Advanced Normalization Tools for Cardiac Motion Correction

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Introduction

Motion correction for dynamic contrast MR myocardial perfusion is of significant research interest and has resulted in several techniques generally characterized as rigid or non-rigid image registration-based. To bring together interested researchers for discussion and comparison of methods for correction of motion artefacts and the development of performance benchmarks of such techniques, the Statistical Atlases and Computational Modeling of the Heart (STACOM) workshop committee organized a motion correction challenge to be held in conjunction with international 2014 conference of the Medical Image Computing and Computer Assisted Intervention (MICCAI) Society.

Data

For comparative evaluation, each team was given MR perfusion data described by the organizers:

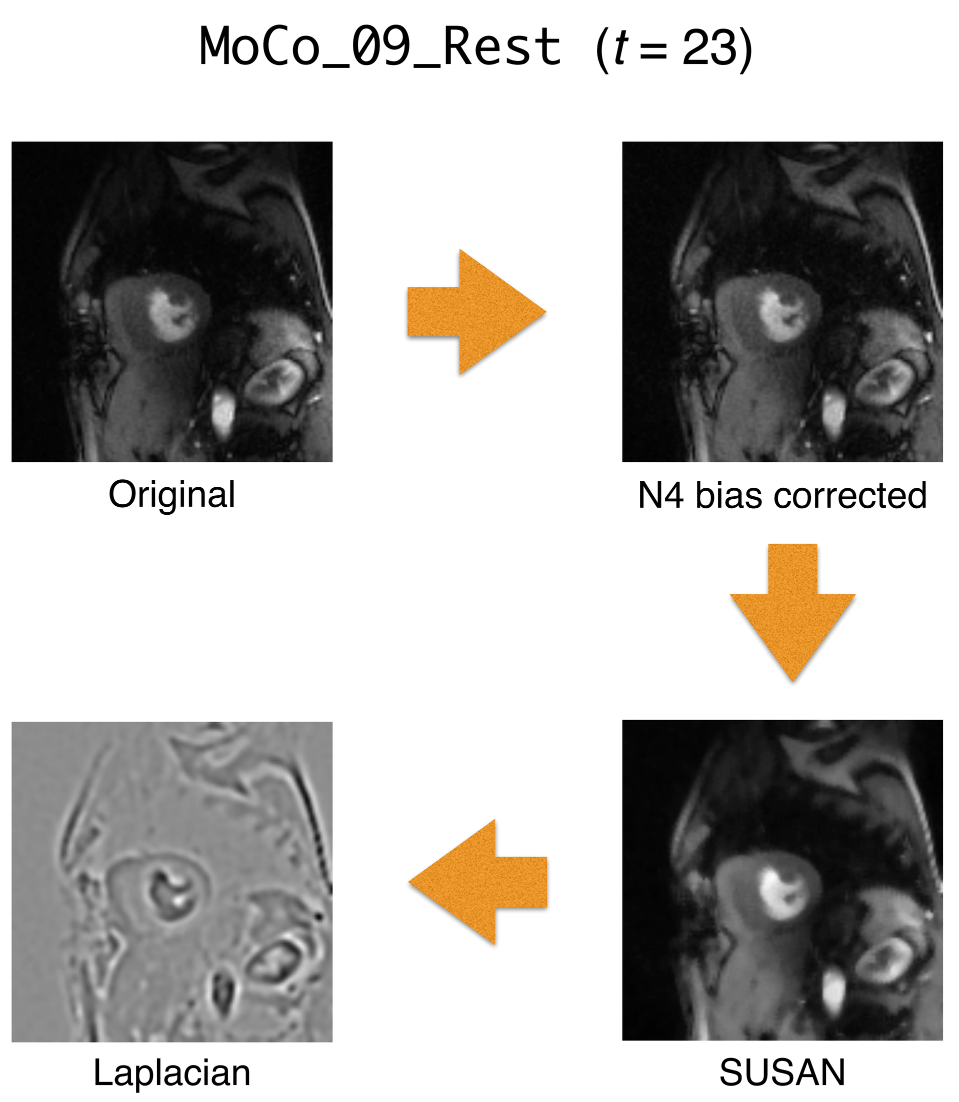
> The evaluation dataset consists of 10 cases from two centres: the University of Utah and University of Auckland. For each case, a single short axis slice time series at rest and at stress is provided. The Utah datasets were acquired using a saturation-recovery radial turboFLASH sequence at rest and during adenosine infusion (140 μg/kg/min), as described in [3]. Contrast was 5 cc/s injection of Multihance (Gd-BOPTA) at 0.02 mmol/kg for the rest and 0.03 mmol/kg for the stress. Four of these subjects have known coronary artery disease. The Auckland cases were acquired using a saturation-recovery Cartesian turboFLASH sequence at rest and during adenosine infusion (140 μg/kg/min). Contrast was 0.04 mmol/kg Omniscan (gadodiamide). None of the Auckland cases have overt coronary disease. Expert-drawn contours only at a reference frame, chosen when contrast is present in both ventricles, were provided to the participants.

Preprocessing

Given the temporal image variability and other confounds (e.g., noise), a multivariate image registration strategy was employed made possible by recent developmental work to the Insight Toolkit [2]. This strategy involved the following three derived images:

- N4 bias corrected [6],
- noise-filtered, structure-preserving SUSAN image [4], and
- low level Laplacian-based edge detection.

Sample preprocessed images used:



B-Spline SyN Multivariate Image Registration

Theory

The Symmetric Normalization (SyN) diffeomorphic approach [1] to pairwise image registration minimizes the following symmetric formulation:

$$\inf_{\phi_1} \inf_{\phi_2} \left[\int_0^{0.5} \left(\|v_1(t)\|_L^2 + \|v_2(t)\|_L^2 \right) dt + \int_\Omega \Pi_\sim \left(I \circ \phi_1^{-1}(\mathbf{x}, 0.5), J \circ \phi_2^{-1}(\mathbf{x}, 0.5) \right) d\Omega \right] \quad (1)$$

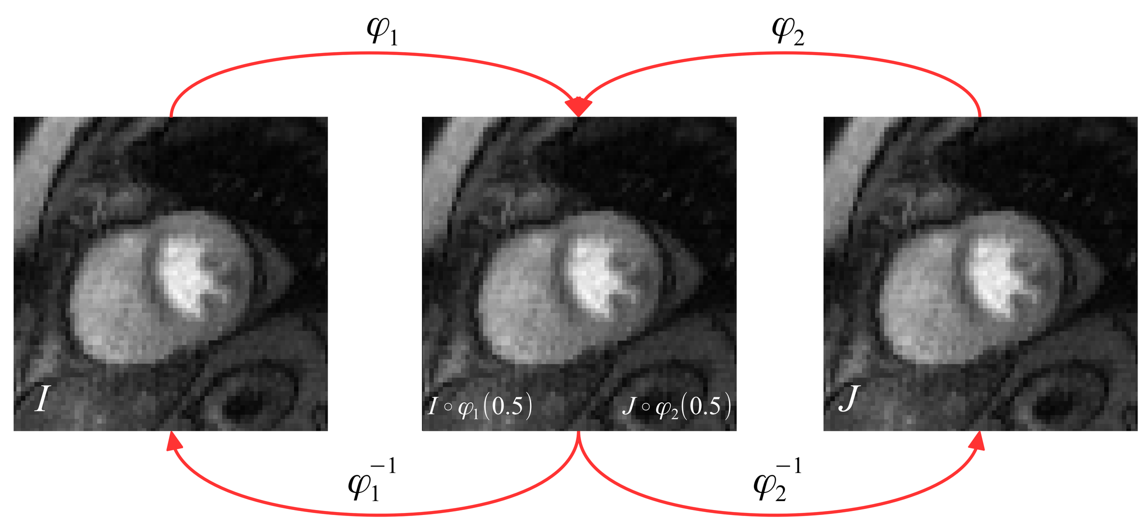
where

$$\frac{d\phi_i(\mathbf{x},t)}{dt} = v_i(\phi_i(\mathbf{x},t),t),\ \ \phi_i(\mathbf{x},0) = \mathbf{Id},\ \ i \in \{1,2\} \quad (2)$$

and $\Pi_\sim$ is an arbitrary similarity metric (or metrics).

Greedy B-Spline SyN variant

A greedy variant of Eq. (1) was also proposed in [1] for purposes of tractability and illustrated below.



Images I and J are registered by finding the optimal two transform pairs (ϕ_1, ϕ_1^{-1}) (ϕ_2, ϕ_2^{-1}) which map to/from the respective images to the midway point. Regularization using a fast B-spline fitting algorithm provides a contrast to the traditional Gaussian smoothing and has demonstrated measurable improvement in brain MR image normalization [5].

Transform composition to reference frame

SyN yields both the forward and inverse transforms between images I and J denoted as $I \underset{b}{\leftrightsquigarrow} J$ (where 'b' denotes "B-spline SyN"). Thus, to transform any image, I_t, at time point, t, to the reference image, I_R, temporally located at time, $t = r$, we simply concatenate the transforms either forwards

$$I_R \underset{b_r}{\leftrightsquigarrow} \underset{b_{r+1}}{\leftrightsquigarrow} \cdots \underset{b_{t-2}}{\leftrightsquigarrow} \underset{b_{t-1}}{\leftrightsquigarrow} I_t \quad (3)$$

or backwards

$$I_R \underset{b_{r-1}}{\leftrightsquigarrow} \underset{b_{r-2}}{\leftrightsquigarrow} \cdots \underset{b_{t+1}}{\leftrightsquigarrow} \underset{b_t}{\leftrightsquigarrow} I_t. \quad (4)$$

By concatenating transforms, only a single interpolation is performed for each normalization to the reference frame.

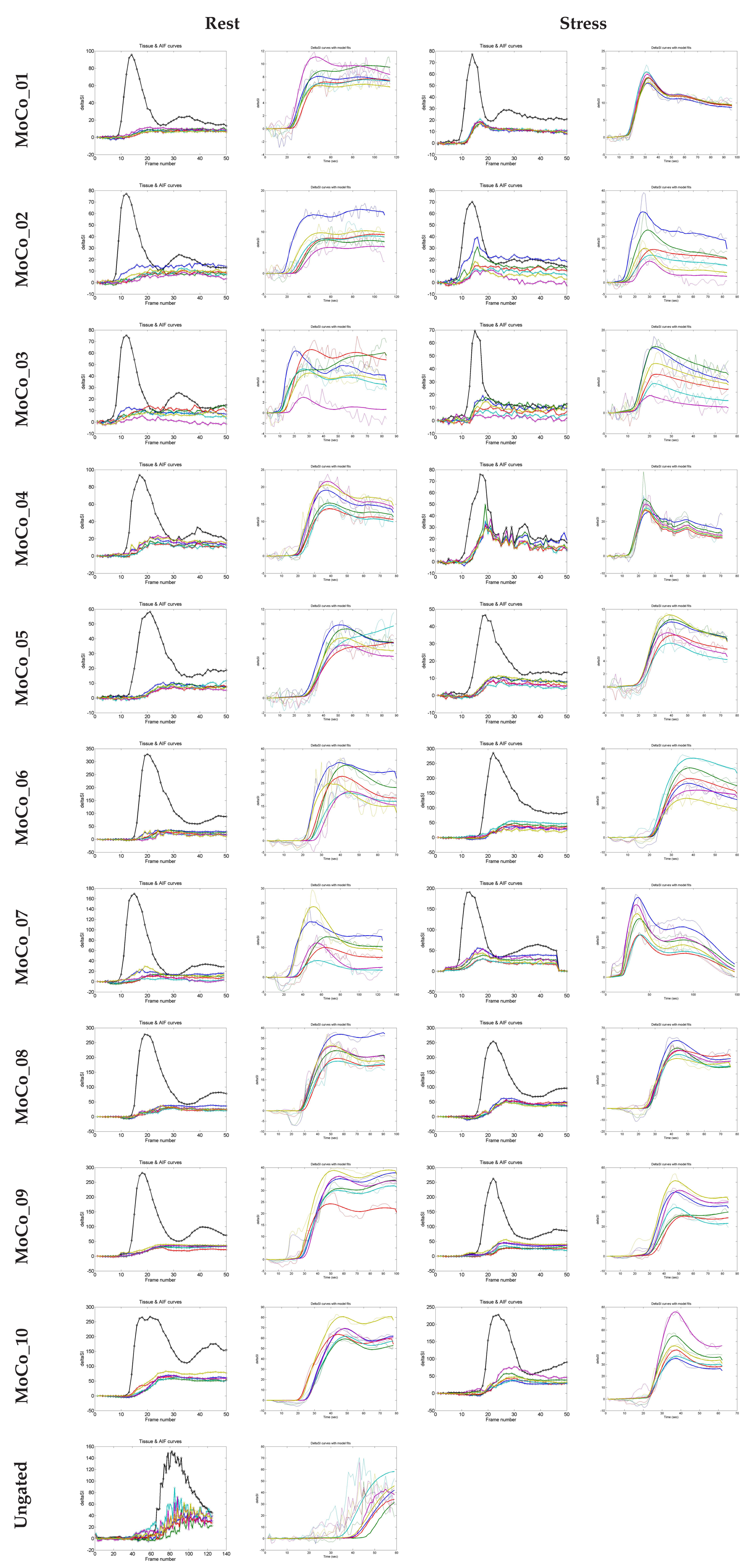
ANTs Code

```
# Input image pairs include:
#    * N4 bias corrected
#    * Structure-preserving noise reduction (SUSAN) of N4 images
#    * Laplacian filtering of SUSAN images.

antsRegistration --dimensionality 2 \
                 --output ${outputPrefix} \
                 --winsorize-image-intensities [0.01,0.99] \
                 --use-histogram-matching 1 \
                 --transform BSplineSyN[0.1,2x2,0] \
                 --metric CC[${n4Fxd},${n4Mvng},1,6] \
                 --metric Demons[${susanFxd},${susanMvng},1,1] \
                 --metric Demons[${laplacianFxd},${laplacianMvng},1,1] \
                 --convergence [100x70x50,1e-8,10] \
                 --shrink-factors 4x2x1 \
                 --smoothing-sigmas 1x0.5x0vox
```

Evaluation

Tissue and arterial input function time plots



K^{trans} values for all data for all 6 ROIs.

	ROI$_1$	ROI$_2$	ROI$_3$	ROI$_4$	ROI$_5$	ROI$_6$
MoCo_01 (rest)	0.7646	0.793	0.6472	0.6223	1.1396	0.6169
MoCo_01 (stress)	2.991	3.3591	3.3946	3.8864	3.6427	2.9233
MoCo_02 (rest)	1.26	0.8393	0.8038	0.8026	0.621	0.9659
MoCo_02 (stress)	3.6184	4.7307	2.4689	2.1684	2.0884	4.6189
MoCo_03 (rest)	1.3238	1.0138	1.9537	1.4278	0.6698	1.2323
MoCo_03 (stress)	4.6317	4.482	2.5719	2.2236	1.2169	3.3639
MoCo_04 (rest)	2.4826	1.958	1.7667	2.0848	3.0735	2.516
MoCo_04 (stress)	6.6083	10.1963	9.2774	10.0296	10.7357	8.875
MoCo_05 (rest)	1.6678	1.4952	0.8095	0.8683	1.1663	1.318
MoCo_05 (stress)	2.4283	2.6987	2.0908	1.9775	2.3872	3.0467
MoCo_06 (rest)	0.9946	1.2878	1.1367	0.7262	0.8156	0.865
MoCo_06 (stress)	2.1543	2.6292	2.1322	2.59	1.4002	1.4648
MoCo_07 (rest)	0.6009	0.5397	0.4214	0.2904	0.8107	1.234
MoCo_07 (stress)	2.8381	2.2815	1.8141	1.7029	2.7065	2.8503
MoCo_08 (rest)	1.0315	0.8754	0.7959	0.7106	0.9726	1.0769
MoCo_08 (stress)	3.1103	2.9066	2.2222	2.369	2.4781	1.796
MoCo_09 (rest)	1.0073	0.8589	0.7194	0.8689	1.1375	1.1258
MoCo_09 (stress)	1.939	0.9883	1.0515	1.6527	1.9416	2.2943
MoCo_10 (rest)	2.734	2.3579	2.2832	2.3316	2.822	2.743
MoCo_10 (stress)	2.2161	3.8051	2.9618	2.234	5.6507	2.9052
Ungated	2.3471	3.0672	2.6664	3.7773	3.5338	2.7093

References

[1] B. B. Avants, C. L. Epstein, M. Grossman, and J. C. Gee. Symmetric diffeomorphic image registration with cross-correlation: evaluating automated labeling of elderly and neurodegenerative brain. *Med Image Anal*, 12(1):26–41, Feb 2008.

[2] B. B. Avants, N. J. Tustison, M. Stauffer, G. Song, B. Wu, and J. C. Gee. The Insight ToolKit image registration framework. *Front Neuroinform*, 8:44, 2014.

[3] E. V. R. DiBella, J. U. Fluckiger, L. Chen, T. H. Kim, N. A. Pack, B. Matthews, G. Adluru, T. Priester, S. Kuppahally, R. Jiji, C. McGann, and S. E. Litwin. The effect of obesity on regadenoson-induced myocardial hyperemia: a quantitative magnetic resonance imaging study. *Int J Cardiovasc Imaging*, 28(6):1435–44, Aug 2012.

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[5] N. J. Tustison and B. B. Avants. Explicit B-spline regularization in diffeomorphic image registration. *Front Neuroinform*, 7:39, 2013.

[6] N. J. Tustison, B. B. Avants, P. A. Cook, Y. Zheng, A. Egan, P. A. Yushkevich, and J. C. Gee. N4ITK: improved N3 bias correction. *IEEE Trans Med Imaging*, 29(6):1310–20, Jun 2010.