Grid-Enabled Software Environment for Enhanced Dynamic Data-Driven Visualization and Navigation During Image Guided Neurosurgery

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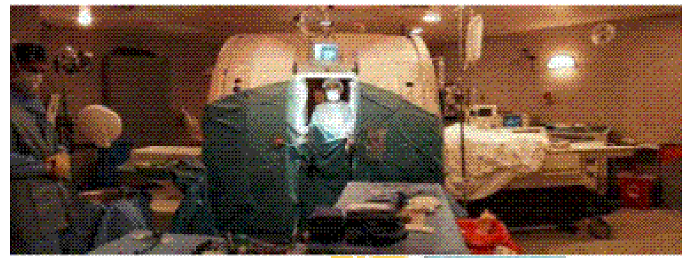

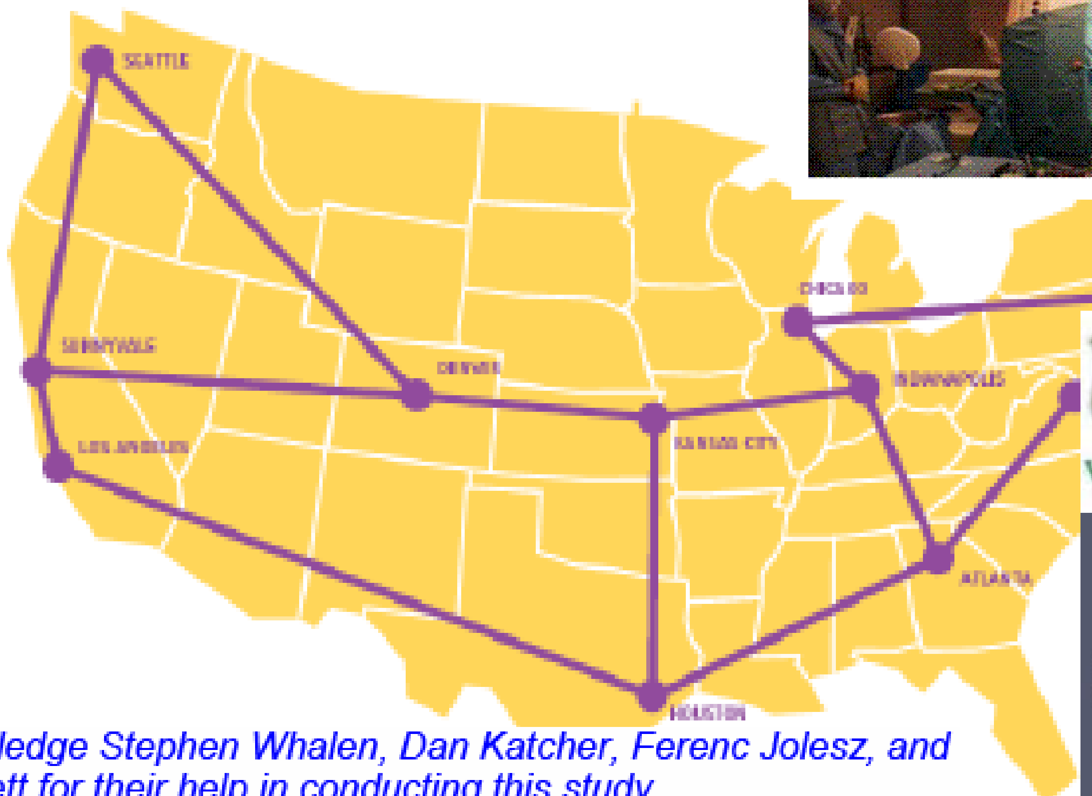

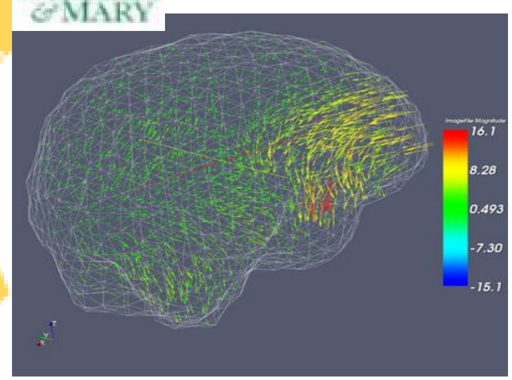

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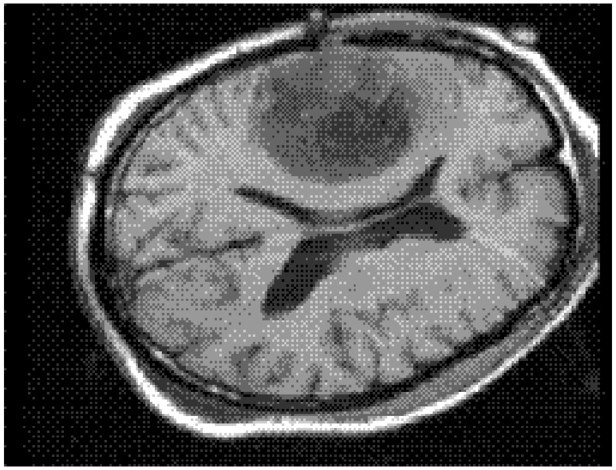
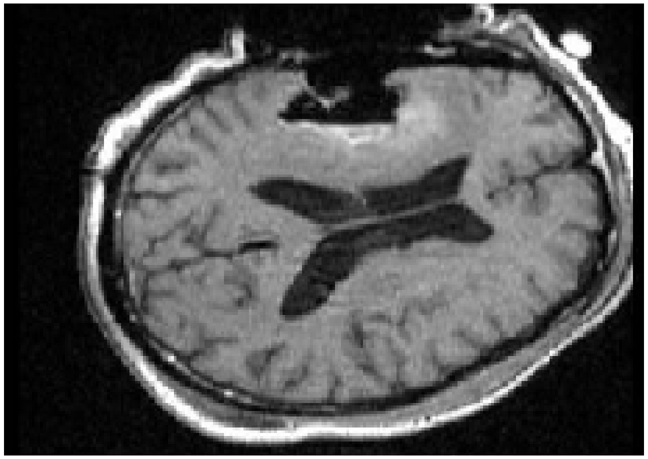
Problem:



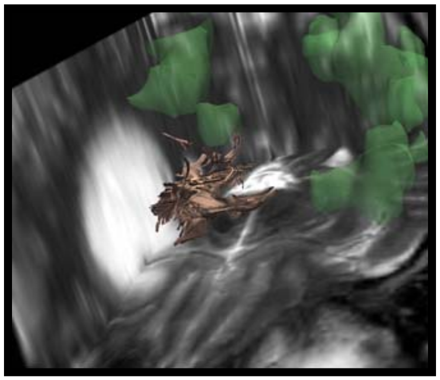


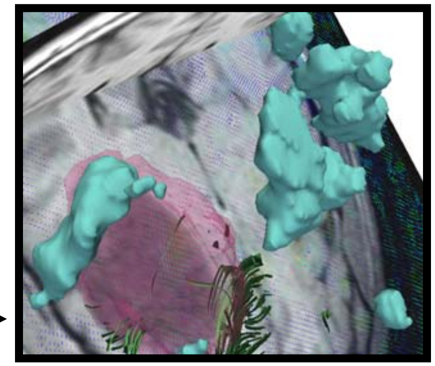
Neurosurgery

- non-forgiving procedure (**accuracy**)
- time-critical (**speed**)

Problem: Brain shift

IMAGE GUIDED NEUROSURGERY





intra-operative scanners can track deformation

Problems:

- Image quality is low compared to pre-operative data
- Time consuming to acquire data like fMRI during surgery using low (0.12-T) to medium (0.5-T) field magnets.

non-rigid registration: wrap pre-operative data into intra-operative images

Requirements

- **Accuracy:** transformation needs to be precise
- **Robust:** the registration should work with poor quality image (0.5T MRI)
- **Fast:** it should not take more than 1 min to complete the registration.

Outline

- Overview of Registration Method
  - Physics based model -- Approximation
    - *outliers*
- Distributed and Grid Computing
  - Performance Improvements
  - Accuracy
- Comparison with State-of-the-art
  - Summary of data from 11 patients
- Summary and Future Work

Pre-processing

- Segment the brain, ventricles, and tumor in pre-operative MRI (1.5T)
- Perform rigid registration with the first intra-operative image -- 256x256x60 T1 MR scan in ~ 4 min (before dura mater opening)
- Generate the patient-specific biomechanical model of the brain using segmented data
- Select blocks in pre-operative segmented image (w/o tumor)

Formulation

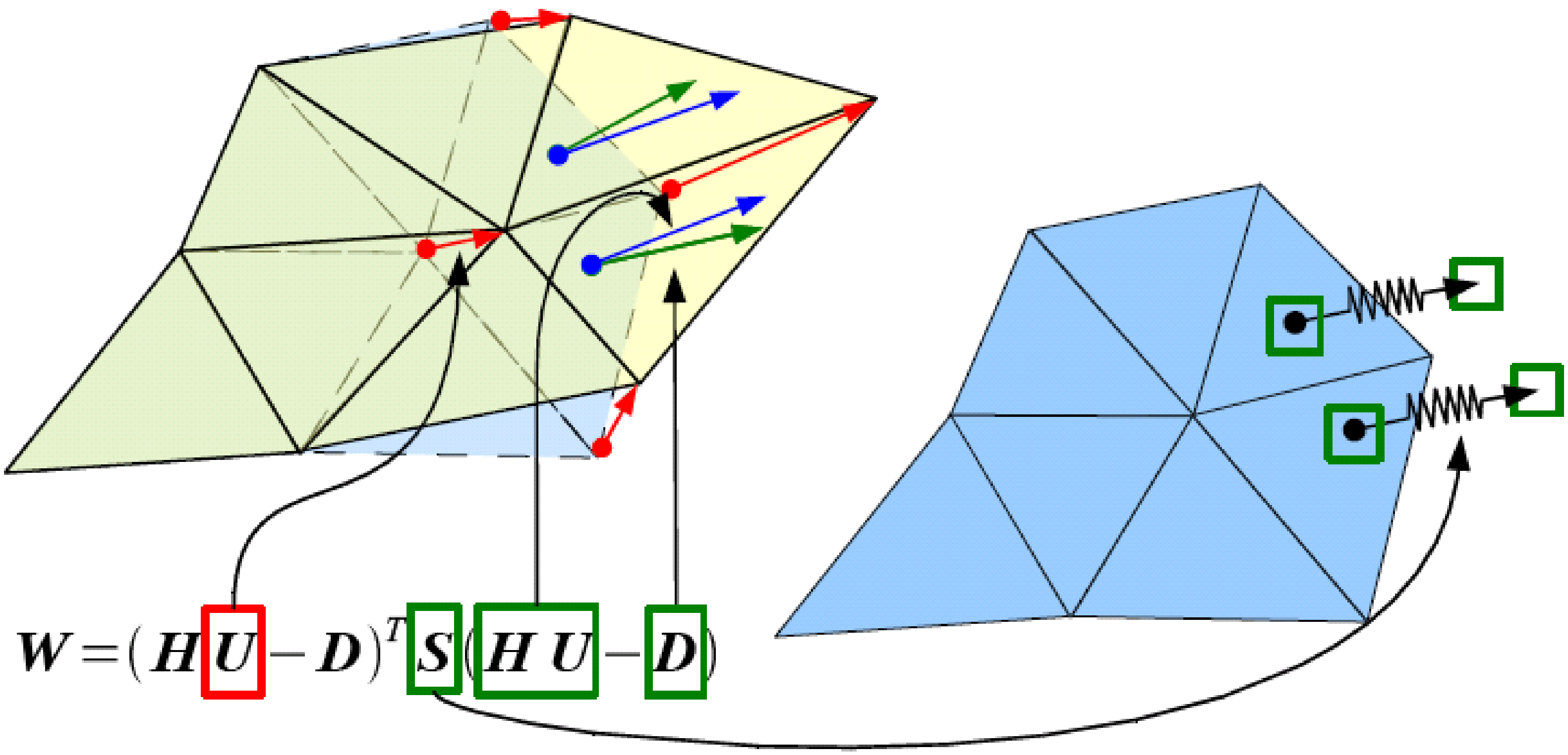
- Elastic matching of two images I_1 and I_2
  - Energy minimization procedure with two terms:
    1. **Mechanical energy** modeled by the physical properties of the depicted object to be deformed
    2. **Matching energy** modeled as the squared differences of images I_1 and I_2

$$\frac{1}{2}\int_{\Omega} \boldsymbol{\sigma}^T \boldsymbol{\epsilon}\, d\Omega + \frac{1}{2}\int_{\Omega} \left(I_1(\mathbf{x}+\mathbf{u}) - I_2(\mathbf{x})\right)^2 d\Omega$$

$\boldsymbol{\epsilon}$ is the strain tensor and $\boldsymbol{\sigma}$ the stress tensor

- Local polynomial transformation (mesh based)

Polynomial Transformation

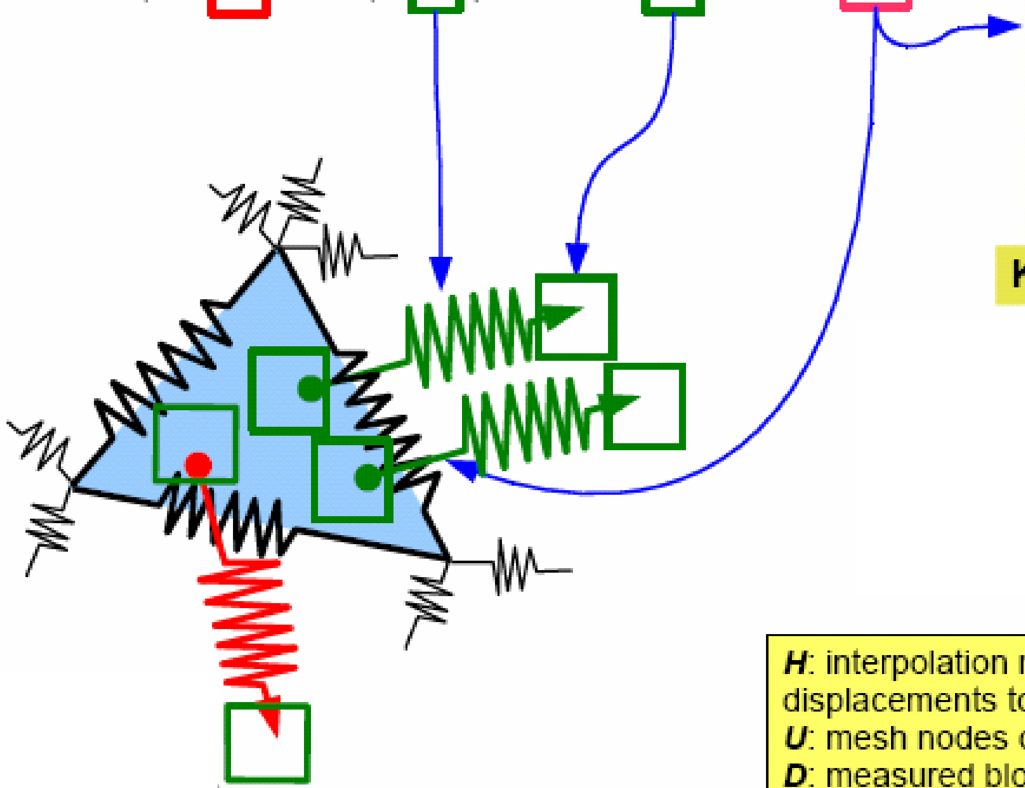


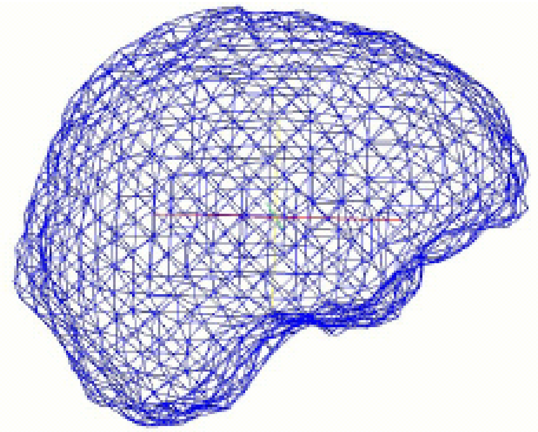
$$W = (H\,U - D)^T\,S\,(H\,U - D)$$

H: interpolation matrix from mesh vertex displacements to the block-matching displacements
U: mesh nodes displacements
D: measured block displacements
S: matching stiffness matrix
(good correlation => higher spring stiffness)

Approximation

$$W = \overbrace{(H\,U - D)^T\, S\, (H\,U - D)}^{\text{matching energy}} + \overbrace{U^T\, K\, U}^{\text{mechanical energy}}$$

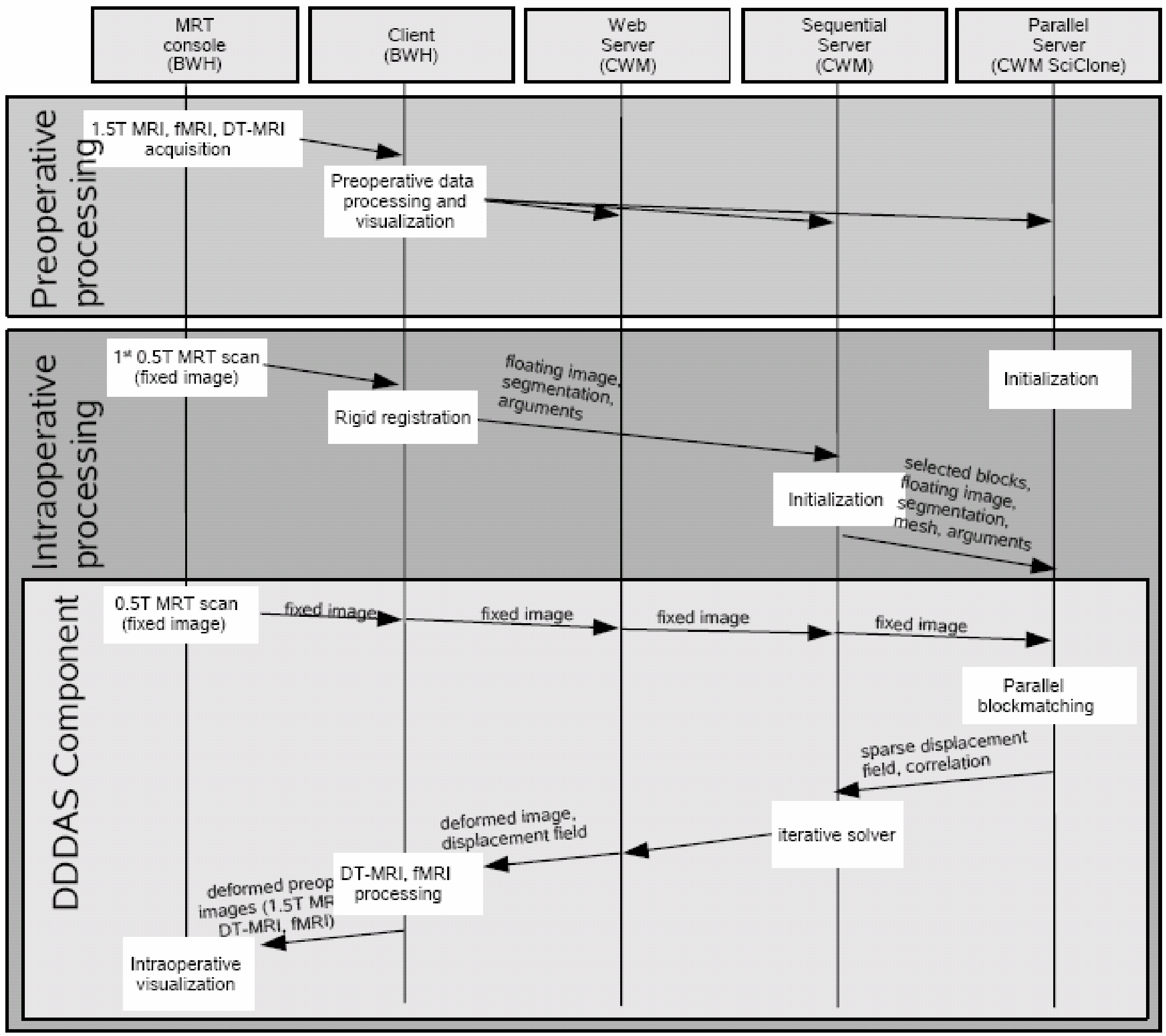




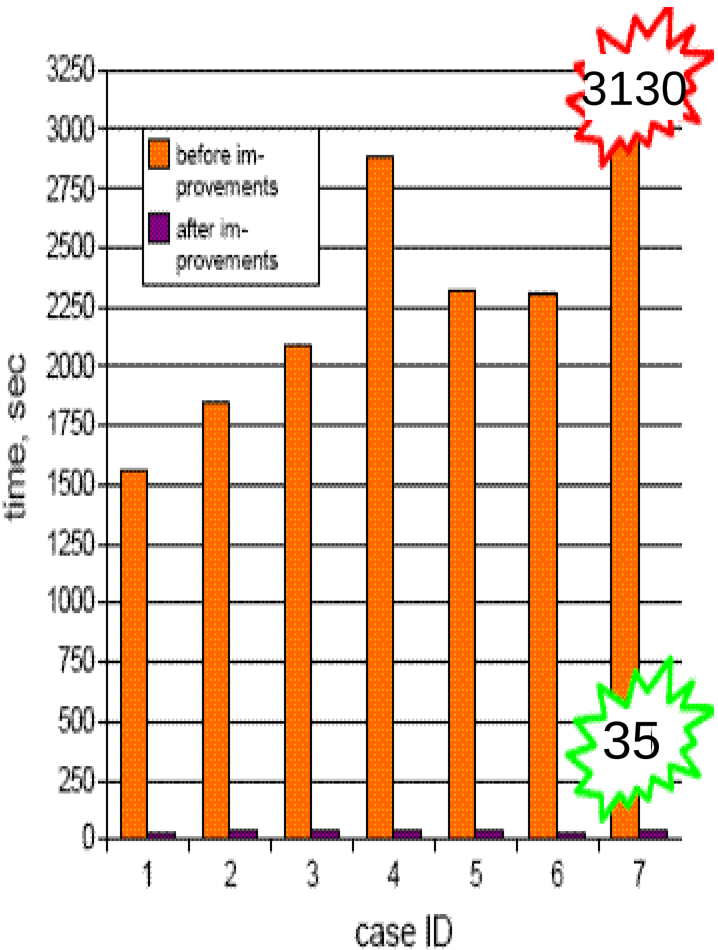
K: mechanical stiffness matrix

H: interpolation matrix from mesh vertex displacements to the block-matching displacements
U: mesh nodes displacements
D: measured block displacements
S: matching stiffness matrix
(good correlation => higher spring stiffness)

Distributed & Grid Computing: Current Setting:



Near Real-time



Setup	ID						
	1	2	3	4	5	6	7
WM-HPC, using original PVM implementation on 4 PEs	1558	1850	2090	2882	2317	2302	3130
WM-SciClone (240 procs), no load-balancing (MPI)	745	639	595	617	570	550.4	1153
Pre- and post-processing on single CS node, BM on WM-SciClone (240 procs), no load-balancing	226	123	182	189	217	174	189
Pre- and post-processing on single CS node, pre-processing in advance, BM on WM-SciClone (240 procs), dynamic load-balancing	35	53	56	47	42	42	48
Pre- and post-processing on single CS node, pre-processing in advance, BM on WM-SciClone (240 procs) and WM-CSLab(29 procs), dynamic 2-level load-balancing for FT	30	40	42	37	34	33	35

(Toward) Real-Time Image Guided Neurosurgery Using Distributed and Grid Computing, (with A. Fedorov , A. Kot, Neculai Archip, Peter Black, Olivier Clatz, Alexandra Golby, Ron Kikinis, Simon K. Warfield), **in SC06**.

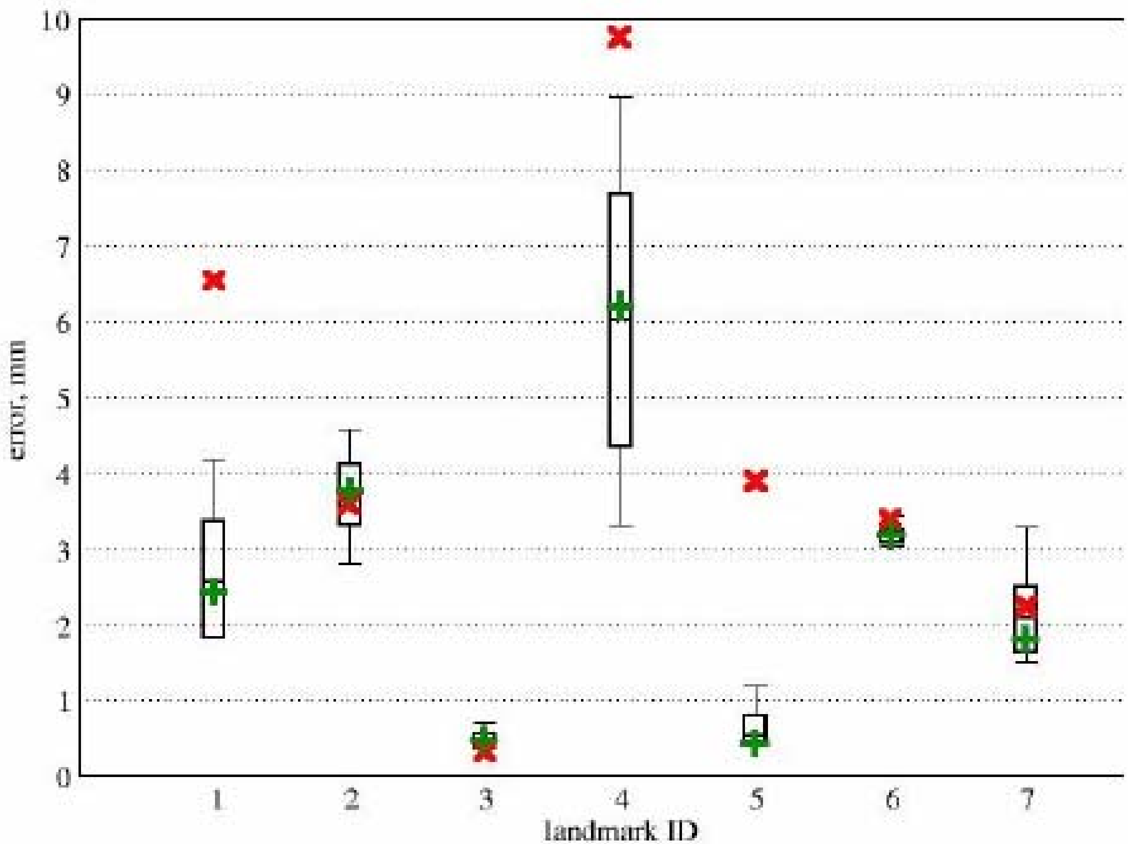
Accuracy

	Tumor position	Sex/ Age	Registration between preoperative and intraoperative scans (95% Haussdorf distance)			
			Max Displacement measured (mm)	Rigid - preop to intraop (mm)	Non-Rigid – preop to Intraop (mm)	Ratio Rigid/Non-Rigid
Case 1	right posterior frontal	F/29	10.68	5.95	1.90	3.13
Case 2	left posterior temporal	M/54	21.03	10.71	2.90	3.69
Case 3	left medial temporal	F/57	15.27	7.65	1.70	4.50
Case 4	left temporal	M/54	10.00	6.80	0.85	8.00
Case 5	right frontal	F/33	9.87	5.10	1.27	4.01
Case 6	left frontal	M/62	17.48	10.20	3.57	2.85
Case 7	right medial temporal	F/50	19.96	9.35	2.55	3.66
Case 8	right frontal	M/40	17.44	8.33	1.19	7.00
Case 9	right frontotemporal	M/28	15.08	7.14	1.87	3.81
Case 10	right occipital	F/56	9.48	5.95	1.44	4.13
Case 11	left frontotemporal	M/34	10.74	4.76	0.85	5.60

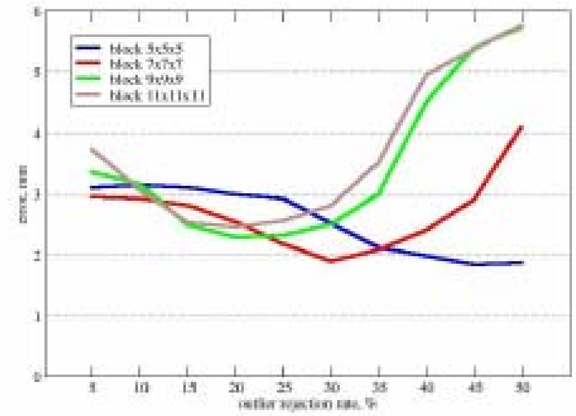
Table 1. Numerical accuracy results for the non-rigid registration algorithm and its comparison with conventional rigid-registration.

Non-rigid alignment of preoperative MRI, fMRI, DT-MRI, with intra-operative MRI for enhanced visualization and navigation In image-guided neurosurgery (with N. Archip, O. Clatz, A. Fedorov, A. Kot, S. Whalen, D. Kacher, F. Jolesz, A. Golby, P. Black, S Warfield) in **NeuroImage** (in press), Feb. 2007.

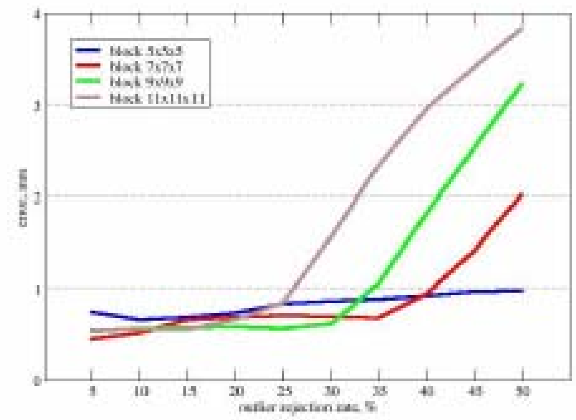
Accuracy



error, mm
0
1
2
3
4
5
6
7
8
9
10
1
2
3
4
5
6
7
landmark ID



block 5x5x5
block 7x7x7
block 9x9x9
block 11x11x11
5
10
15
20
25
30
35
40
45
50



block 5x5x5
block 7x7x7
block 9x9x9
block 11x11x11

Summary

- The method is less accurate where it is needed most, near by the tumor
  - Better selection of outliers
- Real-time search of the parametric space for the model - accuracy
  - Grid computing – multiple registrations
    - Intra-operative validation of results
- Future Work:
  - Can modeling and simulations together with intra-operative imaging reduce the frequency of disruptive intra-operative scans?

Problem: parameter search

get the number of rejection steps n_R from user
get the fraction of total blocks rejected f_R from user
for $i = 0$ to n_R **do**
    $F_i \Leftarrow KU_i$
    $U_{i+1} \Leftarrow [K + H^T SH]^{-1}[H^T SD + F_i]$
    for all blocks k **do**
        compute error function ξ_k
    end for
    reject $\frac{f_R}{n_R}$ blocks with highest error function ξ
    recompute S, H, D
end for
repeat
    $F_i \Leftarrow KU_i$
    $U_{i+1} \Leftarrow [K + H^T SH]^{-1}[H^T SD + F_i]$
until convergence

description	default setting
Young modulus (E)	694 Pa
Poisson's ratio (v)	0.45
selected block fraction (f_B)	10%
block connectivity ($bConn$)	26
block size ($bSize$)	$7 \times 7 \times 7$
window size ($wSize$)	$11 \times 11 \times 25$
search step ($sStep$)	$1 \times 1 \times 1$
# of rejection steps (n_R)	10
rejected blocks fraction (f_R)	25%
energy trade-off (α)	$\frac{trace(K)}{n}$
error model breakup point (λ)	0.5
CG precision (r_{CG})	0.001