Intraoperative Registration of Pathology for Adjuvant Postoperative Radiotherapy

Project 4. Seminar Presentation

Steven Lin

Team: Kareem Fakhoury, Matthew Hauser

Mentors: Dr. Harry Quon, Dr. Jeremy Richmon, Dr. Junghoon Lee

JOHNS HOPKINS WHITING SCHOOL of ENGINEERING ERC | CISST ciis

Overview

- Paper 1:
    - J. B. A. Maintz and M. A. Viergever. **A survey of medical image registration.** *Med. Image Anal.*, 2(1):1 –36, 1998.

- Paper 2:
    - S. Klein, M. Staring, and J. P. W. Pluim**. Evaluation of optimisation methods for nonrigid medical image registration using mutual information and B-splines.** *IEEE Trans. Image Process.*, 16(12):2879 – 2890,December 2007.

Paper 1: A survey of medical image registration

- *Purpose*:
  - A survey to compare and categorize image registration techniques.
  - Characterize registration models based on nine criteria.

JOHNS HOPKINS
WHITING SCHOOL of ENGINEERING
ERC | CISST
ciis

Classification of Registration Methods

I. Dimensionality
II. Nature of Registration
III. Nature of Transformation
IV. Domain of Transformation
V. Interaction
VI. Optimization Procedure
VII. Modalities Involved
VIII. Subject
IX. Object

Classification of Registration Methods

I. Dimensionality
II. Nature of Registration
III. Nature of Transformation
IV. Domain of Transformation
V. Interaction
VI. Optimization Procedure
VII. Modalities Involved
VIII. Subject
IX. Object

JOHNS HOPKINS
WHITING SCHOOL
of ENGINEERING
ERC | CISST
ciis

Dimensionality

- Registered dimensions:
  - 2-D – 2-D
  - 2-D – 3-D
  - 3-D – 3-D
  - Can also depend on time, which would be useful for a progression study

- ***Project Relevance:*** *3-D to 3-D, no time series necessary.*

Classification of Registration Methods

I. Dimensionality
II. Nature of Registration
III. Nature of Transformation
IV. Domain of Transformation
V. Interaction
VI. Optimization Procedure
VII. Modalities Involved
VIII. Subject
IX. Object

JOHNS HOPKINS WHITING SCHOOL of ENGINEERING ERC | CISST ciis

Nature of Registration - Extrinsic

- Rely on artificial objects
- Objects may be:
  - Invasive (e.g. screw markers)
  - Non-invasive (e.g. skin markers)

JOHNS HOPKINS
WHITING SCHOOL
of ENGINEERING

ERC | CISST

ciis

Nature of Registration - Intrinsic

- Based on the image of the patient
  - *Landmark based:*
    - User identify points of visible anatomy. This means a small amount of data compare to entire image set, good for faster registration.
    - Often used in combination with other registration basis.
  - *Segmentation based:*
    - Extracted structure is fit to the second image
    - In deformable, a template is deformed to fit a second image
  - *Voxel property based:*
    - Operate by reducing image grey values, into important parameters
    - Use full image content

Nature of Registration

- ***Project Relevance:***
  - *Need extrinsic markers in order to map intraoperative to pre-operative.*
  - *Dr. Lee has suggested the usage of landmark based pre-registration with other methods.*
  - *Deformable segment may involve initial pre-registration and a deformed model that is sufficiently similar to a defined template. However, this would no be an issue in our application.*
    - *Dr. Lee suggested local constraints to eliminate registration errors that would come from very similar anatomy.*
  - *Full image voxel based registration may be of use.*

JOHNS HOPKINS
WHITING SCHOOL of ENGINEERING

ERC | CISST

ciis

Classification of Registration Methods

I. Dimensionality
II. Nature of Registration
III. Nature of Transformation
IV. Domain of Transformation
V. Interaction
VI. Optimization Procedure
VII. Modalities Involved
VIII. Subject
IX. Object

JOHNS HOPKINS WHITING SCHOOL of ENGINEERING ERC | CISST ciis

Nature of Transformation

- Rigid – only translation/rotation
- Affine – maps parallel lines onto parallel lines
- Projective – maps lines onto lines
- Curved (elastic) – lines onto curves

Domain of Transformation

- Local transformation – composite of multiple transformation on sub-images
- Global transformation – single transformation on image
- *Project Relevance – we will most likely adopt composite of curved and rigid local transformations based on where soft tissue is removed*

JOHNS HOPKINS WHITING SCHOOL of ENGINEERING ERC | CISST ciis

Classification of Registration Methods

I. Dimensionality
II. Nature of Registration
III. Nature of Transformation
IV. Domain of Transformation
V. Interaction
VI. Optimization Procedure
VII. Modalities Involved
VIII. Subject
IX. Object

JOHNS HOPKINS WHITING SCHOOL of ENGINEERING ERC | CISST ciis

Interaction

- Interactive – user guided
- Semi-automatic – may be user initialized, steered or both
- Automatic

- *Project Relevance - Elastix, the package where this paper is referenced, uses a semi-automatic registration method. The algorithm is selected but the user can alter the parameters*

JOHNS HOPKINS
WHITING SCHOOL of ENGINEERING
ERC | CISST
ciis

Classification of Registration Methods

I. Dimensionality
II. Nature of Registration
III. Nature of Transformation
IV. Domain of Transformation
V. Interaction
VI. Optimization Procedure
VII. Modalities Involved
VIII. Subject
IX. Object

Optimization Computed

- Parameters computed through an explicit fashion
- Parameters searched by optimizing a cost function

- *Project Relevance: Elastix uses an algorithm that searches for the parameters through maximizing a mutual information similarity measure.*

Classification of Registration Methods

I. Dimensionality
II. Nature of Registration
III. Nature of Transformation
IV. Domain of Transformation
V. Interaction
VI. Optimization Procedure
VII. **Modalities Involved**
VIII. Subject
IX. Object

JOHNS HOPKINS WHITING SCHOOL of ENGINEERING

ERC | CISST

ciis

Modalities

- Monomodality – registration between same type of image (e.g. CT-CT)
- Multimodality - registration between different types of image (e.g. CT-MR)

- *Project Relevance: The core of this project is in the monomodality CT-CT registration. The registration of intraoperative to pre-operative is done with Polaris-CT.*

Classification of Registration Methods

I. Dimensionality
II. Nature of Registration
III. Nature of Transformation
IV. Domain of Transformation
V. Interaction
VI. Optimization Procedure
VII. Modalities Involved
VIII. Subject
IX. Object

JOHNS HOPKINS WHITING SCHOOL of ENGINEERING ERC | CISST ciis

Subject and Object

- *Project Relevance: Our project involves a intrasubject registration, where the object is the head.*

Discussion of Paper 1

- Useful in identifying the algorithms to look for
- Explain certain functionalities in Elastix
- Provide future research papers and methods

Paper 2: **Evaluation of optimisation methods for nonrigid medical image registration using mutual information and B-splines**

- *Purpose*:
  - Introduce registration techniques that maximize mutual information and constructs a deformation field with cubic B-spline
  - Compare accuracy, precision and convergence properties of eight methods

Optimization

- Family of registration operate by maximizing the mutual information matrix:

$$\hat{\boldsymbol{\mu}} = \arg\min_{\boldsymbol{\mu}} C(\boldsymbol{\mu}; I_F, I_M)$$

- $\mu \equiv$ B-spline coefficients that defines a deformation field
- $C \equiv$ mutual information similarity metric
- I_F is the fixed image
- I_M is the moving, deformed image

JOHNS HOPKINS WHITING SCHOOL of ENGINEERING ERC | CISST ciis

Mutual Information

- Measures information that two random variables share
- Definition of mutual information for discrete random variables

$$MI(\boldsymbol{\mu}; I_F, I_M) = \sum_{m \in L_M} \sum_{f \in L_F} p(f, m; \boldsymbol{\mu}) \times \log_2 \left(\frac{p(f, m; \boldsymbol{\mu})}{p_F(f) p_M(m; \boldsymbol{\mu})} \right)$$

JOHNS HOPKINS WHITING SCHOOL of ENGINEERING ERC | CISST ciis

Optimization Continued

- μ can be found using an iterative optimization

$$\boldsymbol{\mu}_{k+1} = \boldsymbol{\mu}_k + a_k \boldsymbol{d}_k, \quad k = 0, 1, 2, \ldots$$

- a_k is a gain factor, that controls the step size
- d_k is the search direction

- Algorithms vary based on the computation of a_k and d_k
  - Deterministic gradient-based
  - Stochastic gradient-based
  - Evolution strategy

Gradient Descent (GDD and GDL)

$$\boldsymbol{\mu}_{k+1} = \boldsymbol{\mu}_k + a_k \boldsymbol{d}_k, \quad k = 0, 1, 2, \ldots$$

- $d_k = g(\mu_k)$, derivative of the cost function

$$\boldsymbol{\mu}_{k+1} = \boldsymbol{\mu}_k - a_k \boldsymbol{g}(\boldsymbol{\mu}_k)$$

- GDD: $a_k = \frac{a}{(k+A)^{\alpha}}$, with user $a,\ A, \alpha$
- GDL: a_k determined through Moré-Thuente routine

JOHNS HOPKINS WHITING SCHOOL of ENGINEERING ERC | CISST ciis

Quasi-Newton

- Based on Newton-Raphson algorithm

$$\boldsymbol{\mu}_{k+1} = \boldsymbol{\mu}_k - a_k L_k \boldsymbol{g}(\boldsymbol{\mu}_k).$$

- $L_k \approx [H(\mu_k)]^{-1}$, approximation of the inverse Hessian of the cost function. Can be found using the LBFGS method
- a_k is found using Moré-Thuente routine
  - Inexact line search routine that finds a_k so that it satisfies the strong Wolfe conditions

$$C(\boldsymbol{\mu}_{k+1}) \leq C(\boldsymbol{\mu}_k) + c_1 a_k \boldsymbol{d}_k^T \boldsymbol{g}(\boldsymbol{\mu}_k)$$
$$\left|\boldsymbol{d}_k^T \boldsymbol{g}(\boldsymbol{\mu}_{k+1})\right| \leq c_2 \left|\boldsymbol{d}_k^T \boldsymbol{g}(\boldsymbol{\mu}_k)\right|$$

Nonlinear Conjugate Gradient

- Direction determined through linear combination of the gradient and the previous direction

$$\boldsymbol{d}_k = -\boldsymbol{g}(\boldsymbol{\mu}_k) + \beta_k \boldsymbol{d}_{k-1}.$$

- The factor β_k is computed through

$$\beta_k = \max\left(0, \min\left(\beta_k^{\mathrm{HS}}, \beta_k^{\mathrm{DY}}\right)\right)$$

$$\text{Dai} - \text{Yuan}: \quad \beta_k^{\mathrm{DY}} = \frac{\boldsymbol{g}_k^T \boldsymbol{g}_k}{\boldsymbol{d}_{k-1}^T(\boldsymbol{g}_k - \boldsymbol{g}_{k-1})}$$

$$\text{Hestenes} - \text{Stiefel}: \quad \beta_k^{\mathrm{HS}} = \frac{\boldsymbol{g}_k^T(\boldsymbol{g}_k - \boldsymbol{g}_{k-1})}{\boldsymbol{d}_{k-1}^T(\boldsymbol{g}_k - \boldsymbol{g}_{k-1})}$$

Stochastic Gradient Descent (KW, SP, RM)

$$\boldsymbol{\mu}_{k+1} = \boldsymbol{\mu}_k - a_k \widetilde{\boldsymbol{g}}_k$$

- $\tilde{g}_k$ is an approximation of the gradient

- *Kiefer-Wolfowitz:* Finite difference approximation

$$[\widetilde{\boldsymbol{g}}_k]_i = \frac{\mathcal{C}(\boldsymbol{\mu}_k + c_k \boldsymbol{e}_i) - \mathcal{C}(\boldsymbol{\mu}_k - c_k \boldsymbol{e}_i)}{2c_k}$$

$$[\widetilde{\boldsymbol{g}}_k]_i = \frac{\widetilde{\mathcal{C}}_{ki}^{+} - \widetilde{\mathcal{C}}_{ki}^{-}}{2c_k}$$

$$\widetilde{\mathcal{C}}_{ki}^{+} = \mathcal{C}(\boldsymbol{\mu}_k + c_k \boldsymbol{e}_i) + \varepsilon_{ki}^{+}$$

$$\widetilde{\mathcal{C}}_{ki}^{-} = \mathcal{C}(\boldsymbol{\mu}_k - c_k \boldsymbol{e}_i) + \varepsilon_{ki}^{-}$$

JOHNS HOPKINS WHITING SCHOOL of ENGINEERING ERC | CISST ciis

- *Simultaneous Perturbation:*

$$[\tilde{\boldsymbol{g}}_k]_i = \frac{\tilde{\mathcal{C}}_k^+ - \tilde{\mathcal{C}}_k^-}{2c_k[\boldsymbol{\Delta}_k]_i}$$

$$\tilde{\mathcal{C}}_k^+ = \mathcal{C}(\boldsymbol{\mu}_k + c_k\boldsymbol{\Delta}_k) + \varepsilon_k^+$$

$$\tilde{\mathcal{C}}_k^- = \mathcal{C}(\boldsymbol{\mu}_k - c_k\boldsymbol{\Delta}_k) + \varepsilon_k^-$$

- *Robbins-Monro:* Assume the approximation of the cost function

$$\tilde{\boldsymbol{g}}_k = \boldsymbol{g}(\boldsymbol{\mu}_k) + \boldsymbol{\varepsilon}_k$$

  - Approximation done with randomly selected subset of voxels at each iteration

JOHNS HOPKINS WHITING SCHOOL of ENGINEERING ERC | CISST ciis

Evolution Strategy

- Based on natural selection
- Each iteration has three phases: *Offspring generation, selection, recombination*
- *Offspring generation*: set of λ direction is found in $\mathcal{N}(0, C_k)$.
- *Selection*: the P directions that has the lowest value in the cost function, $\mathcal{C}(\boldsymbol{\mu}_k + a_k \boldsymbol{d}_k^{(\ell)})$, are found
- *Recombination*: All P directions are summed with weighing factors

$$\boldsymbol{d}_k = \sum_{p=1}^{P} w_p \boldsymbol{d}_k^{(p;\lambda)}$$

JOHNS HOPKINS WHITING SCHOOL of ENGINEERING ERC | CISST ciis

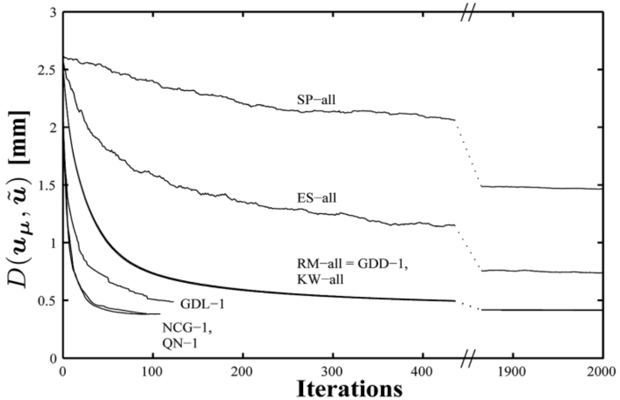
Experiments and Results

- Four CT of the heart
- Known deformation field $\tilde{u}$ generated with randomly placed Gaussian blobs.
- Accuracy is evaluated using the following:

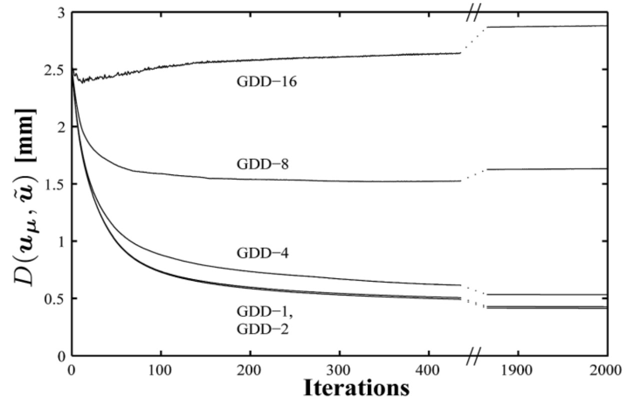
$$D(\boldsymbol{u}_1, \boldsymbol{u}_2) = \frac{1}{|I_F|} \sum_{\boldsymbol{x}_i \in I_F} \|\boldsymbol{u}_1(\boldsymbol{x}_i) - \boldsymbol{u}_2(\boldsymbol{x}_i)\|$$

- Overall, RM is the most accurate.

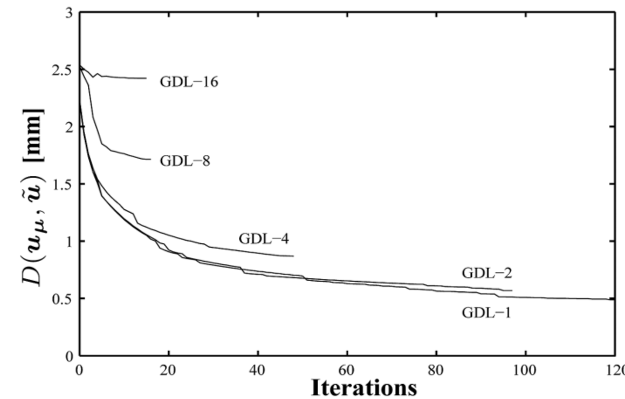
JOHNS HOPKINS WHITING SCHOOL of ENGINEERING ERC | CISST ciis



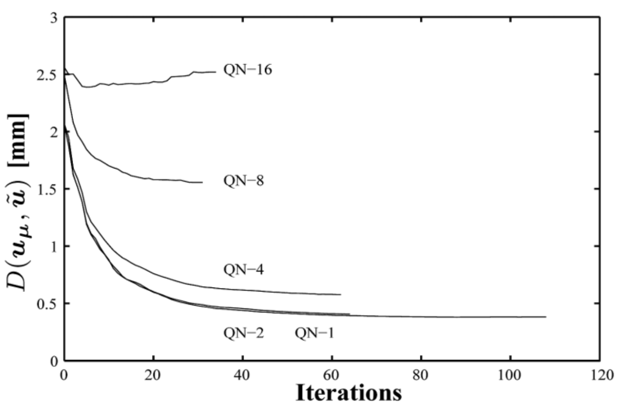
(a) All methods without subsampling



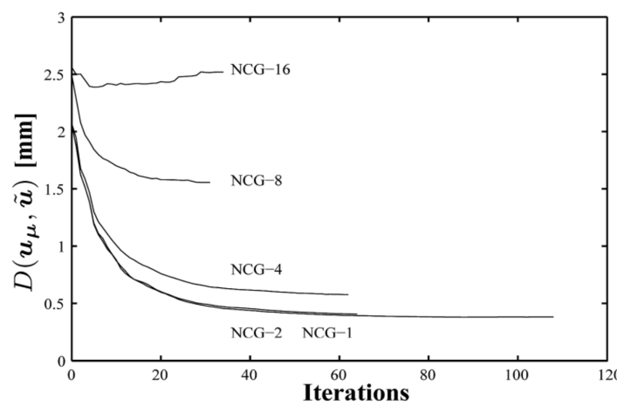
(b) GDD



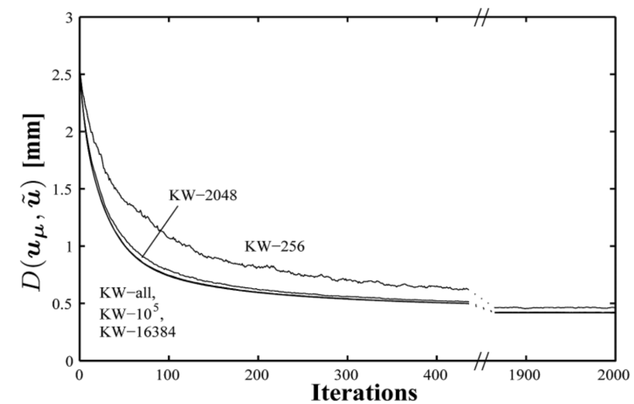
(c) GDL



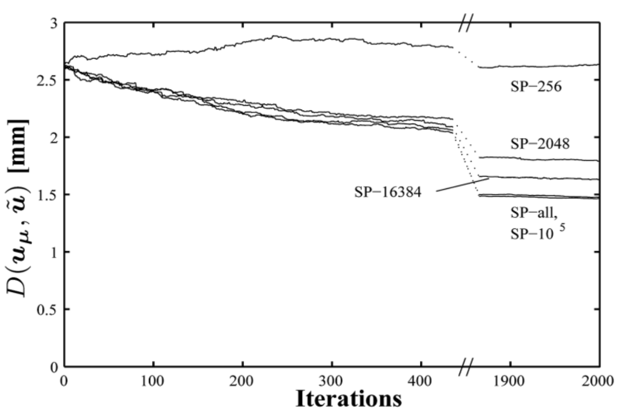
(d) QN



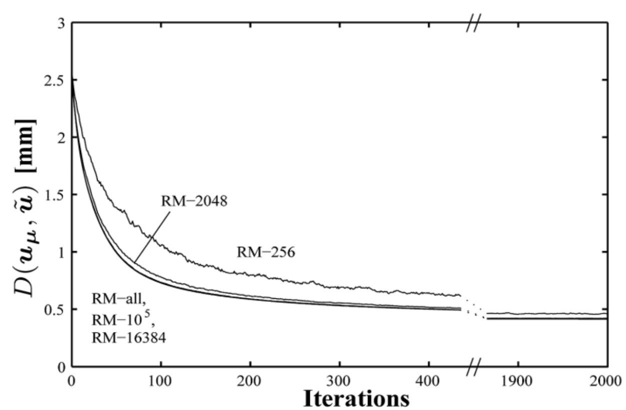
(e) NCG



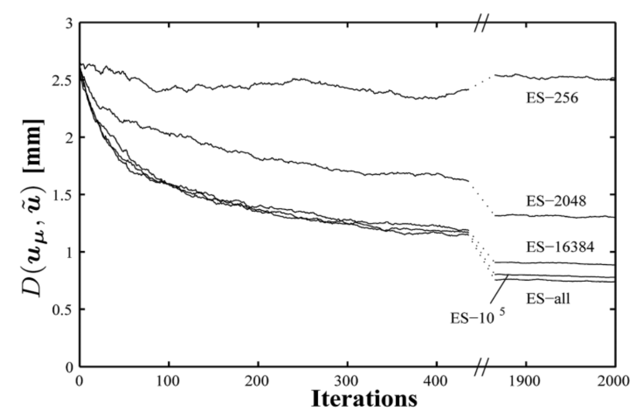
(f) KW



(g) SP



(h) RM



(i) ES

Experiments and Results

- Five patients, chest CT's were taken months apart.
- Images were registered.
- Precision was measured with

$$D(\boldsymbol{u}_1, \boldsymbol{u}_2) = \frac{1}{|I_F|} \sum_{\boldsymbol{x}_i \in I_F} ||\boldsymbol{u}_1(\boldsymbol{x}_i) - \boldsymbol{u}_2(\boldsymbol{x}_i)||$$

- Dice similarity index is used to measure accuracy.

$$\text{overlap} = \frac{2\, V_1 \cap V_2}{V_1 \; + |V_2|} \cdot 100\%$$

- RM was found to be the best method.

JOHNS HOPKINS WHITING SCHOOL of ENGINEERING ERC | CISST ciis

	CT follow-up chest ($t_g \approx 220$ s.)				MR BFFE prostate ($t_g \approx 56$ s.)						MR T1-T2 prostate ($t_g \approx 9$ s.)		
	time avg $[t_g]$	overlap avg $\pm$ sd [%]	precision avg $\pm$ sd [mm]	effect $\mathcal{R}$ avg $\pm$ sd [mm]	time avg $[t_g]$	overlap avg $\pm$ sd [%]	precision avg $\pm$ sd [mm]	effect $\mathcal{R}$ avg $\pm$ sd [mm]	overlap* avg $\pm$ sd [%]	precision* avg $\pm$ sd [mm]	time avg $[t_g]$	precision avg $\pm$ sd [mm]	effect $\mathcal{R}$ avg $\pm$ sd [mm]
rigid		36 ± 15	9.2 ± 7.1			37 ± 11	3.2 ± 1.0					2.9 ± 0.8	
GDL-1	700	76 ± 7	0.1 ± 0.1	1.0 ± 0.4	700	58 ± 5	0.1 ± 0.1	2.2 ± 0.9	58 ± 6	0.2 ± 0.1	100	0.6 ± 0.4	1.4 ± 0.5
GDL-2	100	75 ± 6	0.4 ± 0.1	0.9 ± 0.3	300	58 ± 5	0.2 ± 0.1	2.0 ± 0.9	58 ± 6	0.3 ± 0.2	50	0.7 ± 0.4	1.4 ± 0.5
GDL-4	10	75 ± 7	0.7 ± 0.2	0.6 ± 0.3	40	57 ± 6	0.6 ± 0.2	1.8 ± 0.7	57 ± 6	0.7 ± 0.3	10	1.1 ± 0.6	1.7 ± 0.4
GDL-8	1	71 ± 7	1.3 ± 0.3	0.6 ± 0.3	9	56 ± 6	1.6 ± 0.7	1.6 ± 0.6	55 ± 6	1.8 ± 0.7	2	1.7 ± 0.5	1.2 ± 0.3
GDL-16	0.09	60 ± 12	3.3 ± 2.6	0.9 ± 0.3	1	45 ± 6	3.3 ± 0.9	2.0 ± 0.5	43 ± 6	2.9 ± 1.0	1	3.0 ± 0.8	1.6 ± 0.7
QN-1	200	77 ± 7	0.0 ± 0.0	1.7 ± 0.8	100	58 ± 5	0.0 ± 0.0	4.0 ± 2.0	58 ± 6	0.0 ± 0.0	60	0.0 ± 0.0	4.4 ± 2.1
QN-2	40	76 ± 7	0.2 ± 0.1	1.4 ± 0.6	40	58 ± 5	0.1 ± 0.0	3.9 ± 2.0	58 ± 6	0.1 ± 0.0	20	0.4 ± 0.1	4.8 ± 2.2
QN-4	5	75 ± 7	0.7 ± 0.2	1.3 ± 0.5	8	57 ± 5	0.6 ± 0.6	3.4 ± 1.7	57 ± 6	0.5 ± 0.2	7	1.0 ± 0.6	4.9 ± 1.8
QN-8	0.5	71 ± 7	1.3 ± 0.3	1.4 ± 0.5	1	56 ± 6	1.4 ± 0.6	3.4 ± 1.2	55 ± 6	1.9 ± 0.8	2	1.9 ± 0.9	4.7 ± 1.2
QN-16	0.1	57 ± 7	2.8 ± 0.9	2.4 ± 0.8	0.2	43 ± 5	3.5 ± 0.9	4.0 ± 1.2	40 ± 8	3.2 ± 0.7	0.3	3.9 ± 1.0	4.3 ± 1.6
NCG-1	300	77 ± 7	0.1 ± 0.0	1.4 ± 0.6	200	58 ± 5	0.0 ± 0.0	3.0 ± 1.6	58 ± 6	0.0 ± 0.0	70	0.2 ± 0.2	2.8 ± 1.5
NCG-2	40	76 ± 7	0.2 ± 0.1	1.3 ± 0.6	70	58 ± 5	0.1 ± 0.1	2.8 ± 1.3	58 ± 6	0.2 ± 0.1	30	0.5 ± 0.3	2.8 ± 1.4
NCG-4	5	75 ± 7	0.7 ± 0.2	1.2 ± 0.6	10	57 ± 6	0.7 ± 0.5	2.5 ± 1.1	57 ± 6	0.6 ± 0.3	7	1.1 ± 0.6	3.4 ± 1.2
NCG-8	0.5	71 ± 8	1.4 ± 0.5	1.6 ± 0.6	2	56 ± 5	1.5 ± 0.6	2.3 ± 1.0	55 ± 6	1.7 ± 0.7	2	1.7 ± 0.7	2.7 ± 0.8
NCG-16	0.07	57 ± 9	3.4 ± 2.3	2.8 ± 2.3	0.5	46 ± 6	3.3 ± 0.9	3.0 ± 0.8	41 ± 10	3.3 ± 1.0	0.2	3.6 ± 0.9	3.2 ± 1.1
RM-all	1000	76 ± 7	0.2 ± 0.1	0.6 ± 0.3	2000	57 ± 6	0.4 ± 0.2	1.0 ± 0.4	58 ± 6	0.3 ± 0.2	3000	0.6 ± 0.4	0.9 ± 0.6
RM-10^5	30	76 ± 7	0.2 ± 0.1	0.6 ± 0.2	200	57 ± 6	0.4 ± 0.2	1.0 ± 0.4	58 ± 6	0.3 ± 0.2	700	0.7 ± 0.6	0.9 ± 0.5
RM-16384	5	76 ± 7	0.2 ± 0.1	0.6 ± 0.3	30	57 ± 6	0.4 ± 0.2	1.0 ± 0.4	58 ± 6	0.3 ± 0.2	200	0.7 ± 0.5	0.9 ± 0.5
RM-2048	0.6	75 ± 7	0.5 ± 0.1	0.8 ± 0.3	4	57 ± 6	0.4 ± 0.2	1.0 ± 0.4	58 ± 6	0.4 ± 0.2	30	0.7 ± 0.5	1.0 ± 0.5
RM-256	0.08	58 ± 5	2.6 ± 0.6	5.6 ± 1.1	0.5	57 ± 6	0.7 ± 0.4	1.1 ± 0.4	54 ± 8	1.3 ± 0.8	4	1.6 ± 0.8	2.0 ± 1.0

Discussion of Paper 2

- Paper has demonstrated that the Robbins-Monro method may be the most valuable method.
- Quasi-Newton and Nonlinear Conjugate Gradient method may be used, with lower subsampling factors.
- Useful paper, in both understanding Elastix and future research.

Citations

- J. B. A. Maintz and M. A. Viergever. A survey of medical image registration. *Med. Image Anal.*, 2(1):1 –36, 1998.
- S. Klein, M. Staring, and J. P. W. Pluim. Evaluation of optimisation methods for nonrigid medical image registration using mutual information and B-splines. *IEEE Trans. Image Process.*, 16(12):2879 – 2890,December 2007.

JOHNS HOPKINS
WHITING SCHOOL
of ENGINEERING

ERC | CISST