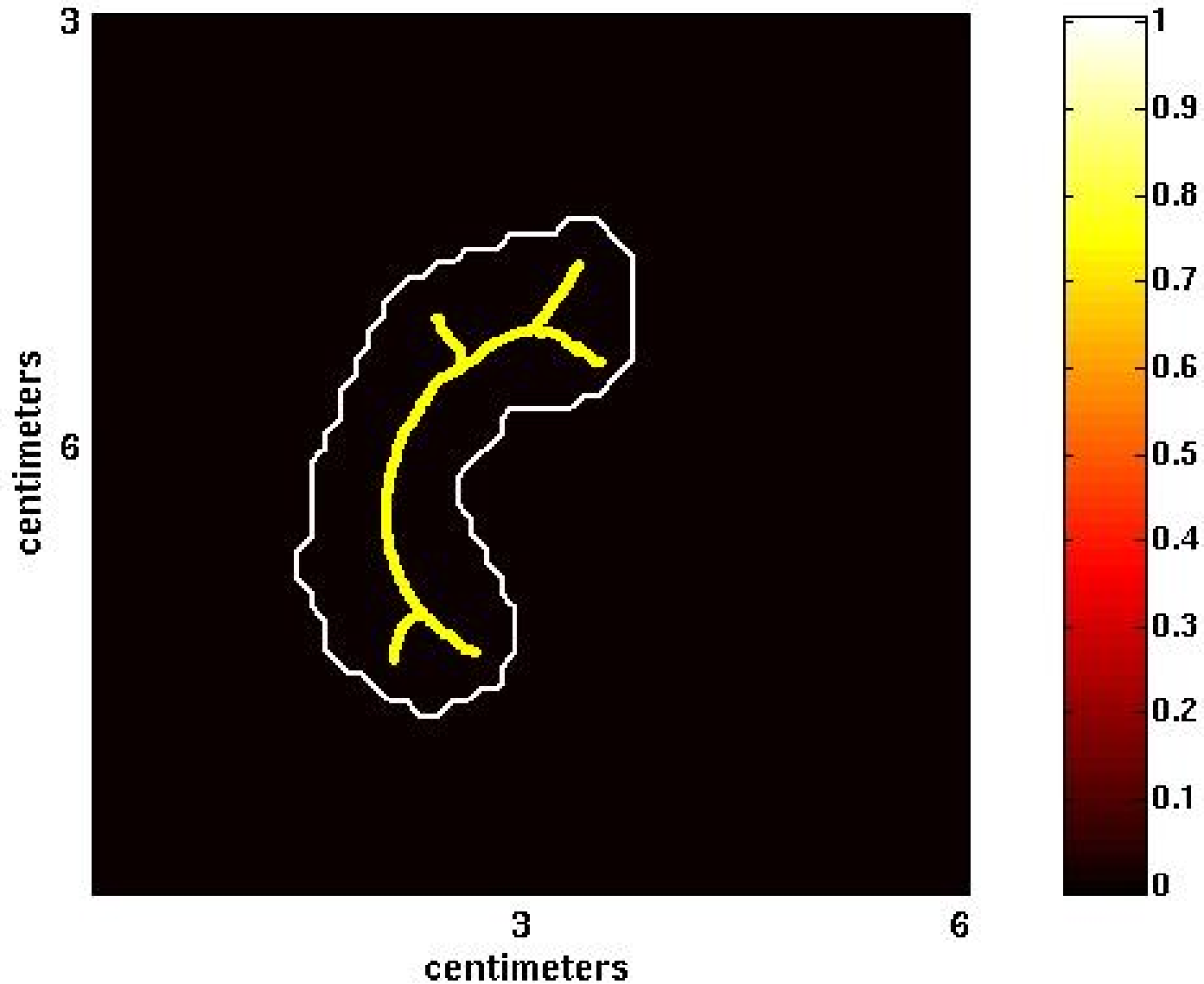
# MIP Problem

$$\begin{aligned} \min_{t_{s,w}, \psi_{s,w}} \quad & \text{Under}(\text{Target}) \\ \text{s.t.} \quad & \text{Dose}(i) = \sum_{s \in S, w \in W} t_{s,w} D_{s,w}(i) \\ & 0 \leq \text{Under}(i) \leq 1 - \text{Dose}(i) \\ & \text{Dose}(\text{Target}) \geq P \sum_{s,w} t_{s,w} \overline{D}_w \\ & \underline{T} \psi_{s,w} \leq t_{s,w} \leq \overline{T} \psi_{s,w} \\ & \sum_{s \in S, w \in W} \psi_{s,w} \leq N \end{aligned}$$

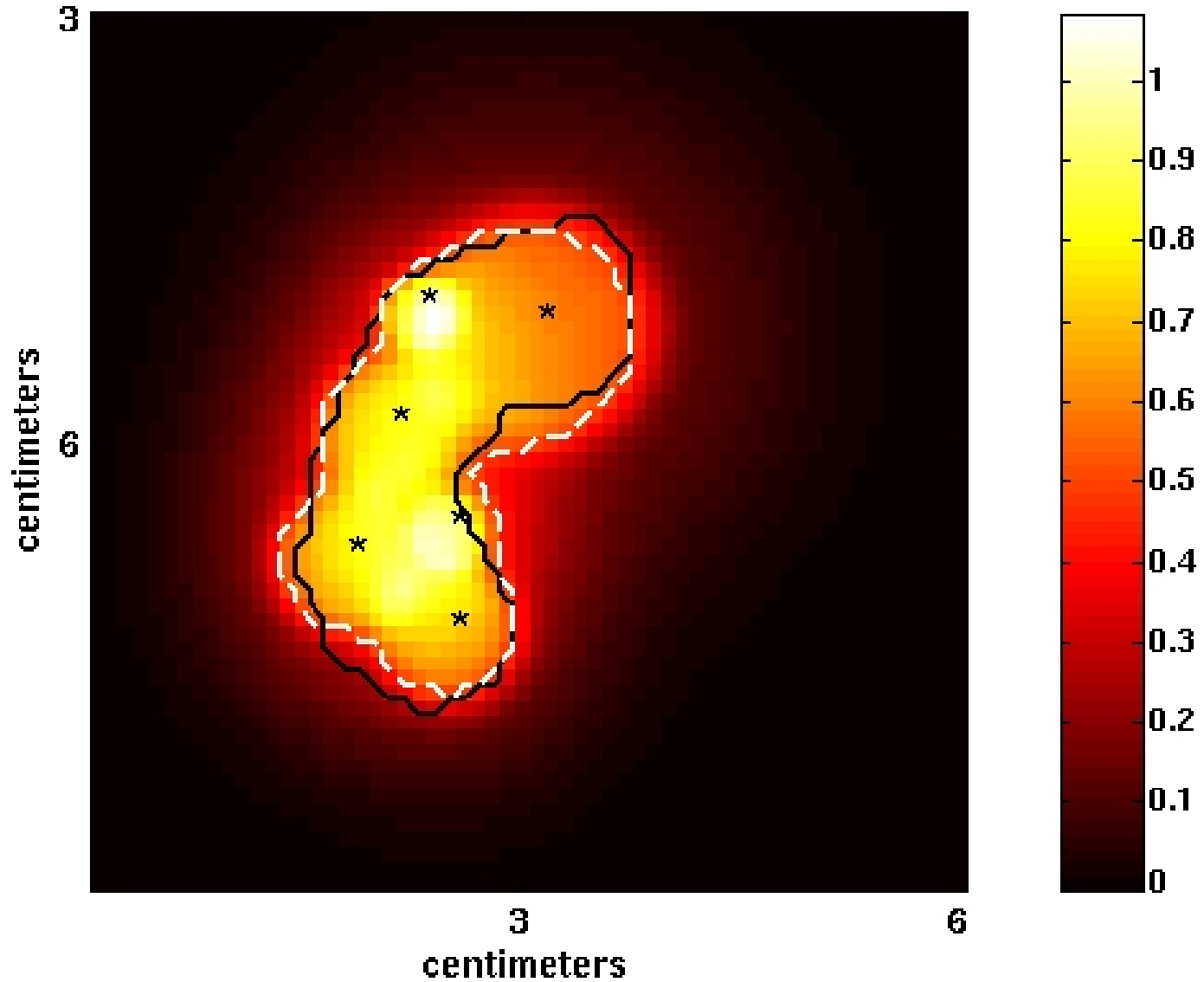
# Target



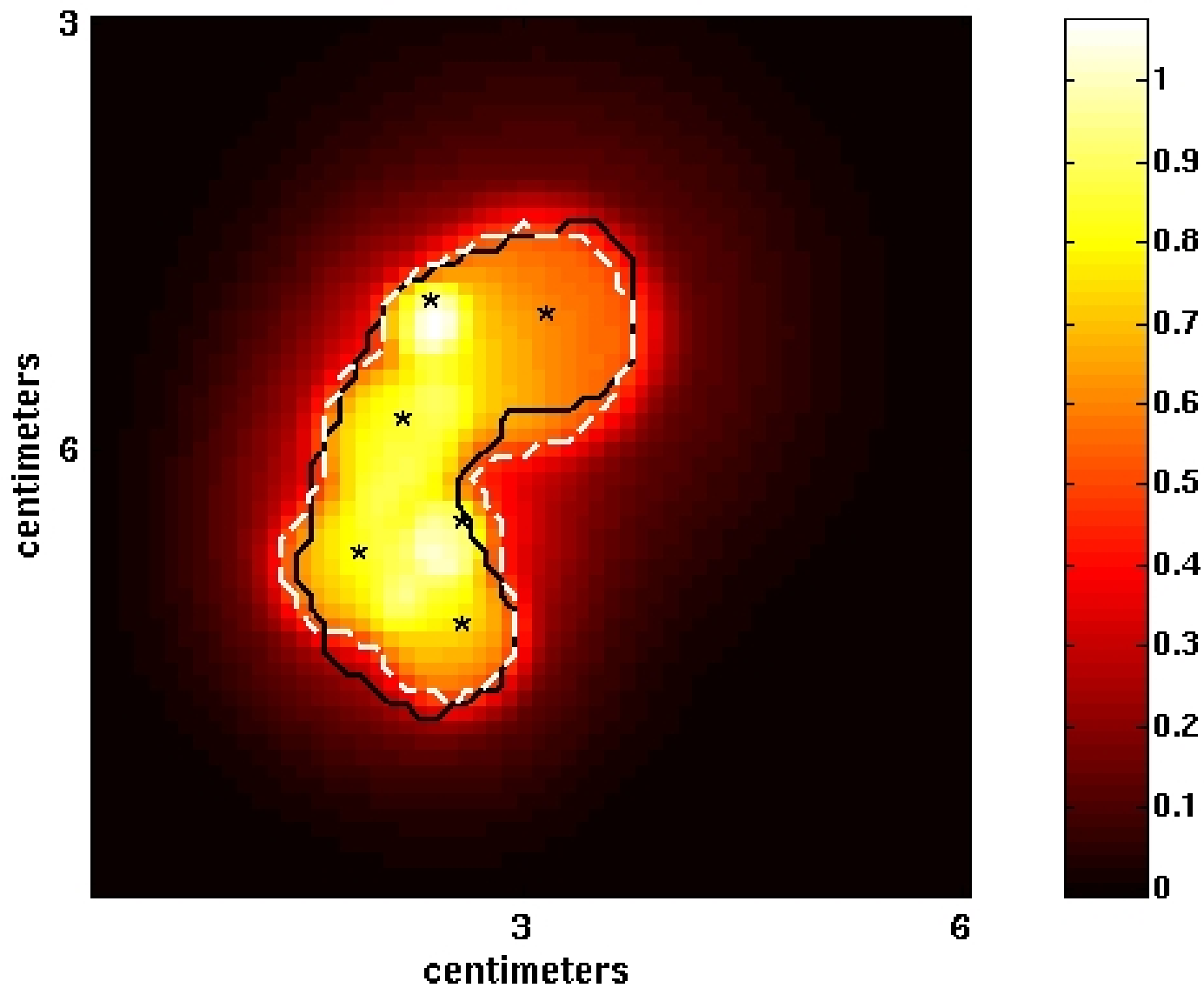
# Target Skeleton is Determined



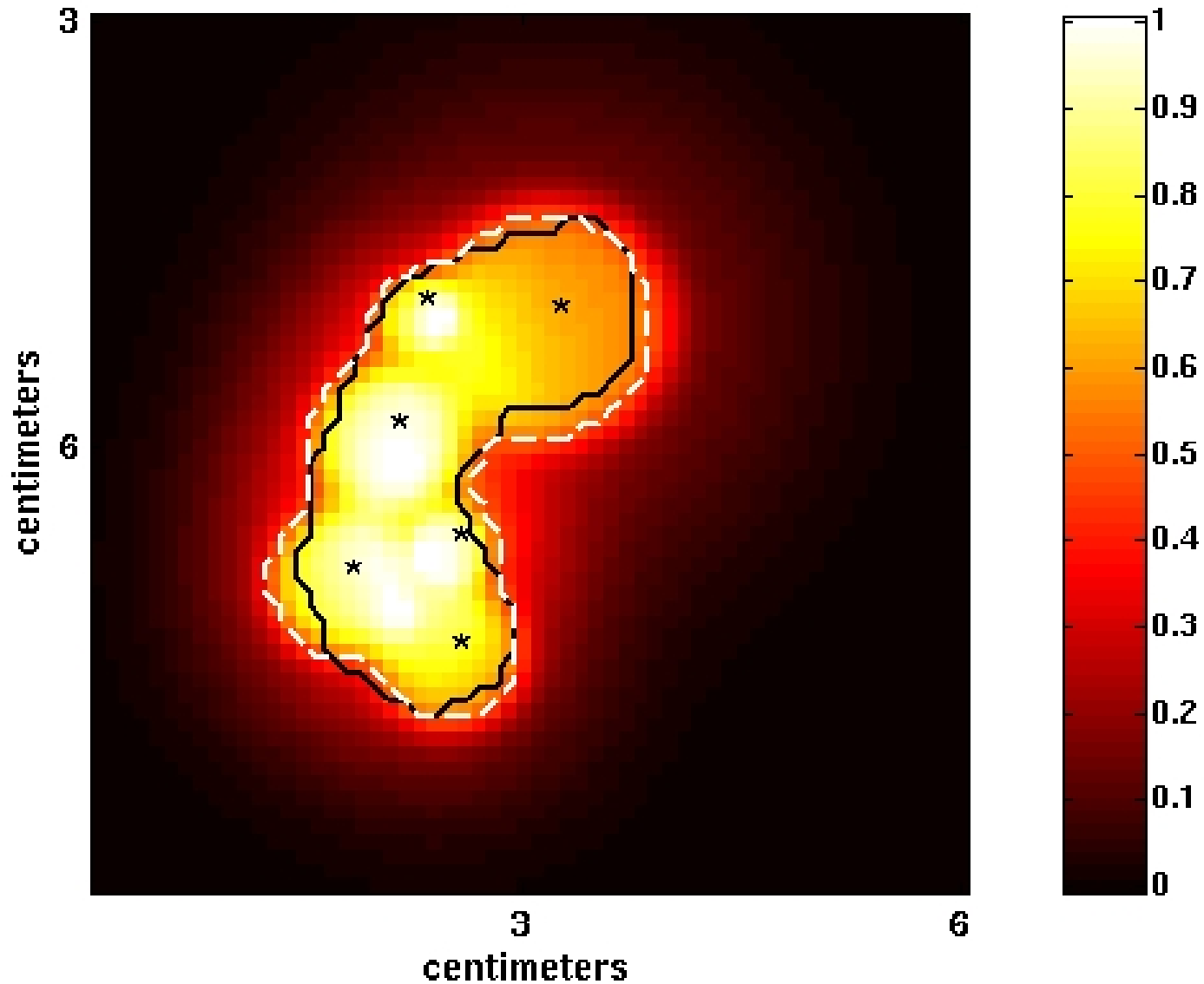
# Sphere Packing Result



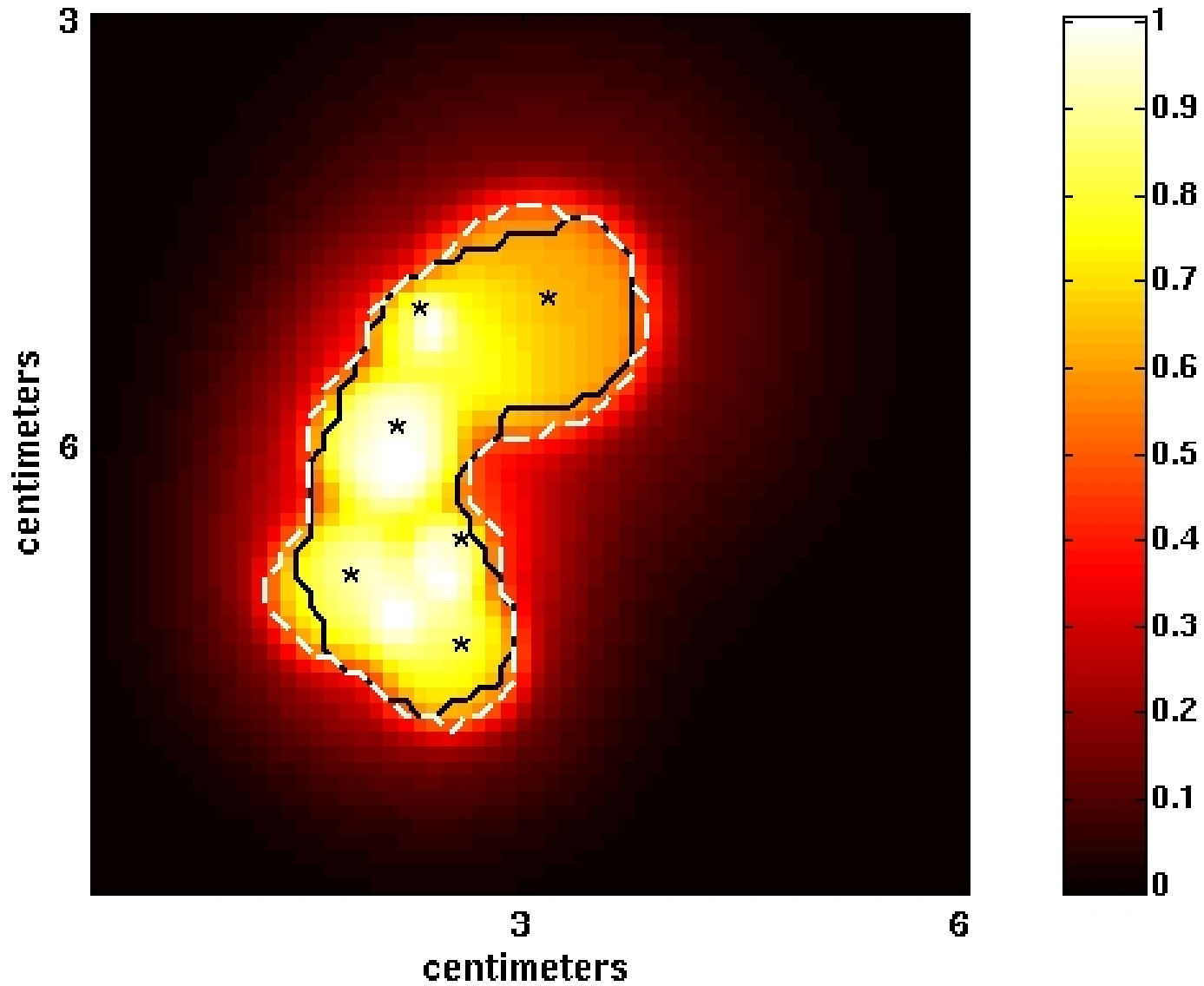
# 10 Iterations



# 20 Iterations

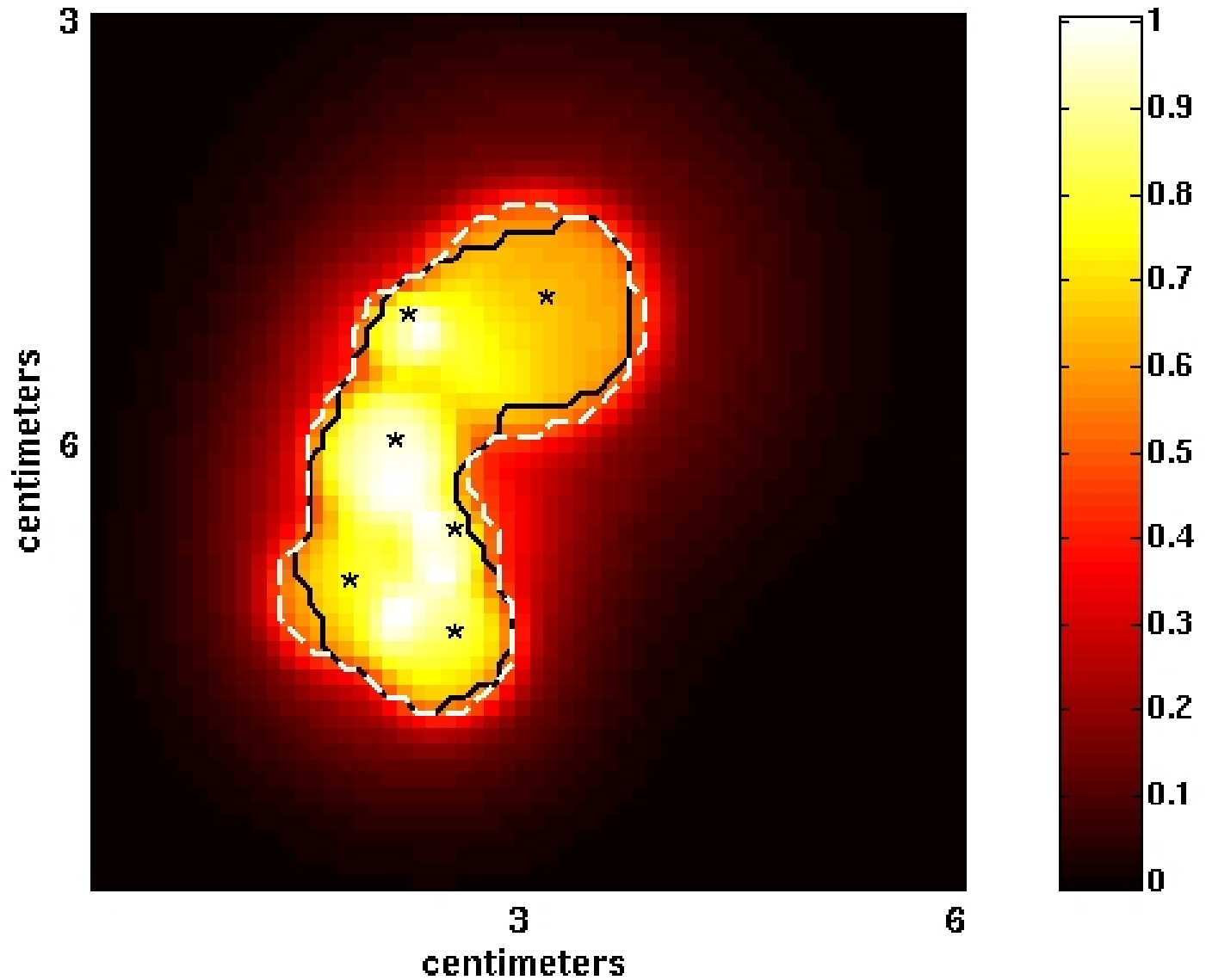


# 30 Iterations





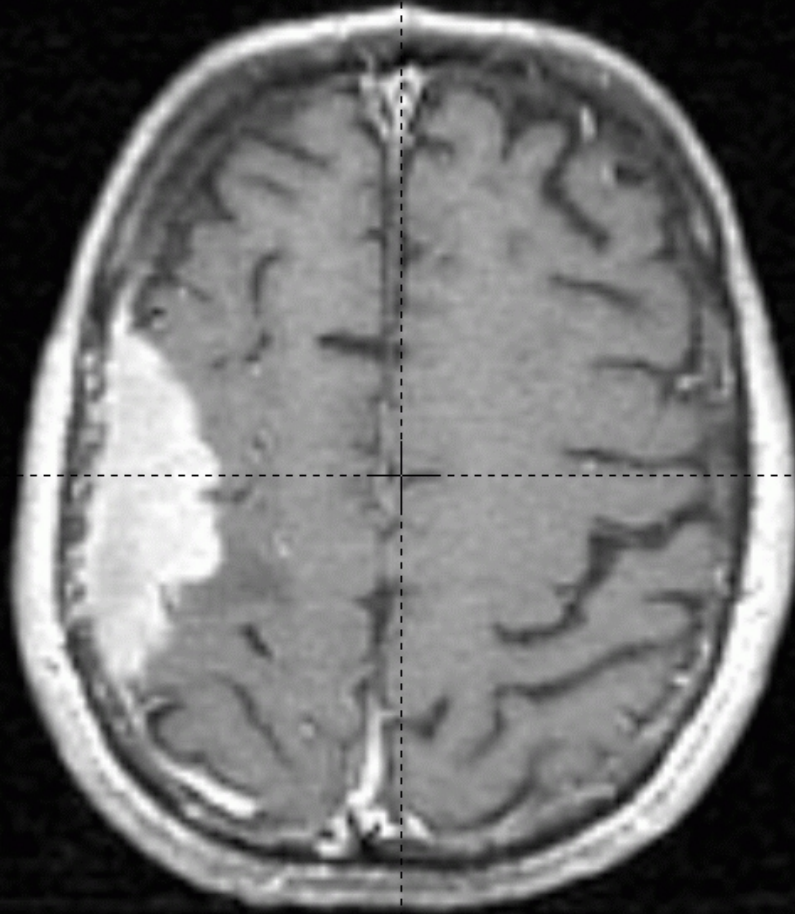
# 40 Iterations



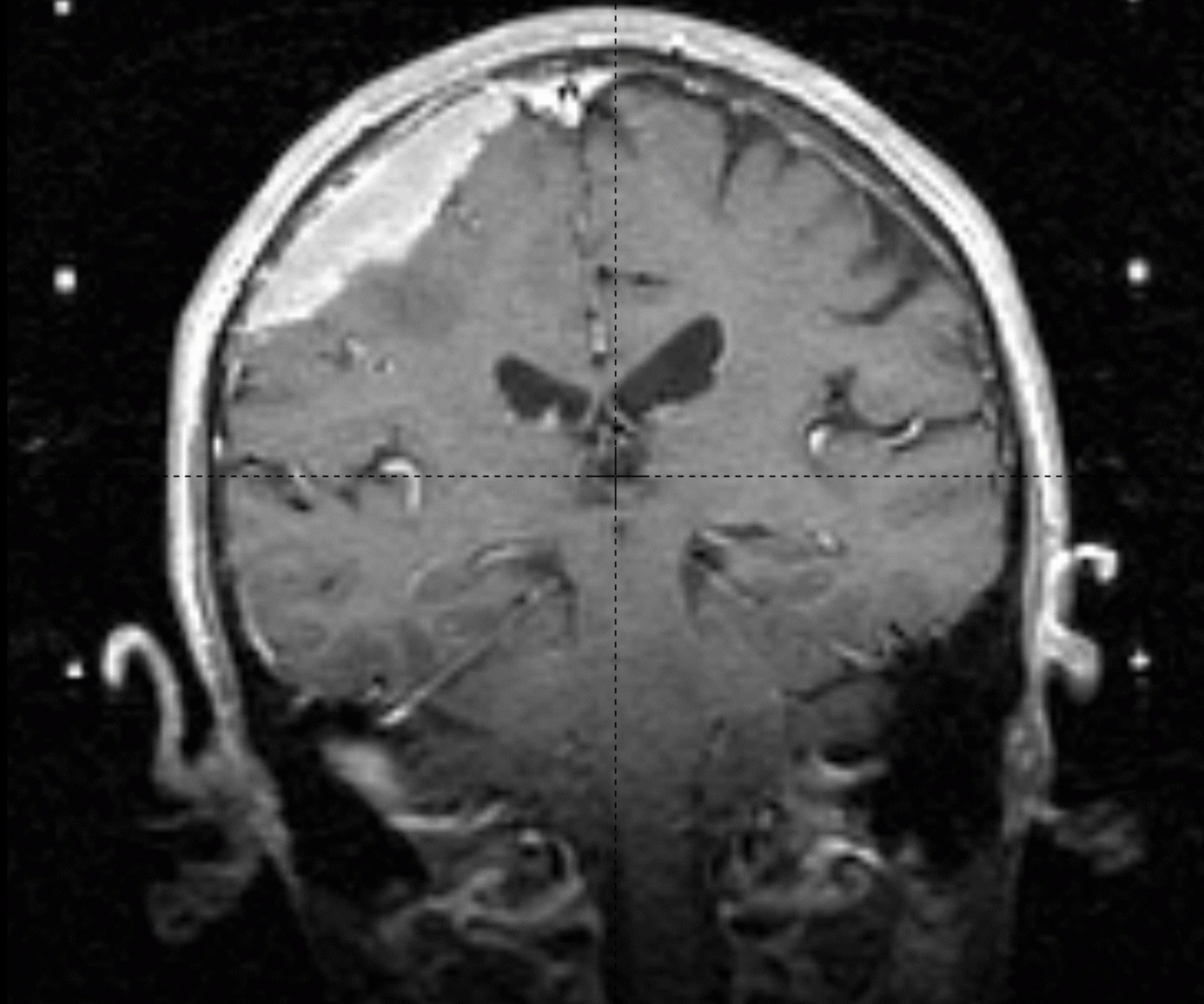
# Status

- Automated plans have been generated retrospectively for over 30 patients
- The automated planning system is now being tested/used head to head against the neurosurgeon
- Optimization performs well for targets over a wide range of sizes and shapes

# Patient 1 - Axial Image



# Patient 1 - Coronal Image

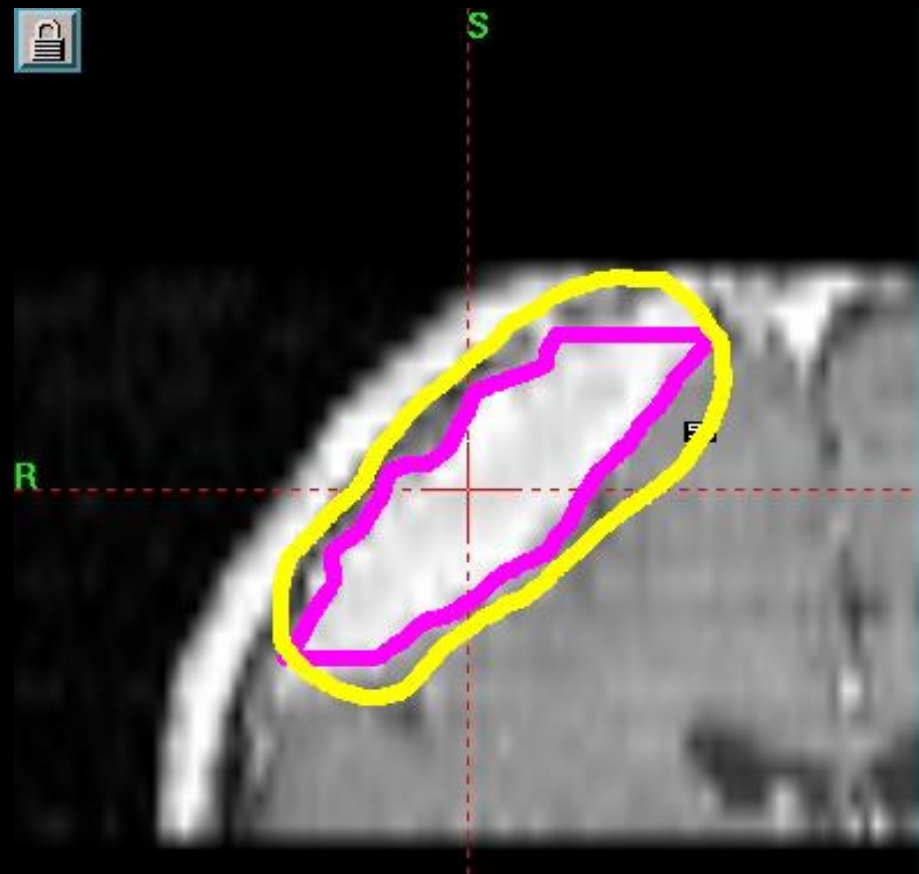


manual



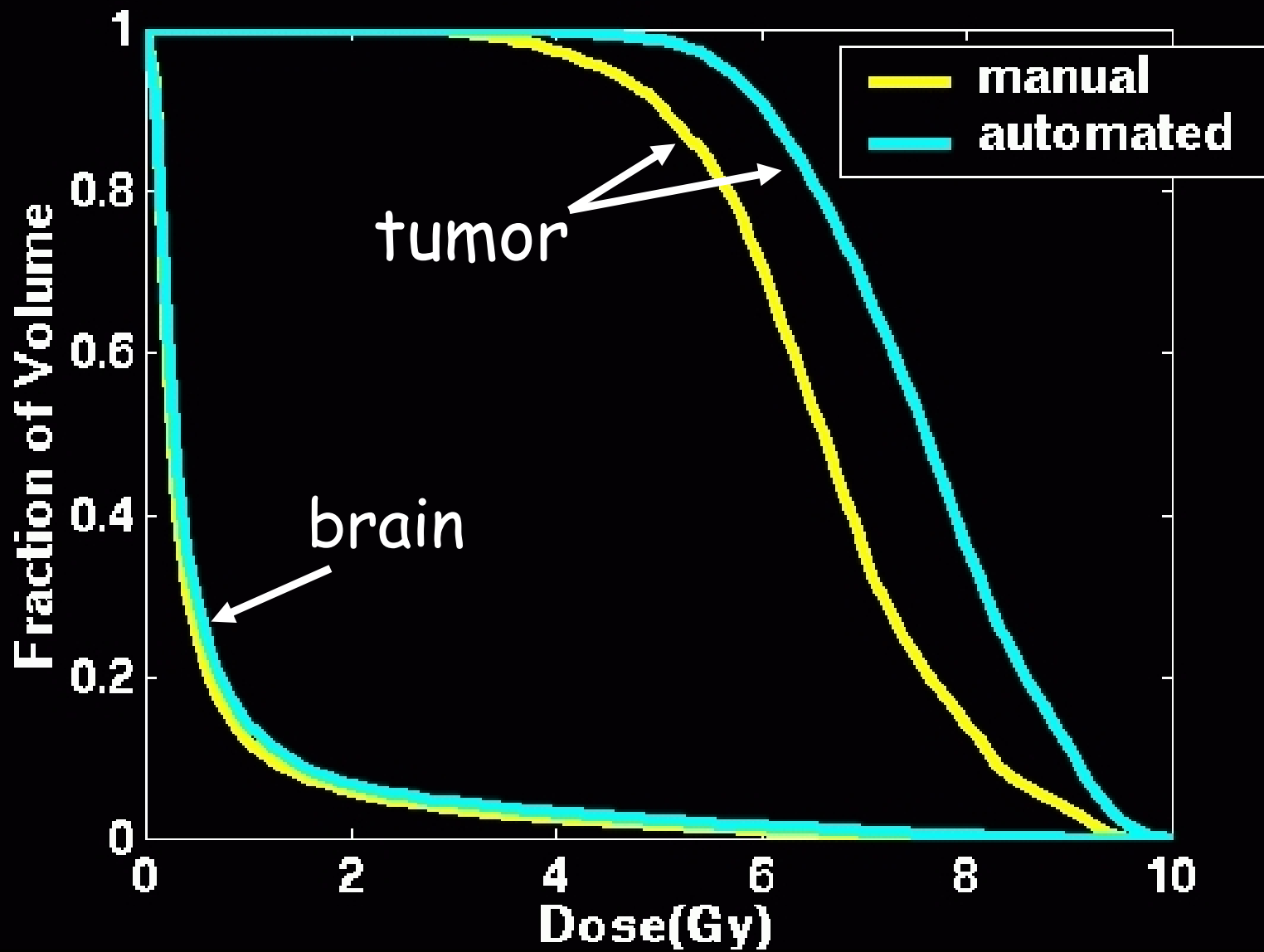
Reconstructed, y: 89.7

optimized



Reconstructed, y: 89.7

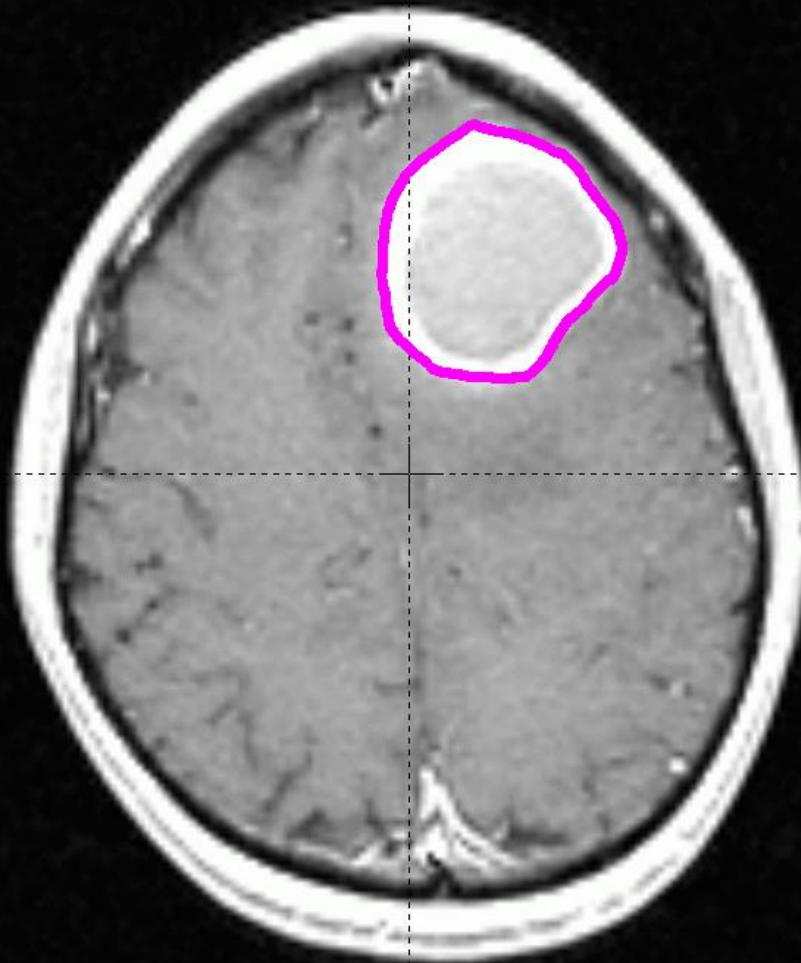




# Patient 2

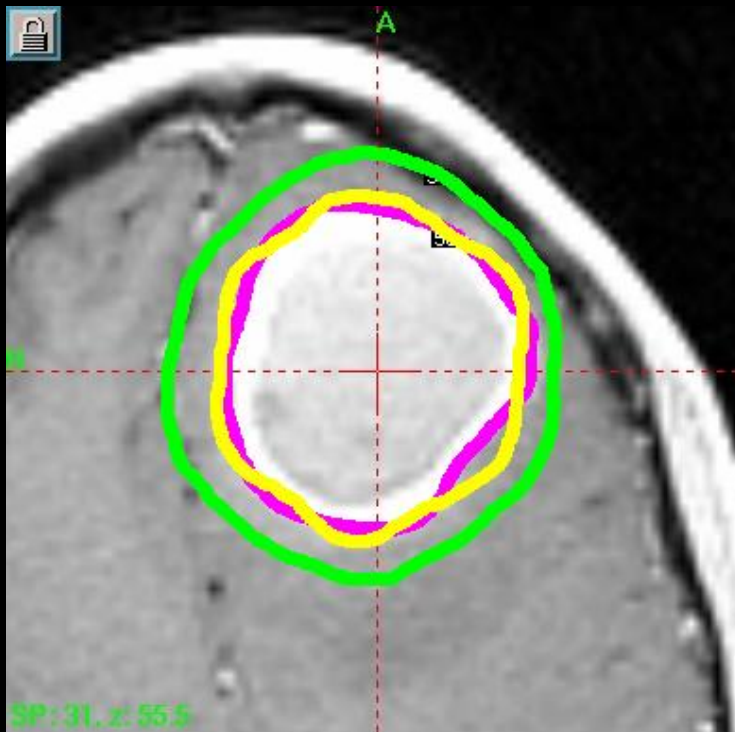


R

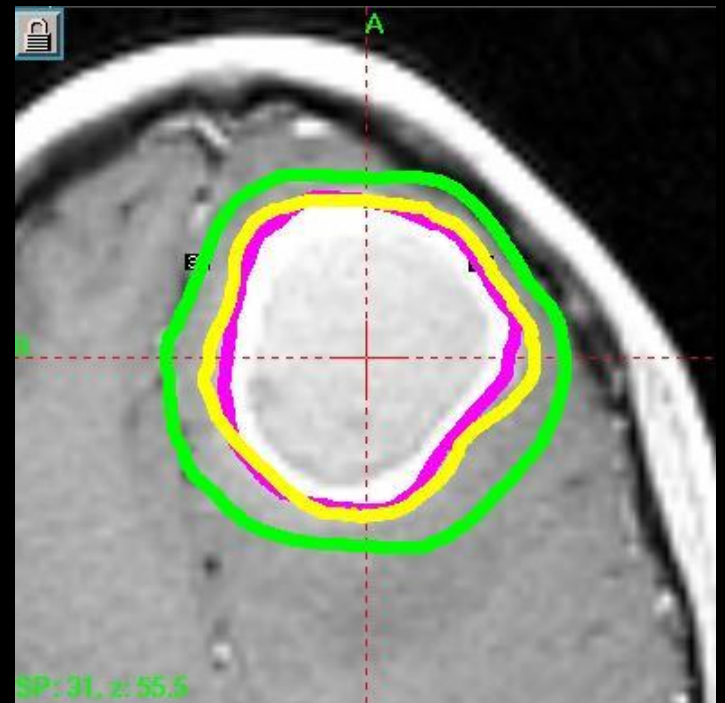


# Patient 2 - Axial slice

15 shot manual



12 shot optimized

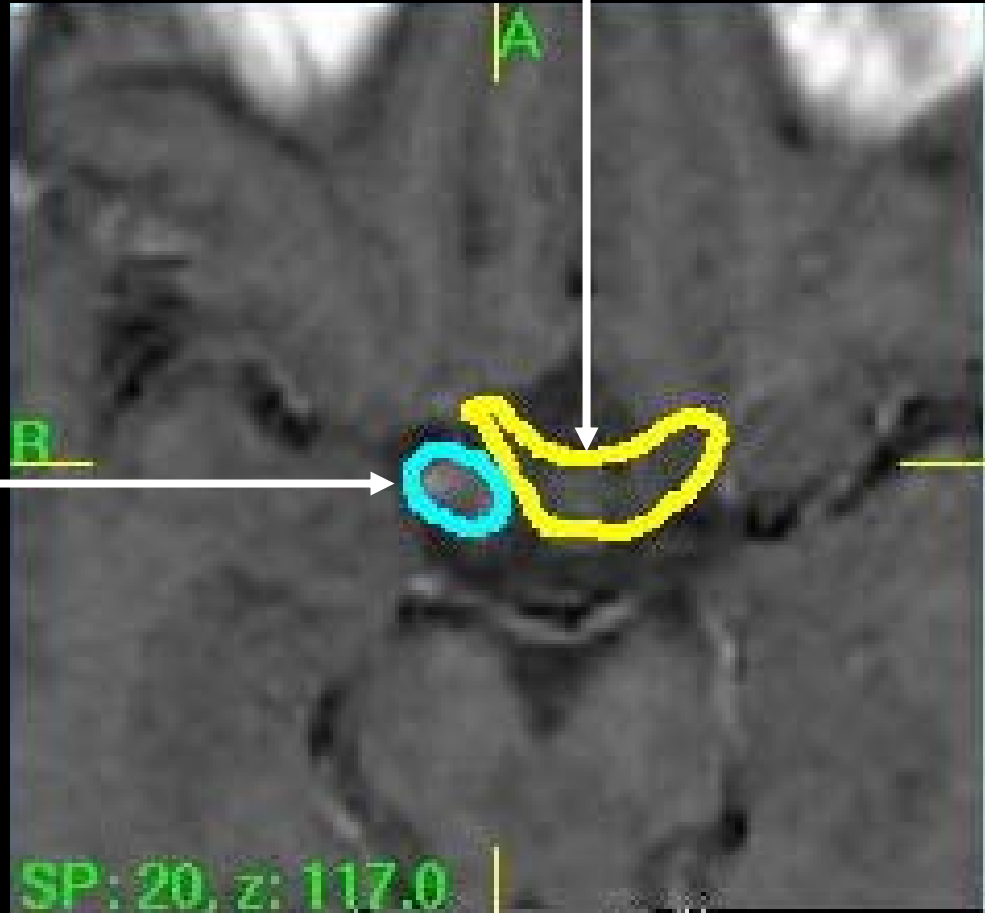


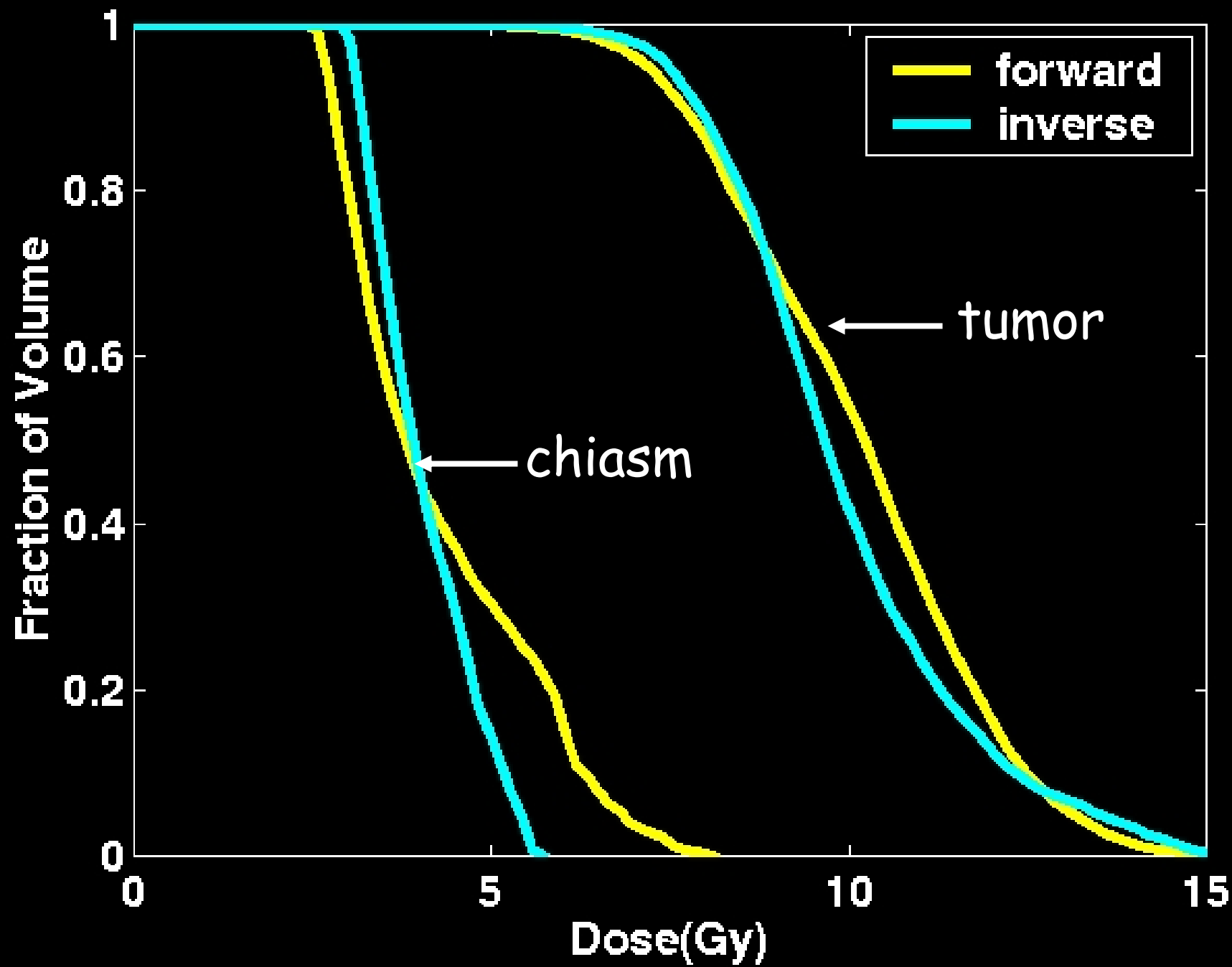


Patient 3

optic chiasm

pituitary  
adenoma

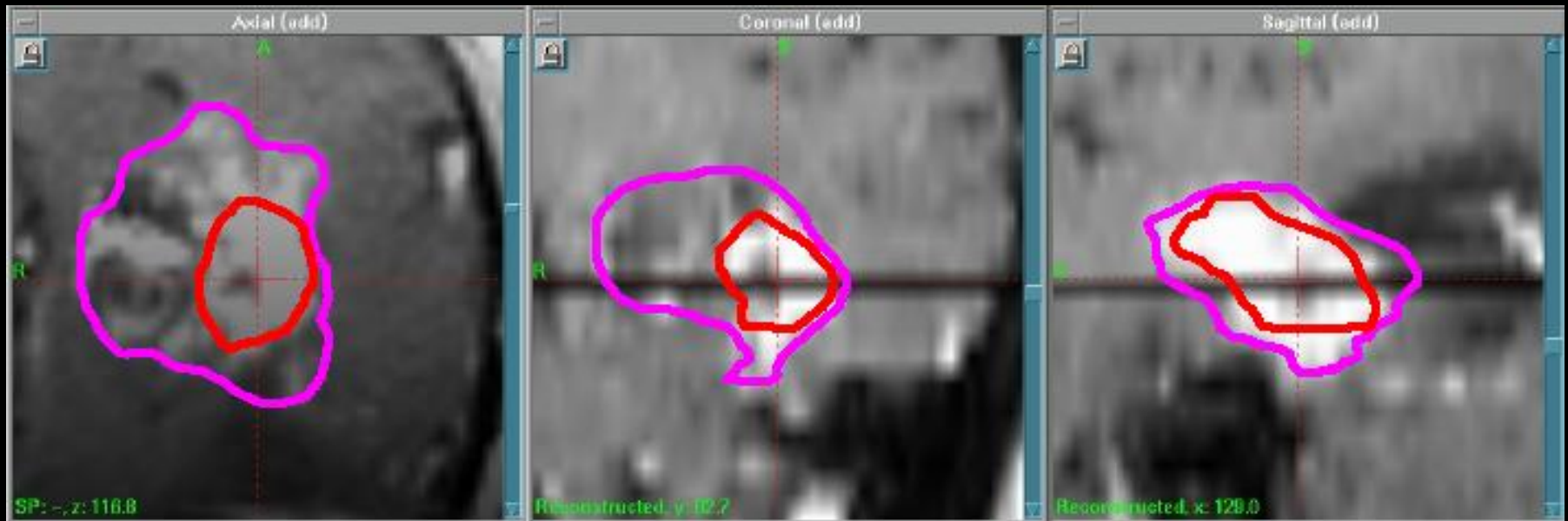


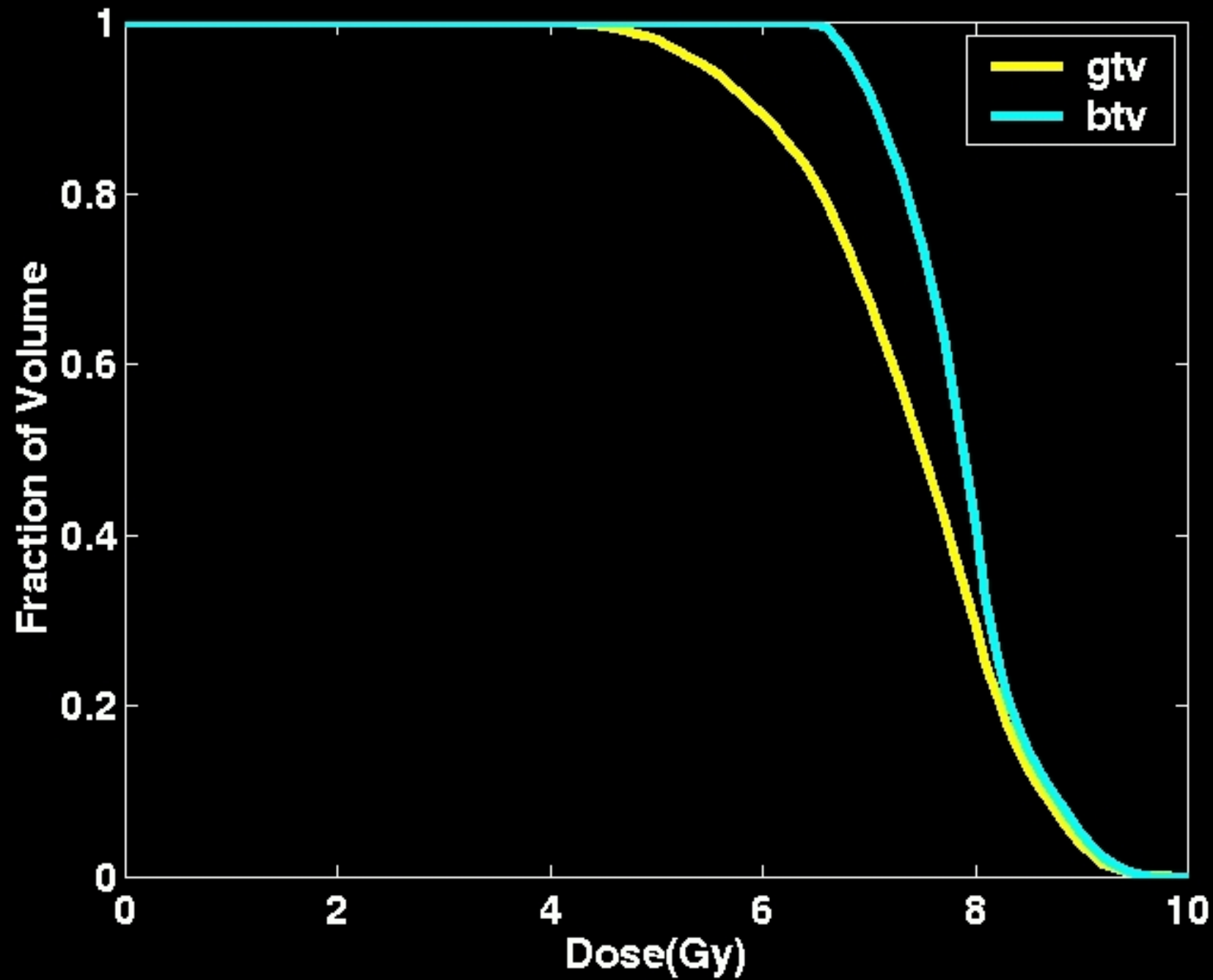


# Localized Dose Escalation

- The dose to the active tumor volume or nodular islands can be selectively escalated while maintaining an acceptable normal tissue dose.
- Applicable to tumors such as cystic astrocytoma or glioblastoma multiforme that are nodular and permeative in nature

# Localized Dose Escalation





# DSS: Estimate number of shots

## - Motivation:

- Starting point generation determines reasonable target volume coverage based on target shape
- Use this procedure to estimate the number of shots for the treatment

## - Example,

- Input:
  - number of different helmet sizes = 2;
  - (4mm, 8mm, 14mm, and 18mm) shot sizes available
- Output:

Helmet size(mm)	4 & 8	4 & 14	4 & 18	8 & 14	8 & 18	14 & 18
# shots estimated	25	10	9	7	7	7

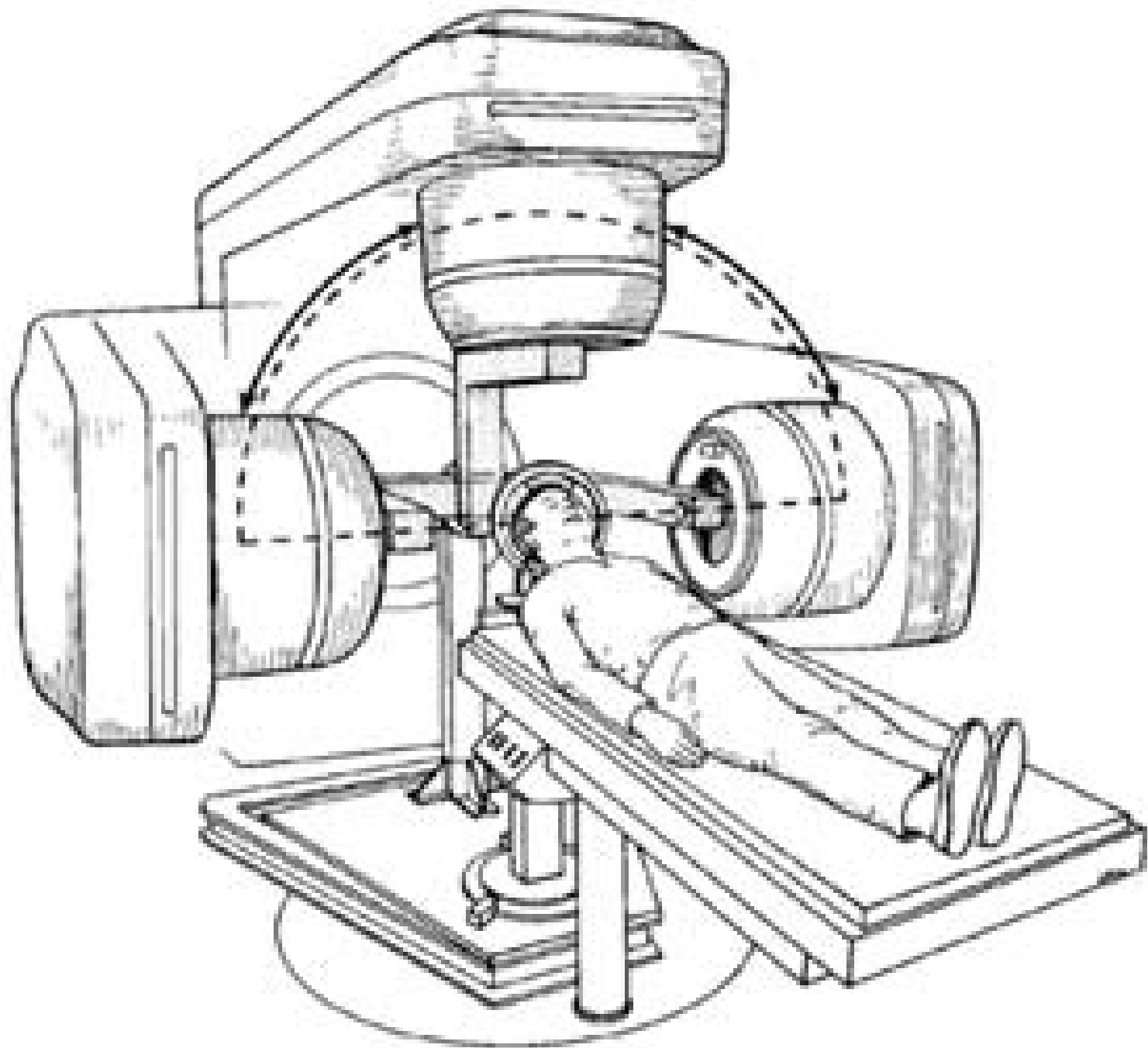
# Optimization as Knowledge Gathering

- Single problem, build model using sequence of optimization problems
- Many examples in literature
- Switch between different problem formats - LP, MIP, NLP
- Modeling system enables quick prototyping

# Conclusions

- Problems solved by models built with multiple optimization solutions
- Constrained nonlinear programming effective tool for model building
- Interplay between OR and MedPhys crucial in generating clinical tool
- Gamma Knife: optimization compromises enable real-time implementation





# Linac Based Radiosurgery

- **Advantages**
  - Cost/space
- **Disadvantages**
  - Machine time
  - Extensive QA procedures
  - Reliability issues

# Linac model

$$\min_{t_{a,c}, x^a} \text{Dose}(\text{NonTarget})$$

subject to

$$\text{Dose}(i) = \sum_{a \in A, c \in C} t_{a,c} D_c(a, x^a, i)$$

$$0.5 \leq \text{Dose}(\text{Target}) \leq 1$$

$$t_{a,c} \geq 0$$

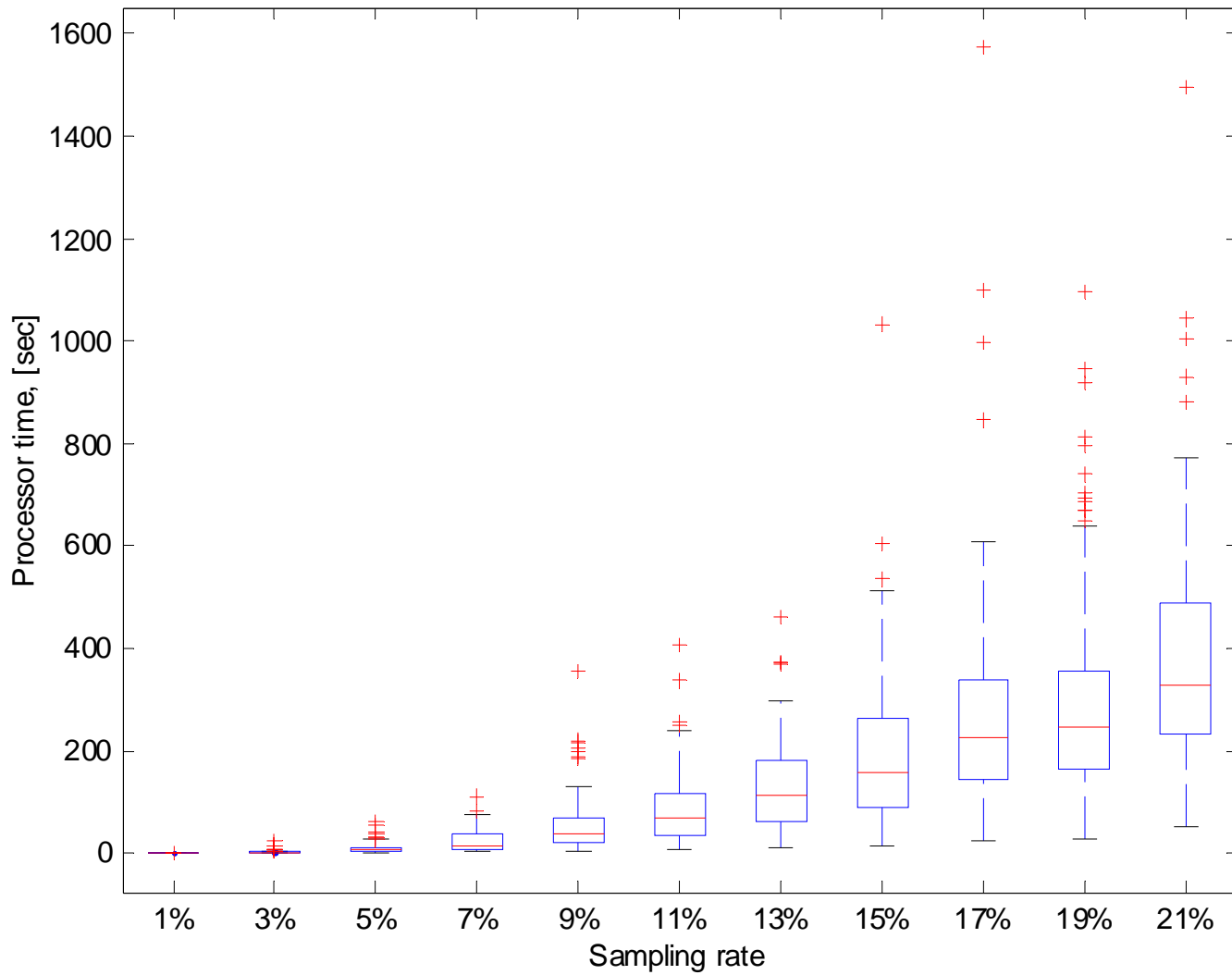
$$|A| \leq N$$

$$x^a \in W$$

# Problems

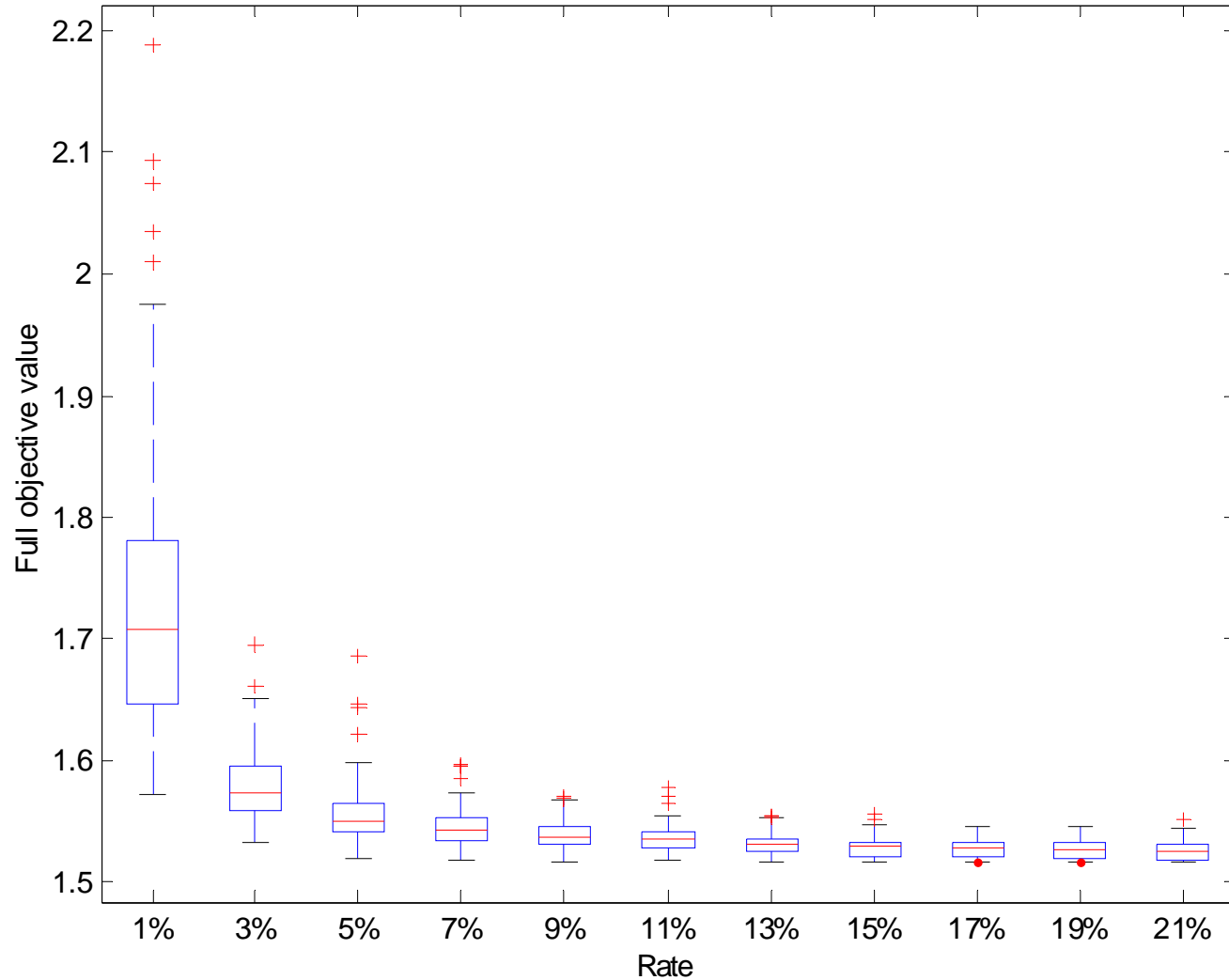
- Large computational times
- Large variance in computing times
  - 5000-12500 sec (for 60,000 voxel case)
- Ineffective restarts (what if trials?)
- Large amounts of data
  
- Try sampling of voxels (carefully)

Pelvis example: solution times for various sample rates;



# Naïve sampling fails

Pelvis example: objective values for various sample rates;



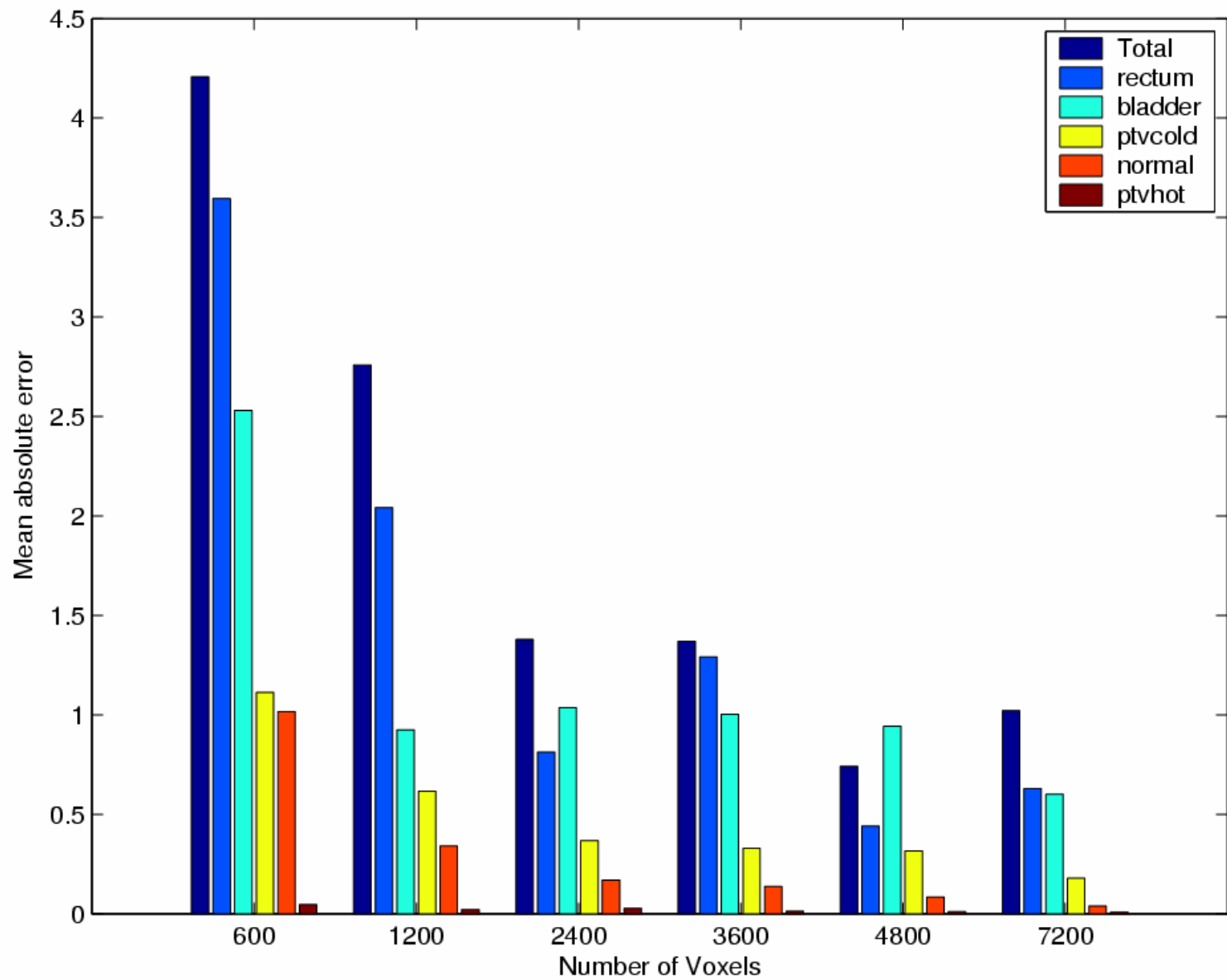
# Multiple samples

- Generate  $K$  instances at very coarse sampling rate
- Use histogram information to suggest promising angles
- How many? (e.g.  $K=10$ )
- How to select promising angles? (frequency  $> 20\%$ )

# True Objective Value

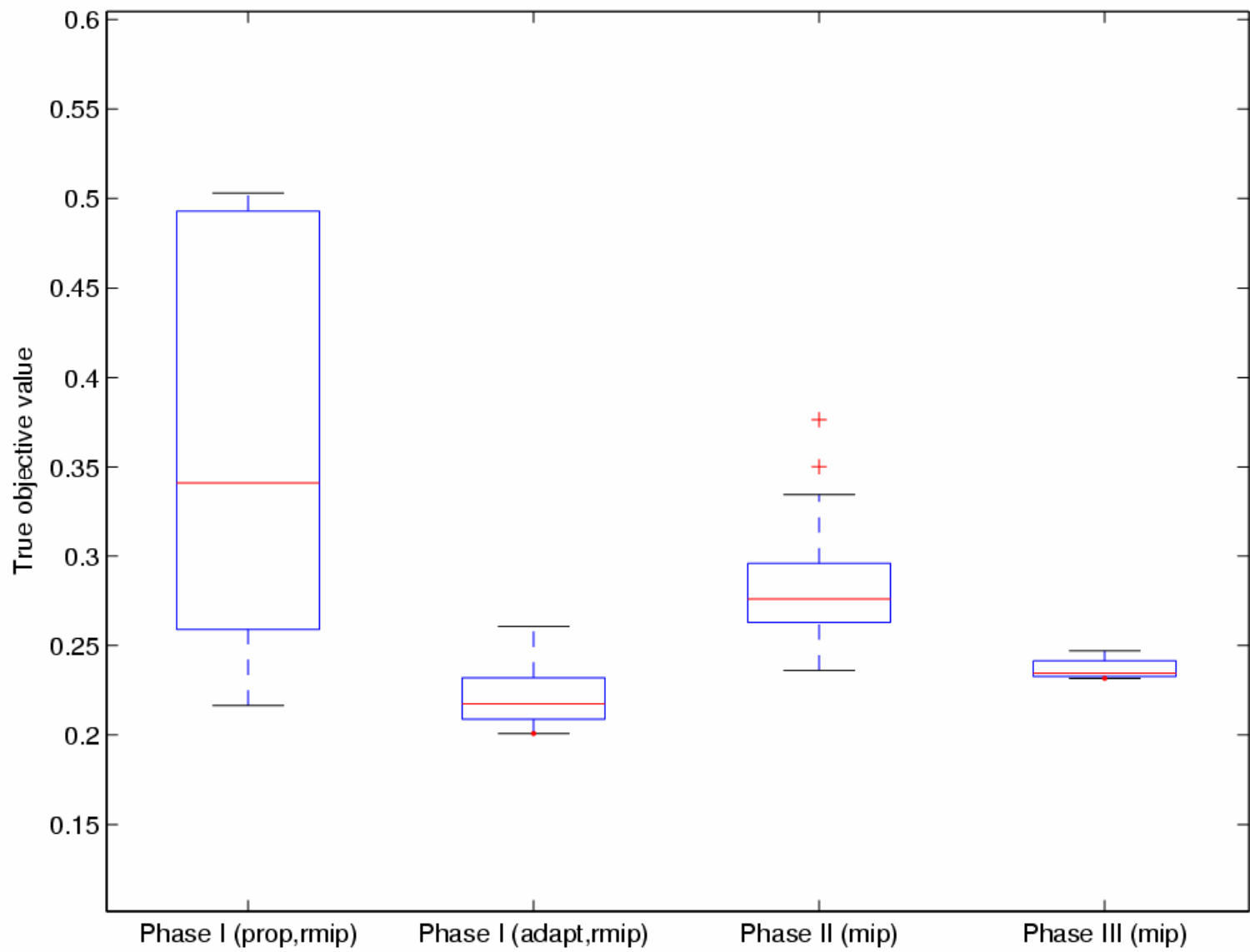
- >20% scheme may lose best solution
- Can calculate the objective function with complete sample cheaply from solution of sampled problem
- Use extra information in 2 ways:
  1. Select only those angles that appear in the best "full value" solutions
  2. Refine samples in organs where discrepancies are greatest





# Sampling Process

- Determine initial sample size
- Phase I: use all angles
  - 10 sample LP's solutions determine  $A_I$
- Phase II: use reduced set of angles
  - 10 sample MIP's determine  $A_{II}$
- Phase III: use further reduced set
  - Increase sample rate, solve single MIP



# Conclusions

- Optimization improves treatment planning
- Adaptive sampling is effective tool for solution time reduction
- Future work needed for more complex delivery devices and for adaptive radiotherapy