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Inverse planning algorithms

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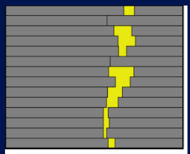
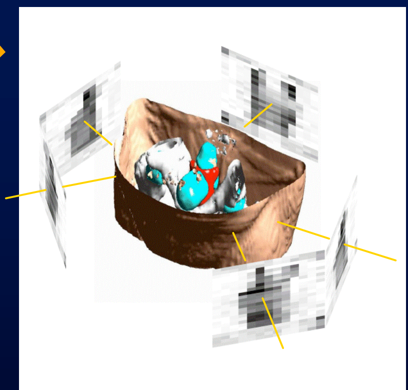
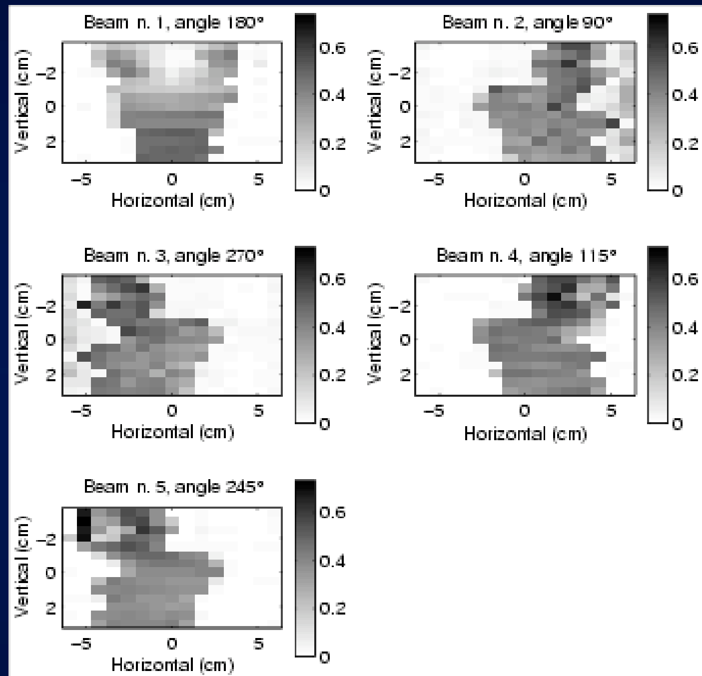
Outline

- Radiotherapy planning: a complex problem
- Concepts of inverse planning
- Inverse planning algorithms
- Cost function and optimization strategy

IMRT (Intensity Modulated Radiation Therapy): a complex system of parameters to modulate







For this case
15 x 14 x 5 = 1050 pencil beam
High -dimensional space where to find the right configuration…

Forward planning

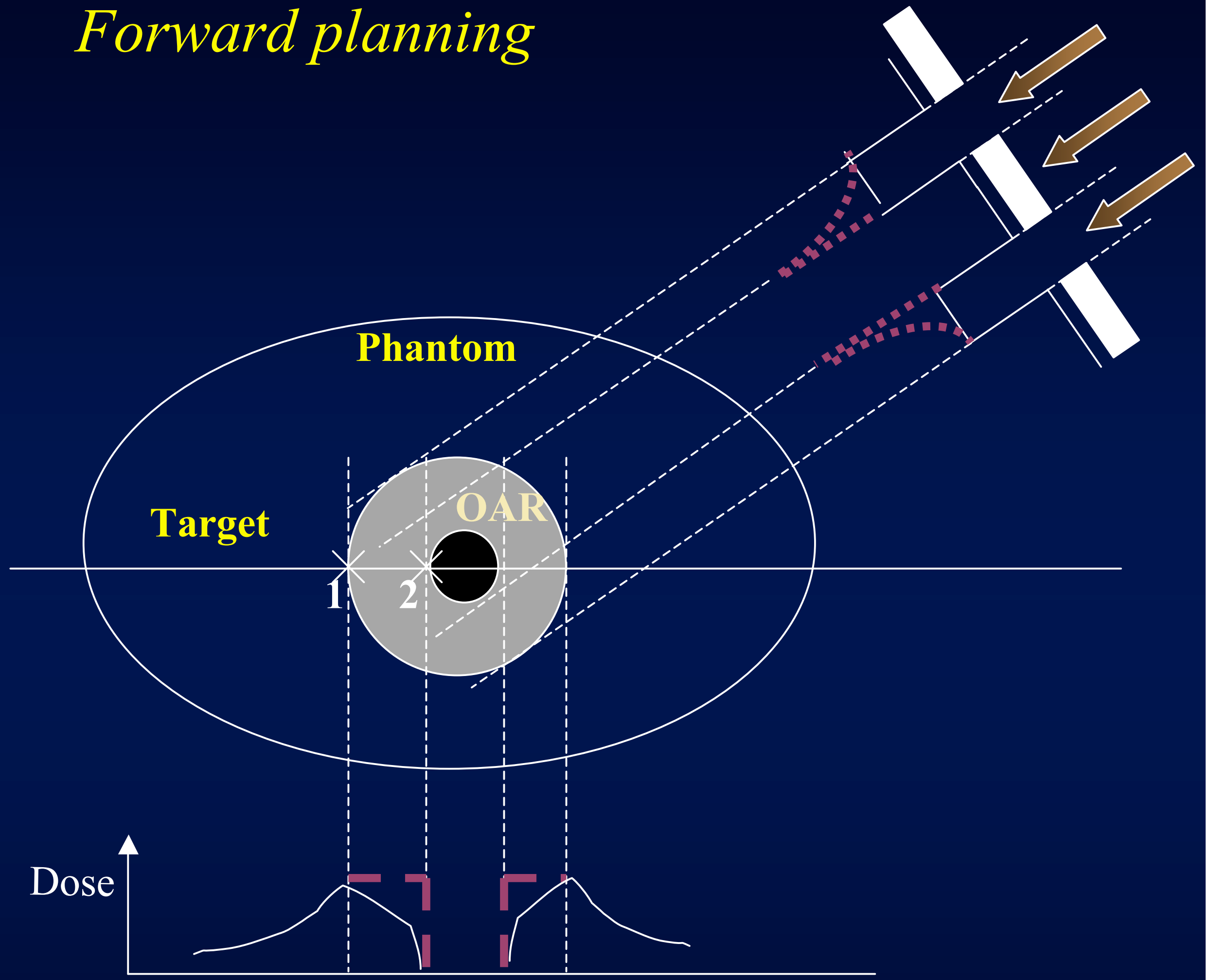
Loading 3D data set of the patient (CT, MRI or other imaging techniques)

Adjusting the treatment parameters

Calculating the resulting dose distribution

Evaluating of the results

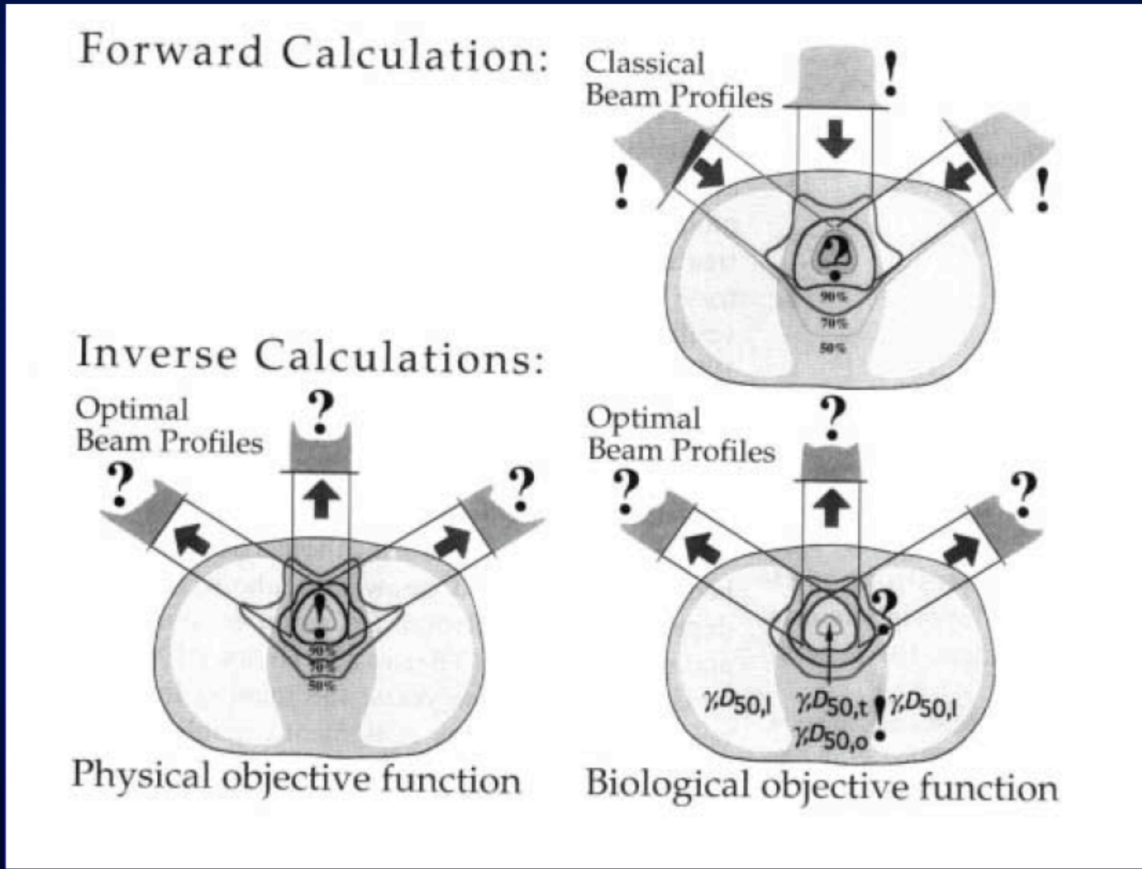
Treatment plan



Forward and Inverse planning

Forward calculation:
To compute the dose distribution in a tissue given a treatment plan;

Inverse calculation:
To find a treatment plan whose execution will achieve a desired dose distribution.



from A.Brahme

…this is too complicated to be planned by conventional forward planning techniques and inverse planning has emerged as a solution

The full benefits of intensity modulated radiation therapy (IMRT) can only be realized through the application of inverse planning techniques. With inverse planning, the desired dose distribution or the desired biological end points are used to specify the goals of the treatment. An optimization algorithm determines the plan parameters that best reflect the treatment goals.

D.M. Shepard et al. In Intensity-Modulated Radiation Therapy: The state of art, AAPM, Medical Physics Monograph No. 29, (2003).

Inverse planning

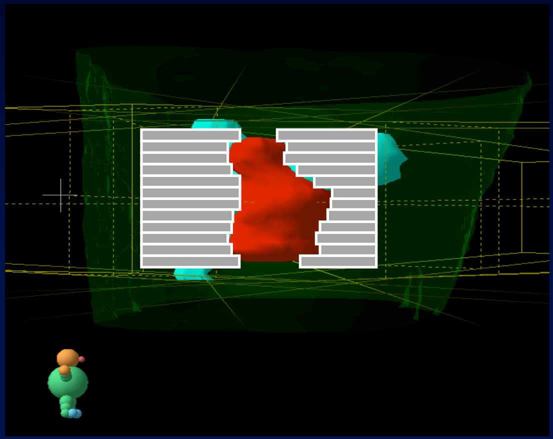
Inverse treatment planning directly defines the desired dose distribution instead of defining beam parameters.

The treatment planner would like to set the constraints in a way that the tumor receives 100% of the prescribed dose, while the risk organs and the healthy tissue receive absolute zero dose.

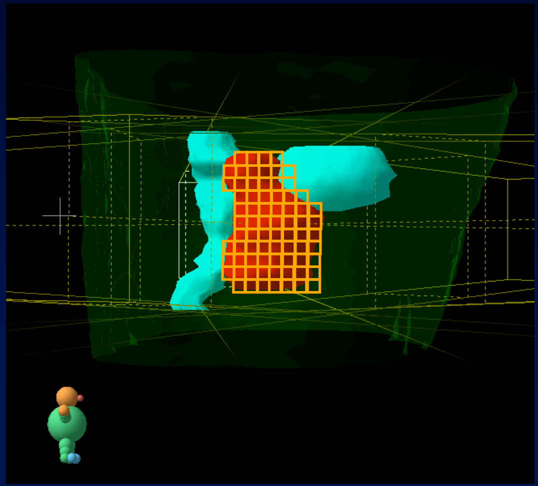
Typically the desired dose distribution is specified by marking forbidden areas (constraints).

Based on the desired dose distribution, an algorithm calculates the ideal beam parameters using optimization techniques.

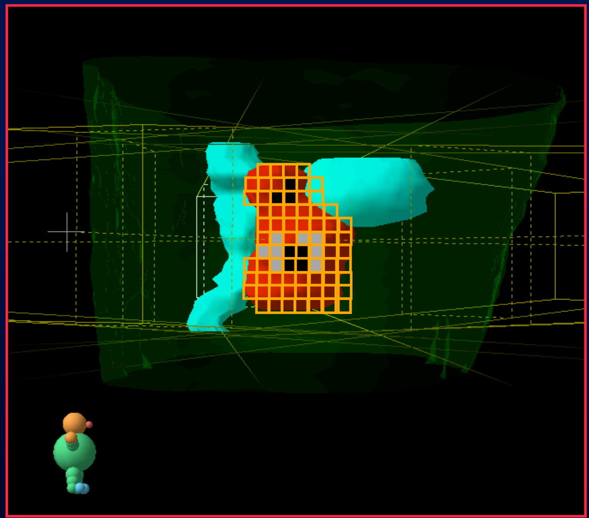
Inverse planning approach



MLC's leaves are shaped to match the BEV of the tumor volume.

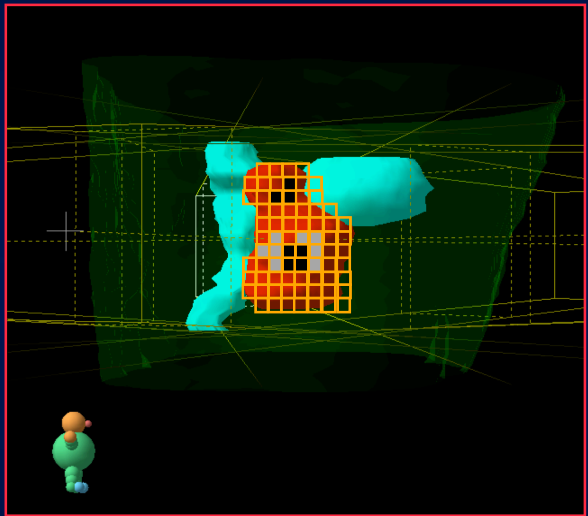


The BEV of the tumor is divided into a series of finite size pencil beams, and the corresponding pencil beam dose distributions are computed.



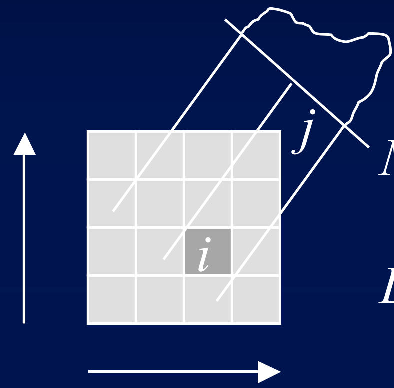
The pencil beam intensities are optimized and the result is an optimized intensity map.

Inverse planning approach



C_i *dose contribution*

W_j *weight*



Modulation of a beam

$$D_i = C_{ij} W_j$$

$D_0 = CW_0$ *desired dose*

$D_b = CW_b$ *best achievable dose*

$$D(\vec{r},\vec{r}\,') = \int_V h(\vec{r},\vec{r}\,') \cdot f(\vec{r}\,') d\vec{r}\,'$$

Cost function

A cost function is a mathematical evaluation of the desired dose distribution

$$Cost\ function = f(D_0 - D_b)$$

Ideally, it should include all of our knowledge of radiotherapy: physical as well as biological dosimetric requirements.

Quadratic cost function

$$F(\vec{x}) = \sum_{R} \sum_{i \in R} \gamma^{R} (d_i - D^{R})^2$$

$$d_i = \sum_{j} a_{ij} x_j$$

a_{ij}	= dose from unmodulated j-th pencil on i-th pixel
$\vec{x}$	= modulation vector
R	= tumor/OAR
d_i	= dose in i-th pixel
γ^{R}	= penalty on R
D^{R}	= dose constraint on R

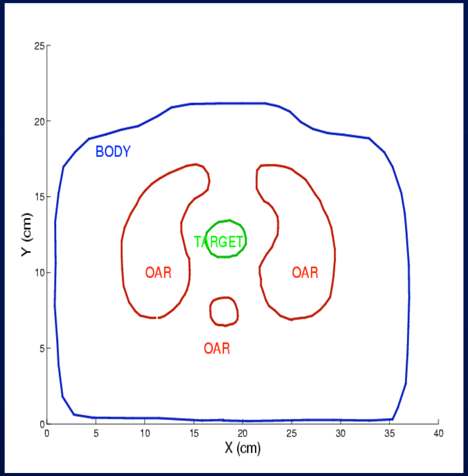
The i-th pixel contribution to cost function F is proportional to the distance between d_i and D^R, with a weight factor γ^R .
Although the gradient of F is linear in *x*, F has a unique minimum when only the target is considered.

Constraints imposed on different OAR bring about in general multiple minima.

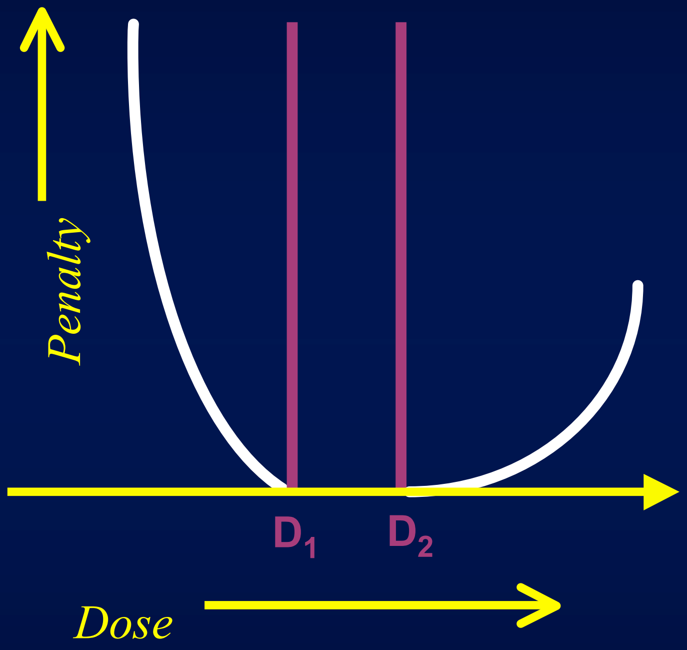
Constraints and organs at risk

Constraints are defined in terms of maximal and minimal dose to be delivered to a given fraction of the volume of each region of interest.
The explicit expression for a DVH-based cost function is given by the sum of all the penalties due to excess dose to the different ROIs, and the penalty due to a defect of dose delivered to the target.

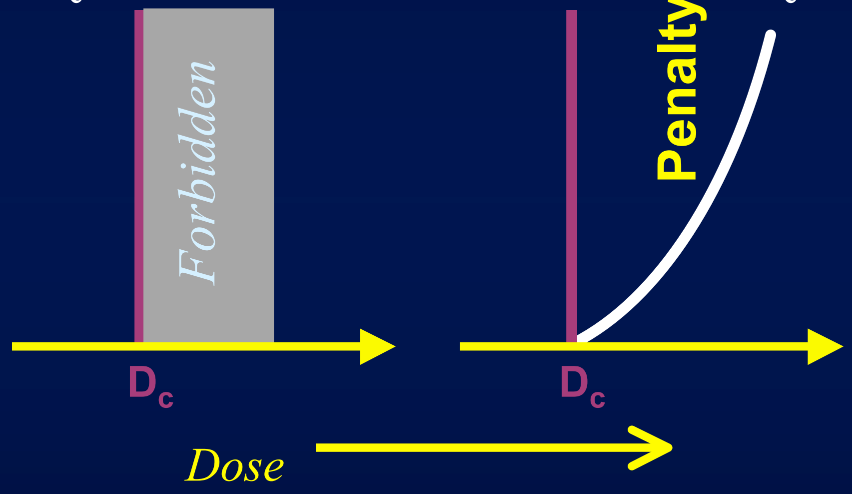
A DVH-based cost function implements ''soft''and "hard" constraints in terms of dose-volume histograms for the organ-at-risk and the target



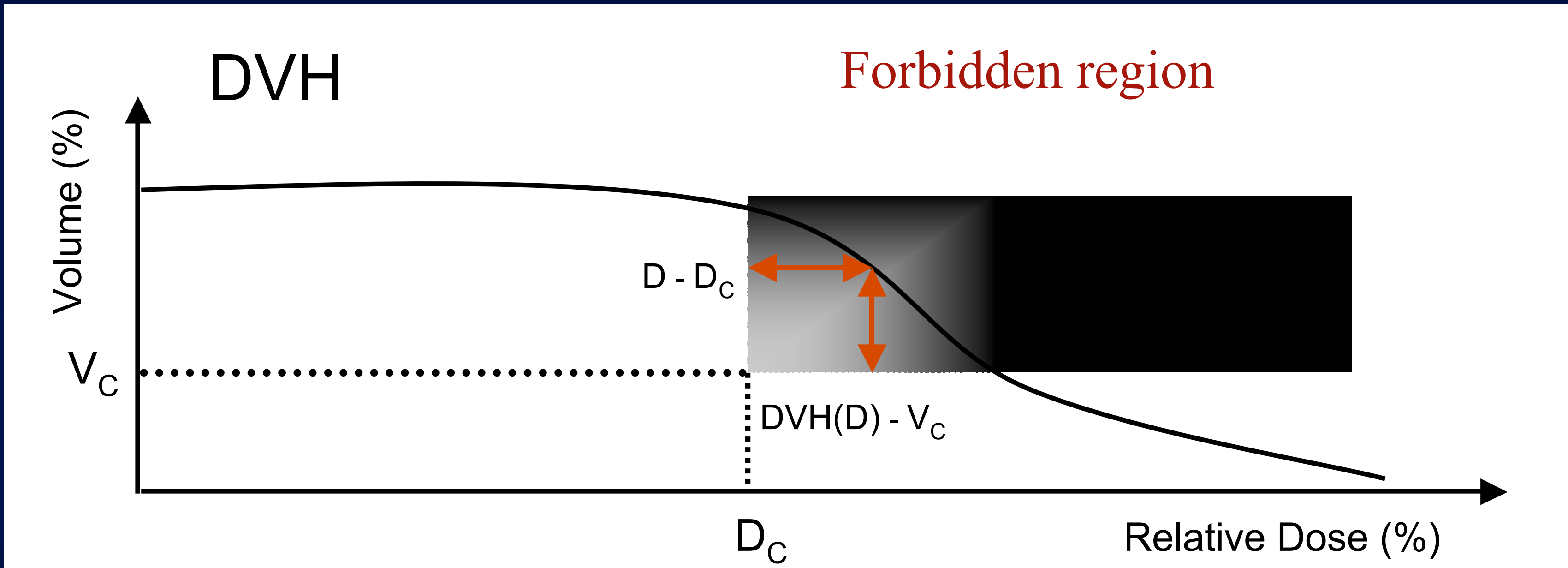
Optimization requires criteria



- Hard constraint: $D < D_c$
- Soft constraint: Penalized if $D > D_c$



Cost function based on DVH



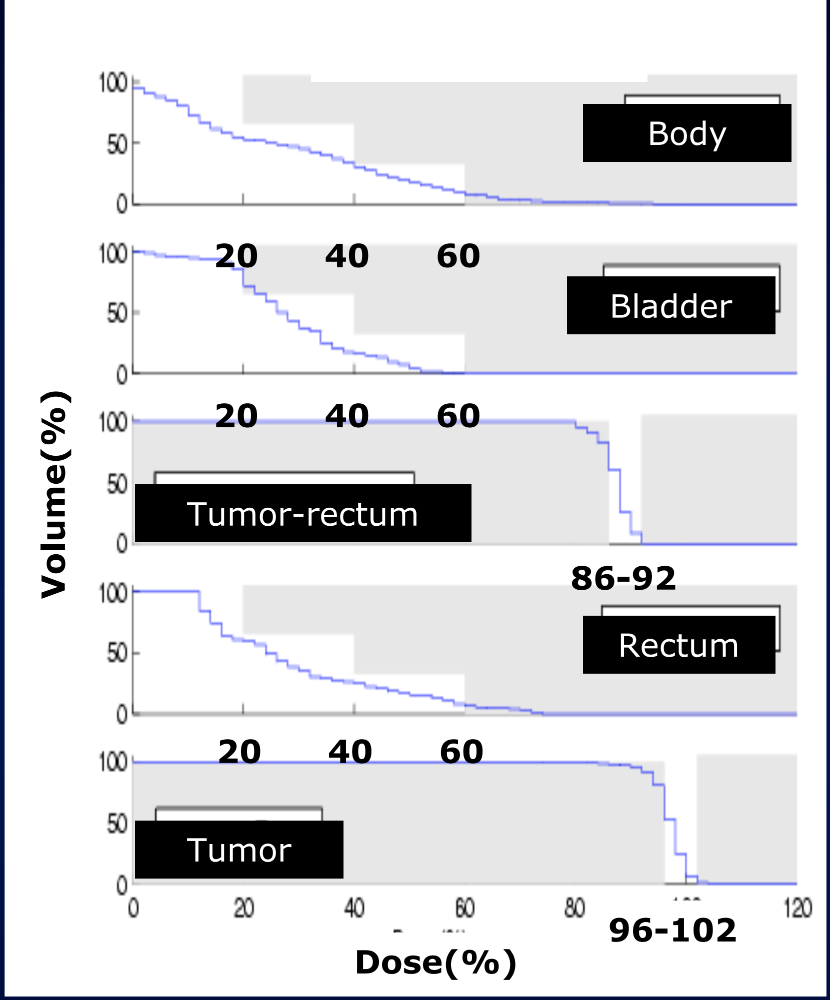
Dose greater than D_C cannot be released to a volume larger than V_C

The DVH bin around D contributes a term $[(D-D_C)\ (DVH(D)-V_C)]^2$ to the cost function

Constraints

	Dose(%	Vol. (%)
Rectum and bladder	60 40 20	0 33 66
Tumor and rectum overlap	86 - 92	100
Tumor	96 -102	100

Ref. Emami et al. 1991

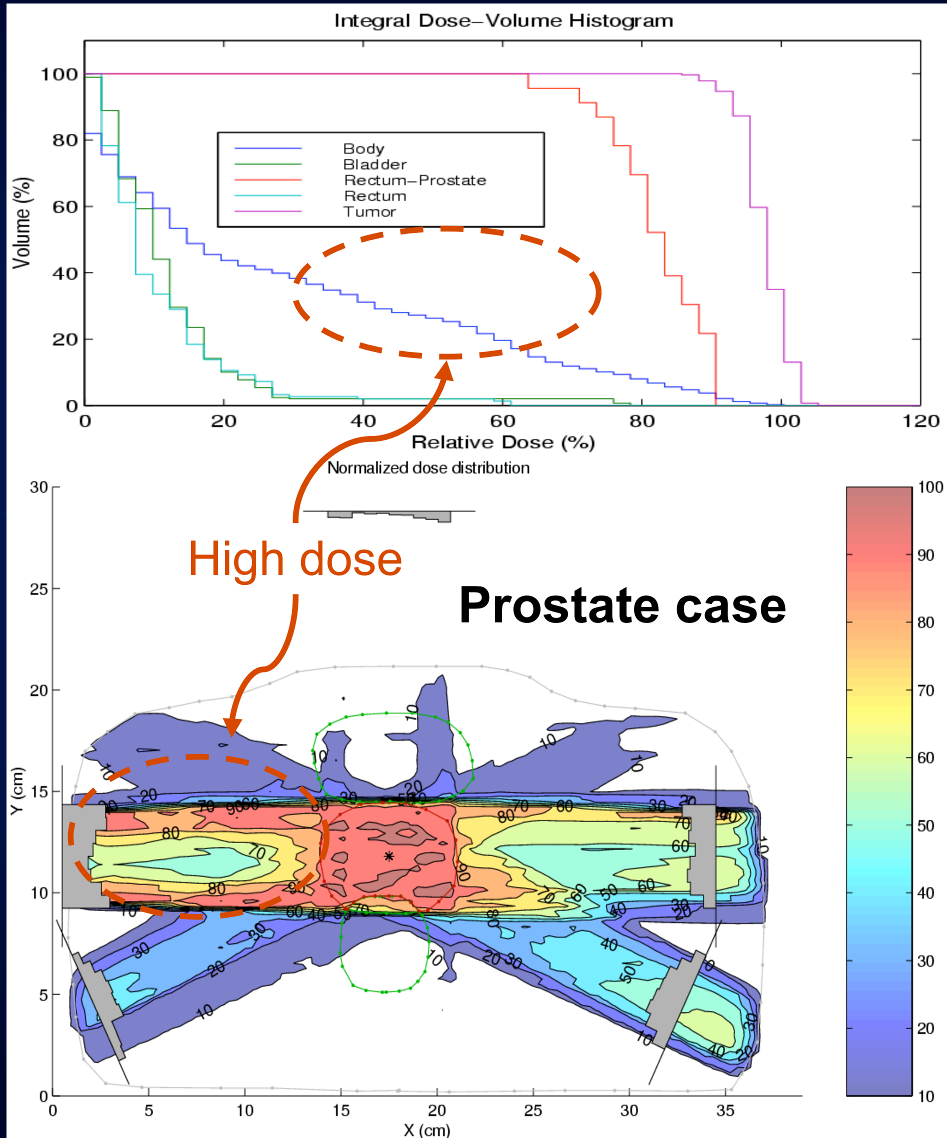


DVHs for a tumor target (prostate cancer) and the considered OARs (rectum, bladder and the body) for a reference beam modulations. The shaded regions are the regions subject to penalty according to the dose-volume constraints.

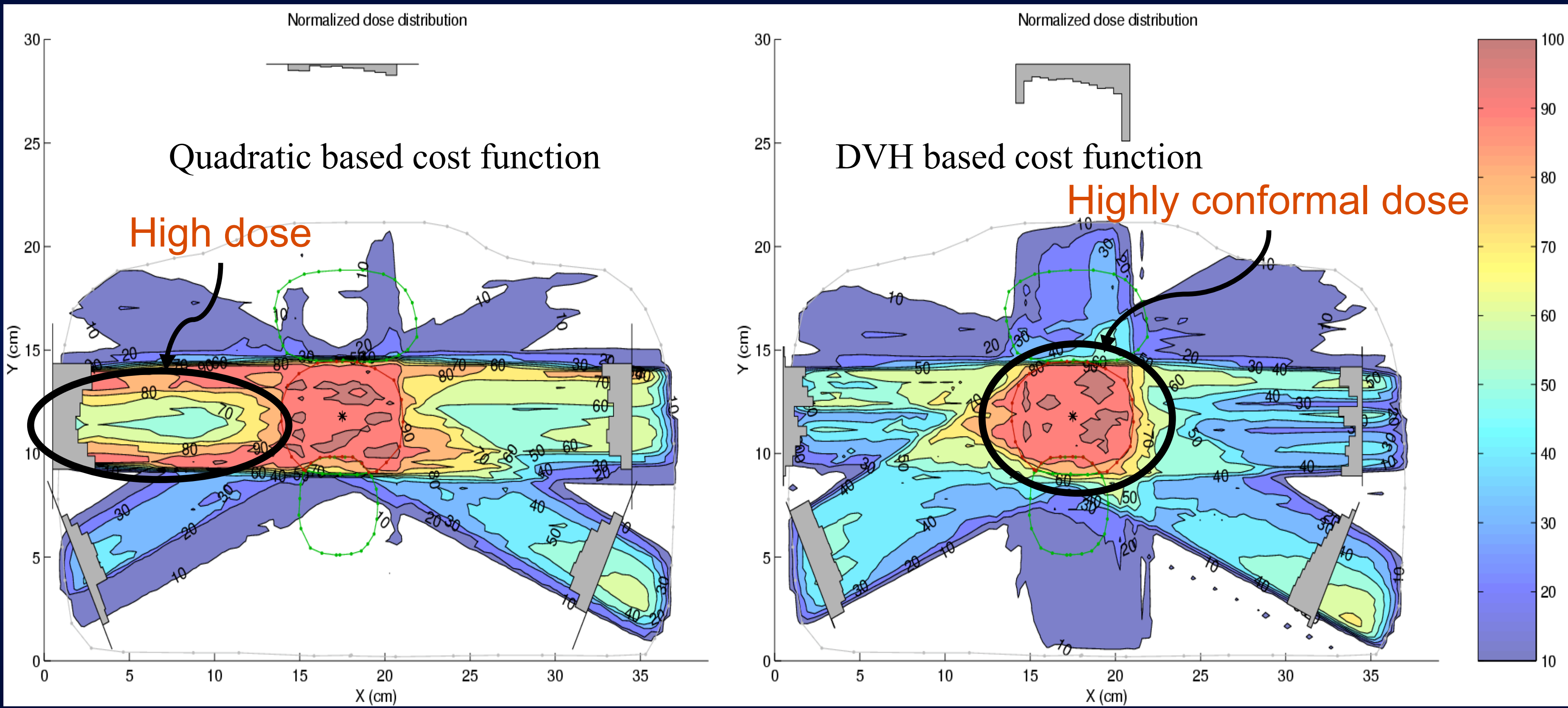
- The case shown would suggest further optimization on penalties for different ROIs (high dose on the body in the figure)

- further optimizations are strongly case-dependent and require fine tuning

- in view of the robustness and case-independence of the optimization process, it is interesting to explore the implications of different choices for the cost function



Choosing the cost function

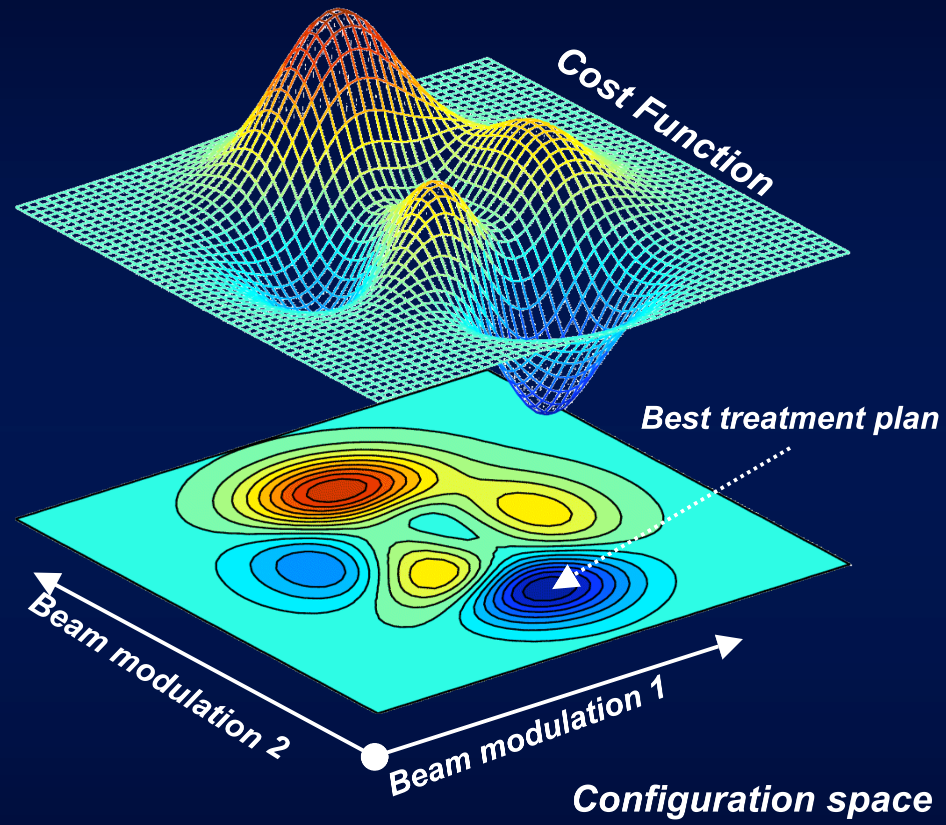


S. Marzi, M. Mattia, P. Del Giudice, B. Caccia and M. Benassi
"*Optimization of intensity modulated radiation therapy: assessing the complexity of the problem*"
Ann. Ist. Sup. Sanità 37(2): pp. 225-230; 2001

Optimization

We use the term optimization as it is used in *mathematical optimization*: to define a situation where a *cost function* has to be optimized (i.e. minimized or maximized)

There are many ways to optimize a treatment plan for a given cost function. Most optimization methods use an iterative approach and major differences are the ways for search directions and step-lenght.

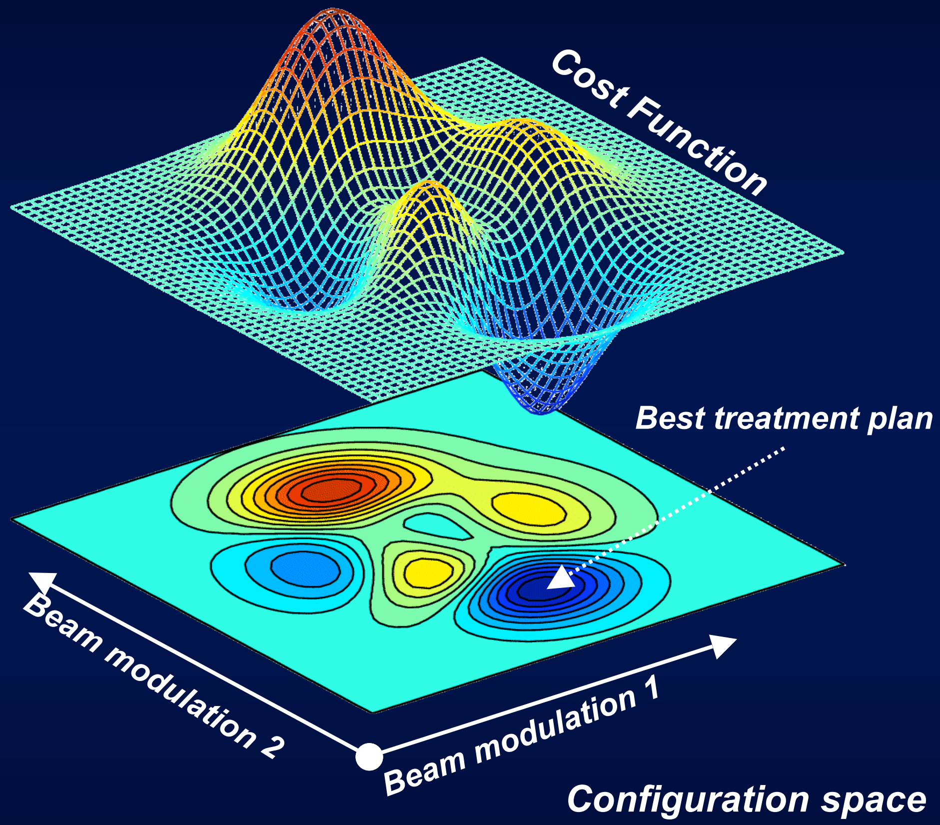


An inverse planning system may use any optimization algorithms

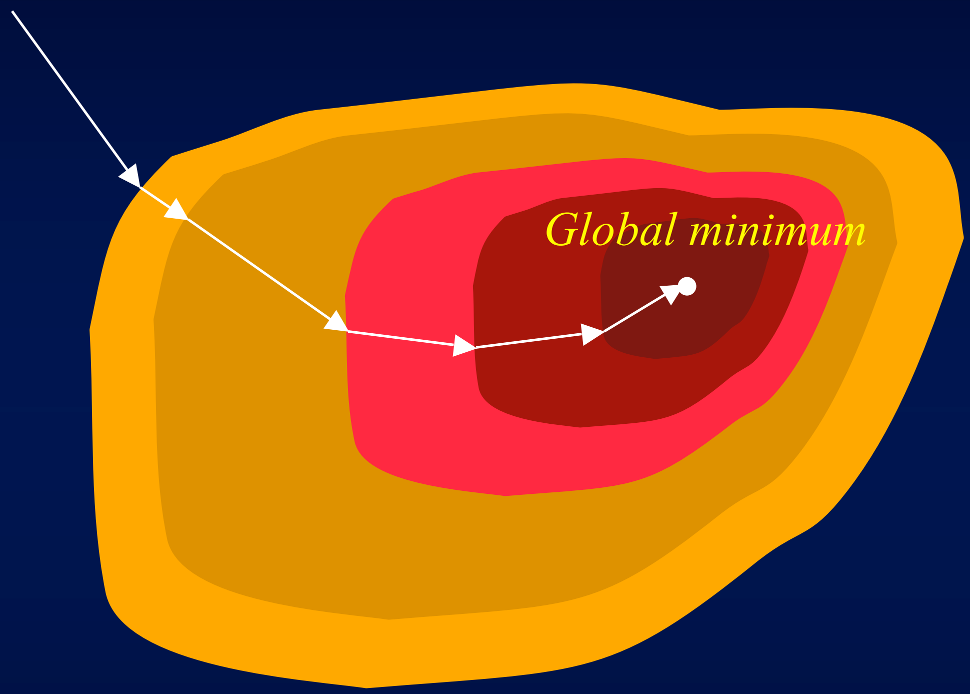
Optimization strategies

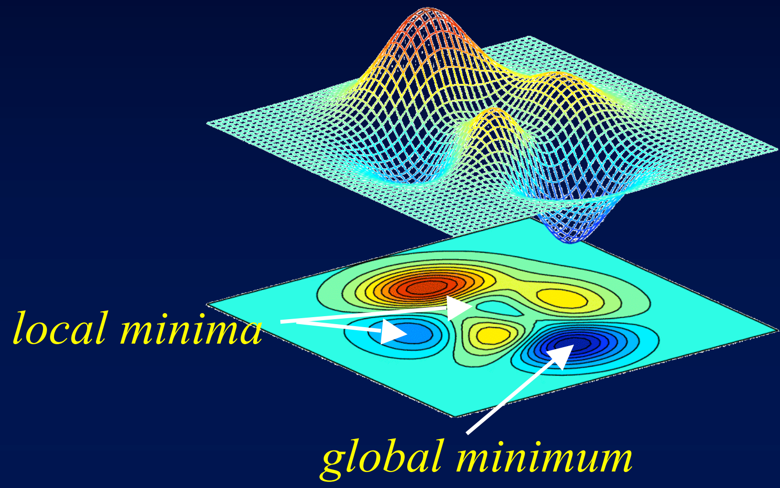
deterministic approaches: can range from simple, direct and local approaches like the steepest descent to non local procedures (simplex, ...) or algorithms which exploit memory of the past exploration of the configuration space (taboo search, …)

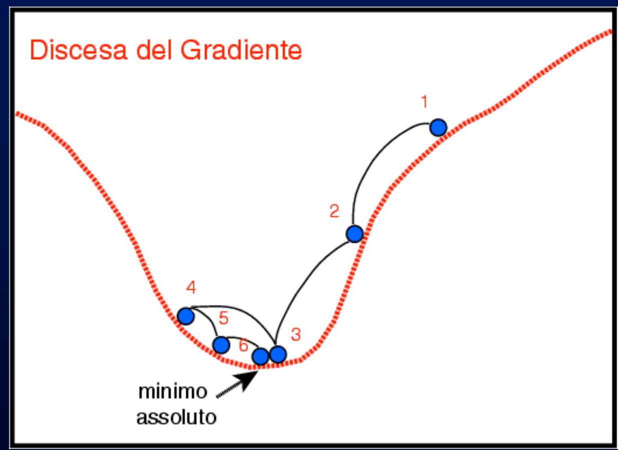
stochastic approaches: noise 'injected' in the motion of the representative point in the configuration space of the system helps getting out of local minima. A well known prototype of such a stochastic procedure is the simulated annealing.



Gradient descent

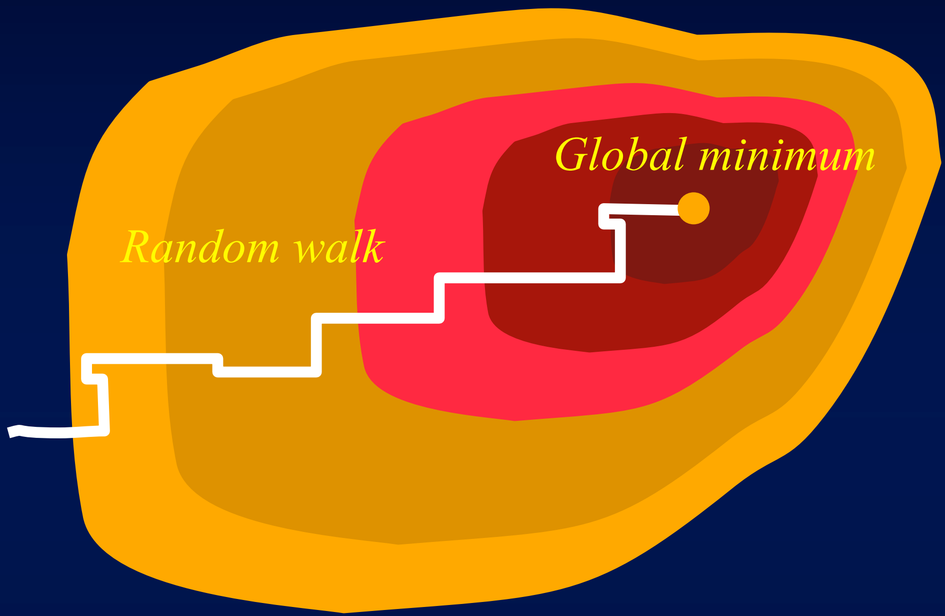


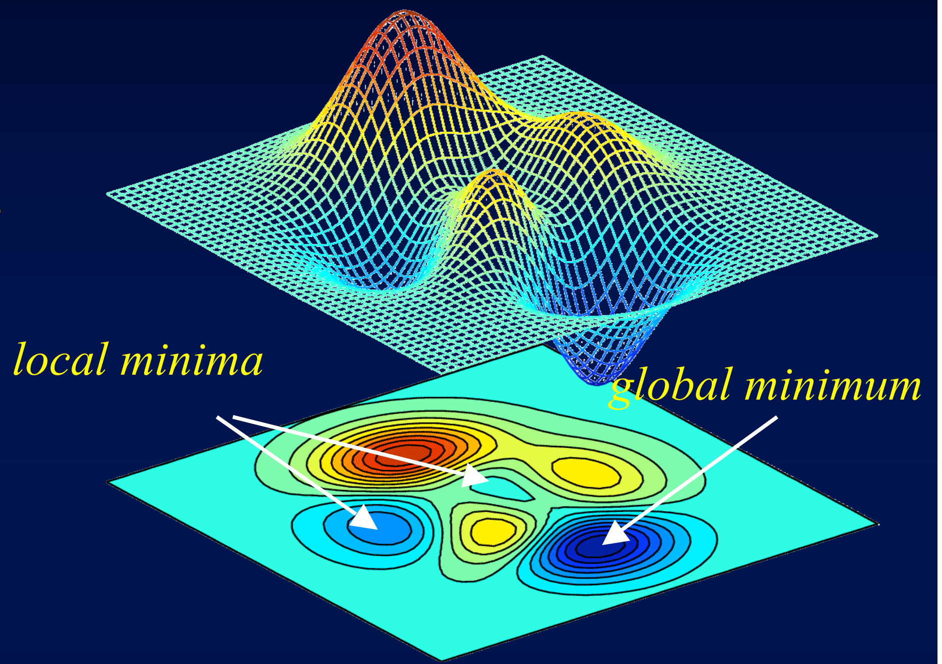




Direction of steepest slope determines
the direction of motion

Simulated annealing

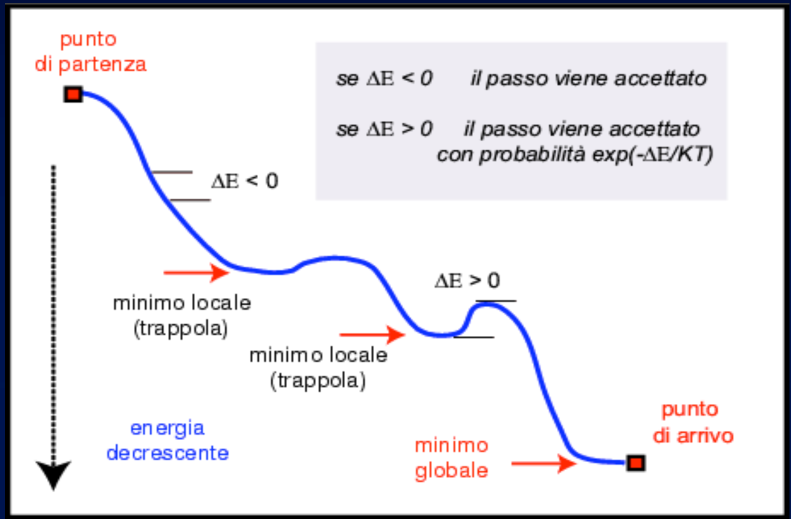




Each step of the SA algorithm replaces the current solution by a random "nearby" solution, chosen with a probability that depends on the difference between the corresponding function values and on a global parameter T (called the temperature), that is gradually decreased during the process direction of motion

Kirkpatrick S. et al.Optimization by Simulated Annealing, Science, 1983;1(220): 671-680.

Simulated annealing

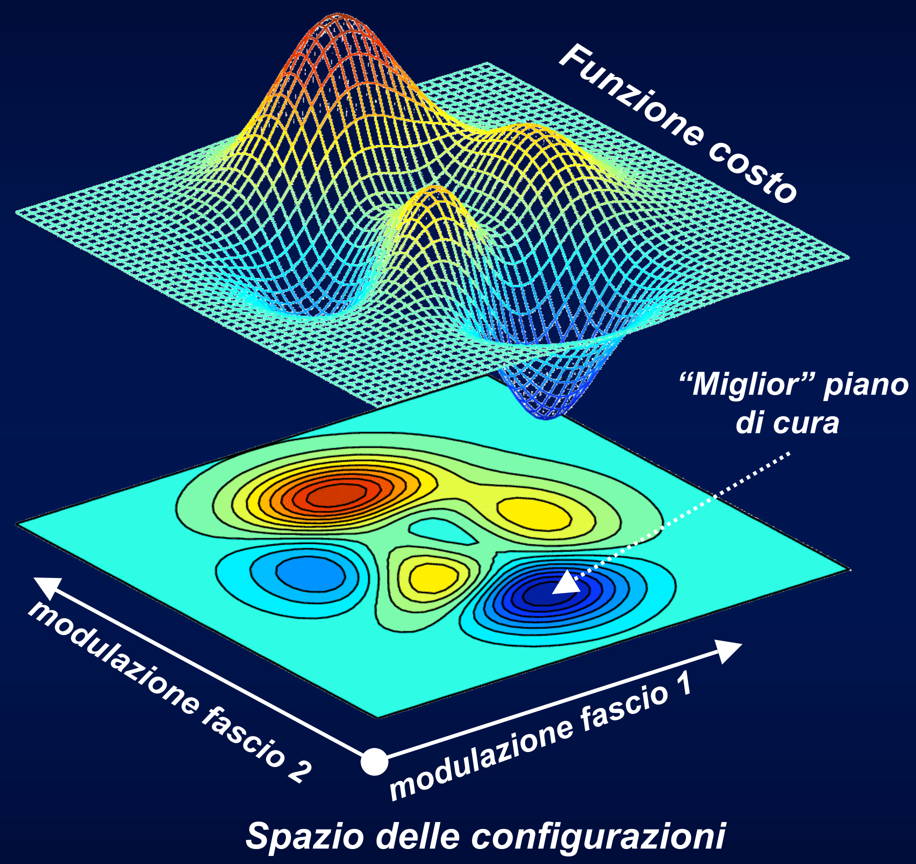


Sistema fisico	Problema di ottimizzazione
Stato	Soluzione possibile
Energia	Costo
Stato fondamentale	Soluzione ottima
Raffreddamento	Ricerca locale

Il "simulated annealing" è un approccio basato su concetti di meccanica statistica,
ed ha un'analogia con il comportamento dei sistemi fisici durante il processo di raffreddamento.

Problems to solve

- High dimensionality (~10^3)
- Local minima
- Computational load

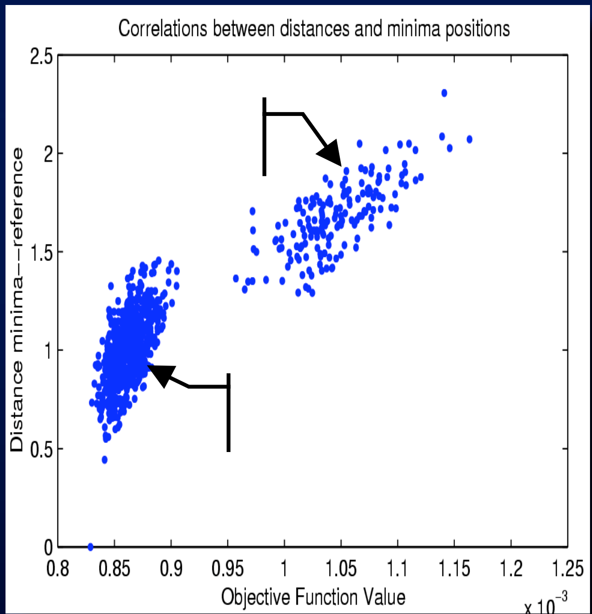


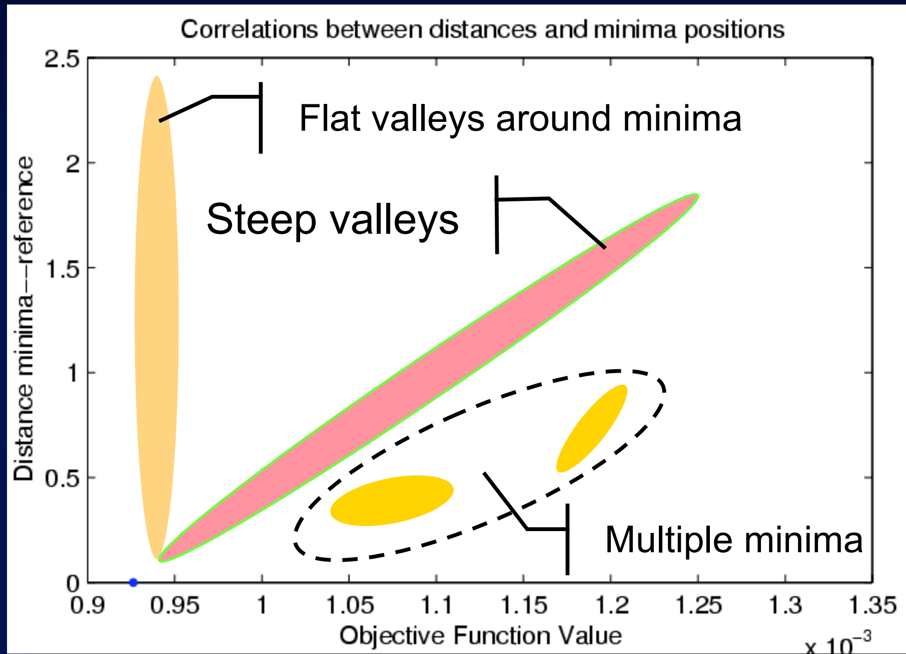
Our approach

Our approach consists of defining a dose-volume cost function, used as quality index of the treatment plan, and minimizing, by means of a downhill iterative procedure, the cost function to achieve the optimal solution. Local minima distribution has been used as an indicator of the complexity of the optimization process. The obtained data have been evaluated by using radiobiological models (the poissonian TCP model and the NTCP relative seriality model) to estimate the clinical impact of the above complexity.

Analysis of the cost function

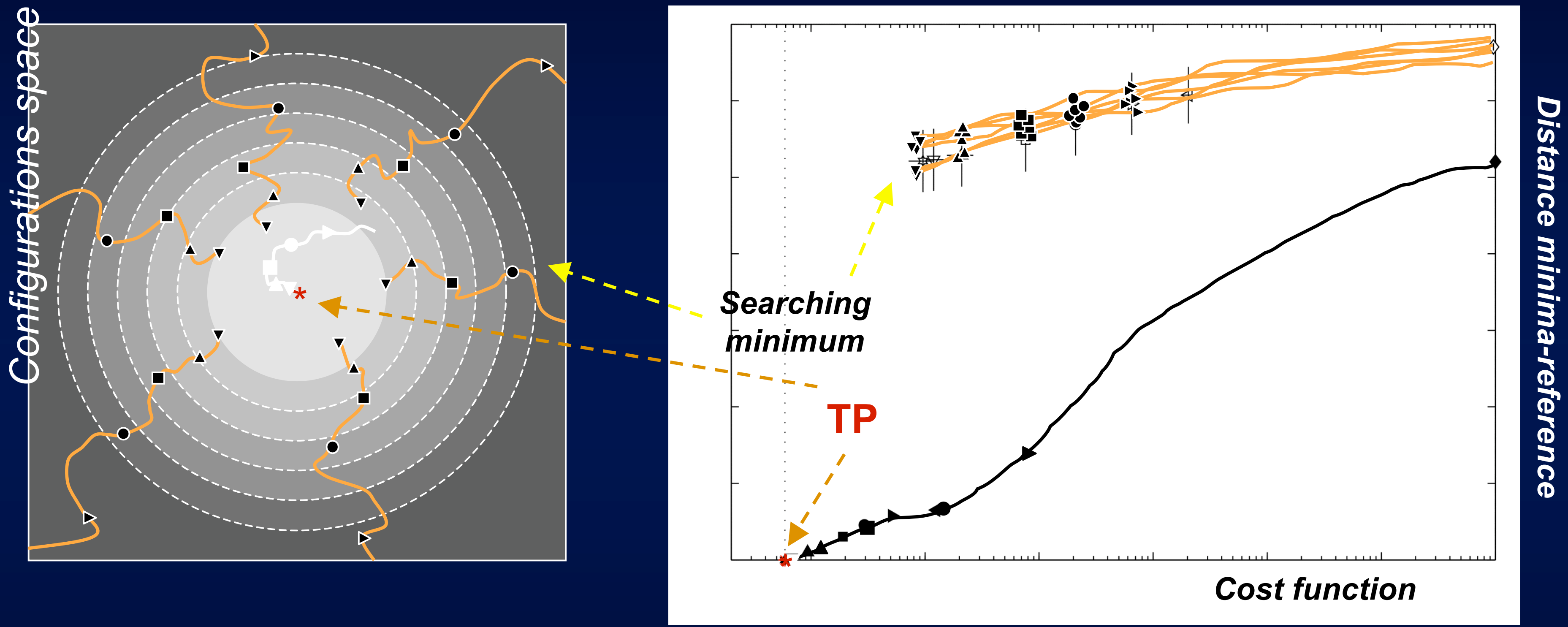
- **How to expose in a compact way the relevant features of the (highly dimensional) cost function**





Number and distribution of minima and their basins of attraction: sampling the configuration space starting from many initial, random modulations and recording the final, optimal state

Analyzing the cost function



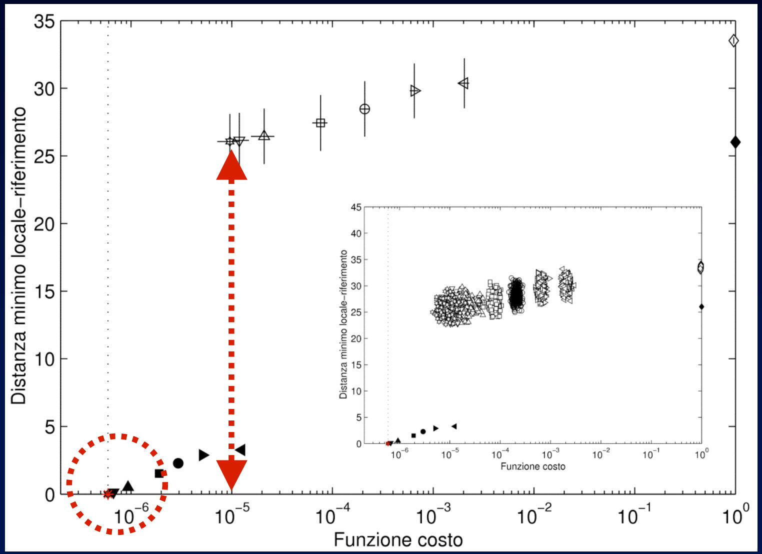
Analisi dello spazio delle configurazioni
Mattia, Del Giudice & Caccia, Med. Phys.(31)5;10052-1060 (2004)

Our approach

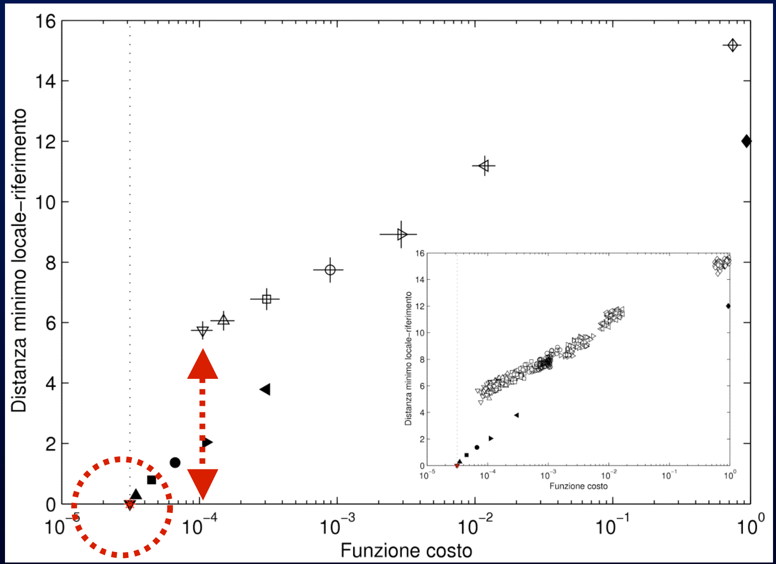
With a cost function based on dose-volume constraints, local minima are distributed on a "spherical" cloud centered around the best treatment plan.

Computational load is reduced

head-neck



prostate



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