MULTI-MODAL IMAGE REGISTRATION USING STRUCTURAL FEATURES

UNIVERSITY OF Waterloo

Keyvan Kasiri, David A Clausi, Paul Fieguth
{kkasiri, dclausi, pfieguth}@uwaterloo.ca

Vision and Image Processing Group
Systems Design Engineering

Motivation

- Incorporating multiple image modalities of the same subject or organ plays an important role for diagnosis and computer-aided surgery.
- Image registration helps clinicians integrate the information obtained from different imaging modalities.
- Of particular interest is registering multiple atlases from different modalities in a multi-atlas segmentation problem.
- Accuracy and computational time are the two major challenges.

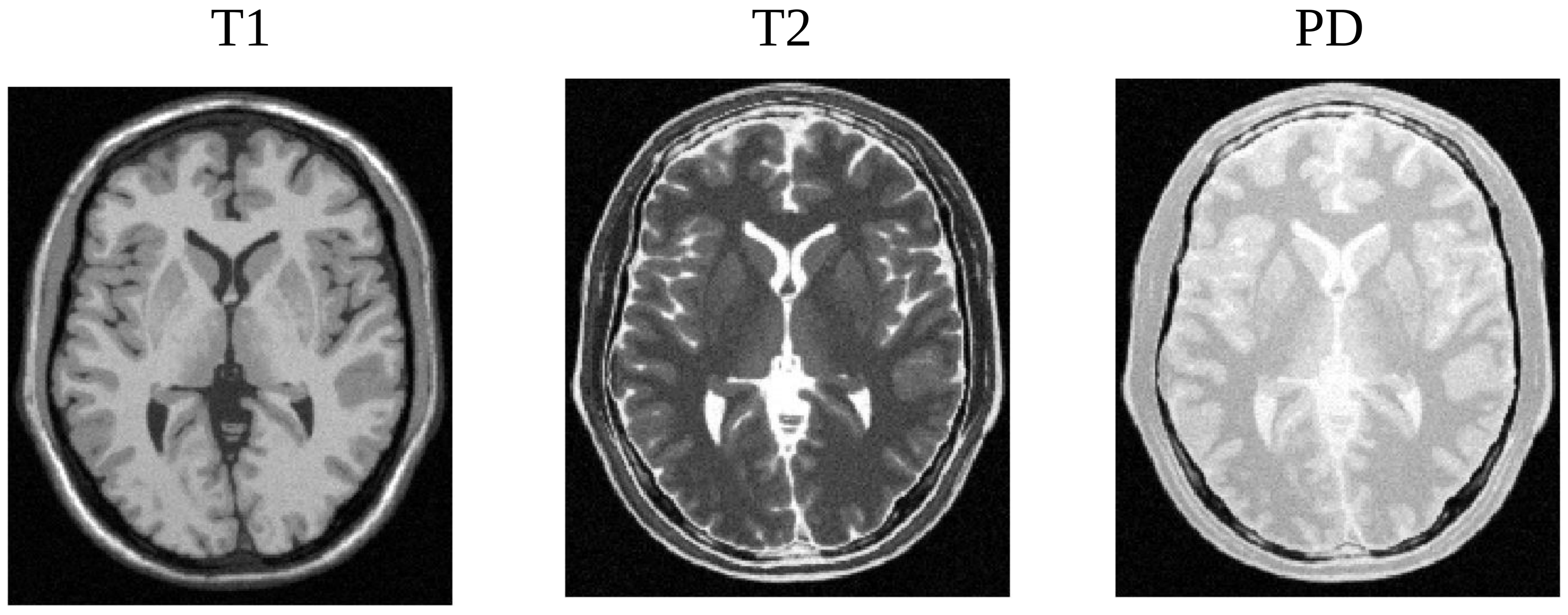
Problem

- Most common method for multi-modal image registration work based on statistical intensity relationship.
- Would be challenging specifically when
  - the intensity relations are not spatially invariant,
  - there is a highly complex intensity relationship.

- **Objective:** To bypass the issue related to complex intensity relationships and simplify the registration procedure by on converting the problem to a mono-modal one.

Fig1. Brain MR images of different Modalities

T1 T2 PD



Methodology

- The problem of registering I_m to I_f can be formulated as estimating the optimal deformation transform:

$$\hat{T} = \arg\min_{T} D\big(I_f, T(I_m)\big),$$

  T and D are the transformation and the dissimilarity measure.
- I_m and I_f will be mapped to a new intensity mapping space using structural features.
- Structural features are extracted by combining phase congruency and edges information of the images.
- **Step 1-Phase congruency (PC):** multi-scale representation of images using an over-complete Log-Gabor complex wavelet transform.

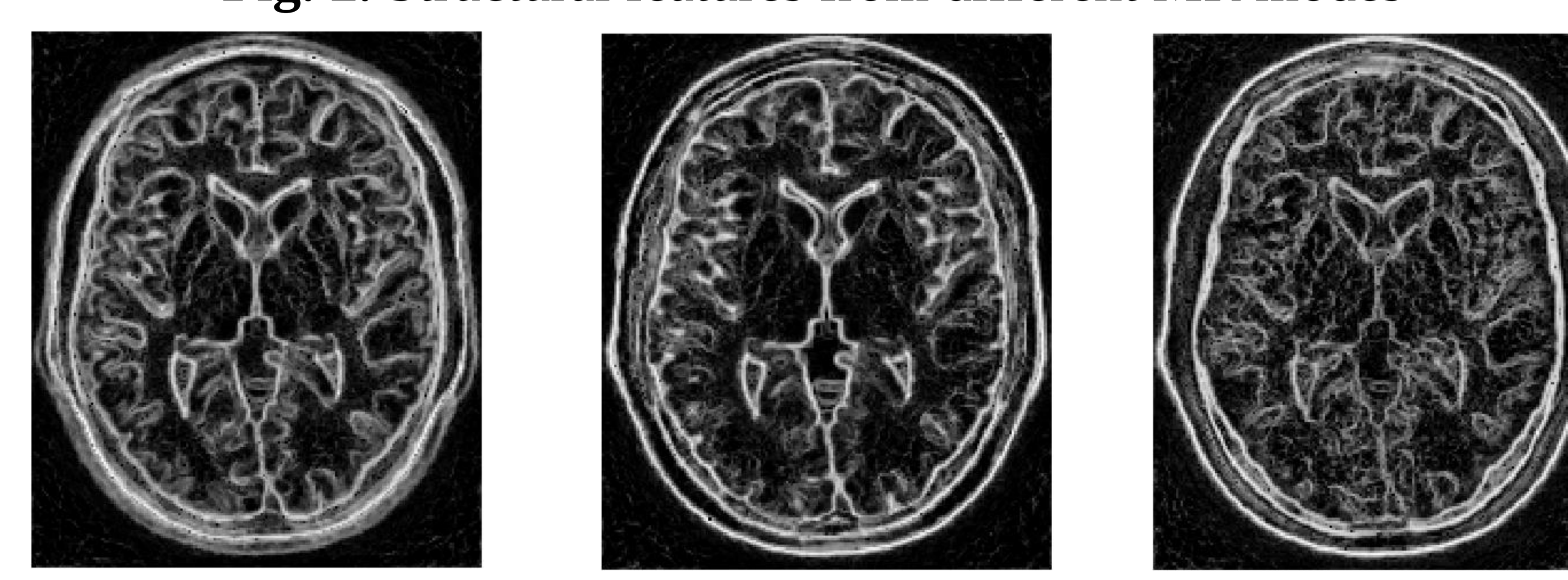
$$\Upsilon_{n,i}(\mathbf{x}) = A_{n,i}(\mathbf{x})\exp\big(j\phi_{n,i}(\mathbf{x})\big),$$

  $A_{n,i}$ and $\phi_{n,i}$ are the amplitude and phase of the complex wavelet coefficient at location $\mathbf{x}$ for nth scale and ith orientation.
- **Step 2-Gradient magnitude (GM)** of images is used to encode contrast information.
- **Step 3-Combination Strategy:**
  - Intensity normalization and histogram equalization,
  - Combining PC and GM

$$J(I) = GM^{\alpha}(I) \otimes PC^{\beta}(I)$$

  $\otimes$ is element-by-element product and $\alpha = 0.5, \beta = 1.$

Fig. 2. Structural features from different MR modes



- Obtaining T using a gradient descent-based optimization modelled by free-form deformation (FFD) model.
- SSD as the similarity measure

$$D\big(J(I_m), J(I_f)\big) = \sum_{\mathbf{x}} \Big|T_{\mathbf{x}}\big(J_{\mathbf{x}}(I_m)\big) - J_{\mathbf{x}}(I_f)\Big|$$

Results

- Target registration error (TRE) as the accuracy measure.
- Comparison with the multi-modal registration based on mutual information (MI) (J. Pluim, 2003, A. Myronenko, 2010)

Fig. 3. Registering a PD slice (red) to a T1 slice (green)

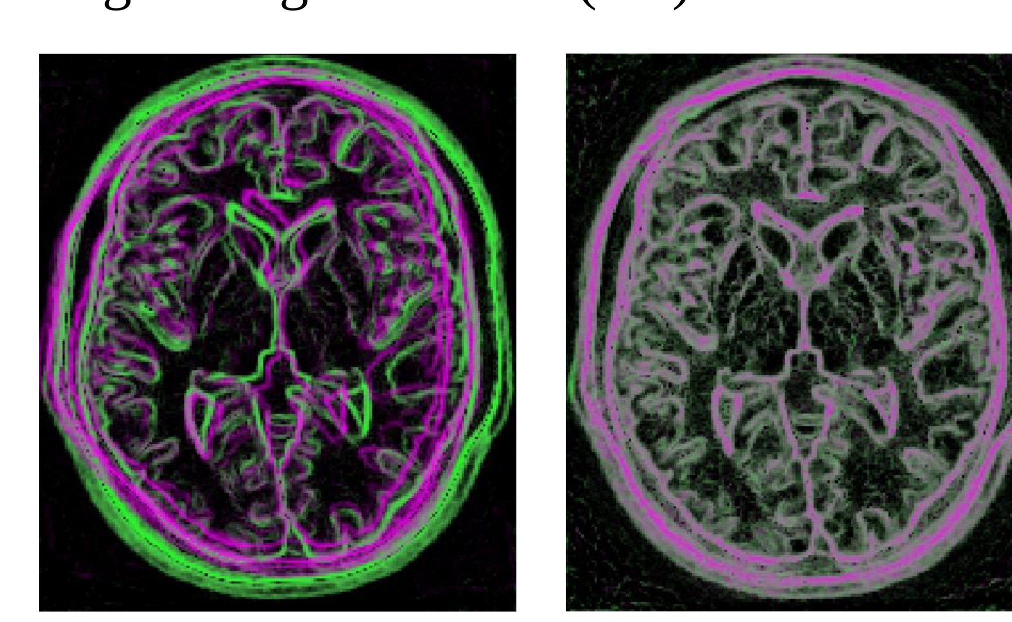


Table. 1. Registration errors with different levels of noise and intensity non-uniformity (INU)

	Modalities					
	T1-T2		T1-PD		T2-PD	
Noise and INU level	MI	Reg	MI	Reg	MI	Reg
3%, 20%	1.74	**1.11**	1.97	**1.59**	2.14	**1.23**
5%, 20%	2.13	**1.89**	2.85	**2.13**	3.48	**2.74**
7%, 20%	3.07	**3.05**	**4.21**	4.28	**5.63**	5.94
3%, 40%	2.34	**1.27**	3.63	1.93	4.83	**2.39**
5%, 40%	3.81	**2.32**	5.64	**3.14**	6.94	**4.03**
7%, 40%	5.11	**7.21**	7.21	**5.03**	8.12	**5.84**
Average	3.03	**2.18**	3.19	**3.02**	4.97	**3.69**

- Higher accuracy is achieved compared to the MI-based method.
- As the non-uniformity increases, the method is shown to be more accurate than the MI-based method