Iterative Fitting After Elastic Registration: An Efficient Strategy for Accurate Estimation of Parametric Deformations

Xinxin Zhang, Christopher Gilliam and Thierry Blu

The Chinese University of Hong Kong

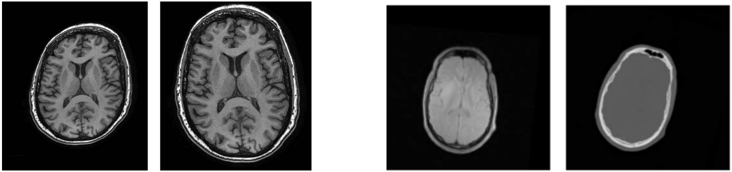
20th September, 2017

Outline

Introduction

Problem Statement

- Medical applications

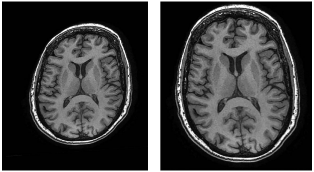


- Remote sensing

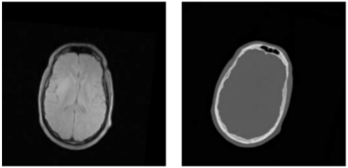
- Others

Problem Statement

- Medical applications



monomodal



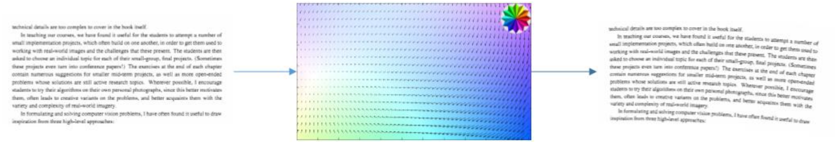
multimodal

- Remote sensing

- Others

Problem Statement

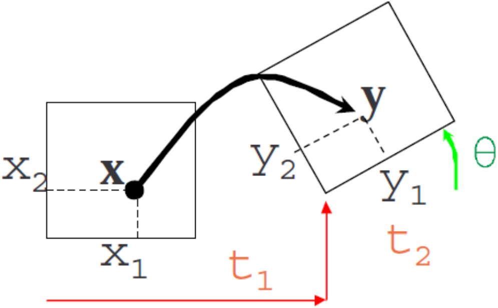
- $I_{\text{target}}(z) = I_{\text{source}}(z + u(z))$
  $z = x + iy,\ u(z) = u_x(z) + iu_y(z),$



$I_{\_source}(Z)$ $u(Z)$ $I_{\_target}(Z)$

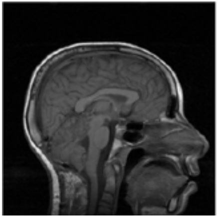
Overview of Current Methods

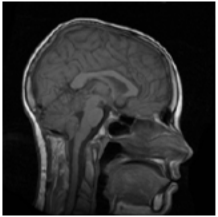
- **Global parametric registration**
  Calculate the parameters of the model.
  Woods, 1992; Woods, 1998; Evangelidis, 2008



Overview of Current Methods

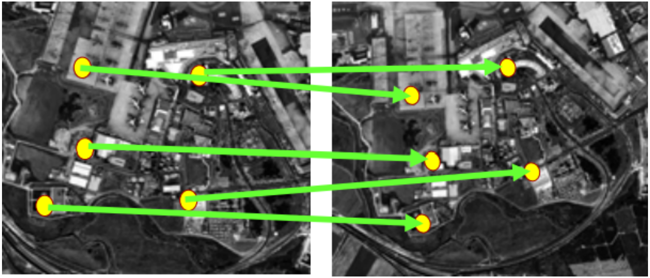
- **Elastic registration**
  Estimate a displacement vector per pixel.
  Arganda-Carreras, 2006; Bajcsy, 1989; Periaswamy, 2003; Klein, 2010; Periaswamy, 2006; Goshtasby, 1988; Kybic, 2003; Bruhn, 2005





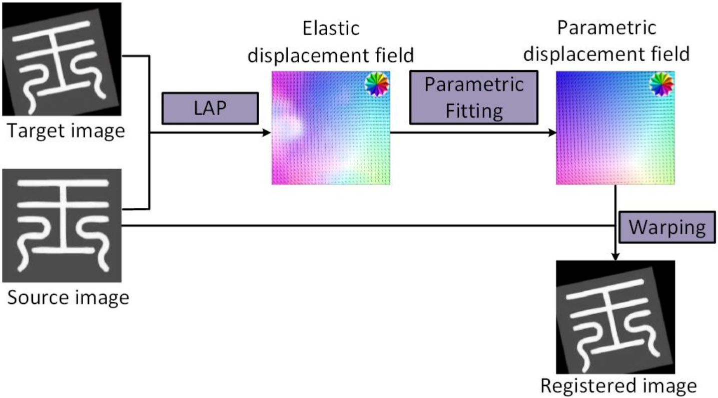
Overview of Current Methods

- **Landmark/Feature-based Registration**
  Establish the correspondence between the extracted features or landmarks from the two images.
  Alhichri, 2003; Davatzikos, 1996; Li, 2009; Ma, 2015



Method

Parametric fitting of the elastic displacement field



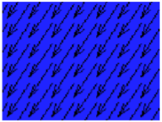
LAP: Local All-Pass Filters

C. Gilliam and T. Blu, "Local all-pass filters for optical flow estimation," *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 1533-1537, 2015.

Parametric model

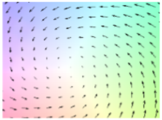
Geometric Transformation

Translation

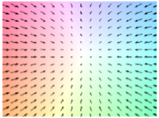


$$u(z) = c_1$$

Rotation

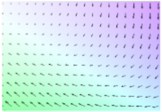


Scaling



$$u(z) = c_2 z$$

This paper



$$u(z) = c_1 + c_2 z + c_3 \bar{z} + c_4 z \bar{z} + c_5 z^2 + c_6 \bar{z}^2$$

Parametric model fitting

Fitting model: $u_{\text{fit}}(z) = c_1 + c_2 z + c_3 \overline{z} + c_4 z\overline{z} + c_5 z^2 + c_6 \overline{z}^2$,

Fitting criterion: $\min_c \sum_{z \in \Omega} |u_{\text{fit}}(z) - u_{\text{LAP}}(z)|^2$,

$c = [c_1, c_2, c_3, c_4, c_5, c_6]^{\mathrm{T}}$ to be calculated.

$\hookrightarrow$ solution of a linear system of equitions

★ Fast, efficient and flexible.

Parametric model fitting

Fitting model: $u_{\text{fit}}(z) = c_1 + c_2 z + c_3 \overline{z} + c_4 z\overline{z} + c_5 z^2 + c_6 \overline{z}^2$,

Fitting criterion: $\min_c \sum_{z \in \Omega} |u_{\text{fit}}(z) - u_{\text{LAP}}(z)|^2$,

$c = [c_1, c_2, c_3, c_4, c_5, c_6]^{\mathrm{T}}$ to be calculated.

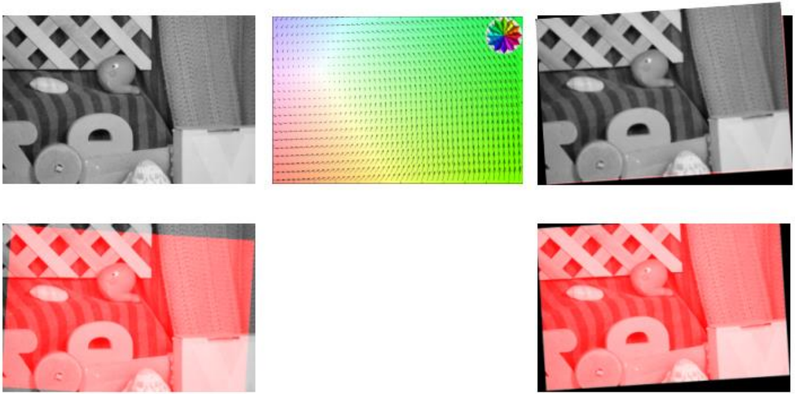
$\hookrightarrow$ solution of a linear system of equitions

★ Fast, efficient and flexible.

Choosing reliable pixels to fit parameters

Source image

Target image

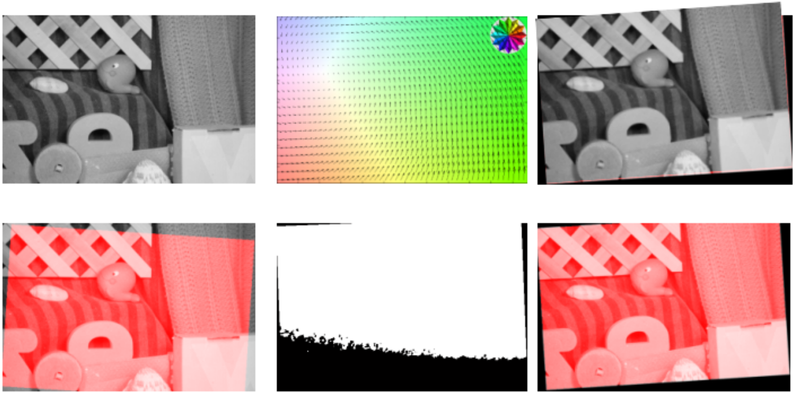


Common region

Choosing reliable pixels to fit parameters

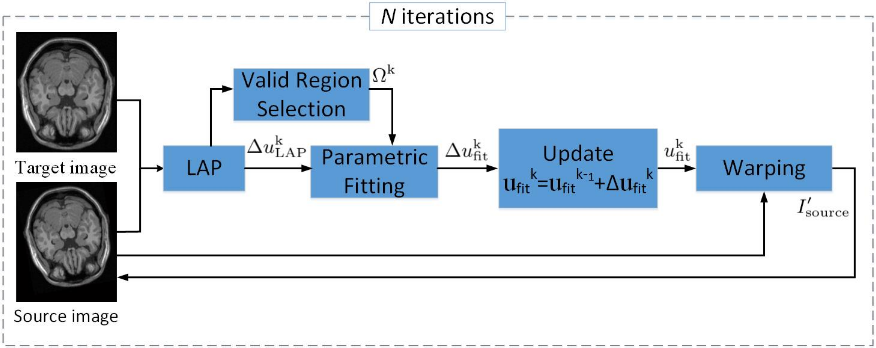
Source image

Target image



Valid region

Flow chart of the proposed method



- $\Delta u^{k}_{\mathrm{LAP}}$: the displacement estimated by the Local All-Pass Filters (LAP) in the kth iteration.
- u^{k}_{fit}: the displacement estimated by polynomial fitting in the kth iteration.
- $\Delta u^{k}_{\mathrm{fit}}$: the displacement increment estimated by polynomial fitting in the kth iteration.
- Ω^{k}: valid region in the kth iteration.

Experimental results

Comparison with the state-of-the-art

Synthetic images

Table: Error comparison for the iterative fitting method and the state-of-the-art image registration methods.

		Noiseless Image			Noisy Image (15dB)			Gaussian Blurry Image			Missing Information		
		E_{Med}	E_{Mean}	Time	E_{Med}	E_{Mean}	Time	E_{Med}	E_{Mean}	Time	E_{Med}	E_{Mean}	Time
Parametric algorithms	Ours	**0**	**0**	18.45	**0.238**	**0.430**	19.08	**0.505**	**0.590**	32.22	**0**	**0**	38.58
	AECC	0.851	1.155	9.10	0.908	1.229	9.522	1.001	1.289	8.10	0.907	1.206	9.32
Elastic algorithms	LAP	0.006	1.189	**4.60**	1.799	4.076	**4.52**	3.118	3.415	**5.94**	0.011	2.131	**7.94**
	Demons	5.114	32.874	37.15	7.601	10.241	22.13	6.066	7.497	31.75	5.700	10.575	20.81
	MIRT	3.232	9.931	75.00	7.976	12.065	52.51	7.420	11.467	65.67	7.764	12.661	80.00
	bUnwarpJ	1.3402	1.4107	14.64	1.6763	1.8072	25.07	3.346	4.512	23.80	1.924	7.220	325.38

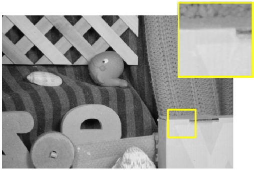
(1) Bold values indicate the best results. (2) The size of images is 388 by 584 pixels. (3) PSNR between the noisy image and original noiseless image is 15dB. (4) Results averaged over 5 different parametric deformation fields (maximum displacement is 16 pixels).

Absolute Error: $E(j) = |u_{\mathrm{GT}}(j) - u(j)|$, $j \in D$, D is the common region
Median Absolute Error: $E_{\mathrm{Med}} = Median(E)$
Mean Absolute Error: $E_{\mathrm{Mean}} = Mean(E)$

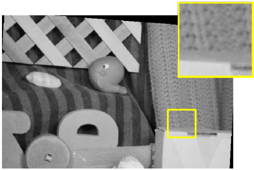
Reference:

AECC: G. D. Evangelidis and E. Z. Psarakis, 2008;
Demons: H. Lombaert, L. Grady, and X. Pennec et al., 2009;
MIRT: A. Myronenko and X. Song, 2010;
bUnwarpJ: I. Arganda-Carreras, C. O. S. Sorzano, and R. Marabini et al., 2006.

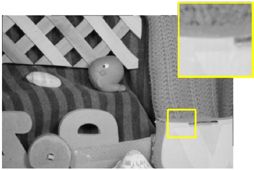
Noiseless images



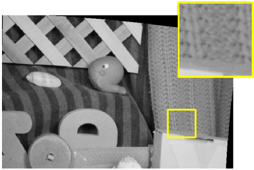
I_{source} and I_{target}



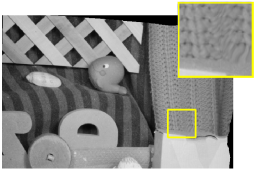
AECC



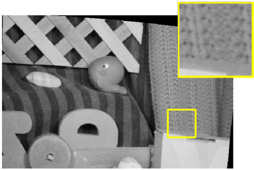
Demons



bUnwarpJ

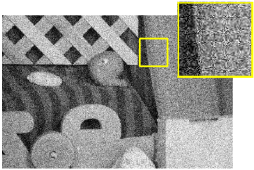


LAP

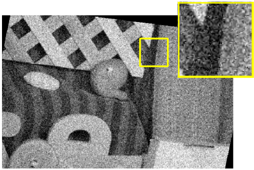


Ours

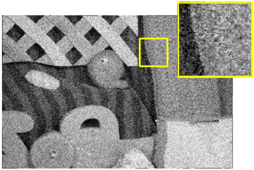
Noisy images (15dB)



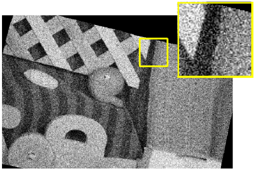
I_{source} and I_{target}



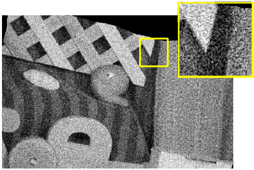
AECC



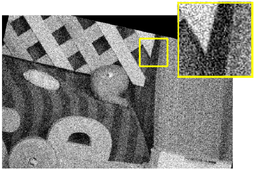
Demons



bUnwarpJ

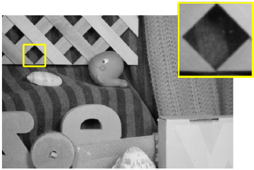


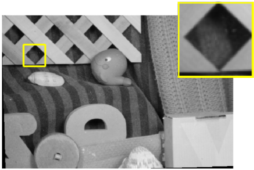
LAP

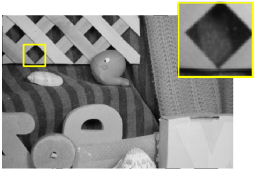


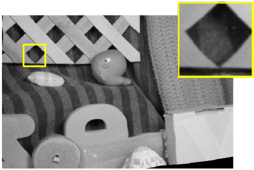
Ours

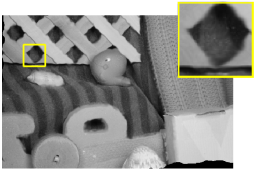
Gaussian blurry images

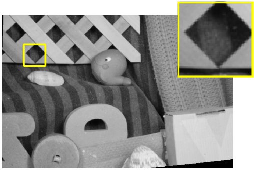

I_{source} and I_{target}


AECC


Demons


bUnwarpJ


LAP


Ours

Real images (400×400)

I_{source} and I_{target}

MIRT 78.74s

Demons 13.90s

AECC 6.67s

LAP 5.39s

Ours 21.32s

Real images (480×640)

I_{source} and I_{target}

MIRT 82.32s

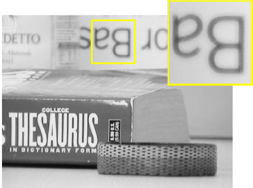
Demons 8.75s

AECC 6.67s

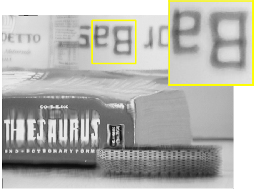
LAP 18.82s

Ours 91.67s

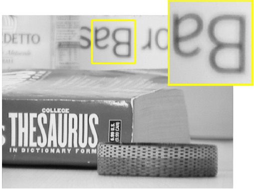
Real images (480×640)



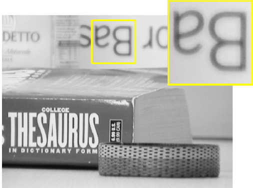
I_{source} and I_{target}



MIRT 104.36s

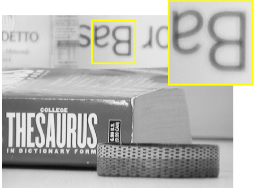


Demons 178.97s



AECC 14.96s

LAP 24.34s



Ours 64.85s

Real images (480×640)

I_{source} and I_{target}

Ours 50.24s

Video stabilization

Input

Output

Conclusion

Highlights

1. Accurate and fast.
2. Flexible and costless to add more parameters.
3. Robust to model mis-match (e.g. noise and blurring).
4. Robust to very large displacement.

Highlights

1. Accurate and fast.
2. Flexible and costless to add more parameters.
3. Robust to model mis-match (e.g. noise and blurring).
4. Robust to very large displacement.

Highlights

1. Accurate and fast.
2. Flexible and costless to add more parameters.
3. Robust to model mis-match (e.g. noise and blurring).
4. Robust to very large displacement.

Highlights

1. Accurate and fast.
2. Flexible and costless to add more parameters.
3. Robust to model mis-match (e.g. noise and blurring).
4. Robust to very large displacement.

Thanks for your attention.