POLITECNICO DI MILANO

UNIVERSIDAD AUTÓNOMA DE SAN LUIS POTOSÍ

IBFM

Elastic Registration Based on Particle Filter in Radiotherapy Images

Aldo Mejia

CONTENTS

MOTIVATION

IMAGE REGISTRATION

A spatial remapping of one image to another to obtain a pixel by pixel correspondence of the same anatomical structures in the two images

- ❖ Important subject in medical image analysis
- ❖ In radiotherapy, allows the estimation of strains possibly caused by increase or reduction of tumors treated with radiation, or by side effects (weight loss or increase / reduction of healthy organs surrounding the tumor)

Rigid registration

- ❖ Global transformation
- ✓ ❖ Find only parameters which describe one transformation
- ✗ ❖ Serious drawbacks when images show complex deformations

Elastic registration

- ❖ Transformation for each pixel
- ✓ ❖ More general than the rigid ones
- ✗ ❖ More computationally demanding, difficult to implement and calibrate

MOTIVATION

PARTICLE FILTER

Easy to implement and powerful enough to achieve complex non-rigid registrations *, **

UNIVERSIDAD AUTÓNOMA DE SAN LUIS POTOSÍ

POLITECNICO MILANO

IBFM

THEORY → REAL

…before its application on a real clinical context, validation of the algorithm accuracy should be performed

*Arce-Santana, et. al. "Image registration guided by particle filter". Lecture Notes in Computer Science, Nov. 2009.

**Arce-Santana, et. al. "A non-rigid multimodal image registration method based on particle filter and optical flow", Lecture Notes in Computer Science, 2010

INTRODUCTION

PARTICLE FILTER

A bayesian approach to estimate states of nonlinear dynamic systems

$I_1 \approx I_2$ related;

$$I_1(x, y) = F(I_2(T(x, y)))$$

$$T([x, y]) = [x, y, 1]\begin{bmatrix} \lambda_x \cos\alpha & -\sin\alpha & 0 \\ \sin\alpha & \lambda_y \cos\alpha & 0 \\ d_x & d_y & 1 \end{bmatrix}$$

Particle $(\theta_k^i) = \begin{bmatrix} \alpha_k^i \\ \lambda_{xk}^i \\ \lambda_{yk}^i \\ d_{xk}^i \\ d_{yk}^i \end{bmatrix}$

GOAL

obtain a posterior pdf at time *k*, through a set of particles with associated weights

PARTICLE FILTER

RIGID REGISTRATION

Prediction State

- Random walking process

$$\theta_k = \theta_{k-1} + \upsilon_{k-1}$$

- Resampling process

n. iterations

Update State

- Recalculated weights according to measurements

$$z_k = MI(I_T(x,y), I_S(T_{\theta_k}(x,y))) + w_k$$

n. particles

ELASTIC REGISTRATION

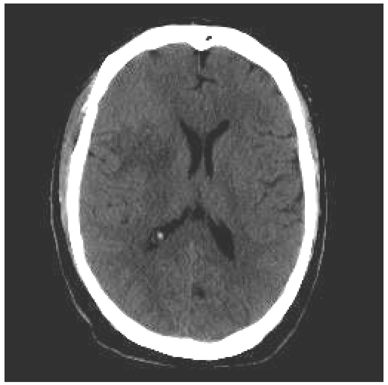
Locally refine each pixel using an optical flow approximation

n. iterations ***regularization factor*** λ

METHODS

Simulated Image Datasets

Original



CT and MRI Images

Controled Deformations

<u>*Moving Least Squares **</u>

- 6 original pivots (60°, 120°, 180°, 240°, 300° and 360°)
- Randomly moved ± 5 – 10 pixels (X-Y axis)

5 deformations for each dataset (CT and MRI)

<u>For evaluation purposes</u>

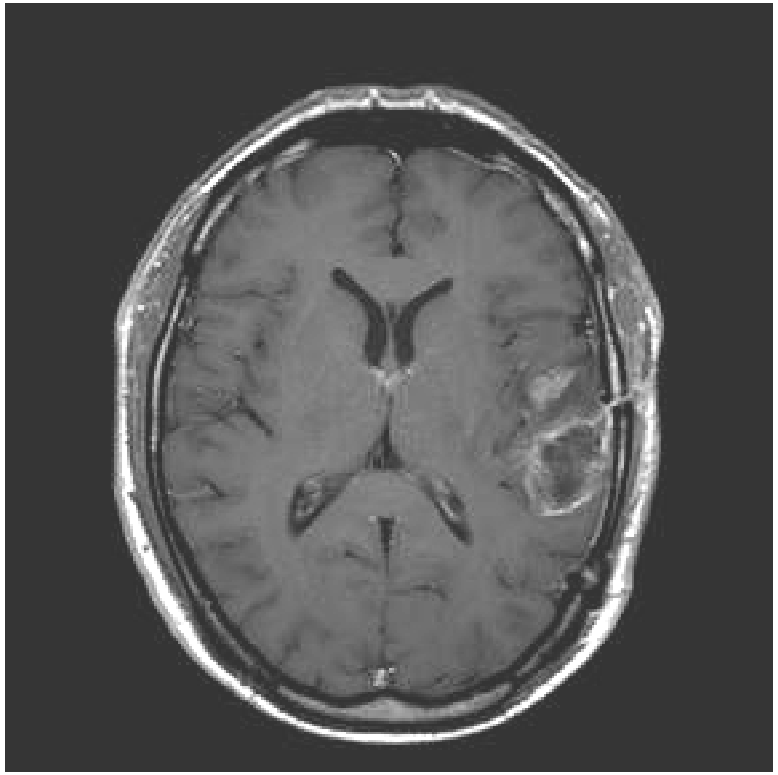
Simulation was intended to study deformations even exaggerated or impossible to find in actual radiotherapy clinical cases

* *"Image Deformation Using Moving Least Squares“, Scott Schaefer, Travis McPhail, Joe Warren*

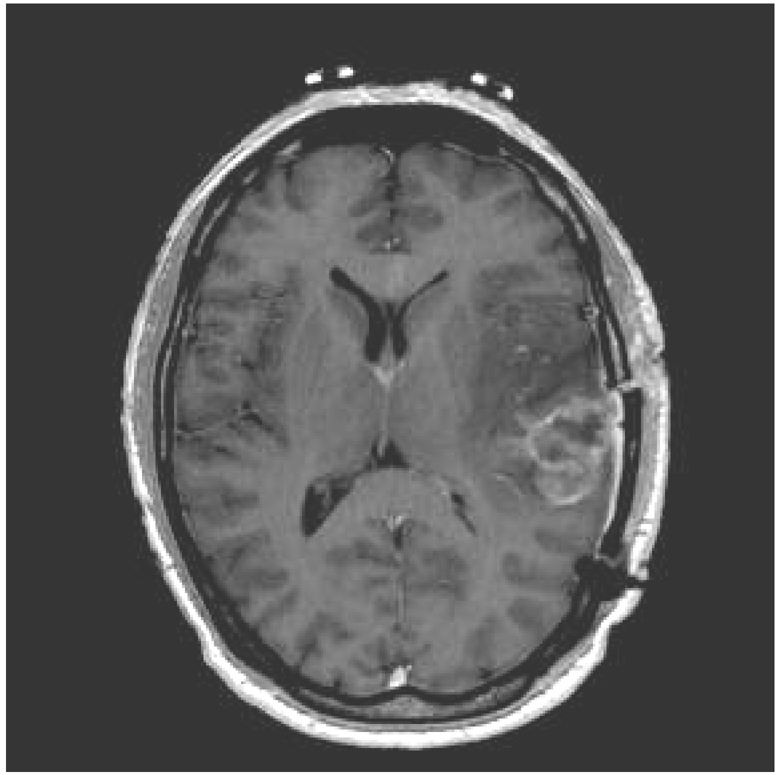
METHODS

Clinical Images

A real clinical case was considered using MRI images acquired before (MRI-Pre) and after (MRI-Post) a radiotherapy treatment.



MRI-Pre

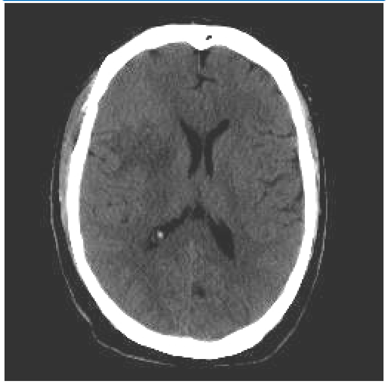


MRI-Post

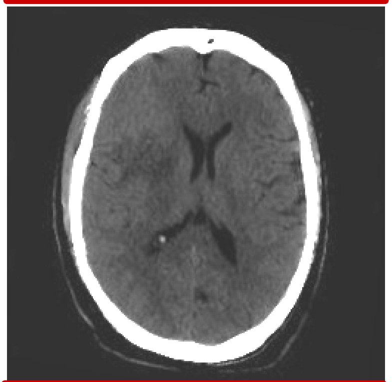
METHODS

Registration accuracy

Original / Pre

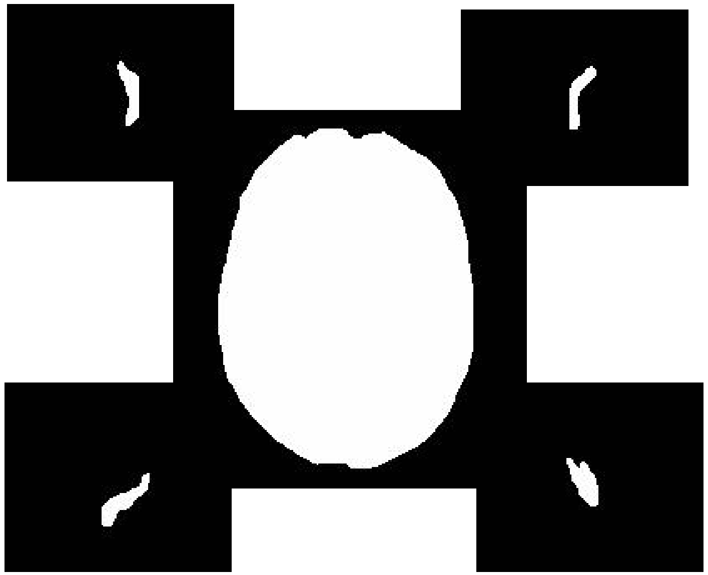


Deformed / Post



Registration

Segmentation



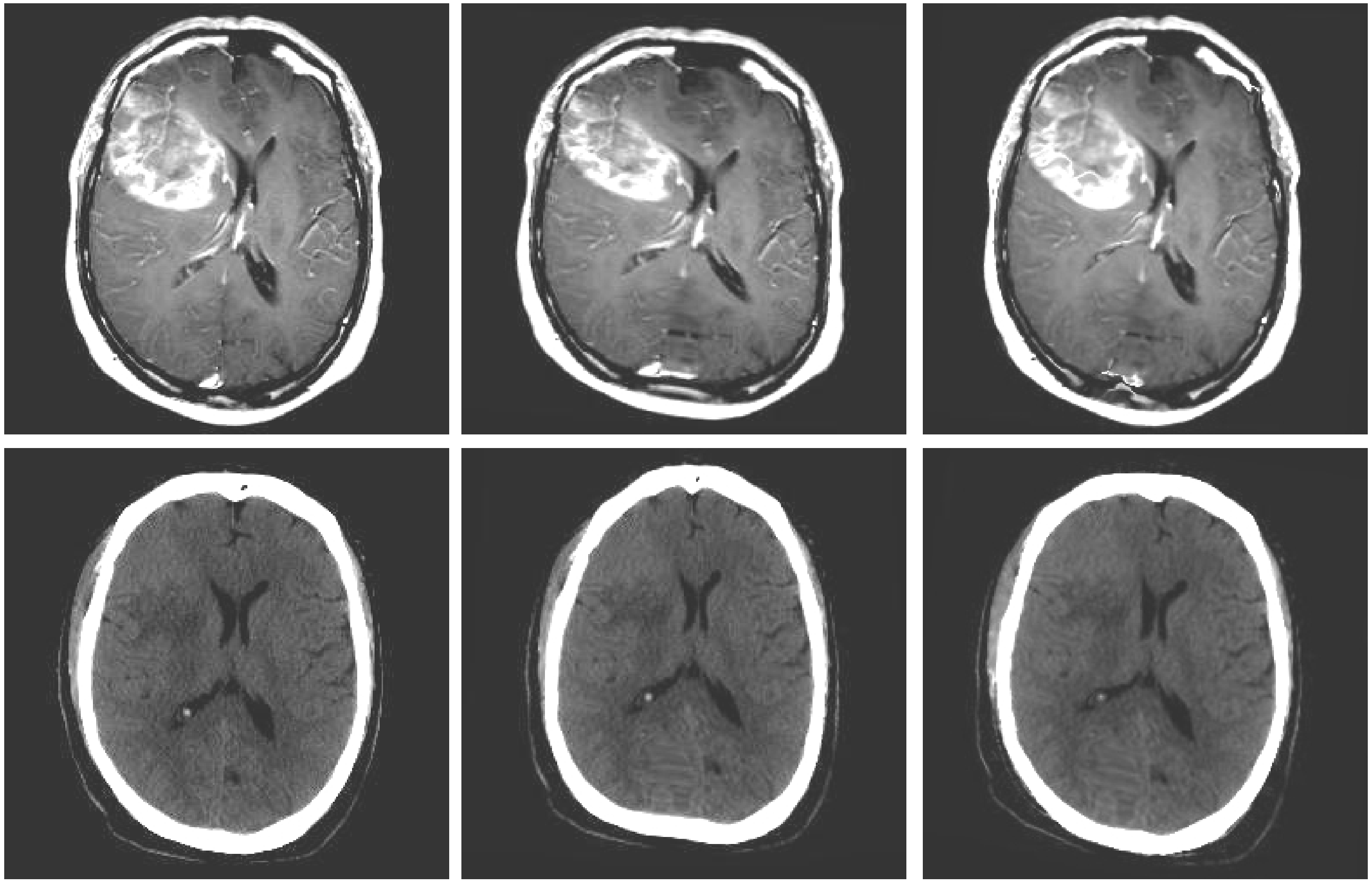
by an expert in radiological with *MIPAV, V.4.4.1*

Contoured Indexes

- ✓ **ASD**
- ✓ **DMAX**
- ✓ **DICE**

RESULTS

Simulated data



* Pixel size =0.819 mm

CT-CT

	ASD(mm)		Dmax(mm)		DICE	
	pre	post	pre	post	pre	post
Def 1	2,31	0,46	6,06	1,99	0,65	0,93
Def 2	3,03	0,45	8,16	2,95	0,45	0,93
Def 3	2,55	0,81	8,19	3,69	0,58	0,86
Def 4	2,08	0,85	6,22	3,34	0,64	0,84
Def 5	3,55	1,45	10,16	5,34	0,44	0,72
mean	**2,70**	**0,80**	**7,76**	**3,46**	**0,55**	**0,86**
SD	**0,59**	**0,41**	**1,68**	**1,23**	**0,10**	**0,08**
median	**2,55**	**0,81**	**8,16**	**3,34**	**0,58**	**0,86**

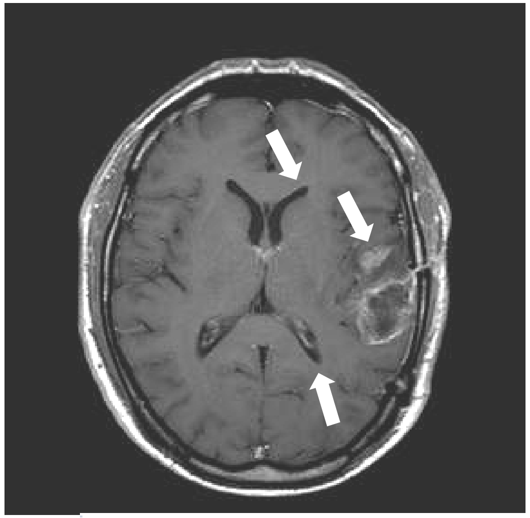
MR-MR

	ASD(mm)		Dmax(mm)		DICE	
	pre	post	pre	post	pre	post
Def 1	2,38	0,40	6,72	2,92	0,55	0,93
Def 2	2,93	0,46	9,58	2,33	0,39	0,92
Def 3	2,59	1,45	8,68	4,78	0,49	0,76
Def 4	2,21	0,61	7,04	3,89	0,54	0,91
Def 5	3,29	1,68	10,32	5,06	0,42	0,72
mean	**2,68**	**0,92**	**8,47**	**3,80**	**0,48**	**0,85**
SD	**0,43**	**0,60**	**1,57**	**1,17**	**0,07**	**0,10**
median	**2,59**	**0,61**	**8,68**	**3,89**	**0,49**	**0,91**

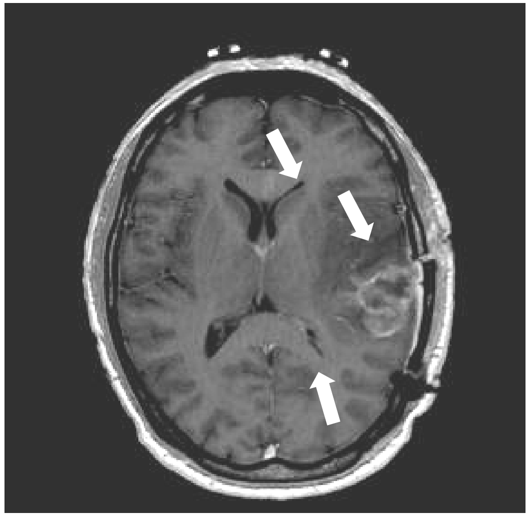
RESULTS

Clinical images

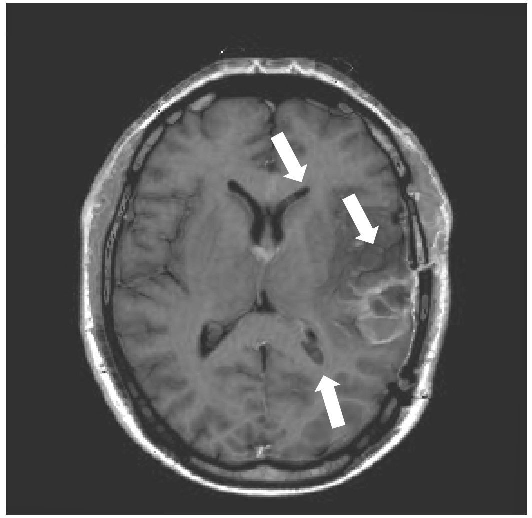
Pre-treatment



Post-treatment



Recovered



	ASD(mm)		*Dmax(mm)*		*DICE*	
	pre	post	pre	post	pre	post
Brain surface	2.01	0.64	5.73	5.73	0.97	0.99
Top left vent	0.66	0.33	2.59	0.82	0.86	0.93
Bottom left vent	2.06	0.43	4.63	1.16	0.37	0.91
Top right vent	1.88	0.63	4.10	2.46	0.72	0.91
Bottom right vent	1.43	0.98	4.10	4.10	0.72	0.83
mean	**1.61**	**0.60**	**4.23**	**2.85**	**0.73**	**0.92**
SD	**0.59**	**0.25**	**1.13**	**2.06**	**0.23**	**0.06**
median	**1.88**	**0.63**	**4.10**	**2.46**	**0.72**	**0.91**

CONCLUSIONS

- In CT and MR images of radiotherapy patients, in both simulated and real environment, registration showed good accuracy, both qualitatively and quantitatively.

- These results, in terms of accuracy, corroborate the advantages already mentioned on PF approach such as easy implementation, robustness to initial parameters and speed processing .

- Extending it to a 3D registration process may be considered as a good new option for radiotherapy applications like patient's follow up treatment.

PERSPECTIVES FOR THE FUTURE

- 3D implementation
  - Rigid 3D registration
  - Elastic 3D registration

- Compare results with the state of the art registration algorithms

- Design and implementation of a Graphic User Interface (GUI)

POLITECNICO DI MILANO

UNIVERSIDAD AUTÓNOMA DE SAN LUIS POTOSÍ

Elastic Registration Based on Particle Filter in Radiotherapy Images

M. Sc. Aldo Rodrigo Mejia Rodriguez

armero83@gmail.com

aldo.mejia@polimi.it