

ABSTRACT

Registration of diffusion weighted datasets remains a challenging task in the process of quantifying diffusion indexes. Respiratory and cardiac motion, as well as echo-planar characteristic geometric distortions, may greatly limit the accuracy in parameter estimation, specially in the liver. This work proposes a methodology for the non-rigid registration of multiparametric abdominal diffusion weighted imaging by using different well-known metrics under the groupwise paradigm. A three-stage validation of the methodology is carried out in a computational diffusion phantom, a watery solution phantom and a set of voluntary patients. Diffusion estimation accuracy has been directly calculated on the computational phantom and indirectly by means of a residual analysis on the real data. On the other hand, effectiveness in distortion correction has been measured on the phantom. Results have shown statistical significant improvements compared to pairwise registration being able to cope with elastic deformations.

INTRODUCTION

◦ Apparent diffusion coefficient (ADC) is sensitive to displacement of water molecules, giving evidences about cellular organization and cell permeability [1] in different tissues.
 ◦ Robust ADC estimation becomes non-trivial, as an exponential signal dropout is observed when the magnetic diffusion gradient strength (the so-called *b-values*) increases.

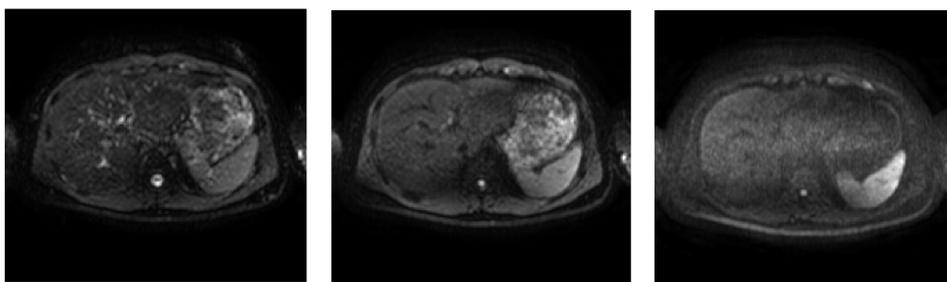


Figure 1: Axial slices of DWI acquisition in a healthy volunteer with *b-values* of 0, 100 and 1000 s/mm^2 (from left to right).

◦ Several confounding factors may greatly affect ADC estimation on the liver; artifacts are very likely to appear during imaging due to respiratory and cardiac motion.
 ◦ Ultrafast sequences, i.e. echo planar imaging (EPI), suffer from geometric distortions as well as local signal dropouts due to magnetic field inhomogeneities.
 ◦ Registration schemes of multiparametric (multiple *b-values*) acquisitions have proven to alleviate the effects of these confounding factors.
 ◦ Groupwise approaches find optimal parameter set using a common reference built out of the whole image space, so that template bias is not present.

METHODS

Groupwise registration of different *b-value* images for robust ADC estimation on the liver. Monoexponential decay model for the DWI images:

$$S(b) = S_0 e^{-b \cdot \text{ADC}} \quad (1)$$

where S represents the image for each *b-value* and S_0 , the image without diffusion gradient.

For the registration scheme, a gradient-descent/ascent procedure is performed for the optimization. Non-rigid deformation model based on 2D B-spline [2] FFDs:

$$\mathbf{T}(\mathbf{x}) = \sum_{j,k} B_E(u_j(x_1)) B_E(u_k(x_2)) \theta_{j,k} \quad (2)$$

Performance assessment of different multimodal metrics formulated under groupwise and pairwise paradigms:

◦ **Variance of the local entropy (VLE).** Local entropy [3] should be preserved along the whole image set. Hence, the pixel-wise metric can be considered as the sum of squared differences of the local entropy images S_N :

$$S_N(\mathbf{I}(\mathcal{N}(\mathbf{x}))) = \frac{-1}{|\mathcal{N}|} \sum_{\mathbf{x}' \in \mathcal{N}} p(I(\mathbf{x}')) \ln(p(I(\mathbf{x}'))). \quad (3)$$

◦ **Entropy of the distribution of intensities (EDI)** [4]:

$$H(\mathbf{x}) \approx \frac{-1}{N} \sum_{n=1}^N \log(p(I_n(T_n(\mathbf{x})))) \quad (4)$$

with $p(I_n(T_n(\mathbf{x})))$ a Parzen window estimation of the pixel intensity distribution. This metric favours those solutions in which pixel intensities are well concentrated in the intensity space.

◦ **Modality independent neighbourhood descriptor (MIND):** an image descriptor, built from within-patch distances D_p and variance estimates V :

$$\text{MIND}(I, \mathbf{x}, r) \propto \exp\left(\frac{D_p(I, \mathbf{x}, \mathbf{x} + r)}{V(I, \mathbf{x})}\right). \quad (5)$$

Afterwards, simple monomodal measures built from MIND differences are used as pixel-wise metric, as described in [5].

◦ **Normalized cross-correlation (NCC):**

$$H(\mathbf{x}) = \frac{1}{N} \sum_{n=1}^N \frac{\langle \overline{I_n(T_n(\mathcal{P}(\mathbf{x})))}, \mu(\mathcal{P}(\mathbf{x})) \rangle^2}{\langle \overline{I_n(T_n(\mathcal{P}(\mathbf{x})))}, \overline{I_n(T_n(\mathcal{P}(\mathbf{x}))} \rangle \langle \mu(\mathcal{P}(\mathbf{x})), \mu(\mathcal{P}(\mathbf{x})) \rangle} \quad (6)$$

where $\mu(\mathbf{x}) = \frac{1}{N} \sum I_n(T_n(\mathbf{x}))$ and $\overline{I(\mathcal{P}(\mathbf{x}))}$ represents the operator over a predefined patch \mathcal{P} as defined in [6].

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RESULTS

Three-fold validation procedure:

- Synthetic experiment on 4D extended cardio-torso (XCAT) computational phantom [7]. Different apnea levels have been simulated and a synthetic deformation field is added for EPI distortion simulation.
- MRI experiment consisting of a pre-design watery solution phantom in order to test the ability of the methods for distortion correction.
- MRI acquisitions on a sample of four healthy volunteers. Axial SENSE DWI and T2 weighted Turbo Spin Echo sequences acquired on a Philips Achieva 3T scanner.

◦ Accuracy in motion compensation and distortion correction measured within the XCAT phantom by means of error distributions on ADC estimation. U-tests have shown significant differences between groupwise and pairwise approaches. EDI and MIND metrics exhibit best, albeit similar performance, specially when compared to the original data ($p < 10^{-9}$).

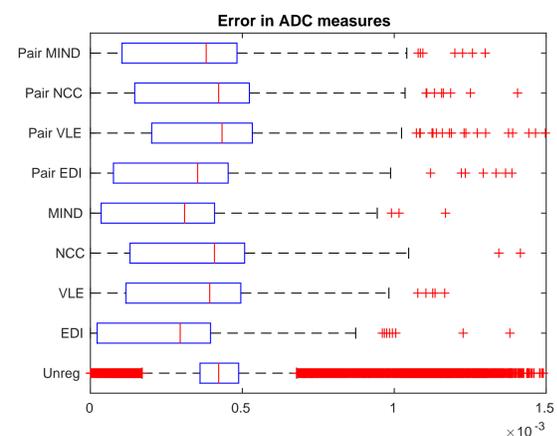


Figure 2: Error on ADC estimation for proposed groupwise and pairwise metrics.

◦ Quantitative analysis, over the MRI phantom, of the overlapping (Dice coefficient) between foregrounds from the registered DWI and the undistorted T2w sequences. No significant differences were found in Dice coefficient distributions between groupwise metrics and its pairwise counterpart. However, Kruskal-Wallis test found significant differences within groupwise metrics ($p = 0.0027$) and with the original data ($p < 10^{-6}$).

◦ For the volunteer data, a goodness-of-fit analysis will measure the discrepancies between registered data and the monoexponential diffusion model in Eq. 1. No differences were found in RSS distributions.

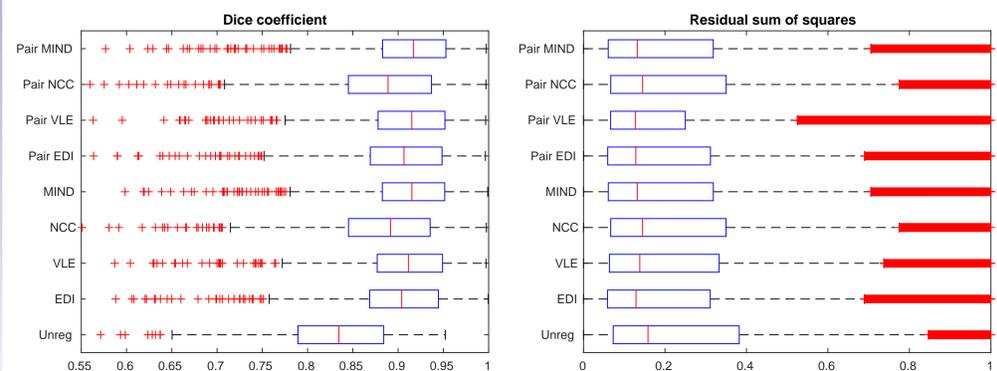


Figure 3: Dice Coefficient distributions for foregrounds of DWI and T2w sequences.

Figure 4: Residual sum of squares distributions obtained from ADC estimation.

CONCLUSIONS

◦ Non-rigid registration framework for motion compensation on multiparametric abdominal DWI acquisitions. Groupwise approaches can deal with signal intensity changes and also correct for geometrical distortions.

◦ Metric choice is also an important issue for outlier removal. However, acquisition parameters and estimation model have had greater impact than the alignment itself, regardless of the metric.

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