YITP International Workshop: Biological & Medical Science based on Physics (Nov.5-7)
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Niche researches between computational image analysis and radiotherapy physics

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Acknowledgements

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My many co-researchers

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All members of my laboratory

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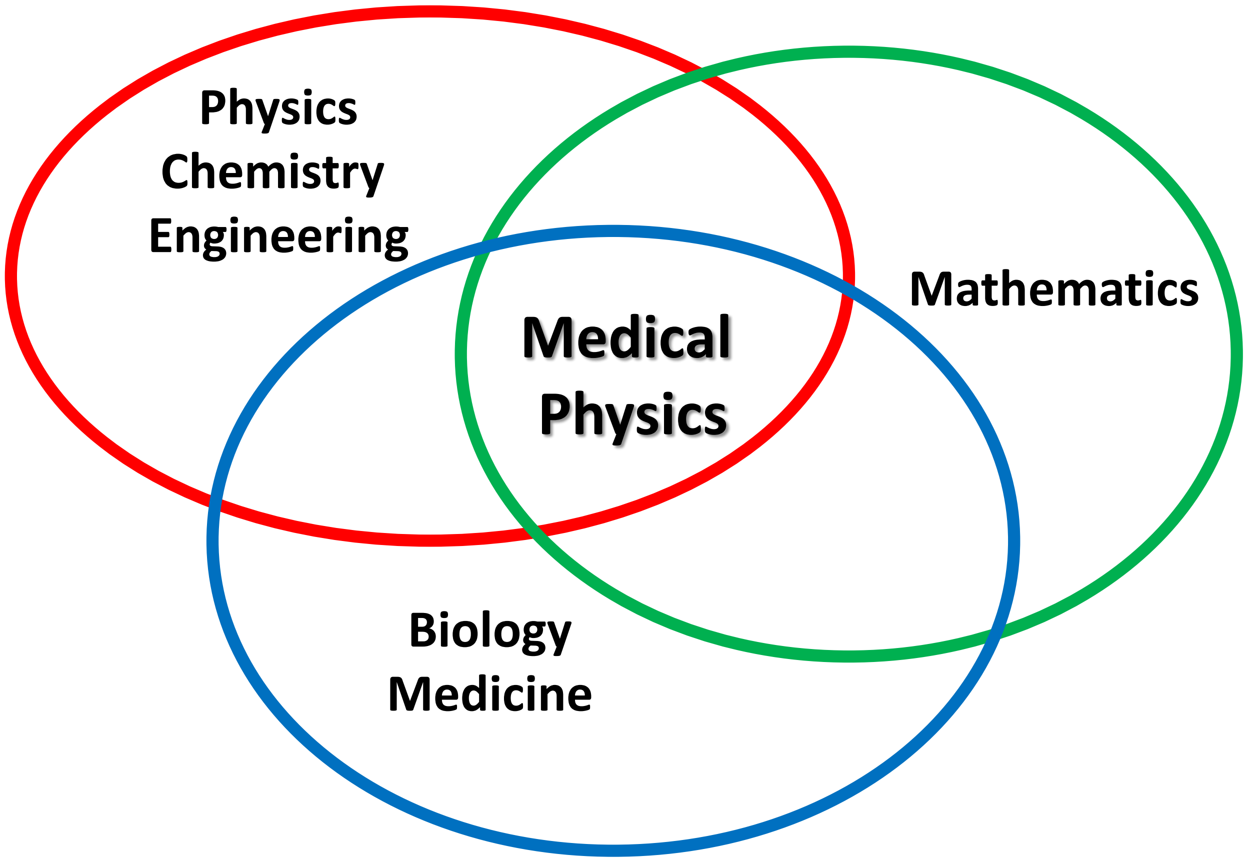
What is medical physics?



My policy

Knowing something about everything is much better than everything about something. Multifaceted knowledge is best!

(一つの事柄についてすべてを知るよりも，すべての事柄について何らかのことを知るほうがずっとよい．知識の多面性が最上である．)(Blaise Pascal)

What is radiation therapy?

What are benefits of radiation therapy with “invisible knife”?

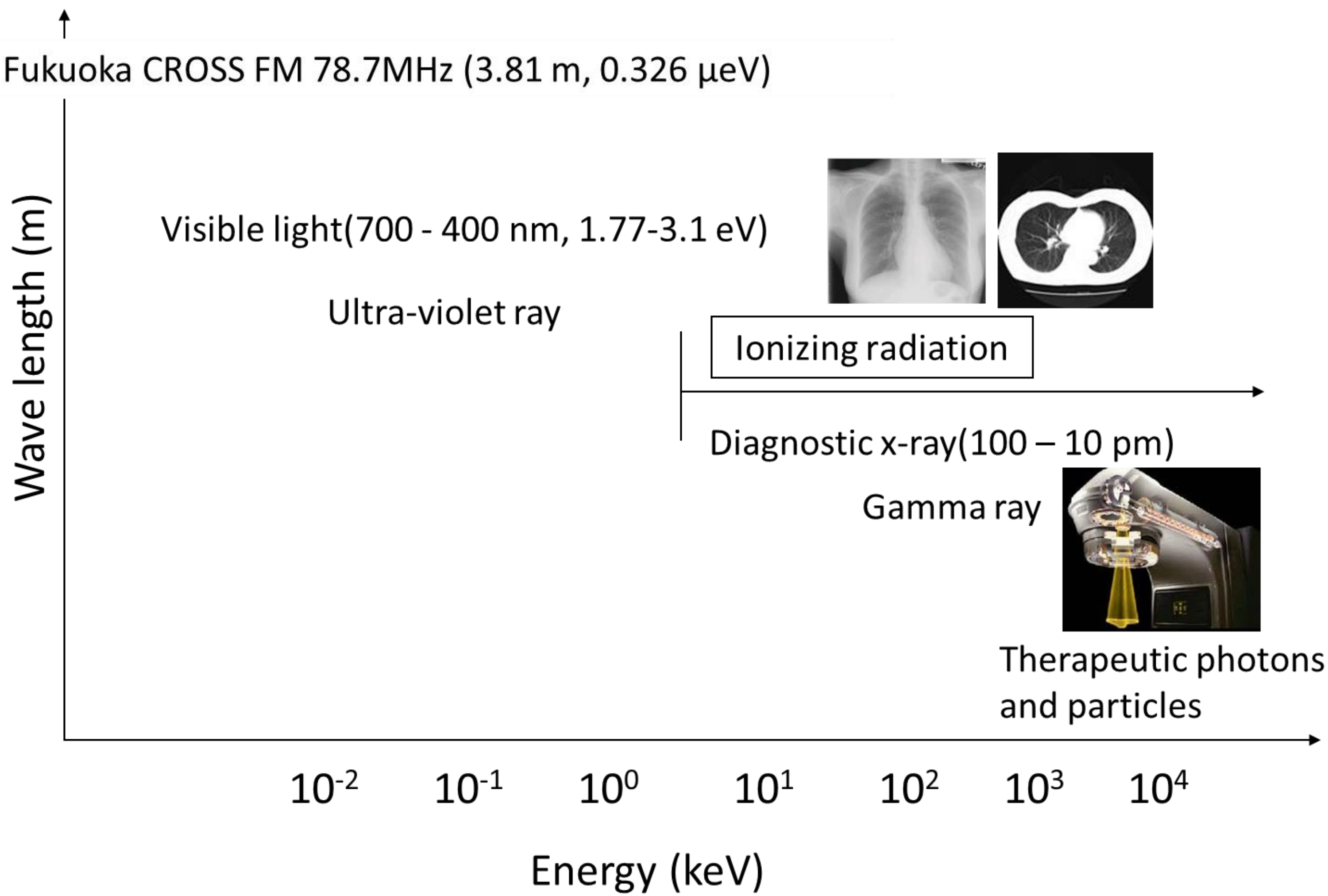
- ✓ Low-impact treatment without surgically cutting patient bodies, which can result in higher quality of life (QOL) of patients

- ✓ Considerably important for Japan, which have been rapidly moving toward an aging society (% of elderly people of 65 years old and over in Japan: around 23% in 2011*)

- ✓ Preservation of organs’ functions and reduction of the physical burden of patients with “**invisible knife**”, particularly elderly patients (breast cancer, prostate cancer, tongue cancer, etc.)

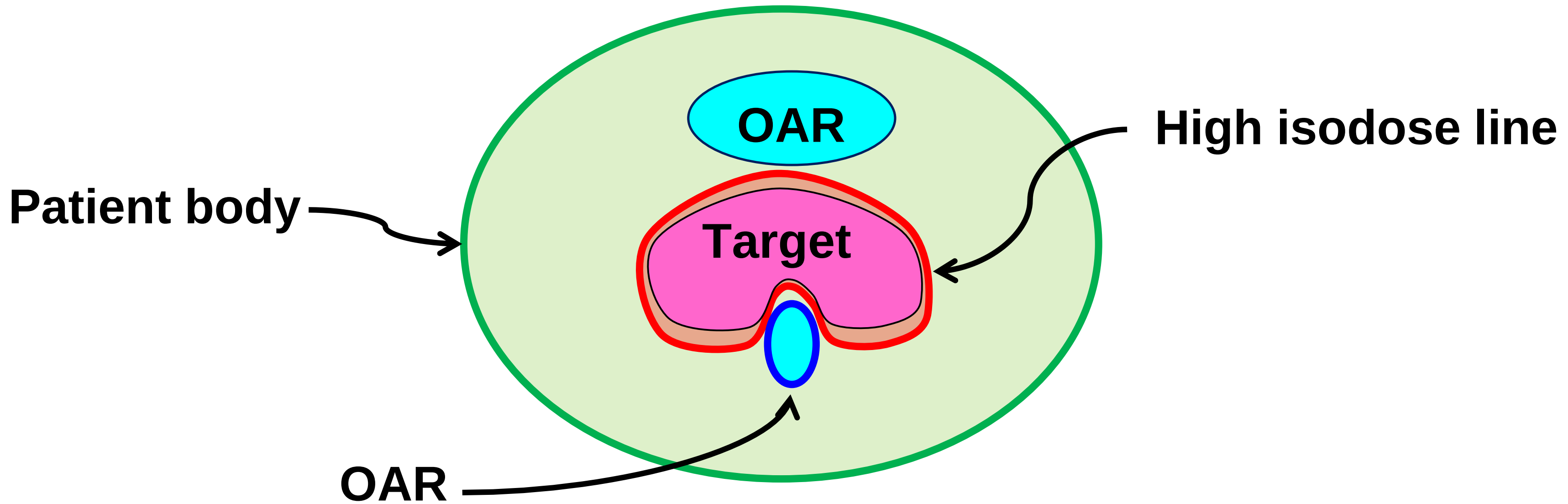
*Ministry of Internal Affairs and Communications (MIC). (2011) http://www.stat.go.jp/data/jinsui/pdf/201102.pdf.

How are physical energies of "invisible knife" radiation



Goal of radiation therapy

To deliver as high dose as possible to tumors (cancer or targets), and cause as little damage as possible to organs at risk (OAR*) and normal tissues

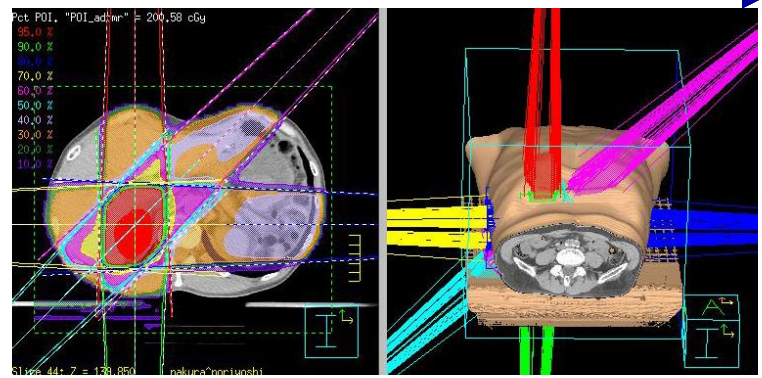


*OAR: organs whose radiation sensitivity may significantly influence treatment planning and/or prescribed dose

How is the radiotherapy procedure?

(1) Diagnosis

(2) CT imaging



(3) Radiation treatment planning (RTP)

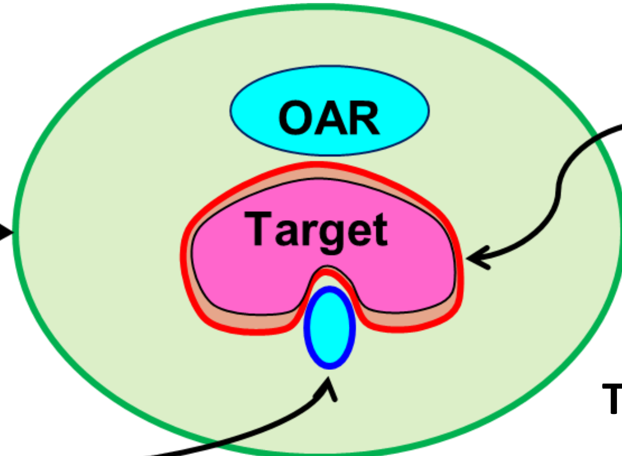
(4) Patient Setup

(5) Treatment in a fraction

Computational image analysis play indispensable roles in all aspects of radiation therapy.

A nature on what medical physics is

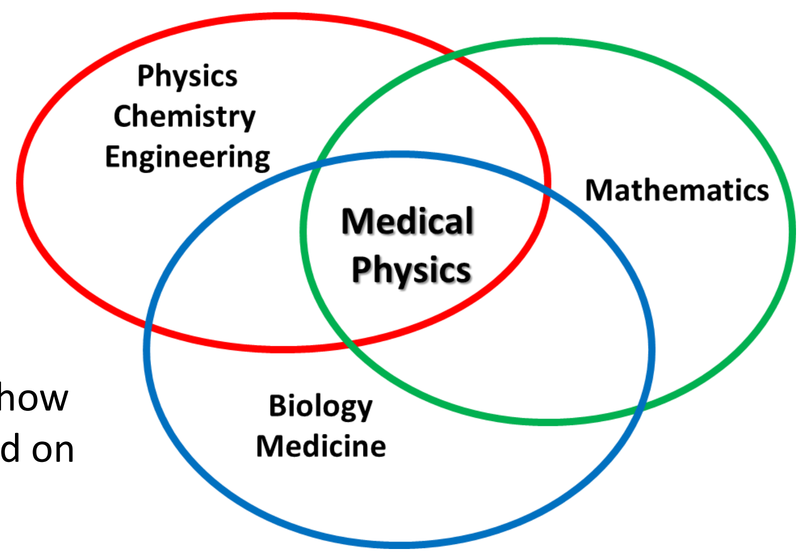
Patient body
Medicine, Anatomy
Physiology*



High isodose line
Radiation physics, Engineering
Mathematics

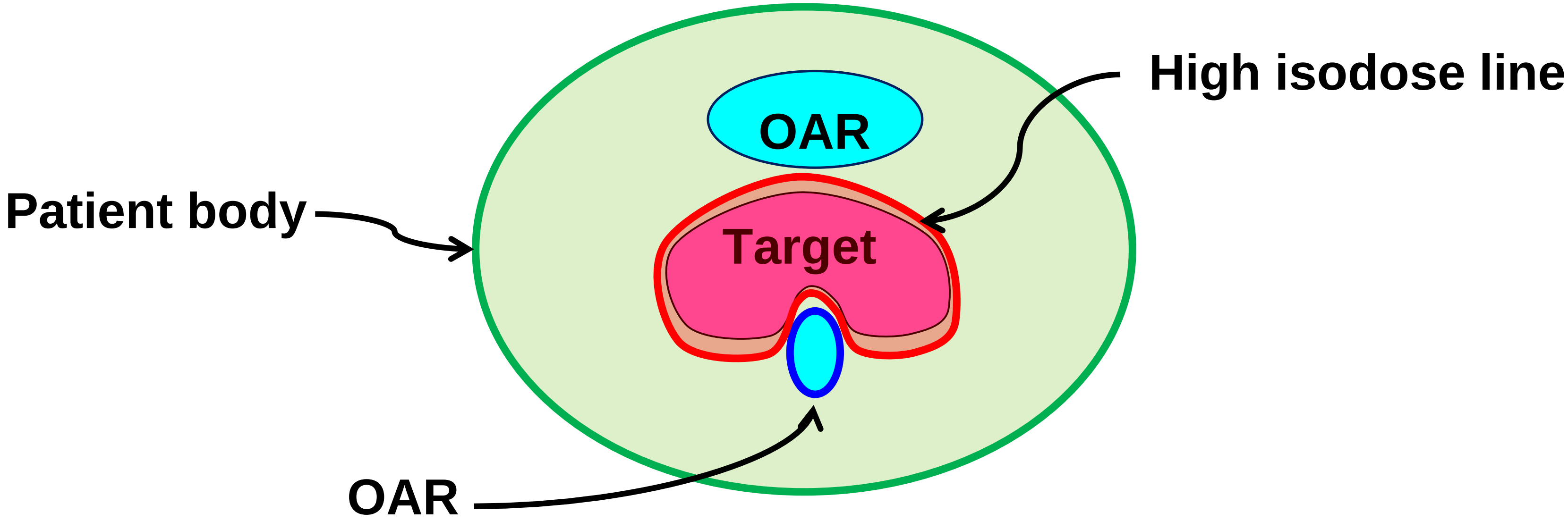
OAR
Anatomy, Biology
Radiation Biology

Target (cancer region) : Pathology**



*A study of how living organisms function such as how lung moves and how electric signals are propagated on nerve cells
**A study of origin, nature, and course of diseases

But,,, we have unavoidable uncertainties!



Physiologically, mistakenly, subjectively

Or physically?

Because we have the uncertainties of patient positions due to “Uncertainty Principal”?

In 1927, Dr. Werner Heisenberg said, “The more precisely the momentum of a particle is determined, the less precisely the position can be known, and vice versa.” (**Uncertainty Principal**)

$$\sigma_x \sigma_p \geq \frac{\hbar}{2}$$

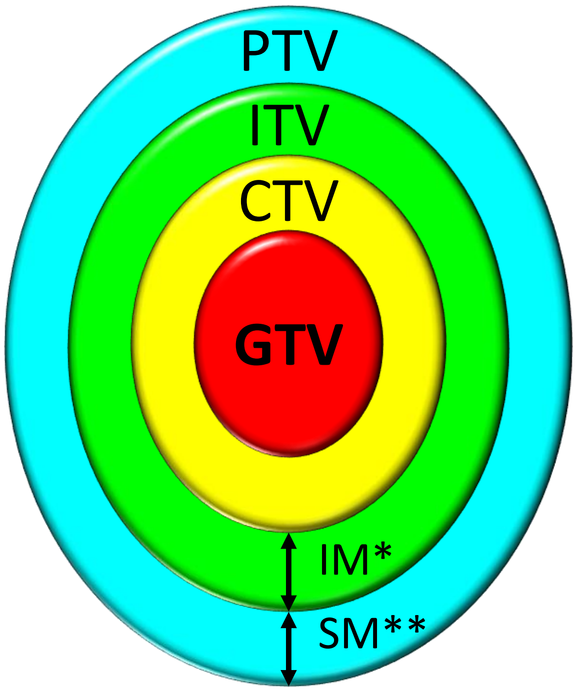
σ_x : uncertainties (standard deviation)of position

σ_p : uncertainties of momentum

$\hbar$: Planck's constant/2π

Definition of target volumes in radiotherapy with taking into account the uncertainties

Margin to guarantee a sufficient dose to a target to take into account the uncertainties



(ICRU report 50 and 62)

GTV : gross tumor volume, defined as visible tumor volume in images

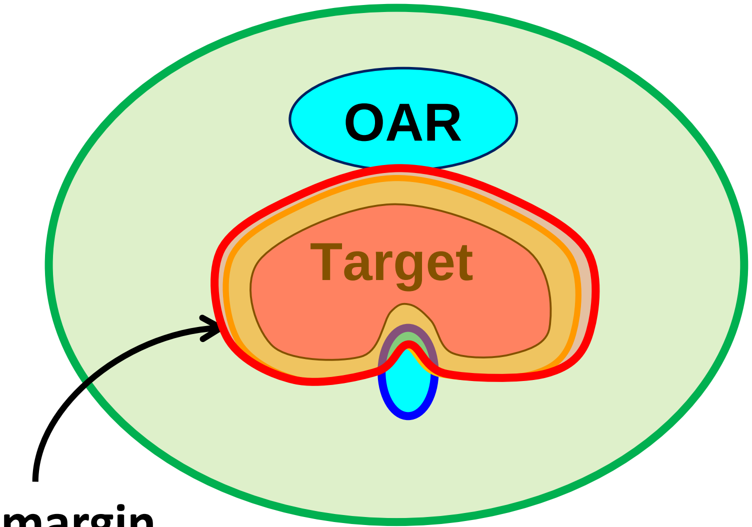
CTV : clinical target volume, defined as GTV + subclinical/invisible invasion

ITV : internal target volume, defined as CTV + IM (internal margin for organ motion)

PTV : planning target volume, defined as ITV + SM (setup margin for setup error)

Several unavoidable uncertainties!

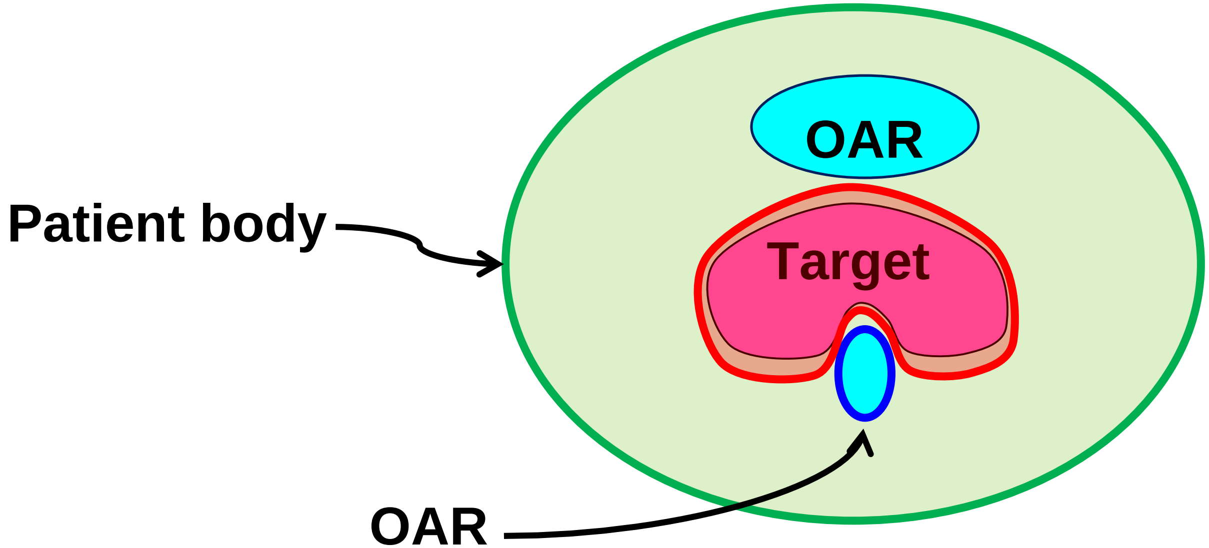
- ✓ Intra- and inter-observer variability of target delineations (drawing outlines of targets)
- ✓ Intra- and inter-fractional variation of the organ position (organ motion)
- ✓ Intra- and inter-observer variability of treatment plans
- ✓ Intra-fractional organ motion during treatment time



Safety margin
(i.e, planning target volume (PTV) margin: geometrical margin to guarantee an enough dose to the target)

Our challenges :
To minimize these uncertainties

That's why you need imaging techniques!



Why we need imaging techniques in RT:

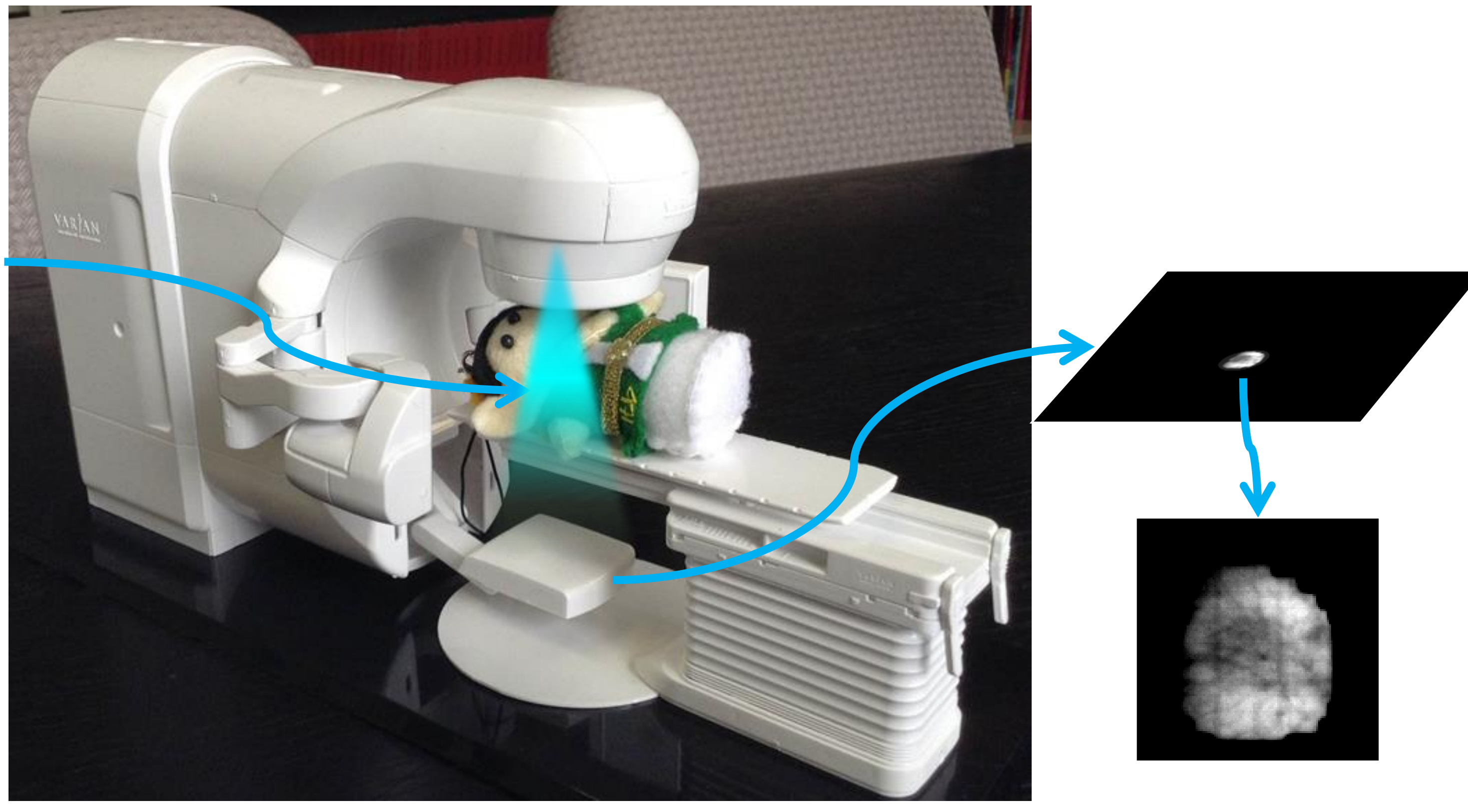
- ✓ Recognition of regions of a target and OAR
- ✓ Understanding of relationship between dose distribution and organs of interests (tumor and OAR)

Imaging on a treatment machine (linac)

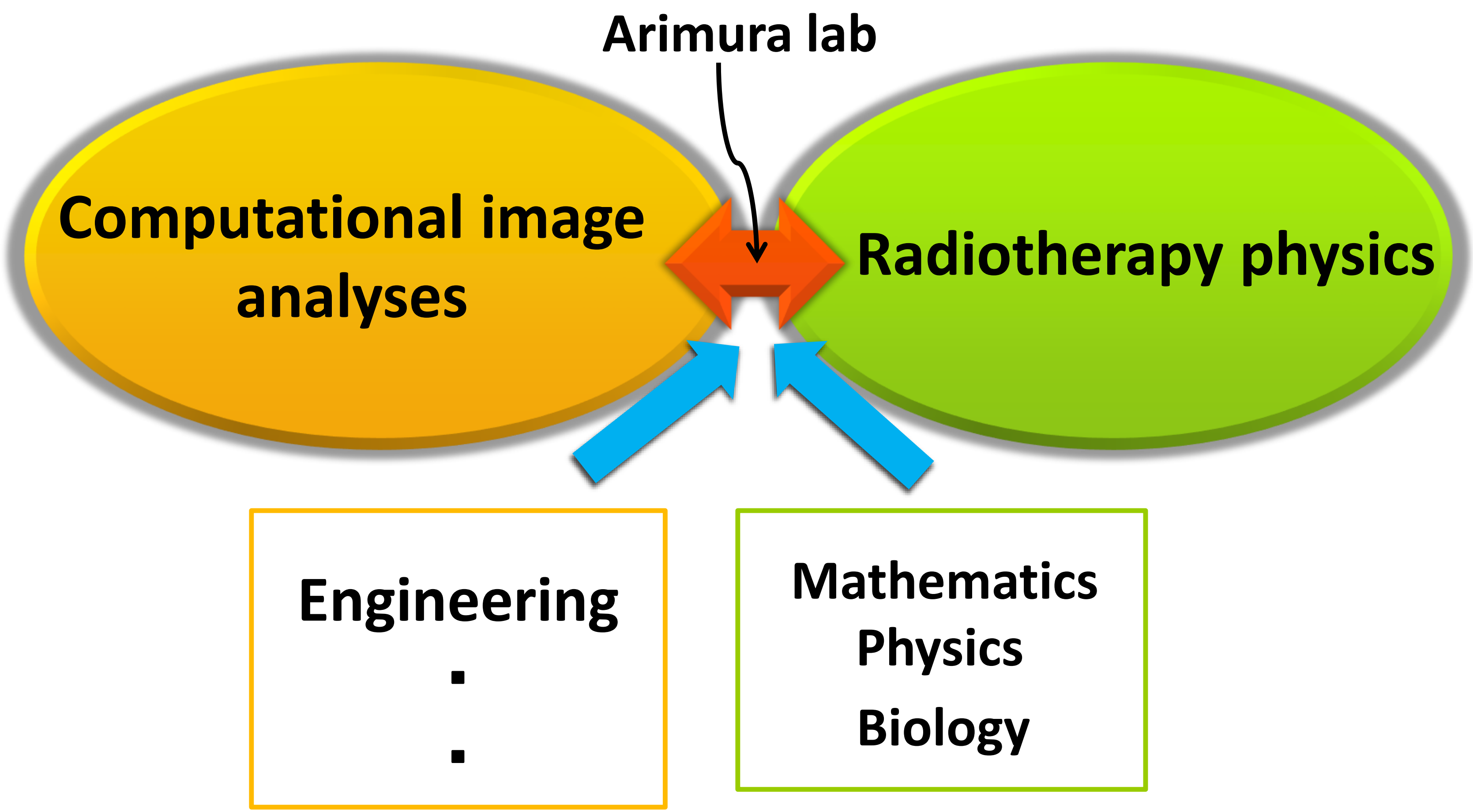
Visualization of target region during treatment time by using an EPID

EPID : electronic portal imaging device

Therapeutic x-ray beam with higher energies (around 1MeV -)



Niche researches in my lab



Niche #1

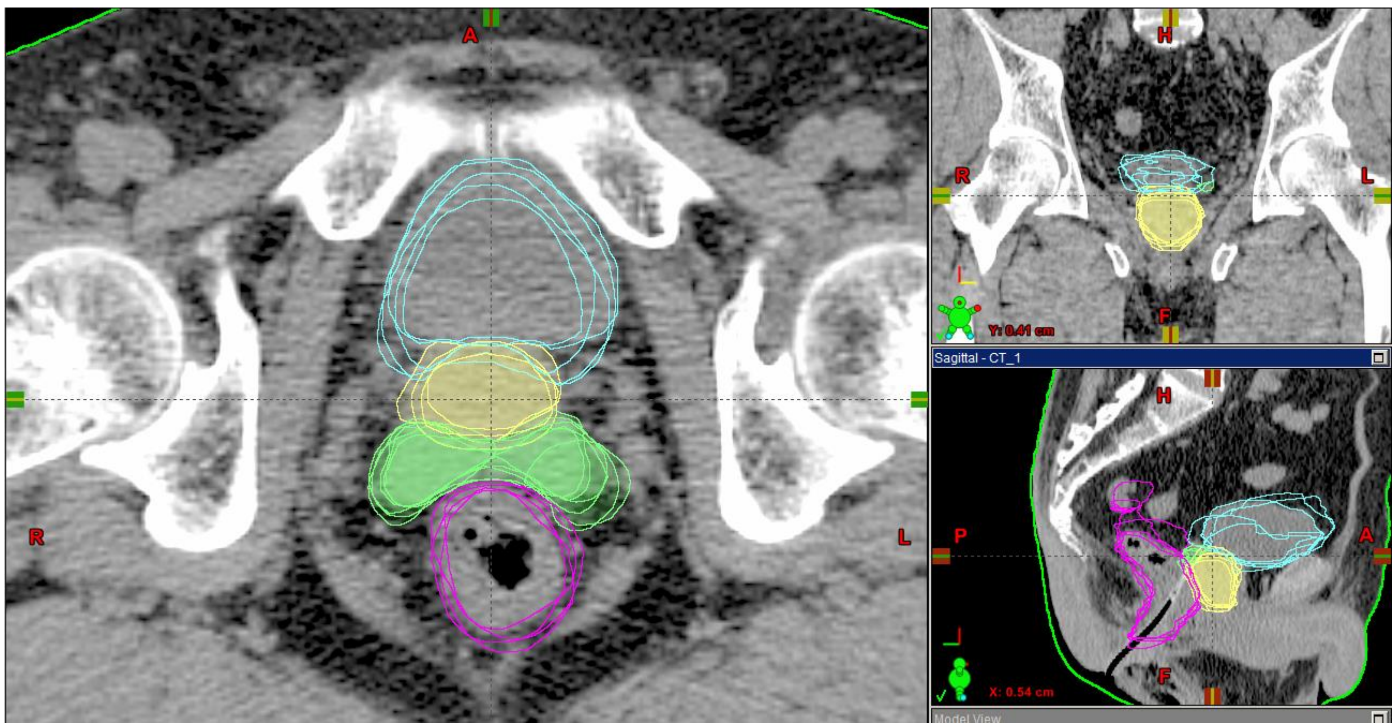
Computational anatomy

×

Automated determination of PTV margin

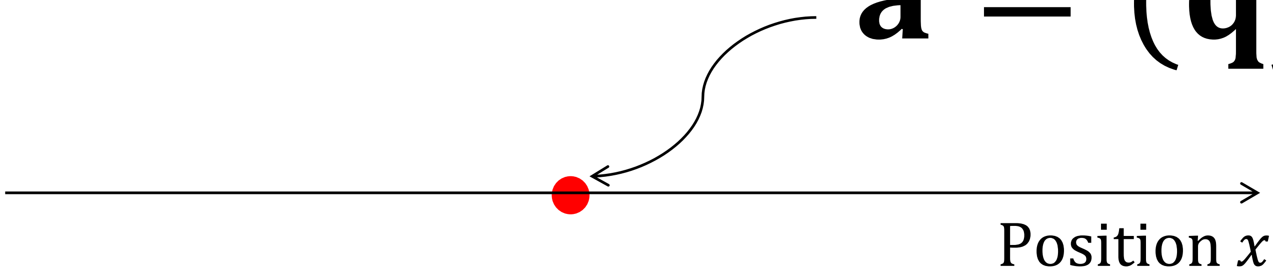
We have not taken into account shape variations in determination of PTV margins

- Only target translations were considered for determination of PTV margins with respect to organ motion.
- We assumed that shape variations of CTV should be taken into account for determination of the PTV margins.



A point computational anatomy in one dimensional space

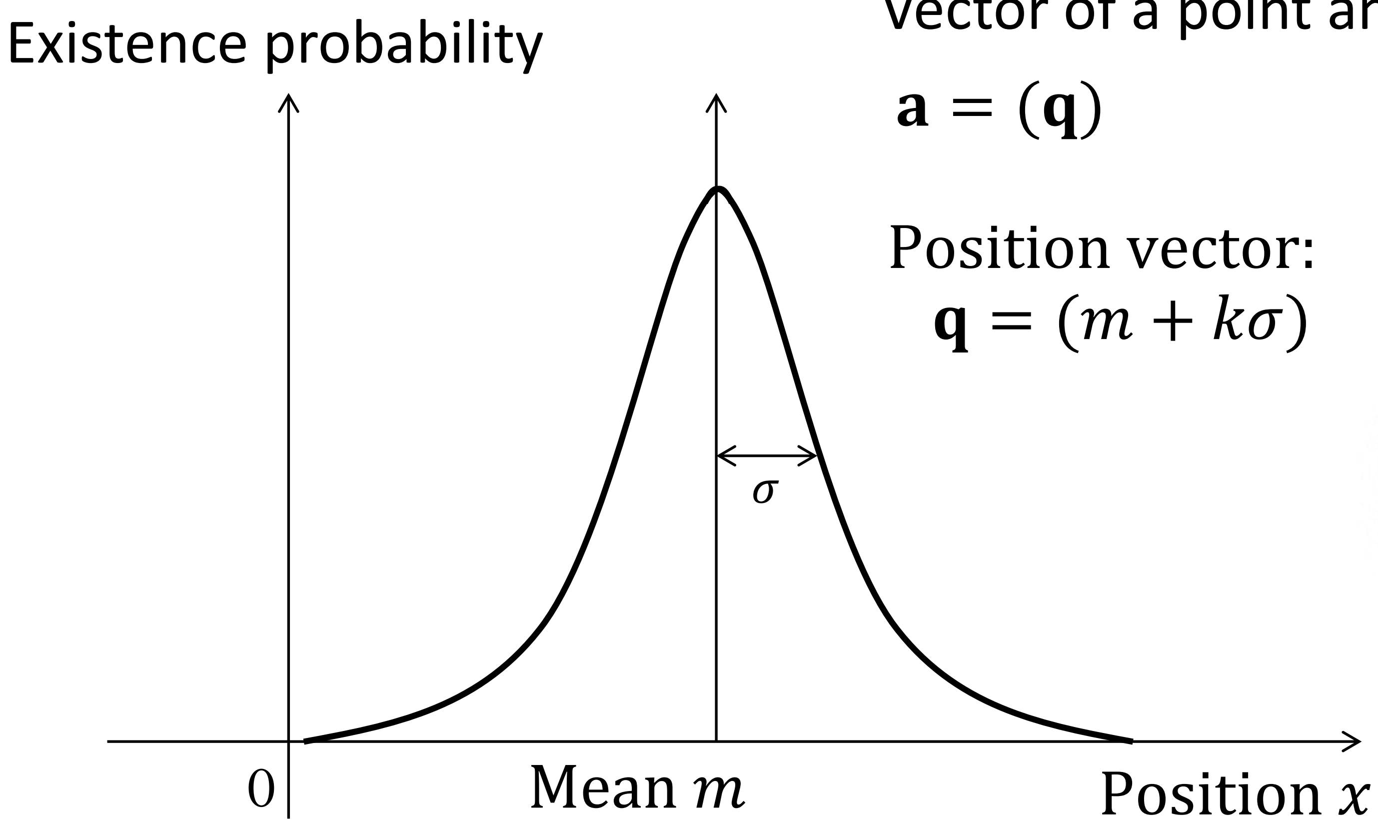
$$\mathbf{a} = (\mathbf{q})$$



$\mathbf{a}$: A vector of a point anatomy

$\mathbf{q} = (x)$: A position vector of a point anatomy in one dimensional (1D) space

A point computational anatomy with uncertainties in 1D space

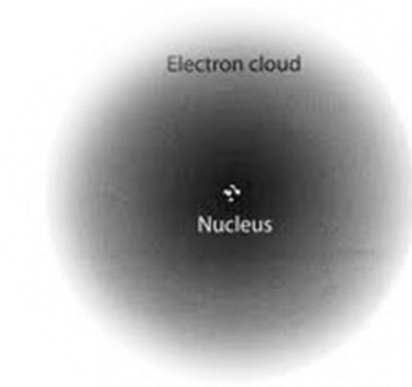


Vector of a point anatomy:

$$\mathbf{a} = (\mathbf{q})$$

Position vector:

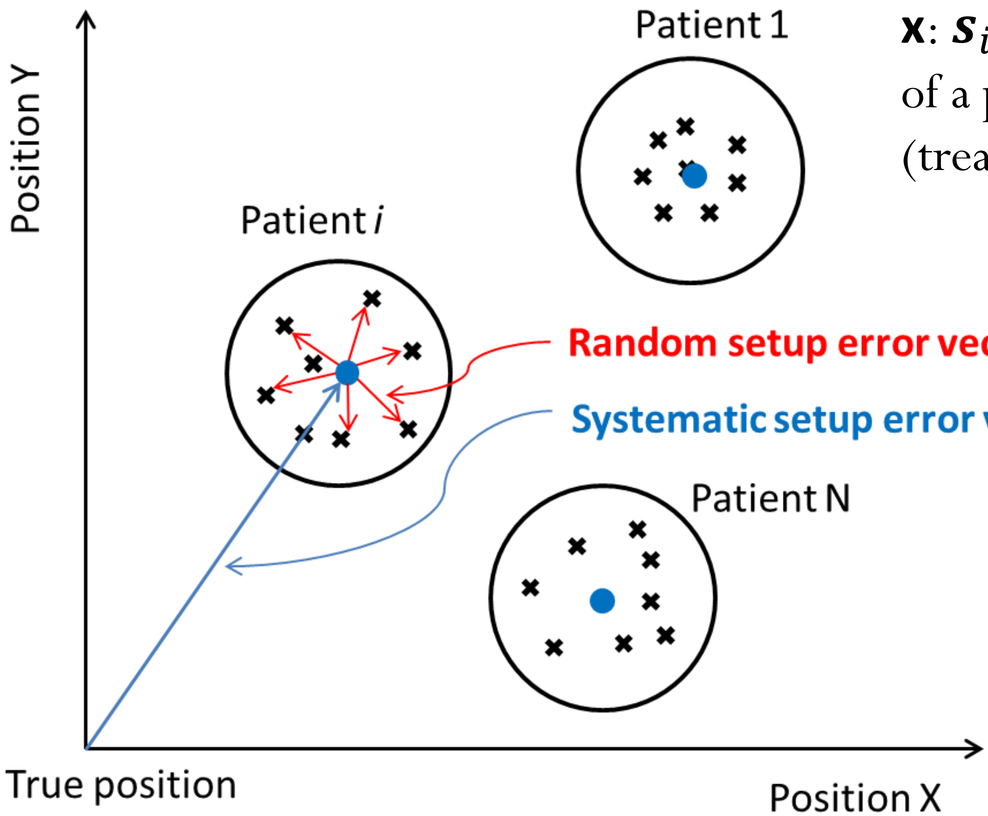
$$\mathbf{q} = (m + k\sigma)$$



1D Gaussian distribution for uncertainties:

$$p(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left\{-\frac{(x-m)^2}{2\sigma^2}\right\}$$

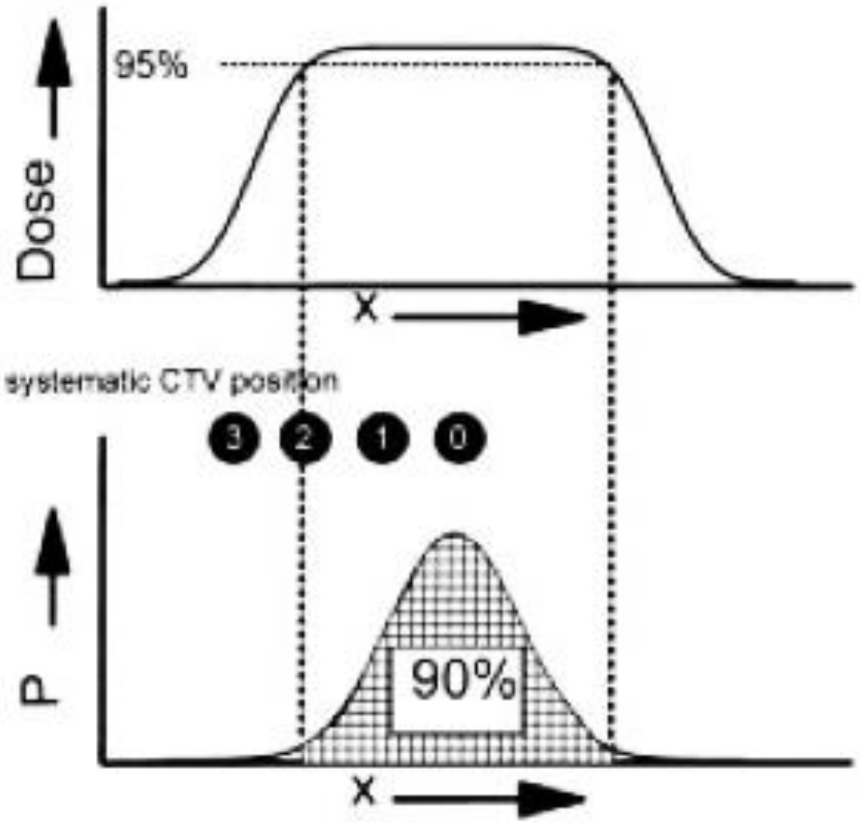
A target of each patient is dealt with as a 3D vector of "a point" target (tumor) in radiation therapy



x: $\boldsymbol{s}_{i,k}$, a 2D position vector for a point target of a patient $\boldsymbol{i}$ ($\boldsymbol{i}$=1 to N) at a *k*th fraction (treatment time) (*k*=1 to M)

Stroom JC, Green Journal 64 (2002) 75–83

M. van Herk said that 95% of a prescribed dose should cover 90% of position variations in all point CTVs



van Herk's safety margin model

PTV margin = $2.5\sigma_s + 0.7\sigma_r$

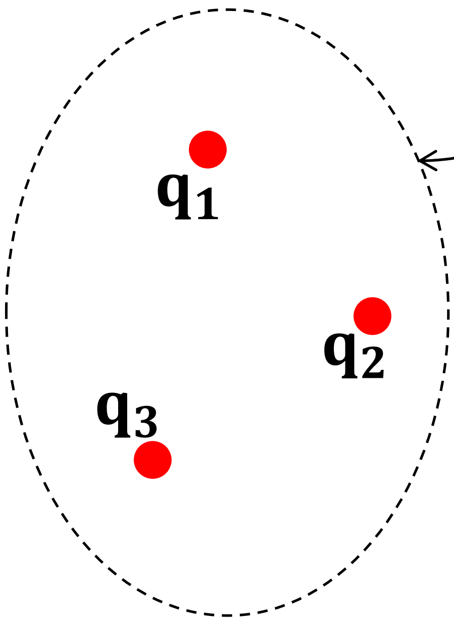
σ_s : Quadratic sum of SD* of all systematic errors

σ_r : Quadratic sum of SD of all random errors

*SD: Standard deviation

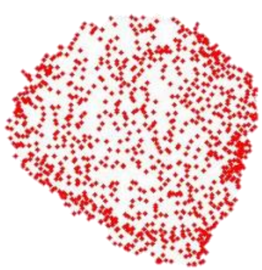
Fig. 3 in a paper of M. van Herk, et al. Red Journal, Vol. 47, No. 4, pp. 1121–1135, 2000

Computational anatomy with three points



$$\mathbf{a} = (\mathbf{q}_1, \mathbf{q}_2, \mathbf{q}_3)^T$$
$$= (x_1, y_1, x_2, y_2, x_3, y_3)^T$$

$\mathbf{a}$: Vector of an anatomy consisting of three points

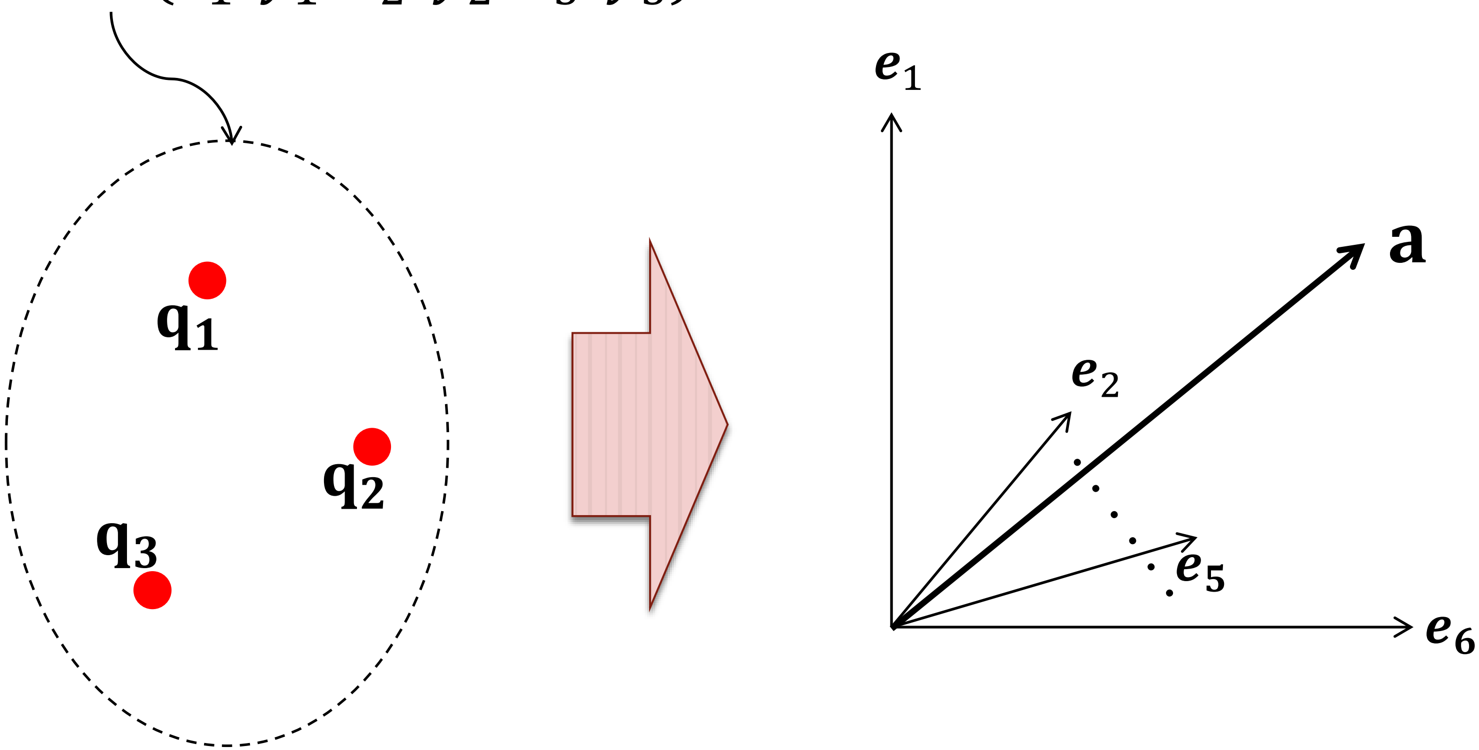


$\mathbf{q}_i = (x_i, y_i)$: 2D-space position vector (row vector) of an anatomy

Computational anatomy in 6D space

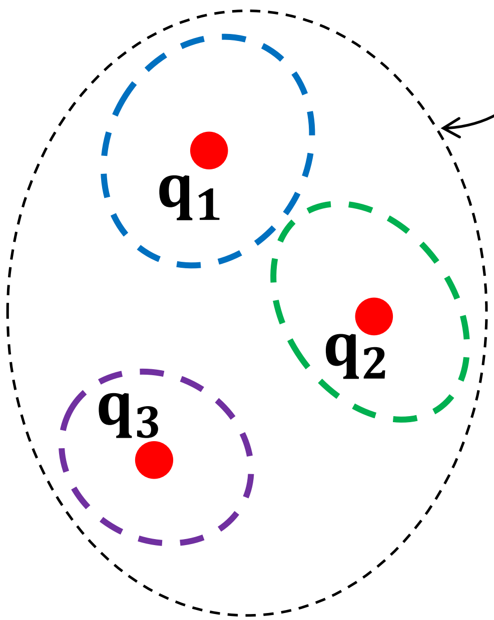
An anatomical shape is expressed by a vector!

$$\mathbf{a} = (\mathbf{q}_1, \mathbf{q}_2, \mathbf{q}_3)^T$$
$$= (x_1, y_1, x_2, y_2, x_3, y_3)^T$$



Computational anatomy with a statistical model in multidimensional space

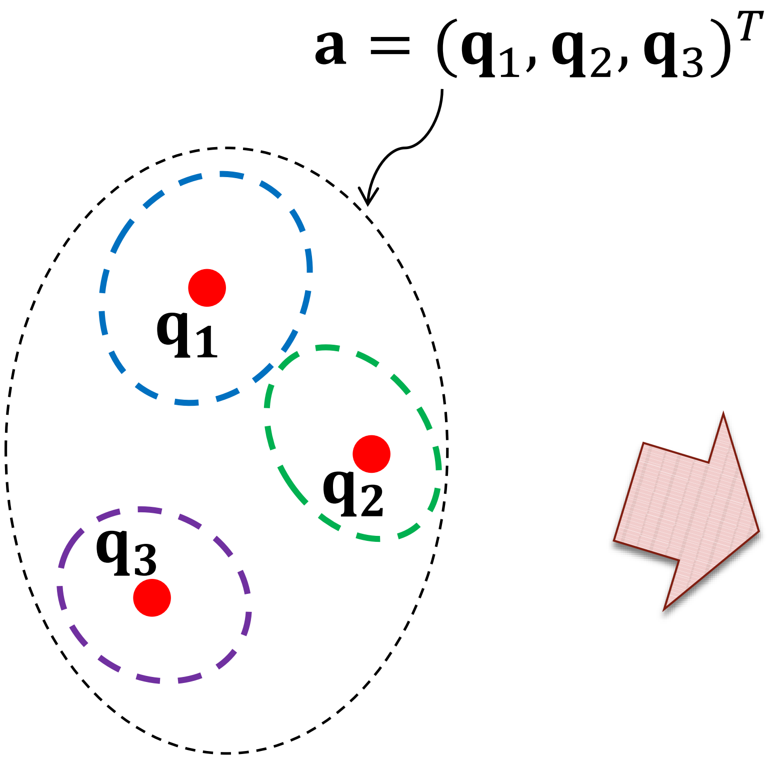
Each point on an anatomical shape may change by patient and/or fraction.



$$\mathbf{a} = (\mathbf{q}_1, \mathbf{q}_2, \mathbf{q}_3)^T$$

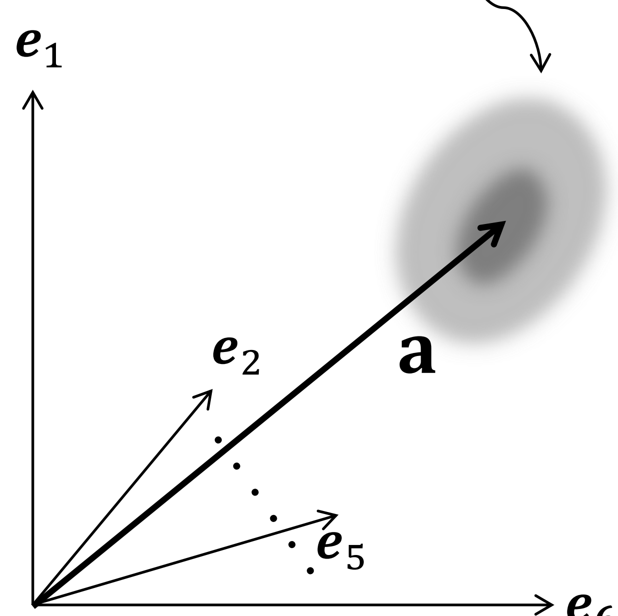
2D Gaussian distribution for uncertainties

Computational anatomy with uncertainties in 6D space



6D Gaussian distribution for uncertainties:

$$p(\boldsymbol{x}) = \frac{1}{\sqrt{(2\pi)^6 |\boldsymbol{V}_6|}} \exp\left(-\frac{1}{2}(\boldsymbol{x}, \boldsymbol{V}_6^{-1}\boldsymbol{x})\right)$$



Covariance matrix V and eigenvectors e_i

Covariance matrix for $\mathbf{a}_i = (x_{1i}, x_{2i}, x_{3i}, y_{1i}, y_{2i}, y_{3i})^T$ is

$$\boldsymbol{V} = \frac{1}{N}\sum_{i=1}^{N} \boldsymbol{a}^{\mathrm{T}} \boldsymbol{a}$$

Variance

$$= \begin{pmatrix} \sum_{i=1}^{N}(x_{1i} - \bar{x}_1)^2/N & & & \\ & \ddots & & \\ & & \sum_{i=1}^{N}(x_{3i} - \bar{x}_3)^2/N & \\ & & & \ddots \\ & & & & \sum_{i=1}^{N}(y_{3i} - \bar{y}_3)/N \end{pmatrix}$$

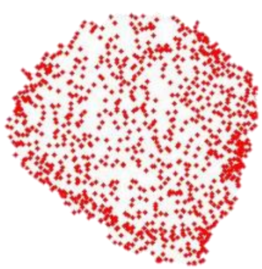
$\boldsymbol{V}$ is $M \times N$ matrix.

$\boldsymbol{x}_i = (x_{1i} \cdots x_{\alpha i} \cdots x_{Mi})^{\mathrm{T}}$
i: Patient number, $1 \le i \le N$
N: Number of patients
α: Point number $1 \le \alpha \le M$
M: Number of points

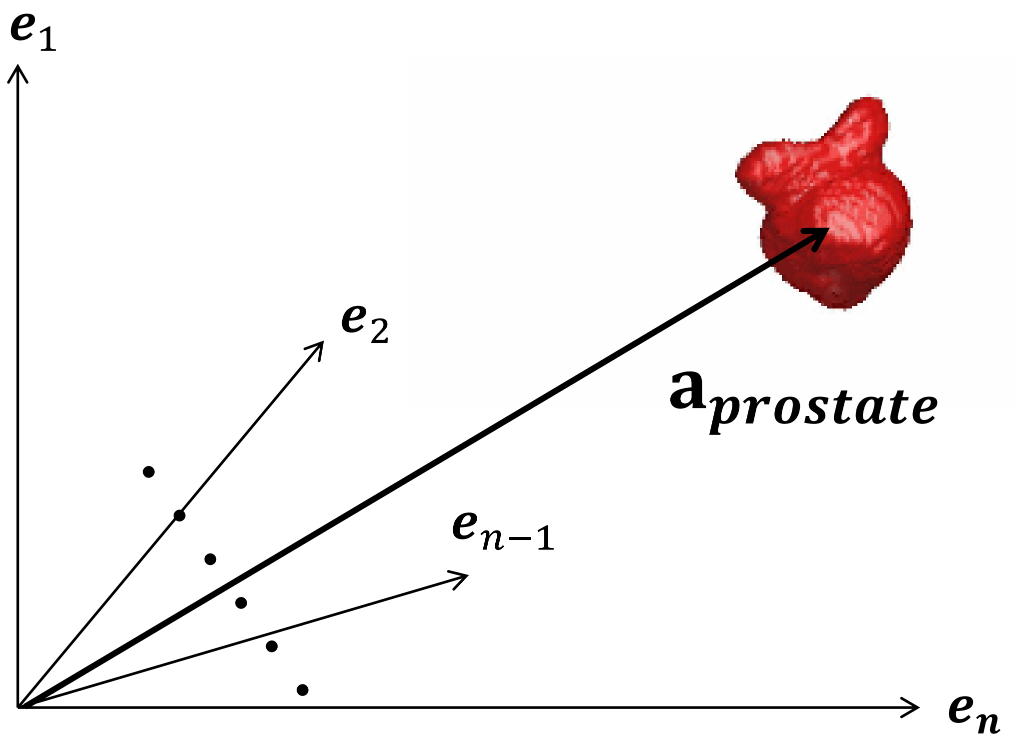
Eigenvectors, $\boldsymbol{e}_1, \boldsymbol{e}_2, \cdots, \boldsymbol{e}_N$, are calculated from this covariance matrix by a singular value decomposition (SVD).

Statistical computational anatomy in multidimensional space

Computational anatomies may be useful for developing mathematical models with uncertainties **to predict something related to anatomy in radiotherapy such as organ translations and/or organ deformations** by patient and/or fraction.

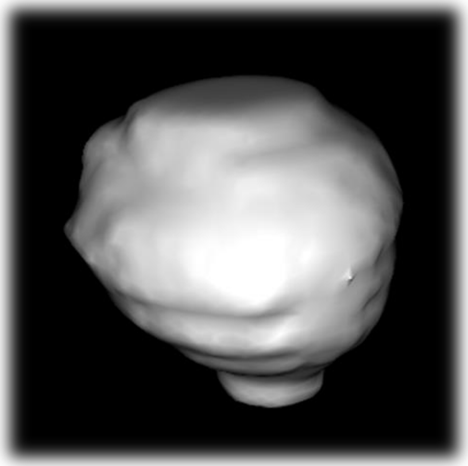


Point distribution model

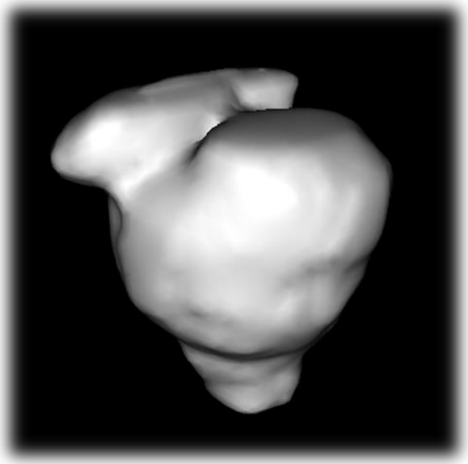


Definition of CTVs for prostate cancer radiation therapy

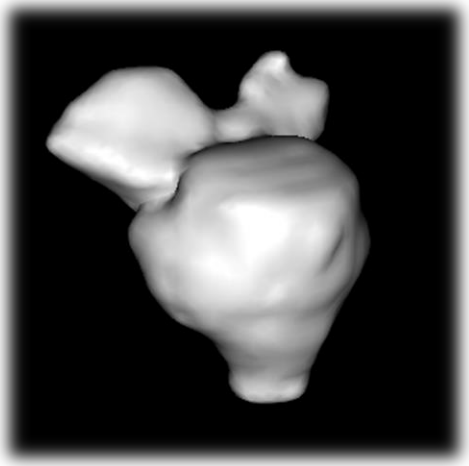
Risk group	PSA*	Gleason score	TNM	Definition of CTV
Low risk	≤10	≤6	T1a - T2a	Prostate
Intermediate risk	10.1 - 20	7	T2b	Prostate＋Seminal vesicles 1cm
High risk	20＜	8 - 10	T2c -	Prostate＋Seminal vesicles 2cm



Low-risk CTV (Prostate)



Intermediate-risk CTV

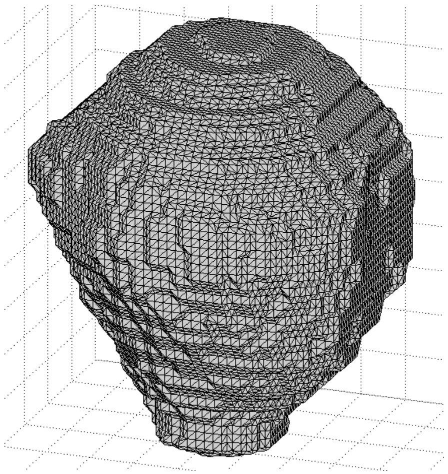


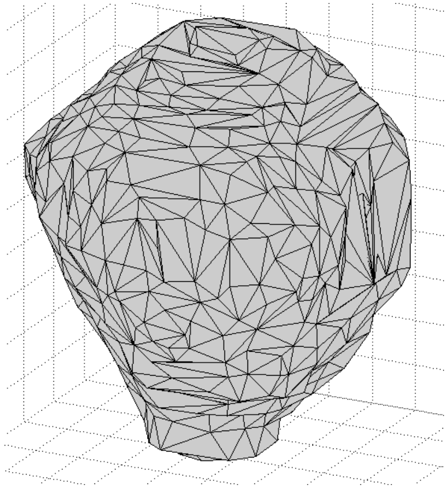
High-risk CTV

*PSA：Prostate specific antigen

How to determine PTV margins including shape variations of CTVs

Manual contouring of CTV
↓
Reading CTV from DICOM-RT*
↓
Production of isotropic CTV
↓
Registration based on centroid matching
↓
Triangulation based on marching cubes method
↓
Decimation of vertices based on quadric error metrics
↓
Determination of correspondences
↓
Calculation of SD** of interfractional shape variations





*DICOM-RT: Digital imaging communications in medicine for radiation therapy
**SD: Standard deviation

Calculation of PTV margins

Anisotropic PTV margins in three directions [LR(x), AP(y), SI(z)] were calculated by using a Yoda's PTV margin model*. The PTV margin in x direction is shown below:

$$\text{PTV margin}\ (x) = 2.1\sigma_s(x) + 0.7\sigma_r(x)$$

$$\sigma_s(x) = \sqrt{\frac{1}{N}\sum_{i=0}^{N}\left(m_{ss}(x,i) - \overline{m_{ss}(x)}\right)^2} \qquad \sigma_r(x) = \sqrt{\sigma_{rs}^2(x) + \sigma_{rf}^2(x)}$$

$\sigma_s(x)$: Square root of quadratic sum of SD of all systematic errors

$\sigma_r(x)$: Square root of quadratic sum of SD of all random errors

$m_{ss}(x,i)$: Systematic error vector of patient setup for i-th patient

$\overline{m_{ss}(x)}$: Mean systematic error vector of patient setup for all patients

$\sigma_{rf}(x)$: SD of random error for interfractional shape variation

$\sigma_{rs}(x)$: SD of random error of patient setup

N: Number of patients

*Yoda K, et al., *Med Phys* 2011; vol.38: 3913-3914

How to obtain interfractional shape variations (Deviation of an organ's surface deformation)

Point distributions of all fractions (j=1 to M) for all patients (i=1 to N)

Co-variance matrix of all fractions for *i*-th patient

SD $\sigma_{rf}(x)$ of on CTV surface derived from $\mathrm{diag}(\boldsymbol{V_i}, x)$:

1st *i*-th patient *N-th*

$$\boldsymbol{V_i} = \frac{1}{M}\sum_{j=1}^{M} \boldsymbol{q}'_{ij}\boldsymbol{q}'^{T}_{ij}$$

$$\sigma_{rf}(x) = \sqrt{\frac{1}{N}\sum_{i=0}^{N} \sigma_{rf}{}^{2}\ (x, i)}$$

$$\sigma_{rf}(x, i) = \sqrt{\frac{1}{P}\sum_{k=0}^{P} \sigma_{rf}{}^{2}\ (x, i, k)}$$

CTV surface position vector:

$$\boldsymbol{q}_{ij} = (x_{ij1}, \cdots, x_{ijP}, y_{ij1}, \cdots, y_{ijP}, z_{ij1}, \cdots, z_{ijP})^{T}$$

$$\boldsymbol{q}'_{ij} = \boldsymbol{q}_{ij} - \overline{\boldsymbol{q}}_{\boldsymbol{i}}$$

No. of points on CTV surface : P

Computational approach for determination of PTV margins based on statistical shape analysis

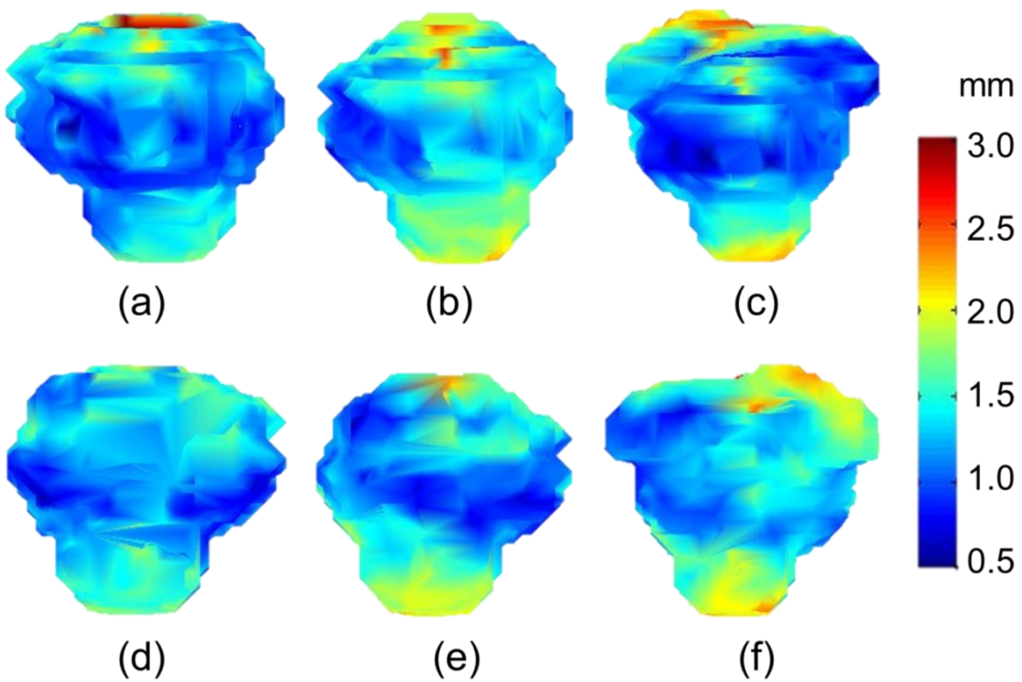


Figure 3 An illustration of local SDs for shape variations projected on the surface of reference CTV for case No.1. (a), (b), and (c) are anterior-posterior view and (d), (e), and (f) are posterior-anterior view of low-risk, Intermediate-risk, high-risk CTV.

PTV margins

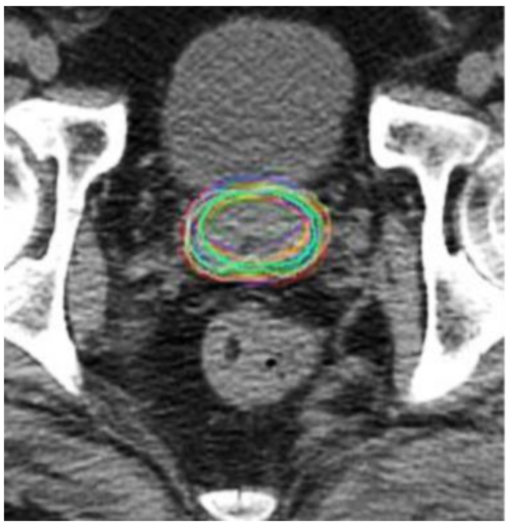
Shibayama Y, et al. AAPM 2015

Niche #2

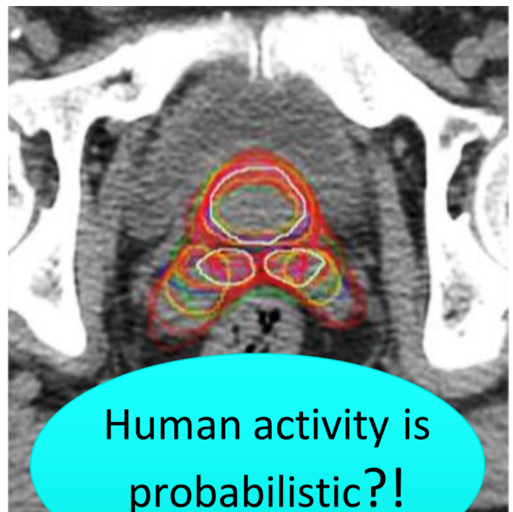
Principal component analysis

Inter-observer variation for tumor contouring

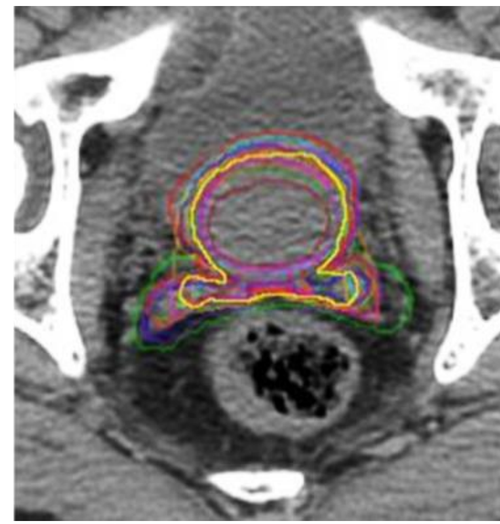
Intra- and inter-observer variability of target delineations (or drawing contours)



Low-risk CTV



Interme… isk CTV



High-risk CTV

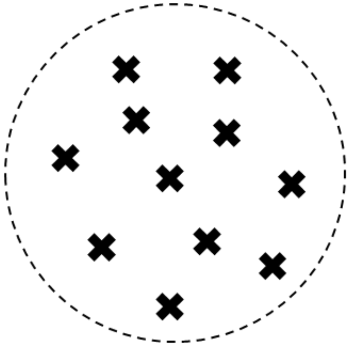
Human activity is probabilistic?!

Statistical shape modeling @ radiation treatment planning

Modeling of interobserver variations of CTV regions using a principal component analysis (PCA) for prostate cancer radiotherapy

Modeling of interobserver variations of CTV

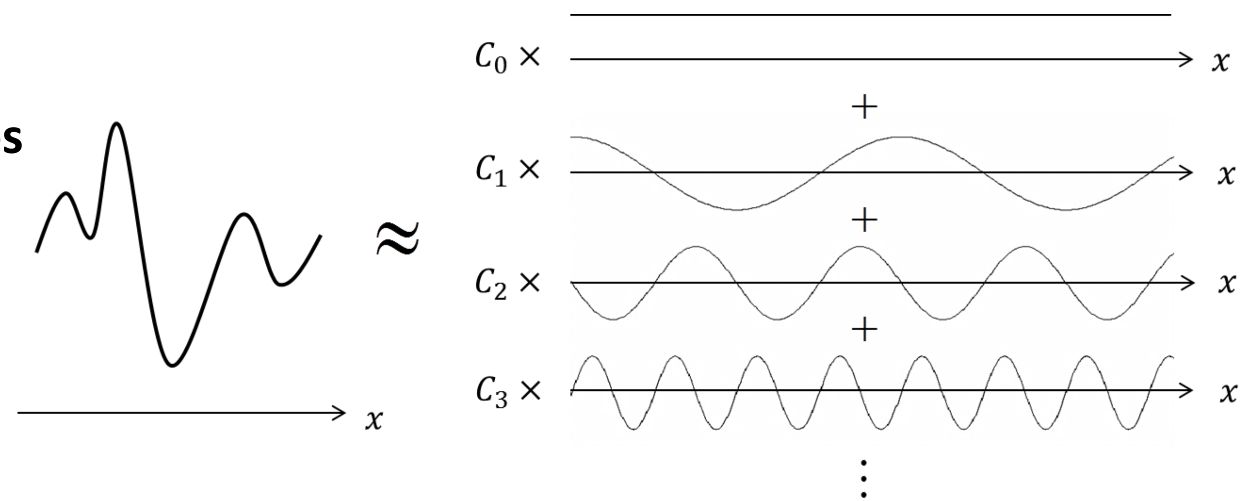
Shibayama S, Arimura H, et al. CARS 2014



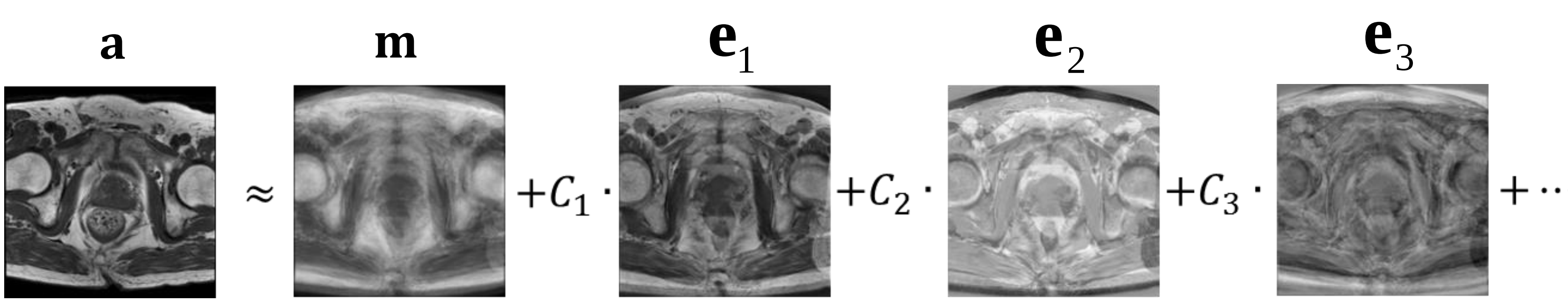
Point distribution model

What is a principal component analysis (PCA)?

Fourier series expansion (linear combination of cos and/or sin waves, which are orthogonal to each other like orthogonal vectors)



Principal component analysis (or Karhunen-Loève transform)



What is the mathematical meaning of PCA?

$$J = \frac{1}{2}\boxed{\|\boldsymbol{x} - (c_1\boldsymbol{e}_1 + c_2\boldsymbol{e}_2 + \cdots + c_N\boldsymbol{e}_N)\|^2} \rightarrow \min$$

Take the derivative of J except for c_i

$$\frac{\partial J}{\partial c_i} = \frac{1}{2}\frac{\partial J}{\partial c_i}\left(\boldsymbol{x} - \sum_{j=1}^{n} c_j\boldsymbol{e}_j , \boldsymbol{x} - \sum_{k=1}^{n} c_k\boldsymbol{e}_k\right) = 0$$

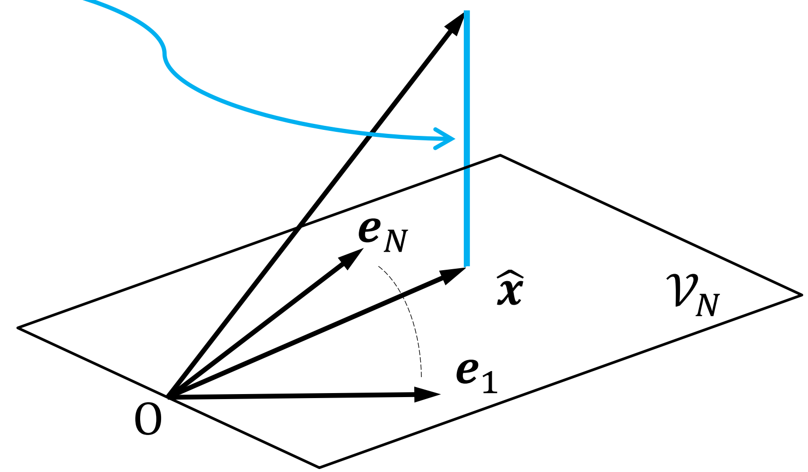
$$\frac{\partial J}{\partial c_i} = c_i - (\boldsymbol{x}, \boldsymbol{e}_i)$$

$$c_i = \boldsymbol{e}_i{}^{\mathrm{T}}\,(\boldsymbol{q} - \overline{\boldsymbol{q}})$$

Therefor, coefficient vector $\boldsymbol{b}$ is

$$\boldsymbol{c} = \boldsymbol{U}^{\mathrm{T}}\,(\boldsymbol{q} - \overline{\boldsymbol{q}})$$

$\boldsymbol{x} = \boldsymbol{q} - \overline{\boldsymbol{q}}$



A projection of a vector $\boldsymbol{x}$ to a low dimensional space

$$\hat{\boldsymbol{x}} = c_1\boldsymbol{e}_1 + c_2\boldsymbol{e}_2 + \cdots + c_i\boldsymbol{e}_i + \cdots + c_N\boldsymbol{e}_N$$

$$\boldsymbol{c} = (c_1\ c_2\ \cdots\ c_N)^{\mathrm{T}}$$
$$\mathbf{U} = (\boldsymbol{e}_1\ \boldsymbol{e}_2\ \cdots\ \boldsymbol{e}_N)$$

Statistical computational anatomy

- Statistical computational anatomy

$$\boldsymbol{a} = \boldsymbol{m} + \mathbf{U}\boldsymbol{c}$$

$$= \boldsymbol{m} + c_1\boldsymbol{e_1} + c_2\boldsymbol{e_2} + \cdots + c_N\boldsymbol{e_N}$$

- Coefficient vector c

  for an unknwn anatomy

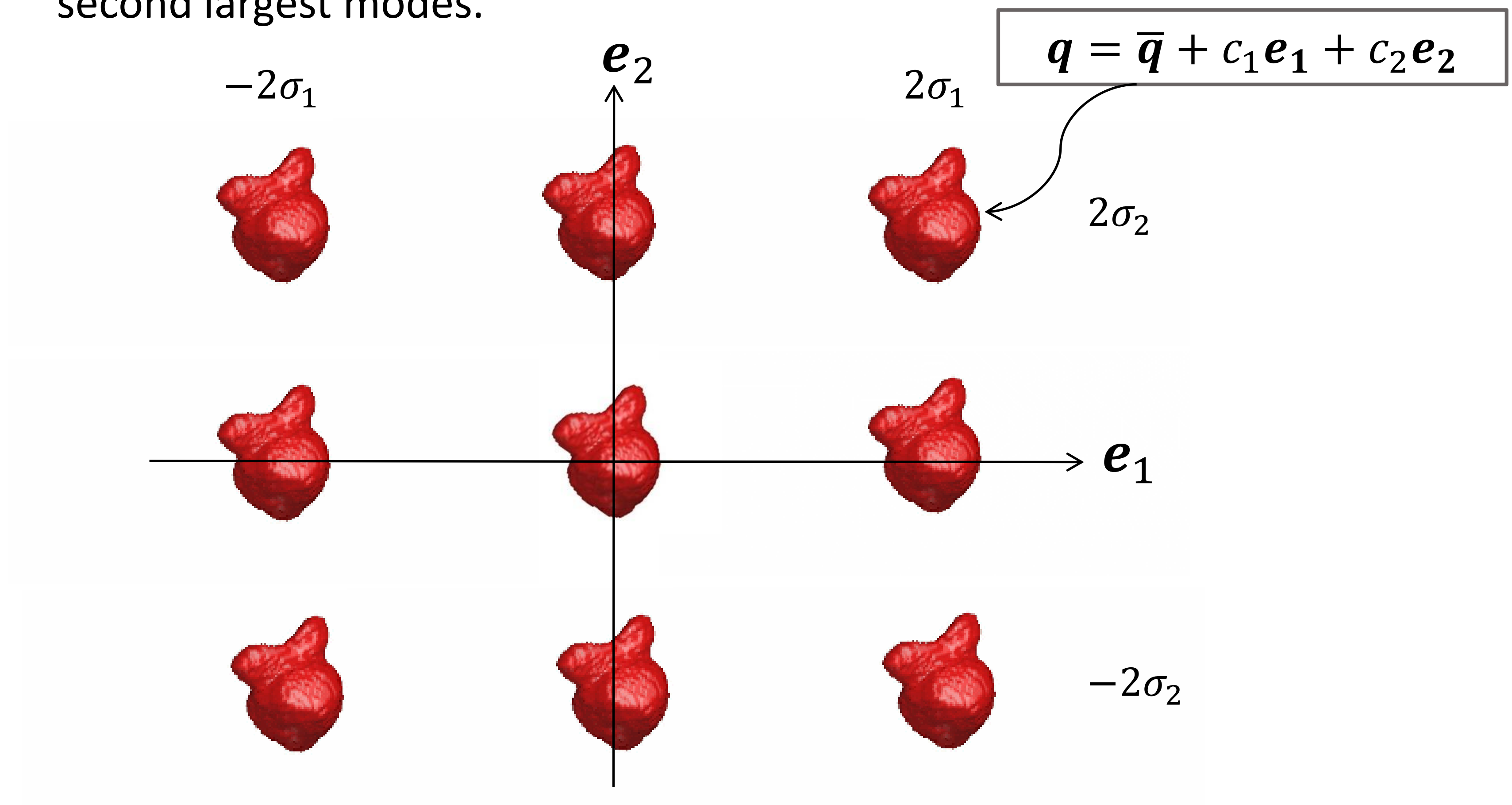
$$\boldsymbol{c} = \mathbf{U}^{\mathrm{T}}\ (\boldsymbol{a}' - \boldsymbol{m})$$

$\boldsymbol{a}'$ **:** an unknown anatomy

$\boldsymbol{a}$ **:** Arbitrary computational anatomy
$\boldsymbol{m}$ **:** Mean CTV
N **:** Number of eigenmodes
$\boldsymbol{c} = (c_1\ c_2\ \cdots\ c_N)^{\mathrm{T}}$
c_i: Coefficient
$\mathbf{U} = (\boldsymbol{e}_1\ \boldsymbol{e}_2\ \cdots\ \boldsymbol{e}_N)$
i: Eigenmode number

Statistical CTV model of a high-risk group with respect to inter-observer variation of contours

Shape variations of statistical CTV model produced by the first and second largest modes.



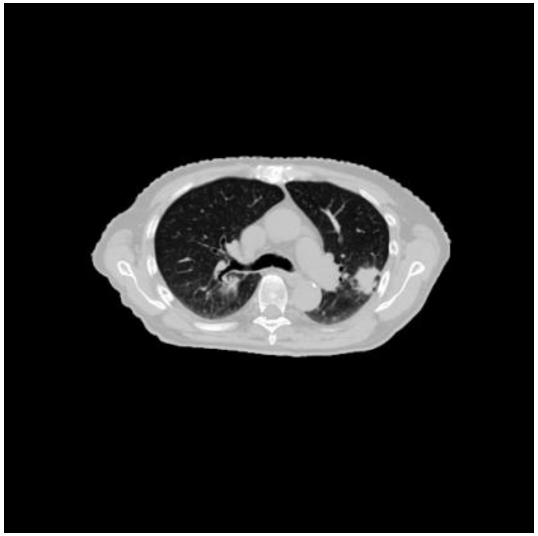
σ_i: Standard deviation corresponding i-th eigenvector

Niche #3

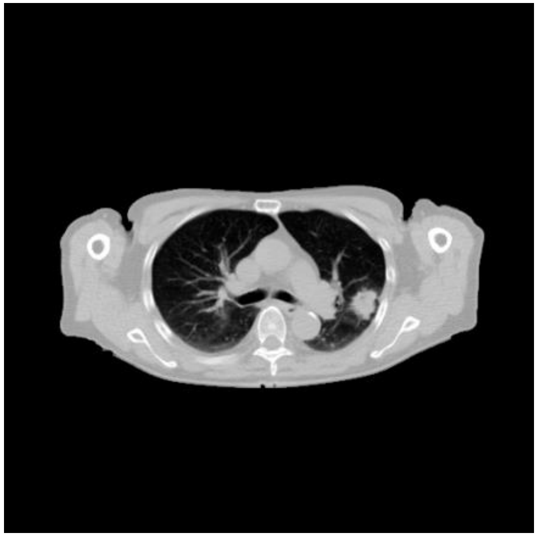
Machine Learning

Automated contouring of tumor regions

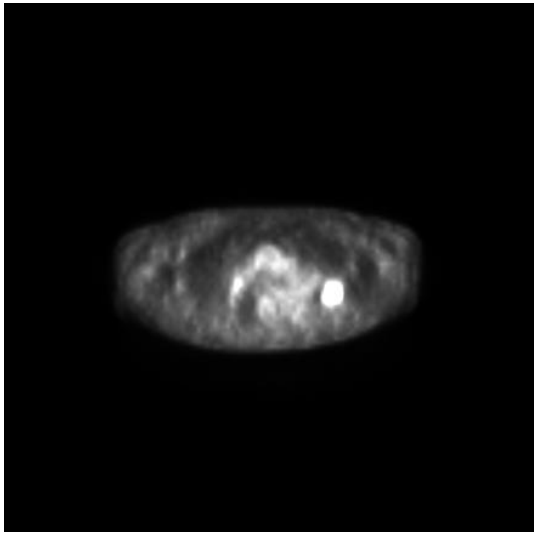
Automated delineation framework of lung tumor regions using three types of images



Planning CT image



Diagnostic CT image



FDG*-PET image
(annihilation radiation imaging)

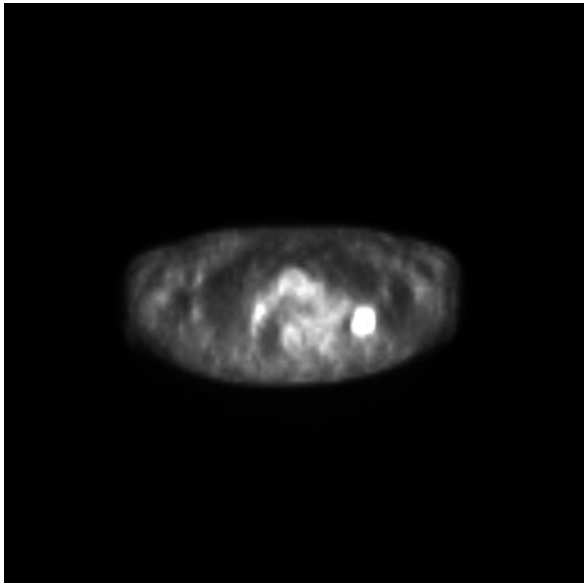
*2-deoxy-2-[fluorine-18] fluoro-D-glucose

Arimura H, et al. *Computational Intelligence in Biomedical Imaging*, Springer Science+Business Media New York, Springer, 2013.

SUV showing metabolic activities of cells including tumor cells

The SUV was calculated as a ratio of the radioactivity concentration of tissue at one time point to the injected dose of radioactivity concentration at that time point, divided by the body weight [*J Nucl Med* 2009;**50**(Suppl 1):11S-20S]:

$$\mathrm{SUV} = \frac{C(kBq/ml)}{D(MBq)/W(kg)}$$



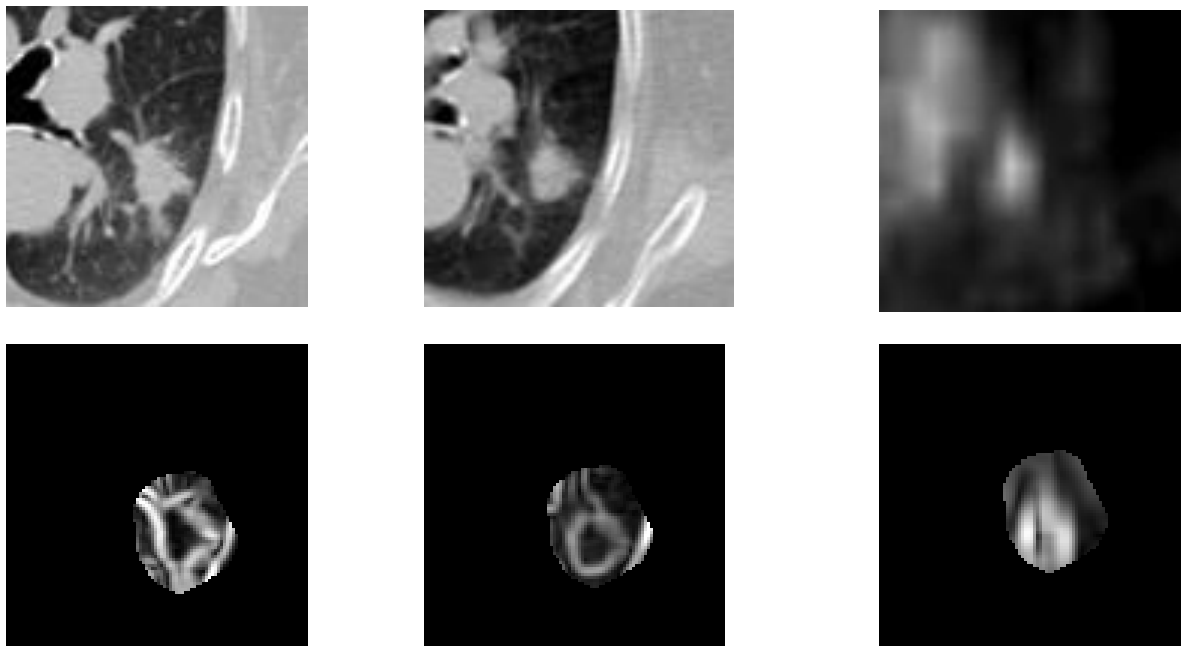
C : radioactivity concentration in kBq/ml obtained from the pixel value in the PET image multiplied by a cross calibration factor

D : injected dose of 18-FDG administered in MBq (decay corrected)

W : body weight of a patient in kilograms

Voxel-based image features obtained from multimodalities

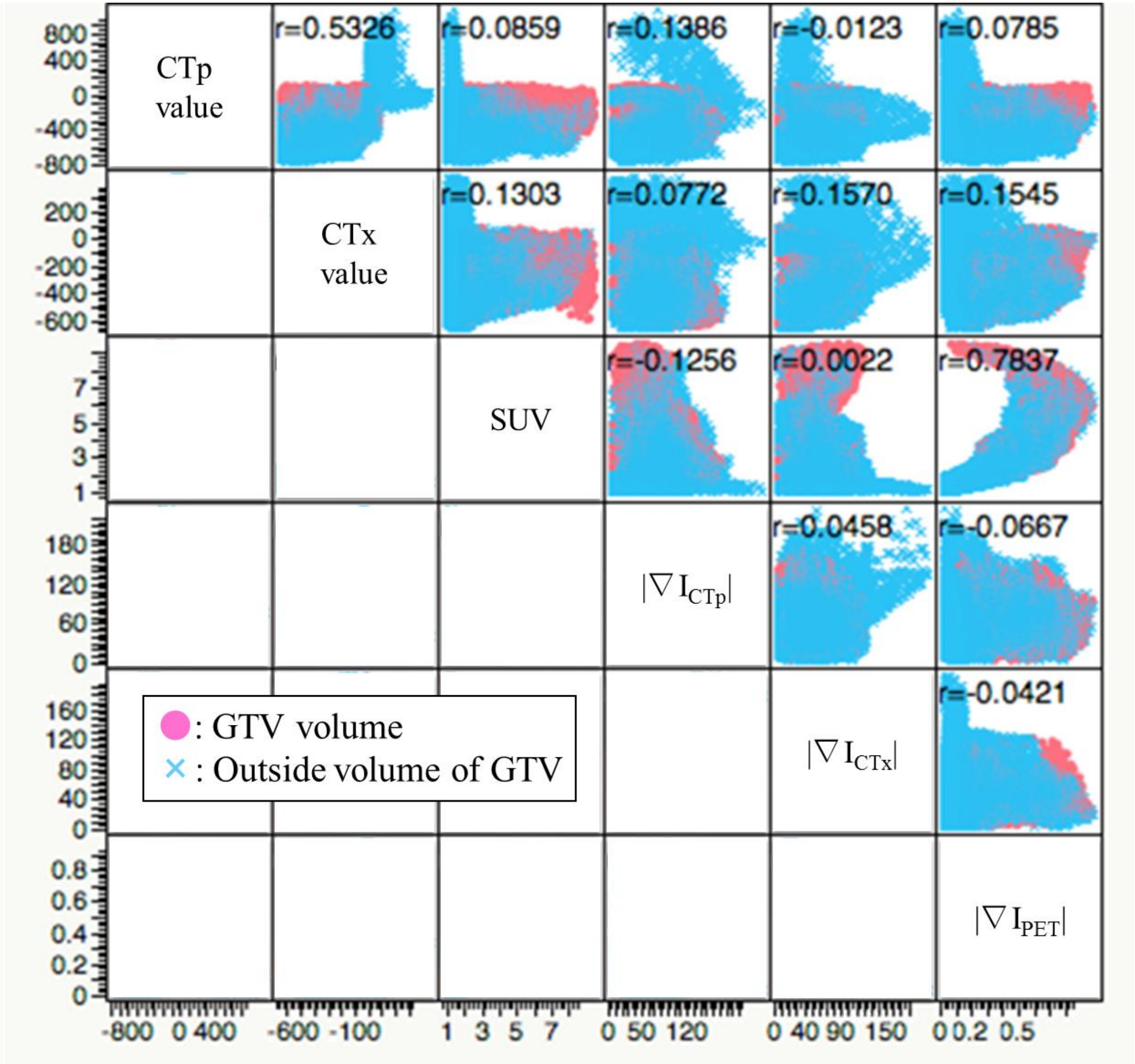
	Planning CT	Diagnostic CT (PET/CT)	PET (PET/CT)
Pixel value			
Magnitude of gradient vector			



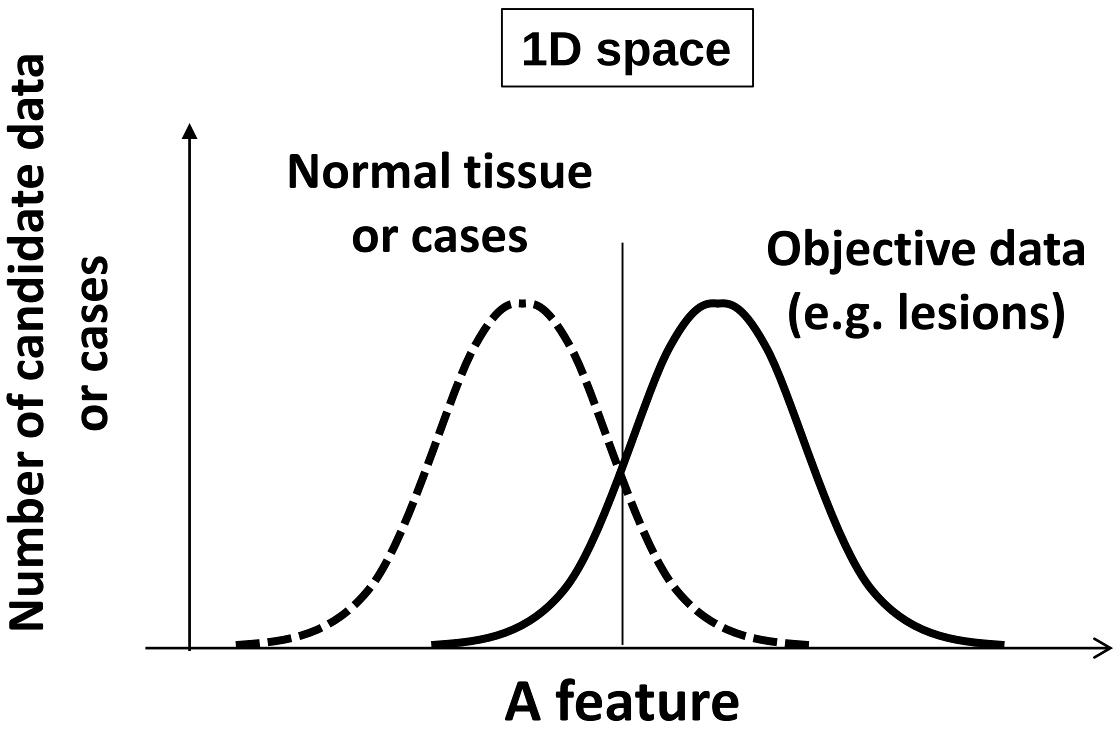
$$f(x, y, z) = ax + by + cz + d$$

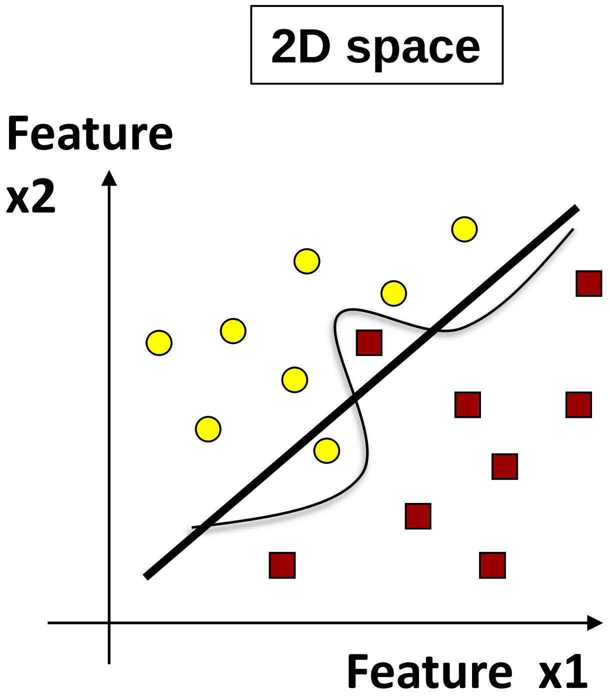
$$G = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2 + \left(\frac{\partial f}{\partial z}\right)^2} = \sqrt{a^2 + b^2 + c^2}$$

Multidimensional space of image features



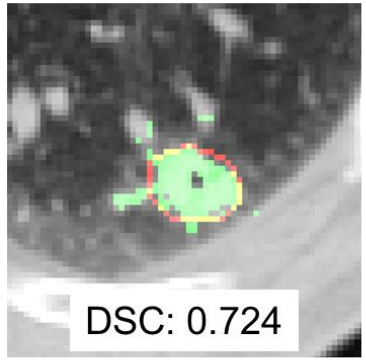
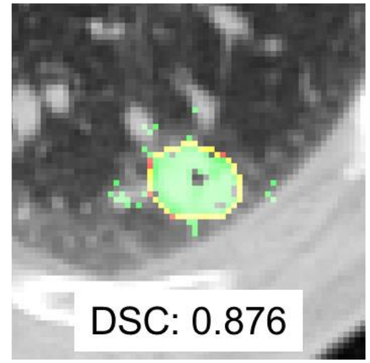
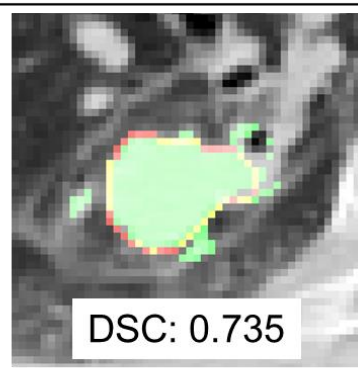
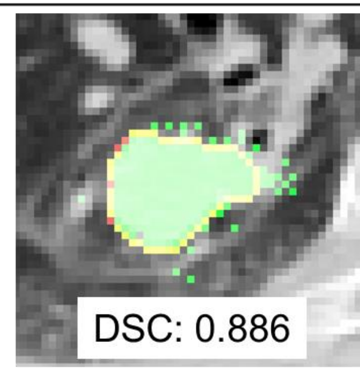
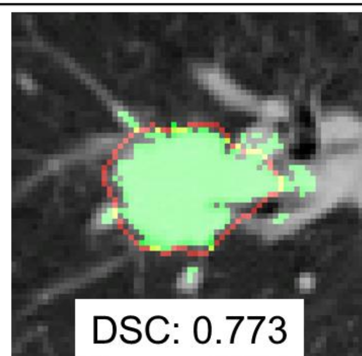
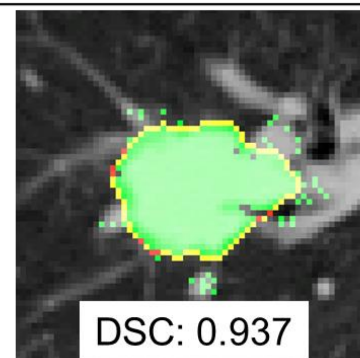
How to classify objective data from all data



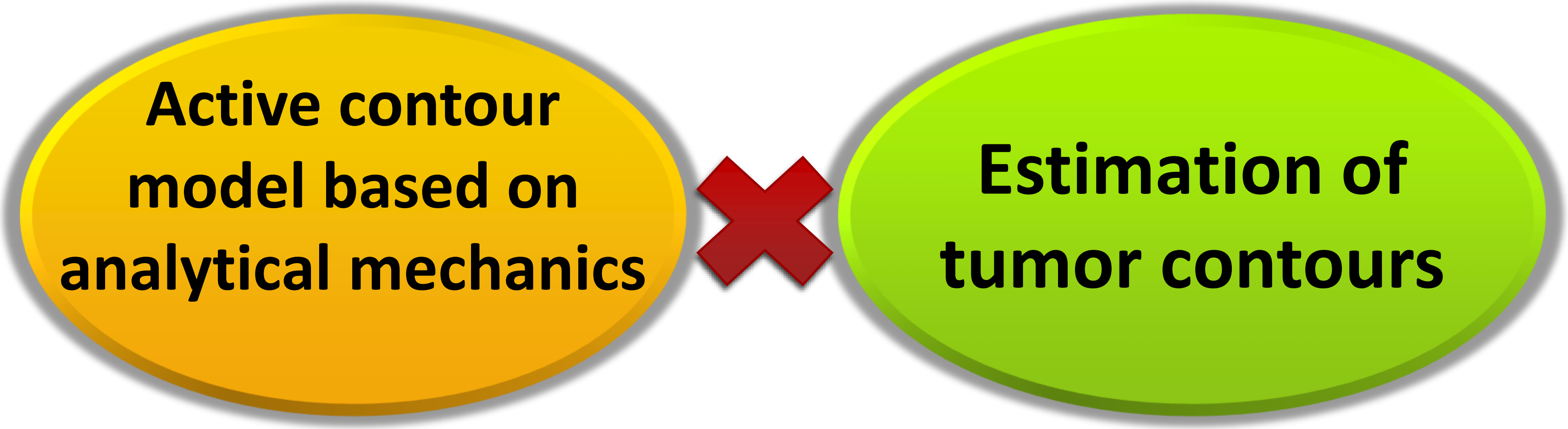


Determination of a linear or non-linear discrimination function to classify objective data from all data

Outputs of a machine learning system

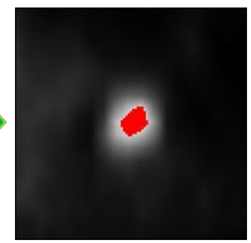
	3 features	6 features
Case 1 (Mixed GGO)		
Case 2 (Solid)		
Case 3 (Solid)		

Niche #4


Active contour model based on analytical mechanics
Estimation of tumor contours

Our basic idea for segmentation of lung tumors

→ **Image registration** →



Initial region based on SUV*

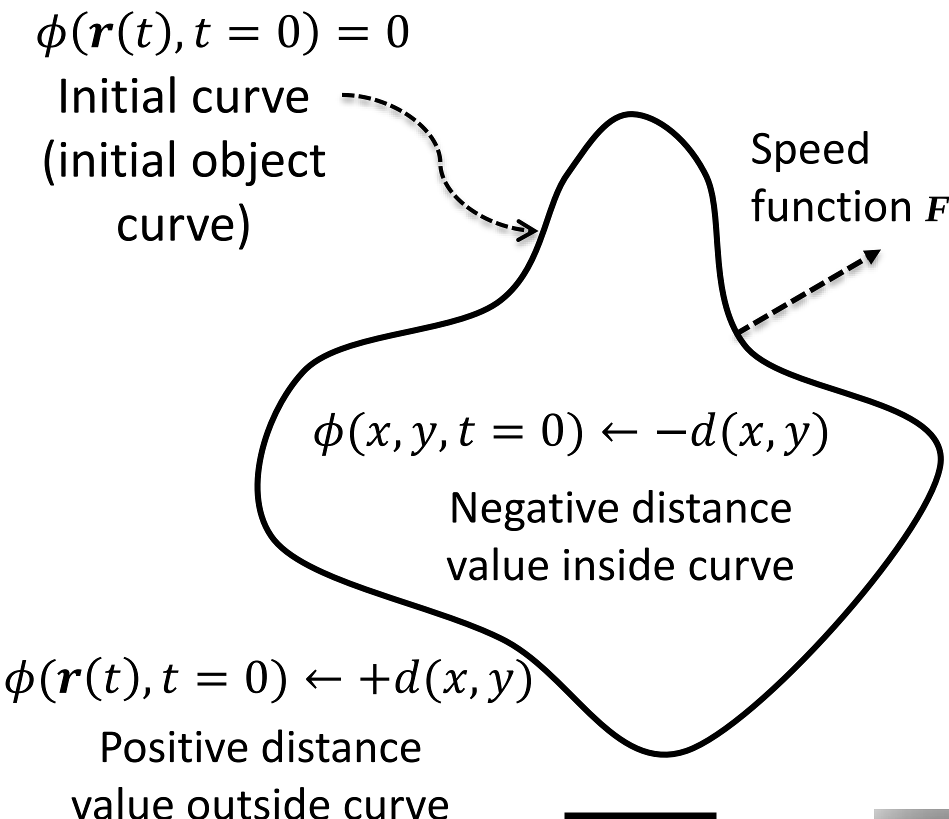
→ **OCS* method based on level set method**

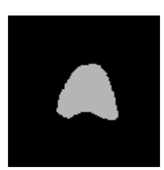
*Standardized uptake value

**Optimum contour selection

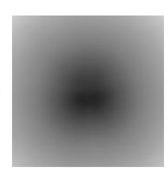
*Jin Z, Arimura H, et al. Journal of Radiation Research 2014

What is a level set method?
Ans. Active contour model





Binary image



Distance image

Definition of a curve: $\boldsymbol{r}(t) = \big(x(t), y(t)\big)$

This curve satisfies :

$$\phi(\boldsymbol{r}(t), t) = 0$$

By chain rule:

$$\frac{\partial\phi(\boldsymbol{r}(t), t)}{\partial t} + \frac{\partial\phi(\boldsymbol{r}(t), t)}{\partial\boldsymbol{r}(t)}\frac{d\boldsymbol{r}(t)}{dt} = 0$$

Finally, the level set equation is obtained as a partial differential equation:

$$\frac{\partial\phi(\boldsymbol{r}(t), t)}{\partial t} + F|\nabla\phi(\boldsymbol{r}(t), t)| = 0$$

What is the meaning of solving the level set equation?

Level set equation:

$$\frac{\partial \phi(\boldsymbol{r}(t), t)}{\partial t} + F|\nabla \phi(\boldsymbol{r}(t), t)| = 0$$

We can transform this equation as a Hamilton-Jacobi equation, which is equivalent to the Euler-Lagrange equation:

$$\frac{\partial \phi(\boldsymbol{r}(t), t)}{\partial t} + H(F, \phi(\boldsymbol{r}(t), t), t) = 0$$

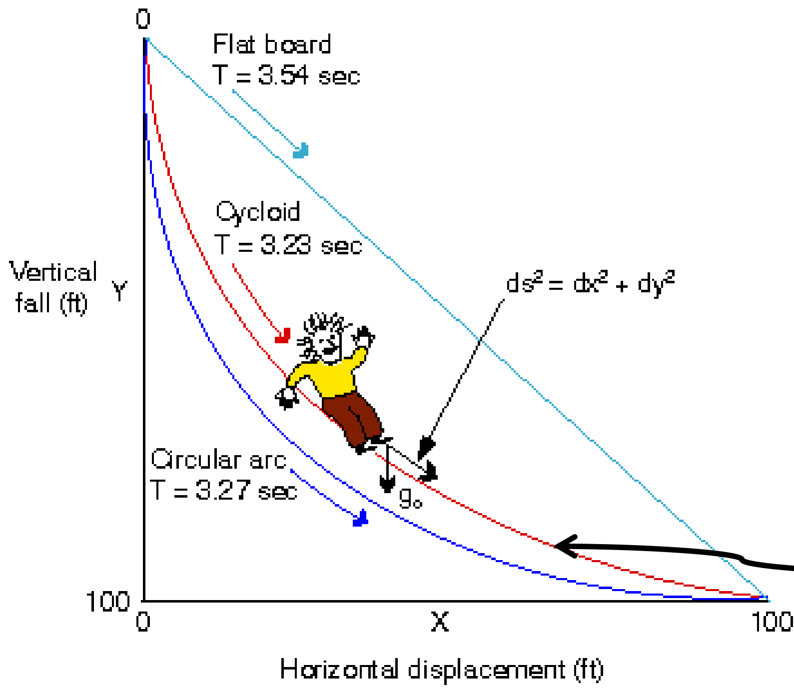
where $H(F, \phi(\boldsymbol{r}(t), t), t) = F|\nabla \phi(\boldsymbol{r}(t), t)|$, which is considered as a Hamiltonian

Solving (Integration) of a Hamilton-Jacobi equation of a contour means the prediction of the contour with a minimum energy (i.e., stable contour) from the analytical mechanics standpoint.

Principal of stationary action (least action)

The trajectory taken by an object between times t_1 and t_2 is the one in which the action is minimized.

Sliding slope problem



Stationary action : $\delta I = 0$

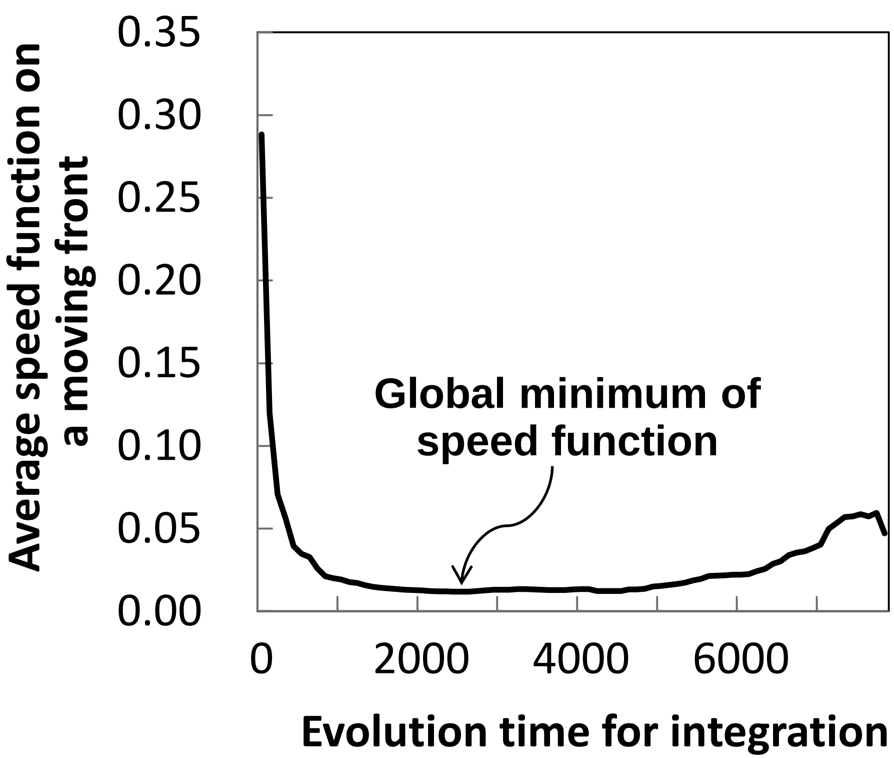
Action (integral of Lagrangian):

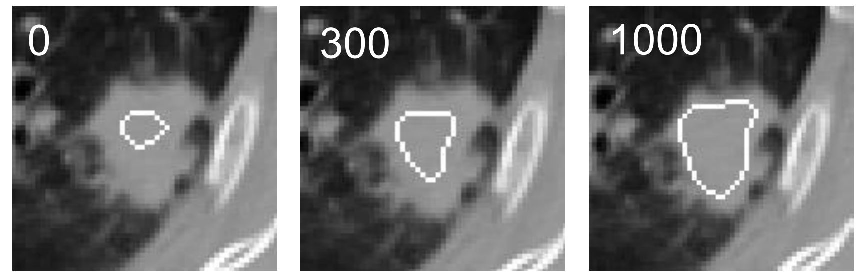
$$I(\boldsymbol{r}) = \int_{t_1}^{t_2} L\big(t, \boldsymbol{r}(t), \boldsymbol{r}'(t)\big) dt$$

Principal of Stationary Action
= Variational Principal

Brachistochrone curve :
curve of shortest path in time

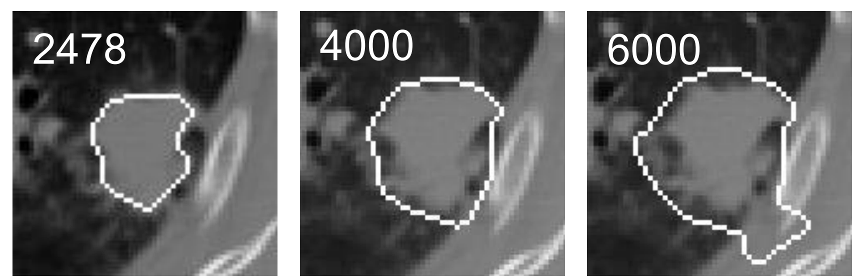
Optimum contour selection (OCS) method: searching for “global” minimum of mean of speed function





Initial contour

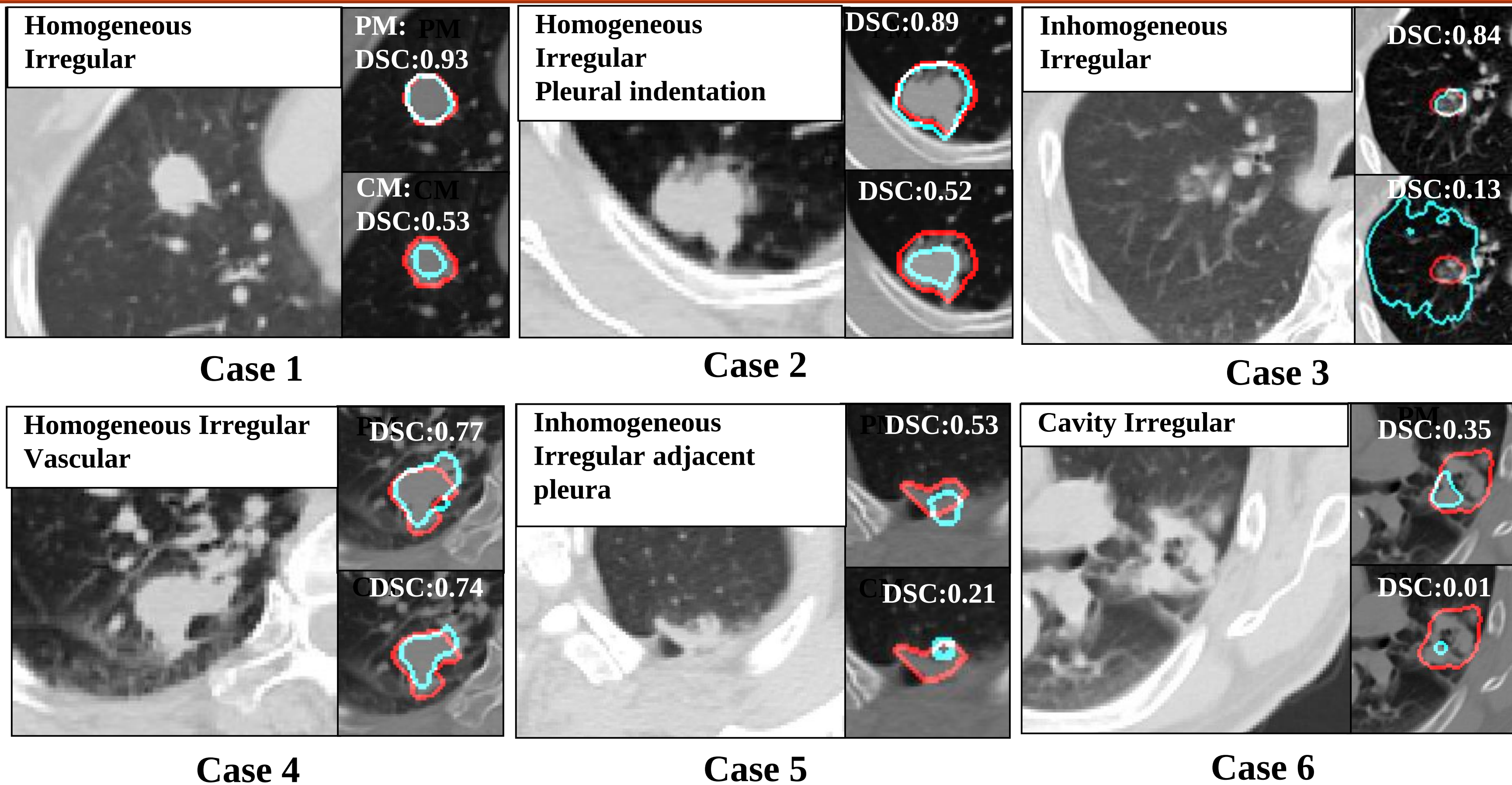
Contours during processing



Optimum contour

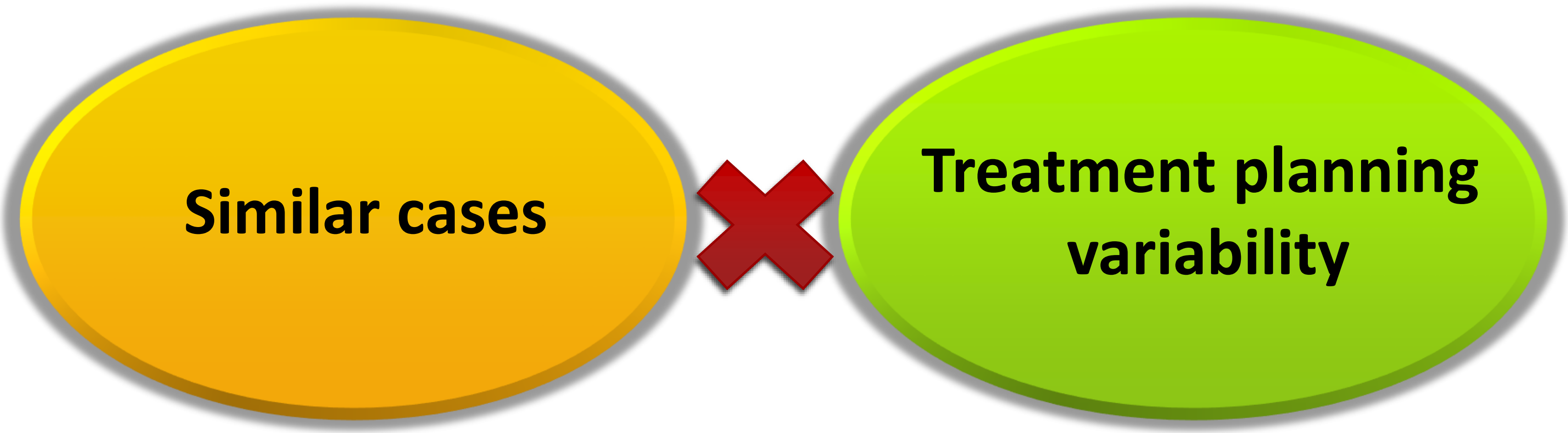
Contours during processing

Comparison in various tumors between results of proposed method and conventional method



: GTV contours determined by radiation oncologists (red line)
: Estimated GTV contours (blue line)
PM : Proposed method
CM : Conventional method

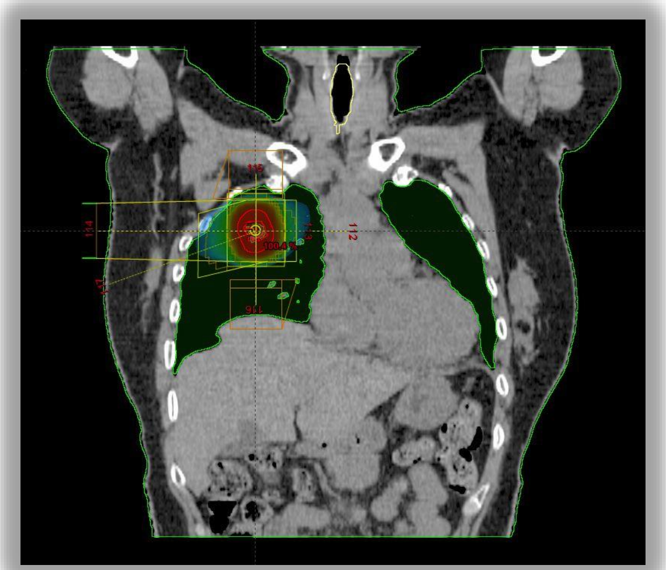
Niche #5



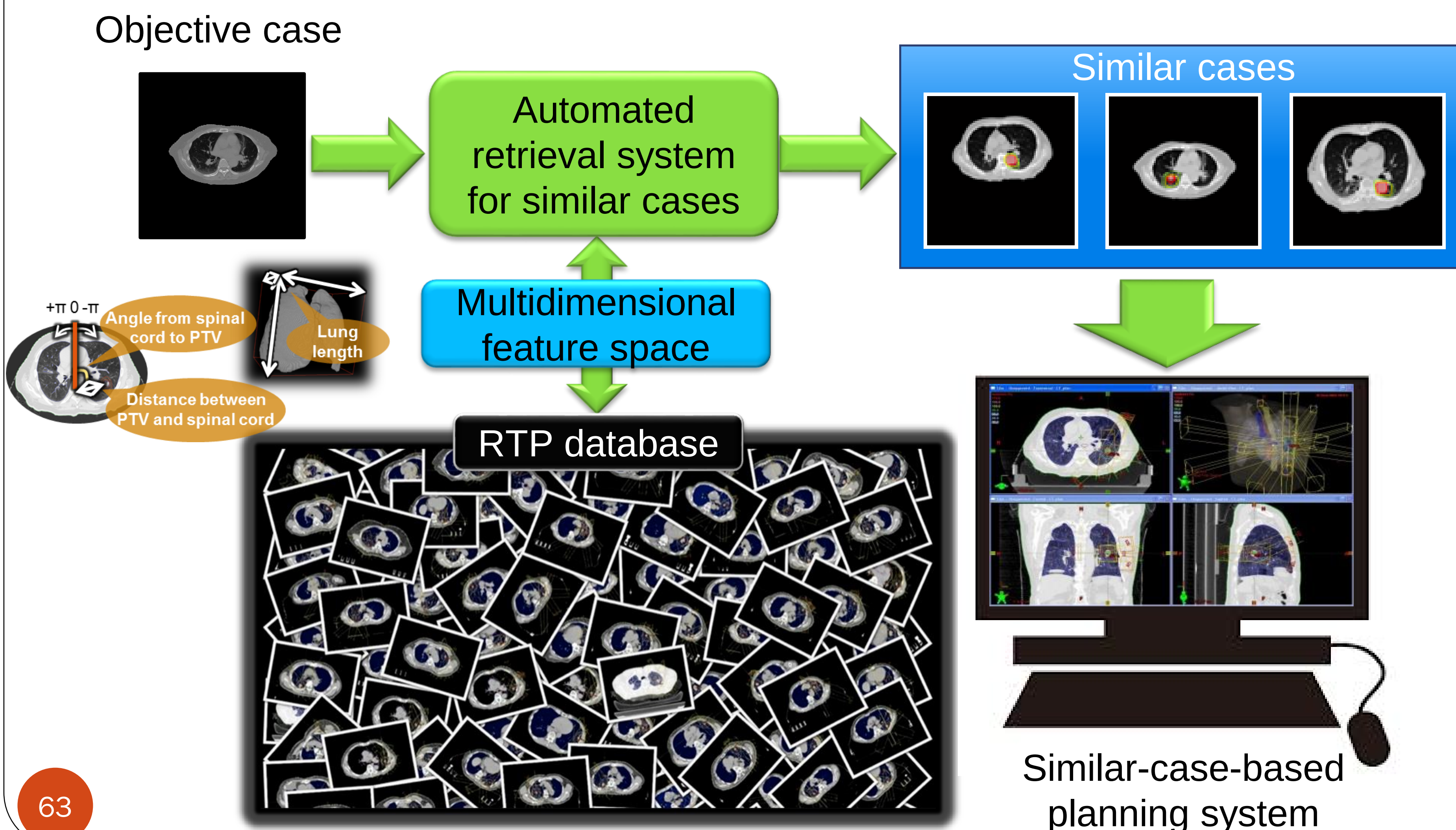
Variability of radiation treatment plans in stereotactic body radiation therapy (SBRT)

- Multiple (5-10) beams in coplanar and non-coplanar directions
- Highly conformal doses to tumors while minimizing doses to surrounding normal tissues

- Beam arrangements, which are manually determined by treatment planners
  - ✓ Reduce planning variation
  - ✓ Time-consuming
  - ✓ Difficult for less-experienced treatment planners

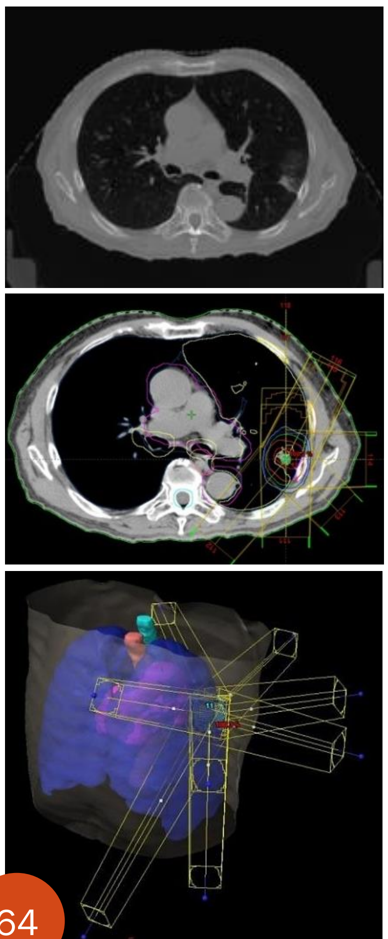


Similar-case based treatment planning system

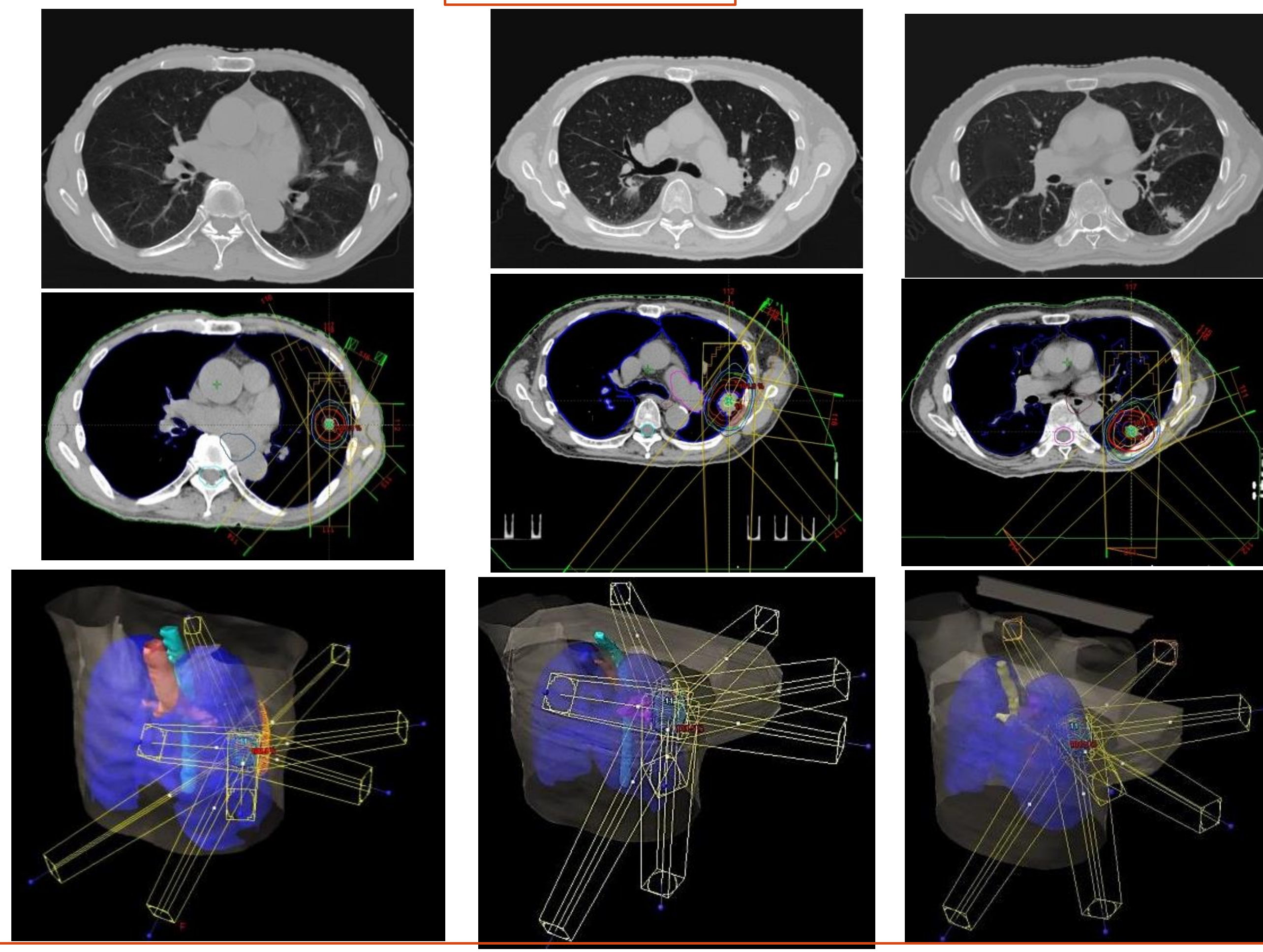


Feasibility of similar cases
(Magome T, JRR 2013;54:569
BioMed Res. Int. 2013, SPIE 2014; 9039)

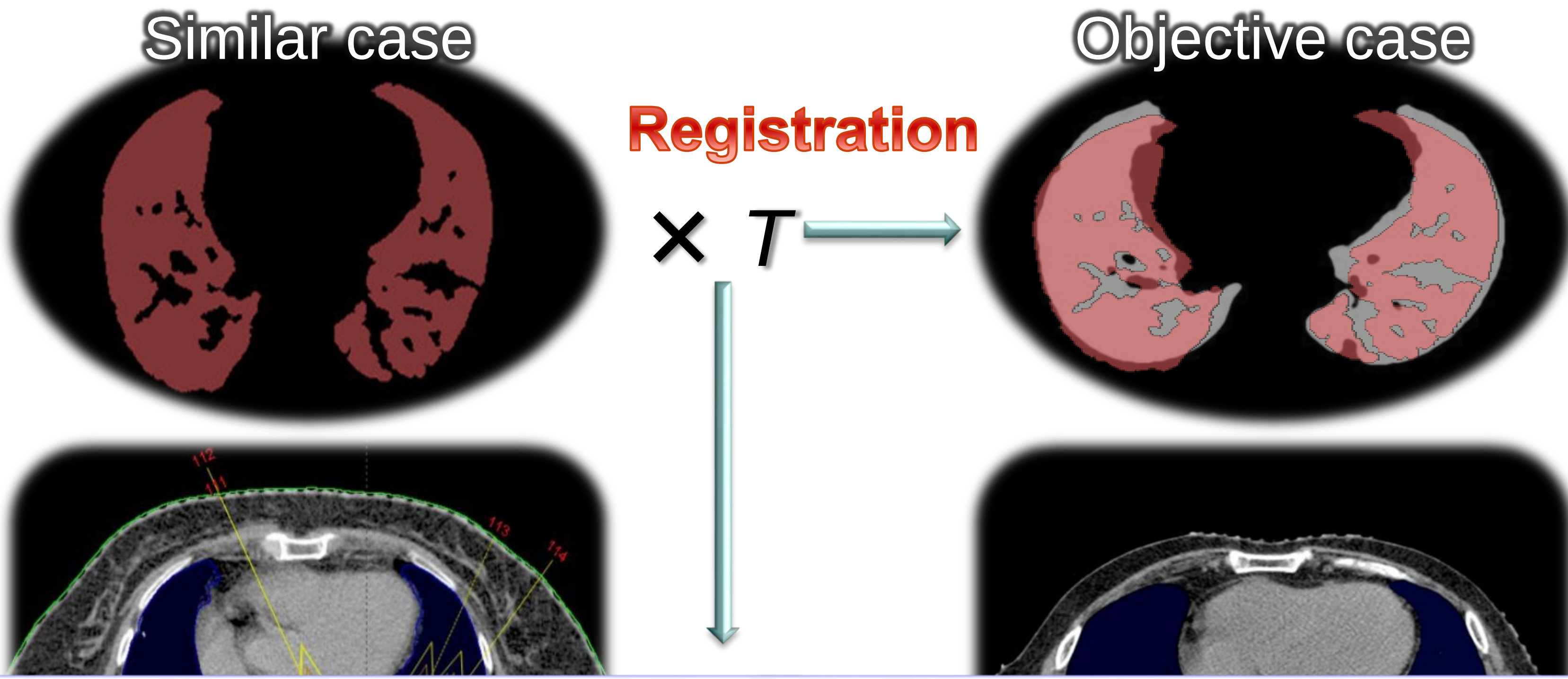
Objective case



Similar cases



How to determine beam directions based on similar cases

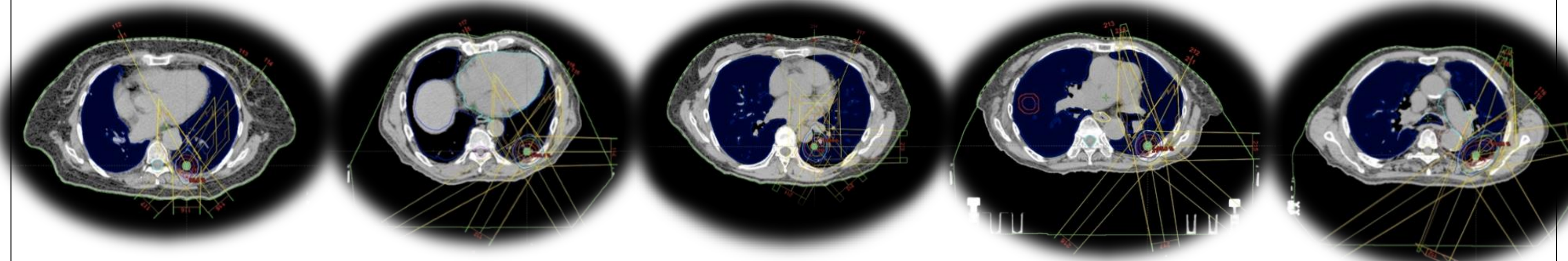


Beam directions of the objective case were automatically determined by registration of the similar case with the objective case.

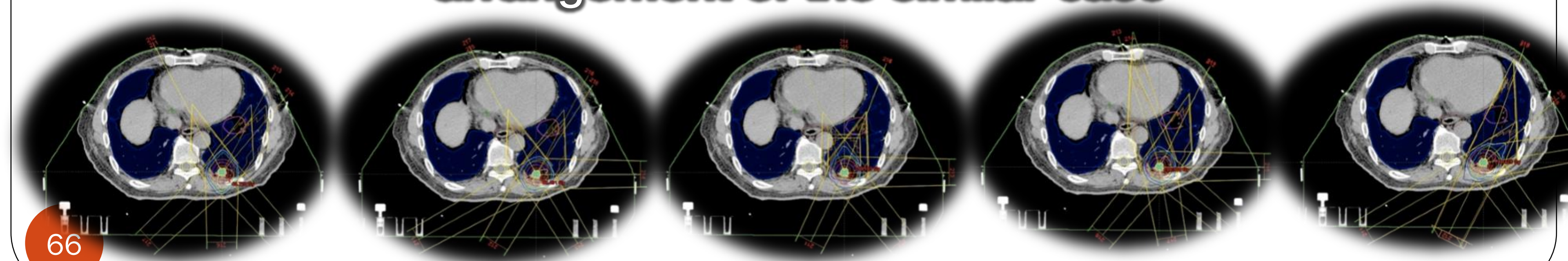
Five similar-case-based beam arrangements

Five most similar cases

1st 2nd 3rd 4th 5th



Modified plan based on each beam arrangement of the similar case



Comparison between original plans and optimized similar-case-based plans

	Original plan	Optimized similar-case-based plan	*P* value
D95 (Gy)	45.5 ± 0.47	46.0 ± 0.60	0.029
Homogeneity index	1.13 ± 0.03	1.13 ± 0.04	0.643
Conformity index	1.70 ± 0.15	1.72 ± 0.17	0.376
TCP (%)	96.0 ± 0.27	96.1 ± 0.30	0.084
V5 (%)	16.0 ± 6.30	14.7 ± 5.43	0.066
V10 (%)	9.96 ± 4.52	9.31 ± 3.53	0.161
V20 (%)	3.98 ± 1.46	4.03 ± 1.33	0.582
Lung mean dose (Gy)	3.03 ± 1.11	2.95 ± 1.03	0.152
NTCP_lung (%)	$6.76 \times 10^{-3} \pm 1.22 \times 10^{-2}$	$5.40 \times 10^{-3} \pm 9.33 \times 10^{-3}$	0.182
Spinal cord max dose (Gy)	6.13 ± 3.62	7.09 ± 5.95	0.465
NTCP_spinal cord (%)	$1.12 \times 10^{-5} \pm 1.90 \times 10^{-5}$	$4.37 \times 10^{-4} \pm 9.51 \times 10^{-4}$	0.187

Niche #6

Machine Learning

×

Prediction of esophageal stenotic ratios

Machine learning framework in artificial neural network (ANN)

Weights in a neural network are determined by using a backpropagation of errors between predicted outputs and teacher signals at a learning step.

Learning

Many learning data

Feature 1
Feature 2
Feature n

Machine learning with ANN

Predicted output y_m

Teacher signal, t_m

$$E = \sum_{m=1}^{M} \|y_m - t_m\|^2$$

Test

Unknown data

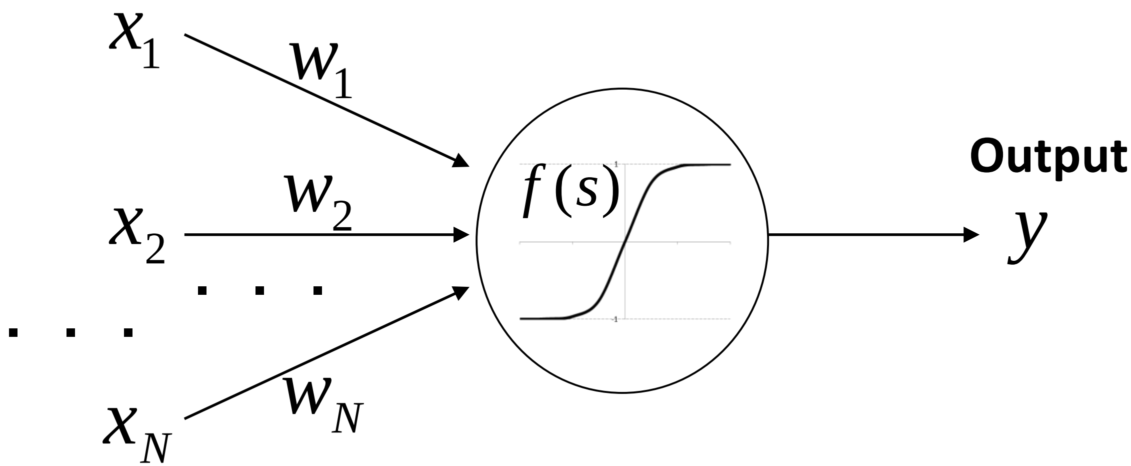
Feature 1
Feature 2
Feature n

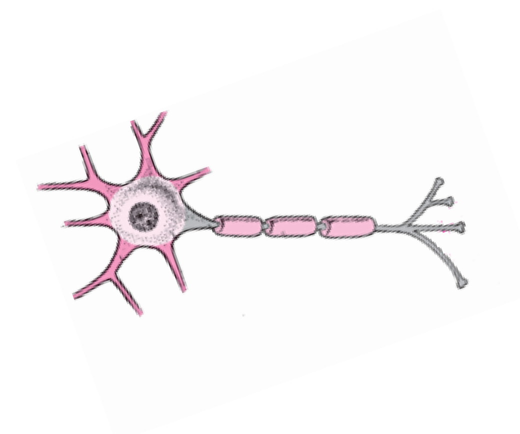
ANN after learning

Predicted output

A computational model of biological neurons

Inputs



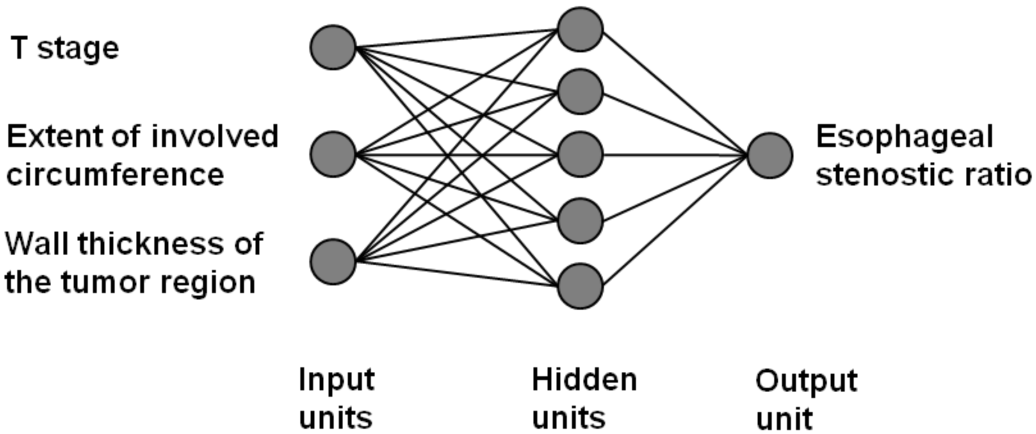


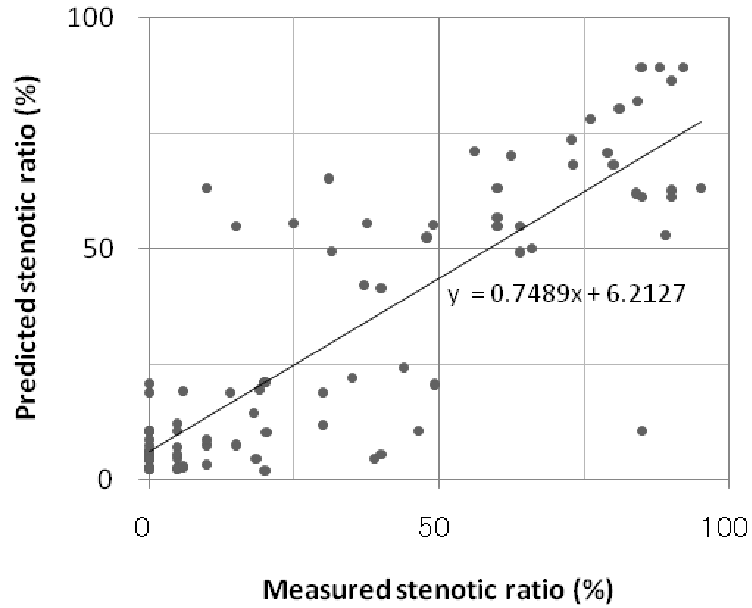
Input-output function

$$y = f(s) \qquad s = \sum_{n=1}^{N} w_n x_n$$

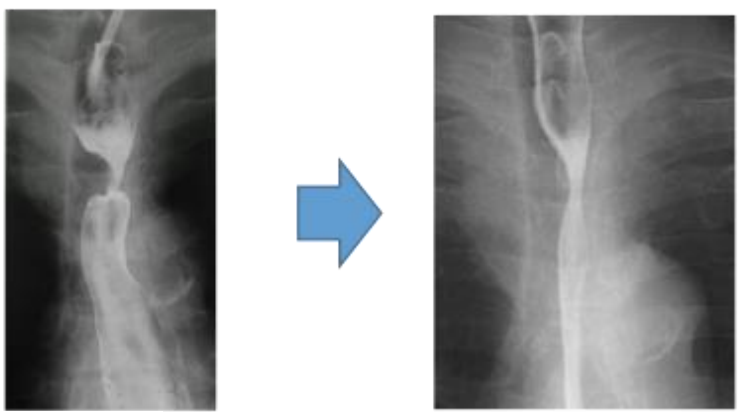
w : Connecting weight

ANN-based approach for prediction of esophageal stenotic ratios in esophageal images





Correlation value : 0.864 (109 cases)

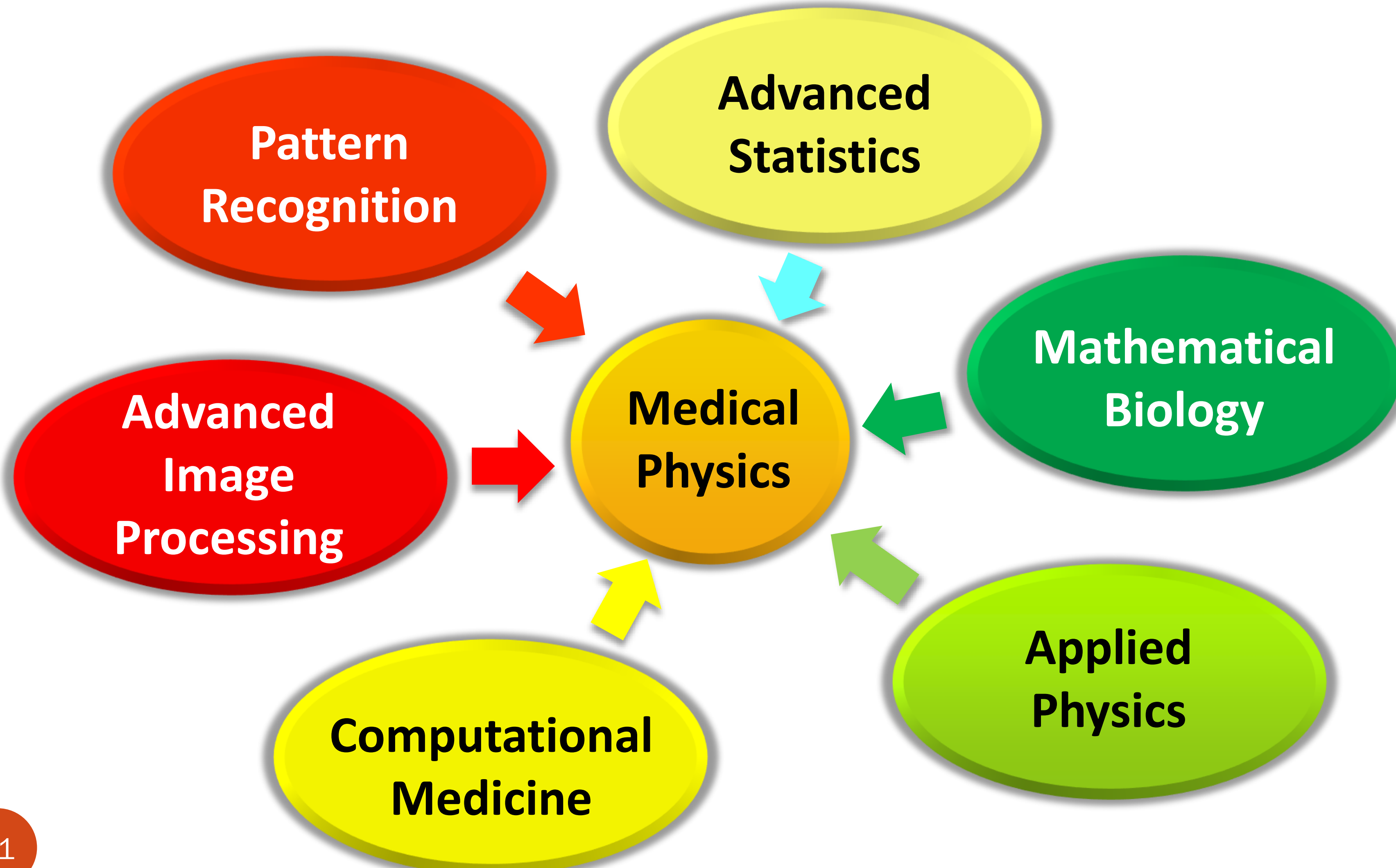


Measured stenotic ratio: 81%

Predicted stenotic ratio: 80%

Atsumi K, Shioyama Y, Arimura H, et al. Red Journal 2012

Medical Physics: Actually niche field based on "colored" collaborations between it and the other fields



Take-home message

I would be very happy if my presentation is helpful to understand ***niche* researches or medical physics researches** to improve the quality of medical cares.

Thanks a lot for your time and listening!

H. *N*. Arimura