

# **Medical Robotics**

## **ALBA system registration for oncological hyperthermia**

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DIPARTIMENTO DI INGEGNERIA INFORMATICA  
AUTOMATICA E GESTIONALE ANTONIO RUBERTI

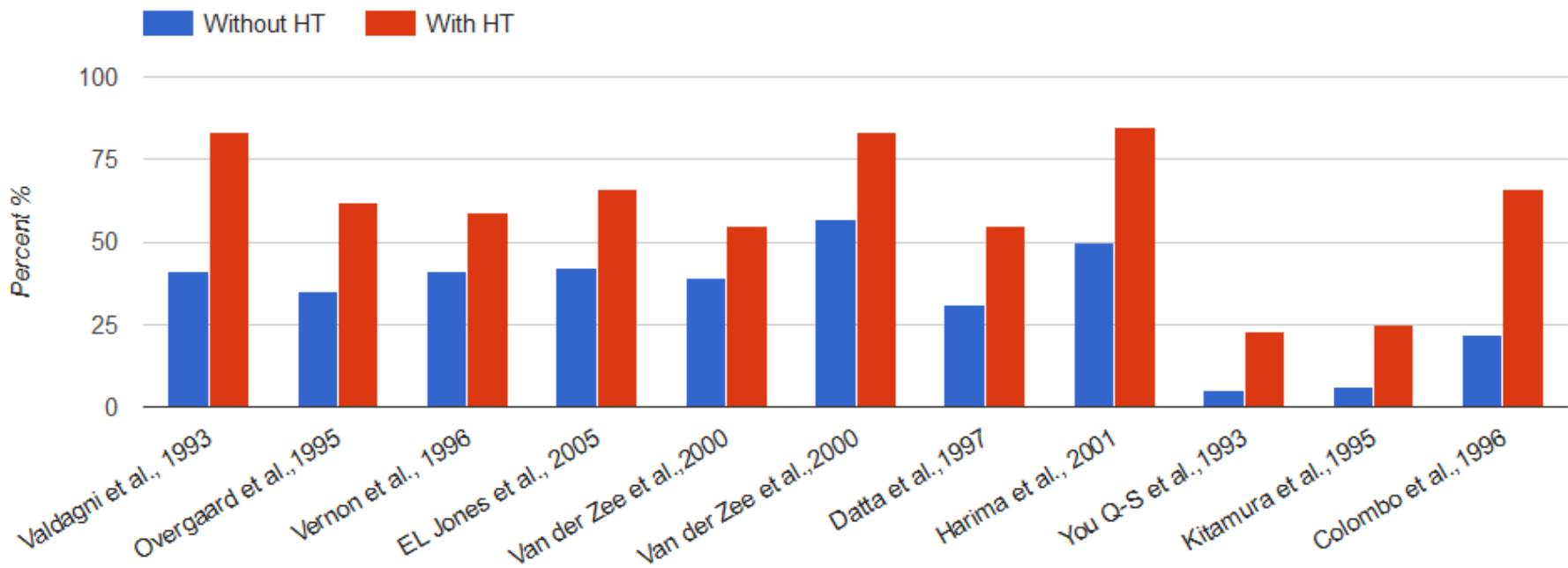


**SAPIENZA**  
UNIVERSITÀ DI ROMA

# oncological hyperthermia

- observation: tumor cells are more sensitive to high temperatures (40° - 45° C) than normal cells
- oncological hyperthermia (HT): therapeutic treatment of superficial or deep cancerous regions (tumors) based on controlled overheating of target organs and tissues
- efficient supporting approach, when combined to standard chemotherapy, radiotherapy or both (**Triple Modality**) the whole treatment consider elements from both 3 approaches
- Anticancer drug doses reduction for patients → fewer side effects

# oncological hyperthermia



<http://www.albahyperthermia.com/hyperthermia-overview.html>

if the tumor is located deeply in the patient, the device used in that in the first image in this slide, where basically the patient is surrounded by an array of antennas that can radiate, at a certain depth, specific radiofrequencies to match the right location of the tumor, where the location is been acquired y preoperative clinical images such as CT scan

# oncological hyperthermia

## treatment techniques

**basic technology:** tissue temperature increase due to absorption of electromagnetic field at radio/microwave frequencies radiated by antennas

### effects

the DNA of these cells is slowly repaired

the hyperthermia allows to inhibit the mechanism to repair tumor cell

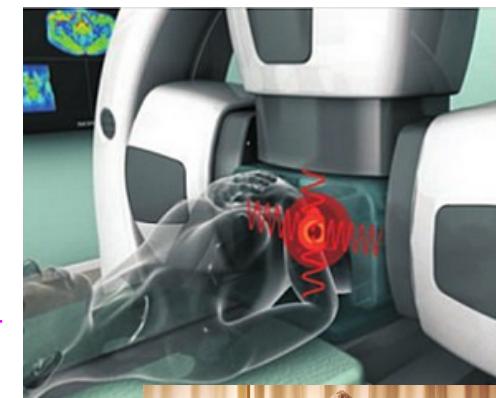
- inhibition of tumor cell repair mechanisms
- increase of blood flow  
oxigenation of the arteria
- greater transport of chemo agent to tumor site

but also

- risk of damaging normal cells

### treatment types

- based on tumor site: deep, superficial
- based on tumor size: local, regional, whole-body



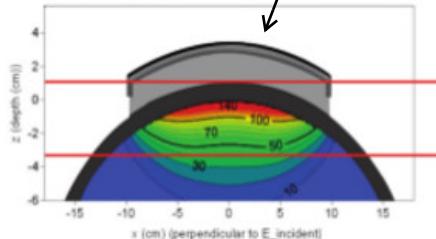
toumor and cancer regions that are at a certain proximity of the skin of the patient

# superficial hyperthermia

## ALBA ON4000 system

- compact integrated technology for **superficial** hyperthermia  
composed by: metal plates
- external applicators (**antennas**) in contact with the patient to supply radiofrequencies and increase tissue temperature
- passive arm to manually move the antenna

representation of spread diffusion produced by antennas(emissions of radiofrequency)



passive arm manually moved by the operator and also the antenna is manually positioned by the operator



- preoperative images, temperature sensors and a monitor to assist the operator at the console in the treatment
- favorable **Specific Absorption Rate (SAR)** guaranteed on muscle and heterogenous tissues

the capability to properly locate the natenna on the patient's tissue is up to this skill of the operator

# superficial hyperthermia

## difficulties and challenges

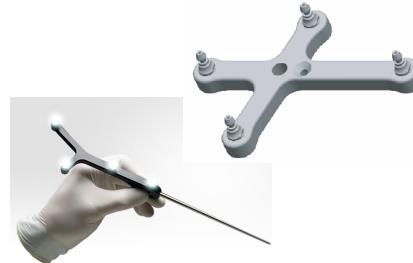
- reaching and maintaining HT temperatures at the desired target
  - no *real-time* tracking in case of movements
- timing and duration of the treatment
  - longer time and lower accuracy than RT
- reproducibility for subsequent treatments
- standardization wrt different tumors in
  - location
  - size
  - morphology



# ALBA ON4000 system

## technological improvement

- add an **external tracking system** in the setup  
to measure the position and orientation of a specific frame of spherical or optical markers
- **NDI Polaris Vega** optical camera sensor + frame of spherical markers

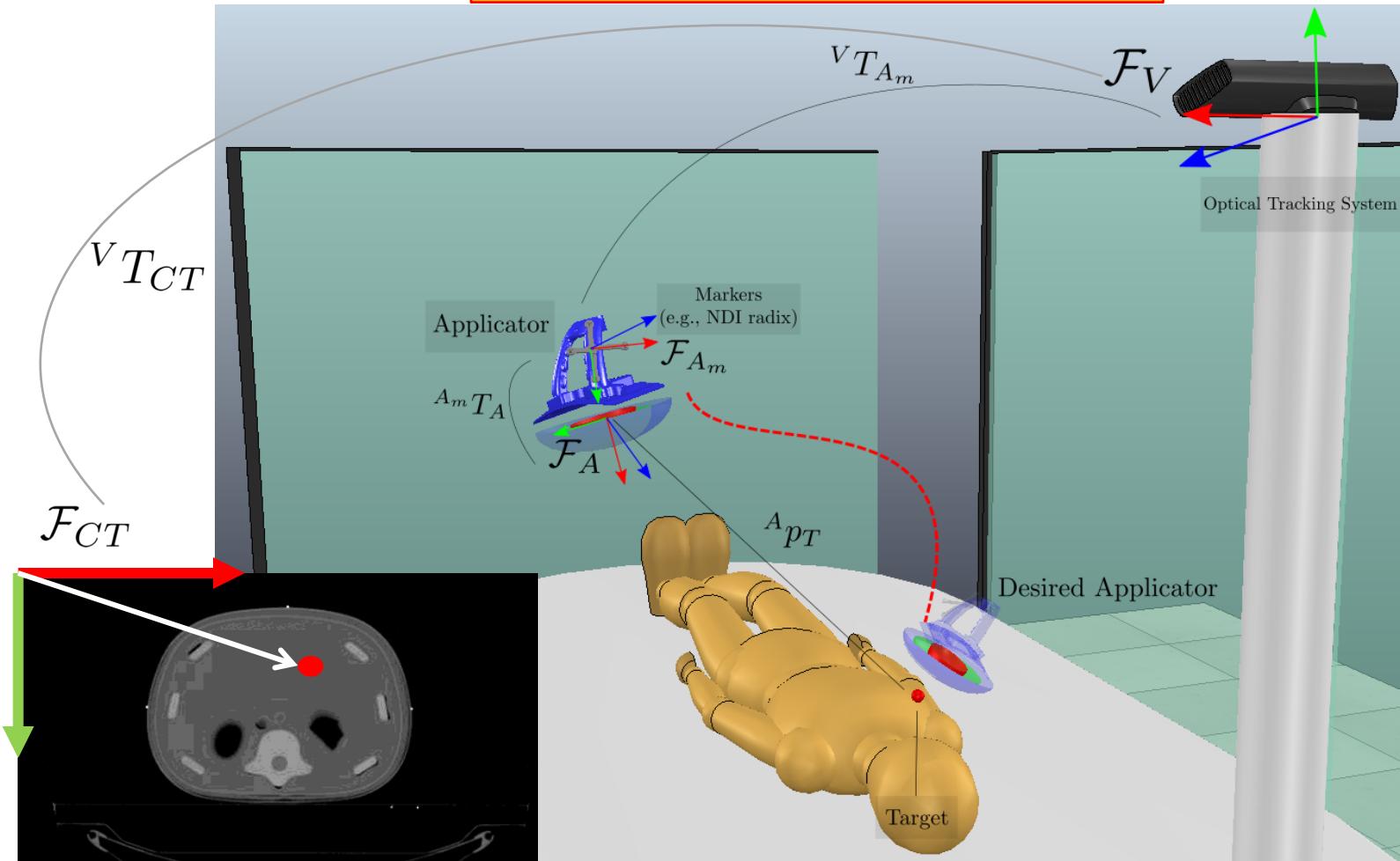


- markers mounted on the antenna for *real-time* tracking
- different reference frames now involved
  - preoperative image (e.g., CT scans), camera, markers, antenna ...
- necessity to transfer location information from one frame to another  
**→ registration**

# ALBA ON4000 system

## setup and frames

goal: register  $\mathcal{F}_{CT}$  against  $\mathcal{F}_V$



# problem formulation

goal: register  $\mathcal{F}_{CT}$  against  $\mathcal{F}_V$

- consider a target T with known position in the CT scan

$${}^A\mathbf{p}_T = [{}^A\mathbf{T}_{Am} | {}^{Am}\mathbf{T}_V | {}^V\mathbf{T}_{CT}] {}^{CT}\mathbf{p}_T$$

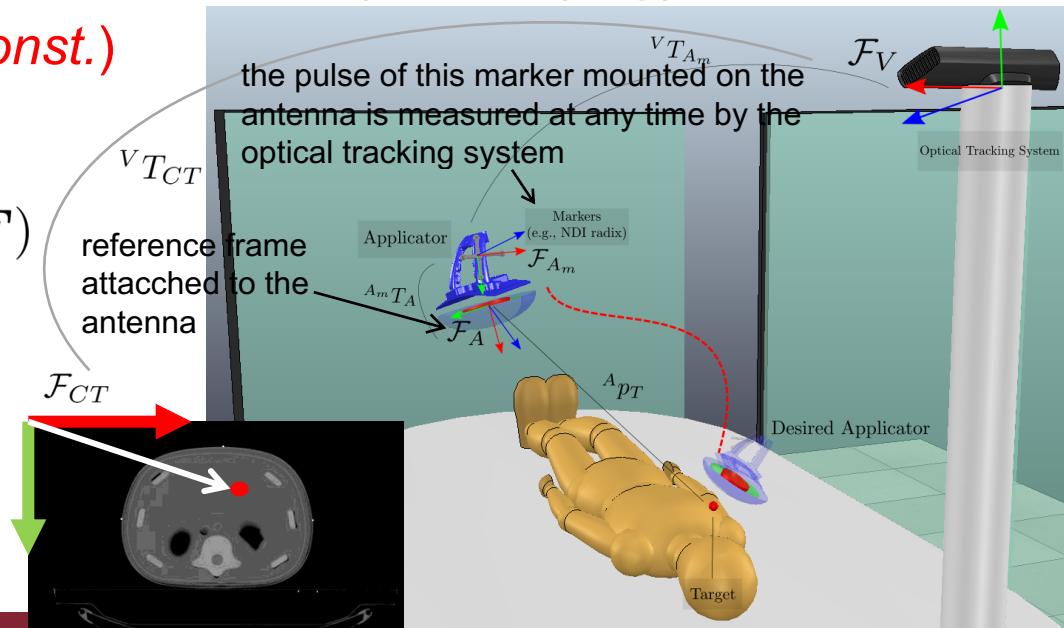
- ${}^A\mathbf{T}_{Am}$ : available from antenna CAD model or calibrated (const.)
- ${}^{Am}\mathbf{T}_V$ : measured through the camera sensor (time-varying)
- ${}^V\mathbf{T}_{CT}$ : **registration output (const.)**



$${}^V\mathbf{T}_{CT} = \arg \min d({}^V\mathbf{F}, {}^V\mathbf{T}_{CT} {}^{CT}\mathbf{F})$$

- in the end, target location known in  $\mathcal{F}_A$

we want for ex. to place the target at the center of the antenna because this part is the maximum specific absorption rate (radiofrequencies are more powerful)



# registration for ALBA ON4000

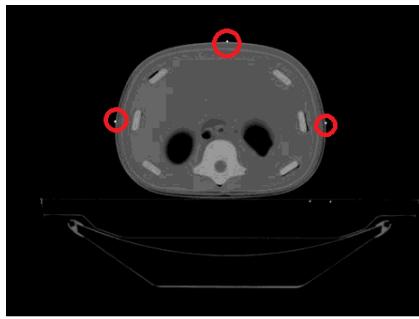
## ICP algorithm

### method

- point-to-point ICP algorithm: one-to-one matching between a set of N points ( $N > 3$ ) in a coordinate frame and the corresponding N points in another coordinate frame

### build correspondences

- **radio-opaque anatomical landmarks** on patient skin
  - visible in preoperative medical images  $\rightarrow {}^{CT}p_i, \forall i = 1, \dots, N$
  - measurable from external NDI camera  $\rightarrow {}^Vp_i, \forall i = 1, \dots, N$



# estimate rigid transformation with known correspondences

- if correspondences are **known** → ICP = standard least-square solver
- use standard methods, e.g., **pseudo-inverse**, **Gauss-Newton**, ...
- **input:**  ${}^V \mathbf{p}_i \longleftrightarrow {}^{CT} \mathbf{p}_i$ ,  $\forall i = 1, \dots, N$
- **unknown:**  ${}^V \mathbf{T}_{CT} = \begin{pmatrix} {}^V \mathbf{R}_{CT} & {}^V \mathbf{t}_{CT} \\ \mathbf{0}^T & 1 \end{pmatrix} = \begin{pmatrix} r_{1,1} & r_{1,2} & r_{1,3} & t_x \\ r_{2,1} & r_{2,2} & r_{2,3} & t_y \\ r_{3,1} & r_{3,2} & r_{3,3} & t_z \\ 0 & 0 & 0 & 1 \end{pmatrix}$   
s.t.:  ${}^V \mathbf{p}_i = {}^V \mathbf{T}_{CT} {}^{CT} \mathbf{p}_i$ ,  $\forall i = 1, \dots, N$

# estimate rigid transformation with known correspondences: pseudo-inverse

- re-arrange terms as  $\mathbf{A}\mathbf{x} = \mathbf{b}$
- here, w.l.o.g.  $N = 4$

$$\begin{pmatrix}
 x_{1,CT} & y_{1,CT} & z_{1,CT} & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
 0 & 0 & 0 & x_{1,CT} & y_{1,CT} & z_{1,CT} & 0 & 0 & 0 & 0 & 1 & 0 \\
 0 & 0 & 0 & 0 & 0 & 0 & x_{1,CT} & y_{1,CT} & z_{1,CT} & 0 & 0 & 1 \\
 x_{2,CT} & y_{2,CT} & z_{2,CT} & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
 0 & 0 & 0 & x_{2,CT} & y_{2,CT} & z_{2,CT} & 0 & 0 & 0 & 0 & 1 & 0 \\
 0 & 0 & 0 & 0 & 0 & 0 & x_{2,CT} & y_{2,CT} & z_{2,CT} & 0 & 0 & 1 \\
 x_{3,CT} & y_{3,CT} & z_{3,CT} & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
 0 & 0 & 0 & x_{3,CT} & y_{3,CT} & z_{3,CT} & 0 & 0 & 0 & 0 & 1 & 0 \\
 0 & 0 & 0 & 0 & 0 & 0 & x_{3,CT} & y_{3,CT} & z_{3,CT} & 0 & 0 & 1 \\
 x_{4,CT} & y_{4,CT} & z_{4,CT} & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
 0 & 0 & 0 & x_{4,CT} & y_{4,CT} & z_{4,CT} & 0 & 0 & 0 & 0 & 1 & 0 \\
 0 & 0 & 0 & 0 & 0 & 0 & x_{4,CT} & y_{4,CT} & z_{4,CT} & 0 & 0 & 1
 \end{pmatrix} = \begin{pmatrix}
 r_{1,1} \\
 r_{1,2} \\
 r_{1,3} \\
 r_{2,1} \\
 r_{2,2} \\
 r_{2,3} \\
 r_{3,1} \\
 r_{3,2} \\
 r_{3,3} \\
 t_x \\
 t_y \\
 t_z
 \end{pmatrix} \quad \begin{matrix} \text{points expressed in} \\ \text{camera frame} \end{matrix} \quad \begin{pmatrix}
 x_{1,V} \\
 y_{1,V} \\
 z_{1,V} \\
 x_{2,V} \\
 y_{2,V} \\
 z_{2,V} \\
 x_{3,V} \\
 y_{3,V} \\
 z_{3,V} \\
 x_{4,V} \\
 y_{4,V} \\
 z_{4,V}
 \end{pmatrix}$$

- solve as

$$\mathbf{x} = \mathbf{A}^\# \mathbf{b}$$

## estimate rigid transformation with known correspondences: pseudo-inverse

can I revert the solution  $x = A^\# b$  back in the previous form?

$$x \rightarrow^V T_{CT} = \begin{pmatrix} {}^V \mathbf{R}_{CT} & {}^V \mathbf{t}_{CT} \\ \mathbf{0}^T & 1 \end{pmatrix} = \begin{pmatrix} r_{1,1} & r_{1,2} & r_{1,3} & t_x \\ r_{2,1} & r_{2,2} & r_{2,3} & t_y \\ r_{3,1} & r_{3,2} & r_{3,3} & t_z \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

Answer: No!

to transform the matrix  $R_{CT}$ , it has to be an orthonormal matrix

- $\det({}^V \mathbf{R}_{CT}) = 1$  is not guaranteed due to **noisy** point correspondences
- the result is not a homogeneous transformation matrix
- move on iterative methods with space conversion operators...

# estimate rigid transformation with known correspondences: Gauss-Newton

- use pseudo-inverse solution as **initial guess**  $\boldsymbol{x}^*$
- iterative method with incremental corrections

euler or YPR angles

- **state:**  $\boldsymbol{x} = (t_x \quad t_y \quad t_z \quad \alpha \quad \beta \quad \gamma) \in SE(3)$
- **measurement:**  $\boldsymbol{z}_i = {}^V\boldsymbol{p}_i \in \mathbb{R}^3, \forall i = 1, \dots, N$
- **meas. function:**  $\boldsymbol{h}_i(\boldsymbol{x}) = {}^V\boldsymbol{R}_{CT}(\alpha, \beta, \gamma) {}^{CT}\boldsymbol{p}_i + {}^V\boldsymbol{t}_{CT}, \forall i = 1, \dots, N$
- **error and Jacobian:**  
$$\boldsymbol{e}_i = \underbrace{\boldsymbol{h}_i(\boldsymbol{x}^*)}_{\text{expected measurement}} - \underbrace{\boldsymbol{z}_i}_{\text{actual measurement}}$$
$$\boldsymbol{J}_i = \left. \frac{\partial \boldsymbol{e}_i(\boldsymbol{x})}{\partial \boldsymbol{x}} \right|_{\boldsymbol{x}=\boldsymbol{x}^*}$$

# estimate rigid transformation with known correspondences: Gauss-Newton

## algorithm

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### Algorithm 1: Gauss-Newton single iteration

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**Result:**  $\mathbf{x}^*$ : the optimal state vector

$\mathbf{H} \leftarrow \mathbf{0}$ ,  $\mathbf{b} \leftarrow \mathbf{0}$ ;

**for**  $i \leftarrow 1$  to  $N$  **do**

$e_i \leftarrow \mathbf{h}_i(\mathbf{x}^*) - z_i$ ;

$\mathbf{J}_i \leftarrow \frac{\partial e_i}{\partial \mathbf{x}} \Big|_{\mathbf{x}=\mathbf{x}^*}$ ;

$\mathbf{H} \leftarrow \mathbf{H} + \mathbf{J}_i^T \boldsymbol{\Omega} \mathbf{J}_i$ ;

$\mathbf{b} \leftarrow \mathbf{b} + \mathbf{J}_i^T \boldsymbol{\Omega} e_i$ ;

**end**

$\Delta \mathbf{x} \leftarrow -\mathbf{H}^\# \mathbf{b}$ ;

$\mathbf{x}^* \leftarrow \mathbf{x}^* + \Delta \mathbf{x}$ ;

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# estimate rigid transformation with unknown correspondences

- if correspondences are **unknown** → ICP=data association + LS solver
- several solutions are possible, e.g., K-D tree, Distance Maps, ...
- «brute force» approaches are also possible with few correspondences if no symmetries occur

**simple idea:** evaluate relative distances between each pair of points in both source and destination sets, compare the two distance sets and gets the minimum value

- starting sets:

$${}^{CT} \mathbf{P} = \begin{pmatrix} {}^{CT} \mathbf{p}_1^T \\ {}^{CT} \mathbf{p}_2^T \\ {}^{CT} \mathbf{p}_3^T \\ {}^{CT} \mathbf{p}_4^T \end{pmatrix} \quad \boxed{\begin{pmatrix} {}^V \mathbf{p}_1^T \\ {}^V \mathbf{p}_2^T \\ {}^V \mathbf{p}_3^T \\ {}^V \mathbf{p}_4^T \end{pmatrix}}$$

$\xleftarrow{\text{---} \times \text{---}} \qquad \qquad \qquad \xrightarrow{\text{---} \times \text{---}}$

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we assume that in our set of points, they are not sorted  
**unsorted!**

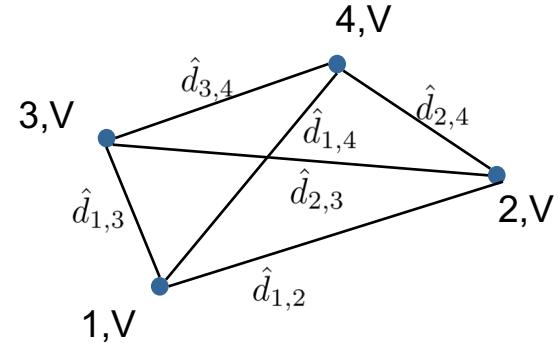
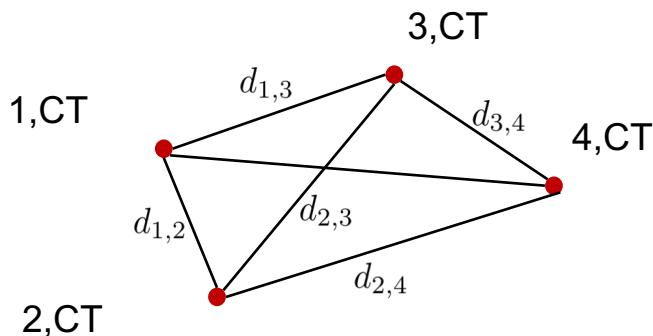
# estimate rigid transformation with unknown correspondences

- define matrix of distances on the two frames

$$\mathbf{D}_{CT} = \begin{pmatrix} 0 & d_{1,2} & d_{1,3} & d_{1,4} \\ d_{1,2} & 0 & d_{2,3} & d_{2,4} \\ d_{1,3} & d_{2,3} & 0 & d_{3,4} \\ d_{1,4} & d_{2,4} & d_{3,4} & 0 \end{pmatrix} = \begin{pmatrix} \mathbf{d}_1^T \\ \mathbf{d}_2^T \\ \mathbf{d}_3^T \\ \mathbf{d}_4^T \end{pmatrix} \quad \mathbf{D}_V = \begin{pmatrix} 0 & \hat{d}_{1,2} & \hat{d}_{1,3} & \hat{d}_{1,4} \\ \hat{d}_{1,2} & 0 & \hat{d}_{2,3} & \hat{d}_{2,4} \\ \hat{d}_{1,3} & \hat{d}_{2,3} & 0 & \hat{d}_{3,4} \\ \hat{d}_{1,4} & \hat{d}_{2,4} & \hat{d}_{3,4} & 0 \end{pmatrix} = \begin{pmatrix} \hat{\mathbf{d}}_1^T \\ \hat{\mathbf{d}}_2^T \\ \hat{\mathbf{d}}_3^T \\ \hat{\mathbf{d}}_4^T \end{pmatrix}$$

$$d_{i,j} = \| {}^{CT}\mathbf{p}_i - {}^{CT}\mathbf{p}_j \| , \forall i \neq j$$

$$\hat{d}_{i,j} = \| {}^V\mathbf{p}_i - {}^V\mathbf{p}_j \| , \forall i \neq j$$

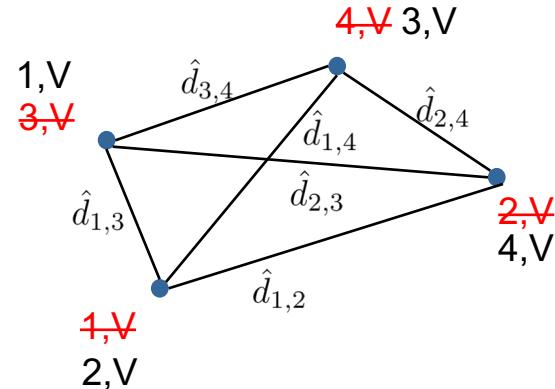
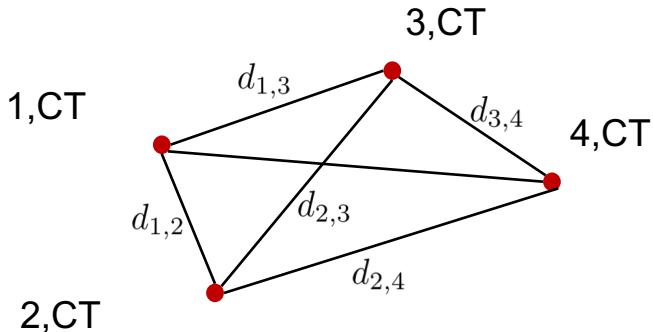


# estimate rigid transformation with unknown correspondences

if the points are matched properly, so the point correspondency are correct, we expect that if we take the 4 point, or an arbitrary point, in one of the 2 RF and we measure the distance between these points and all the other points, this distance will be the same that we measure if we took the same point in the second RF and we measure distances with respect to the other points

$$\mathbf{E}_D = \begin{pmatrix} e_{1,1} & e_{1,2} & e_{1,3} & e_{1,4} \\ e_{1,2} & e_{2,2} & e_{2,3} & e_{2,4} \\ e_{1,3} & e_{2,3} & e_{3,3} & e_{3,4} \\ e_{1,4} & e_{2,4} & e_{3,4} & e_{4,4} \end{pmatrix} = \begin{pmatrix} \mathbf{e}_1^T \\ \mathbf{e}_2^T \\ \mathbf{e}_3^T \\ \mathbf{e}_4^T \end{pmatrix} \quad e_{i,j} = \|\hat{\mathbf{d}}_i^T\| - \|\mathbf{d}_j^T\|, \forall i, j$$

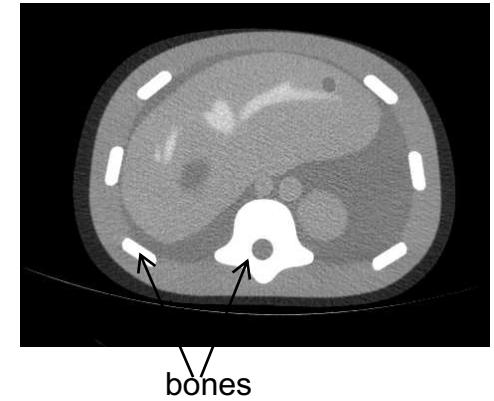
- error matrix:  $l = \arg \min \mathbf{e}_i^T \Rightarrow {}^V \mathbf{P}^*. \text{row}(l) = {}^V \mathbf{P}_u. \text{row}(i)$



# validation



- software solution interfaced with **V-REP** as external visualization tool
  - *replica* of the operative setup in the virtual scene



- professional **abdomen** phantom, with inner tissues and organs, used as target for validation (available in our Robotics Lab)
- customized software architecture designed to interface the NDI Polaris camera with the simulator

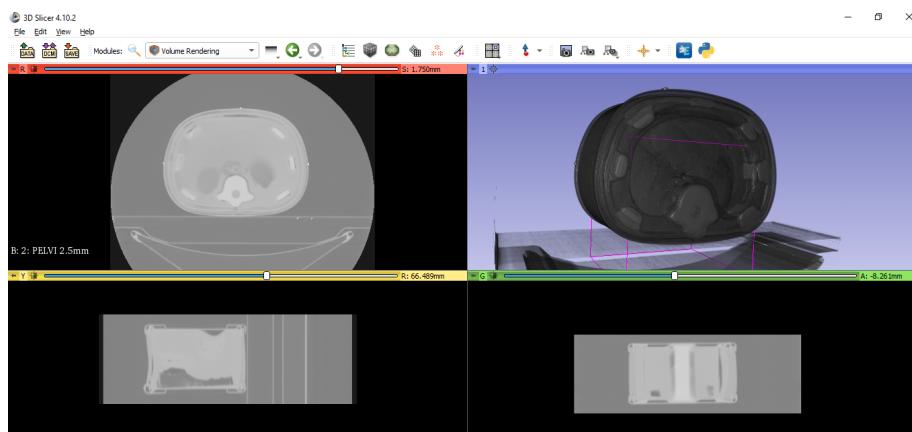
# validation

## phantom 3D model reconstruction

- **4 radiopaque markers** placed on external surface for registration



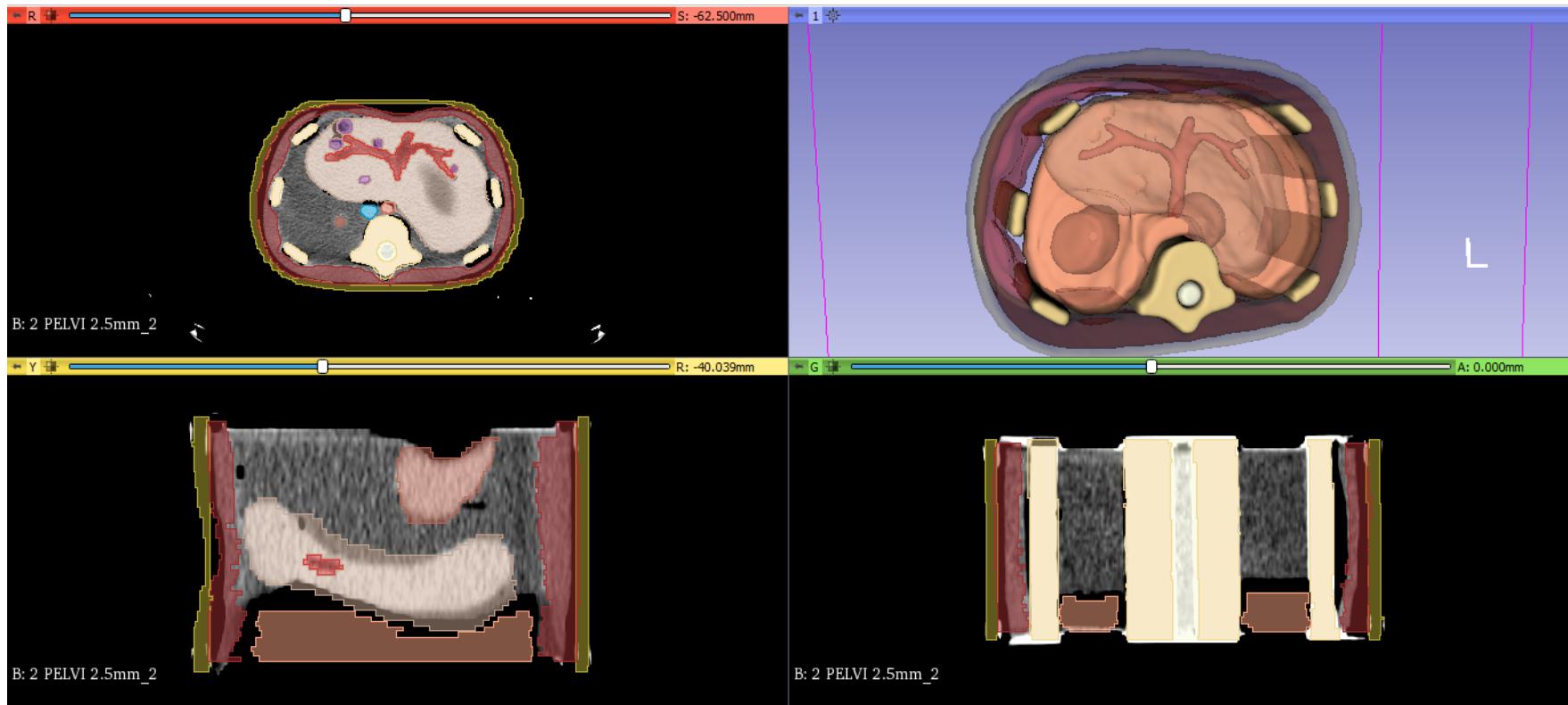
- 3D CT scans available and processed with **3D Slicer** ← software that can be downloaded



# validation

## phantom 3D model reconstruction

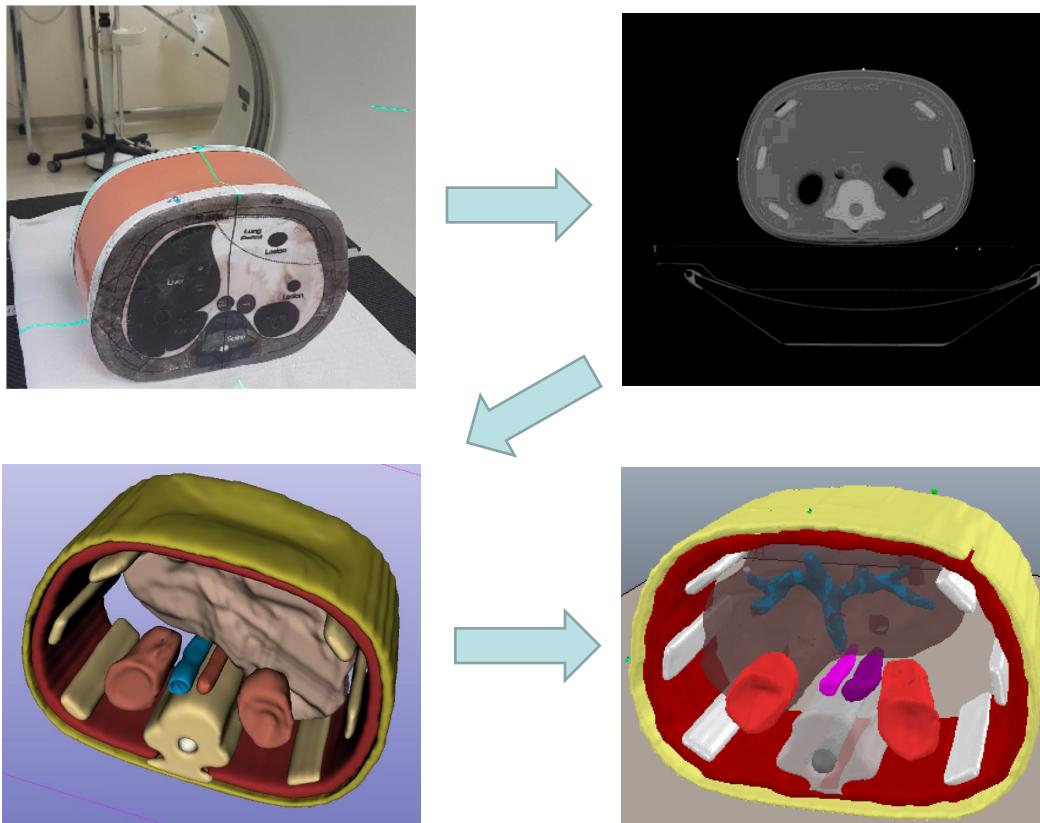
- manual and semi-autonomous tools for **segmentation**
  - free-hand drawing, contour detector, slice interpolation...



# validation

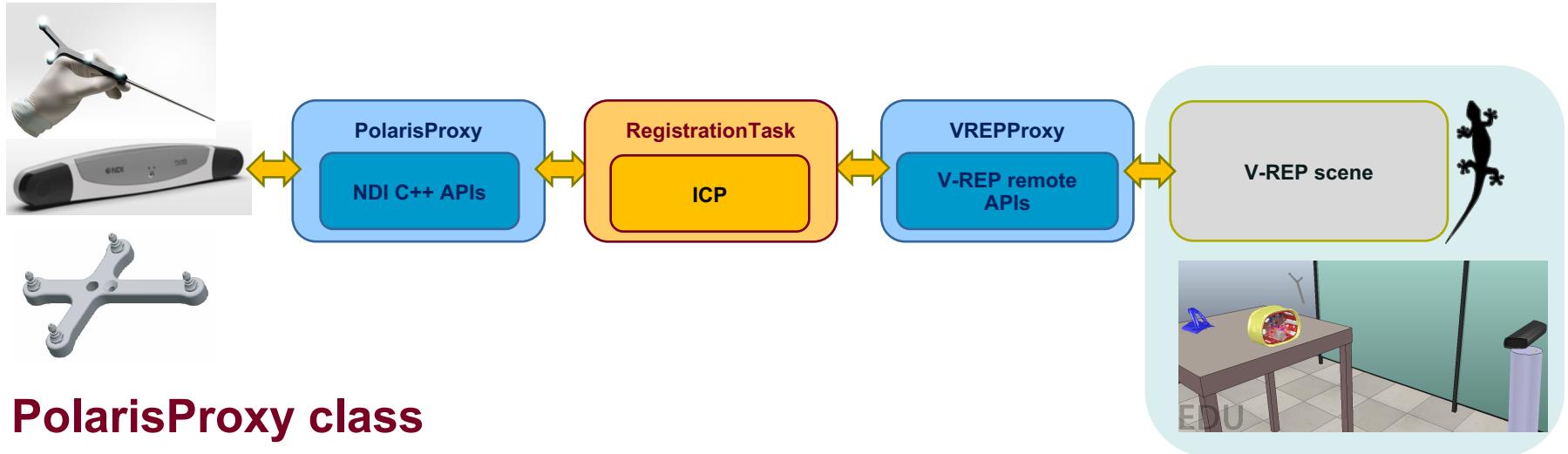
## phantom 3D model reconstruction

- 3D segmented structure models exported and imported in V-REP



# validation

## software architecture



### PolarisProxy class

- query the NDI Polaris camera to read the pose of marker frames
- send data to the *RegistrationTask* class

### RegistrationTask class

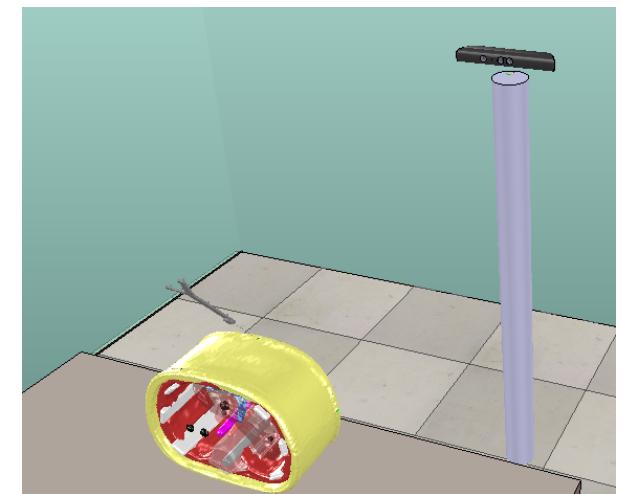
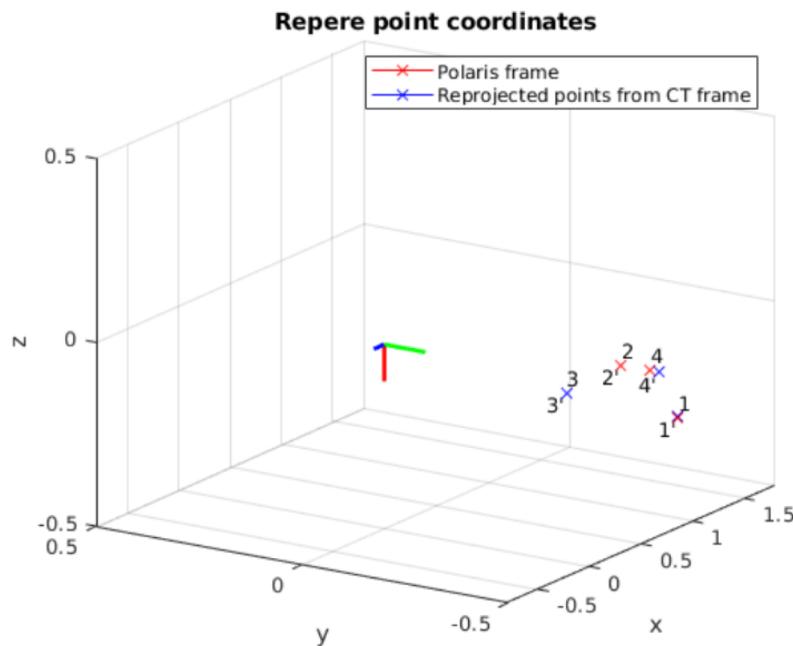
- process pre-acquired and Polaris data to run the ICP algorithm and show the results on the simulator

### VREPPProxy class

- update the V-REP scene with data sent from *RegistrationTask* class

# registration results

- palpation of the phantom with the probe
- Accuracy (RMS error): < 1cm



# Test at IFO in Rome

- validation with more realistic human-like phantom

**Towards an image-guided positioning system for  
radiative applicators in oncological hyperthermia**

**Software demonstration**

**Experimental session at IFO**

**Marco Ferro**