Non-Rigid Multimodal Medical Image Registration using Optical Flow and Gradient Orientation

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Abstract

Optical flow models are widely used for different image registration applications due to their accuracy and fast computation. Major disadvantages to overcome for medical image registration are large deformations and inaccurate regularisation at discontinuities, which cannot be modelled accurately with quadratic regularisers, and an intensity dependent energy term, which does not allow for images of different modalities. In this work we present a multi-level framework utilising multiple warps, which succeeds in estimating larger deformations. We introduce a non-quadratic penalty function, for a better modelling of discontinuities, that are caused by sliding motion of ribs against the lungs during respiration. Our algorithm is extended to multimodal image registration tasks by maximising the local alignment of the image intensity gradient orientation. We demonstrate the findings on synthetic 3D CT data and clinical CT-CT images as well as on CT-MRI data. Quantitative evaluation using the Dice coefficient shows improvements of our new approach for single-modal data for the interface between lungs and ribs compared to a commonly used parametric free form deformations (FFD) method and equally good results for multimodal data.

1 Introduction

Non-parametric registration methods like elastic, fluid or demons [5] demonstrate attractive capabilities for non-rigid medical image applications. These models estimate a dense motion field between two images by minimising a cost function, which usually includes an intensity based data term and a regularisation term to enforce a globally smooth deformation. In contrast, parametric registration using B-splines and FFDs as presented in [7] use a mesh of fixed control points and interpolate the deformation between them with 3D cubic B-splines.

In this work, we show that a non-quadratic penalty function improves the registration accuracy at discontinuities within the motion pattern compared to FFD registration. For images from different modalities, like CT and MRI, mutual information (MI) was found to be a suitable cost measure and is widely used in rigid, affine and parametric non-rigid registration [4]. Variational MI formulations were derived in [3]. However MI is most accurate and robust as a global measure and non-rigid multimodal registration remains an active area of research. We propose to use the local gradient orientation as a minimisation term for non-parametric registration. Boundaries between neighbouring tissues often carry significant information in medical images. The gradient of tissue boundaries might not have the same magnitude for images of different modalities, but should have a consistent orientation. In [6] this finding was used to improve the MI measurement for rigid image registration. We demonstrate that using only the gradient orientation for non-rigid image registration leads to results similar to FFD registration, which is using MI.

2 Method

2.1 Optical Flow Constraint and Regularization

Optical flow registration is based on the assumption that in a local neighborhood the intensities of two images do not change over time: $f(\mathbf{x}+\mathbf{u}, t+\delta t) = f(\mathbf{x}, t)$. For small displacements a first order Taylor expansion yields the optical flow constraint: $\nabla f \cdot \mathbf{u} = 0$, where $\nabla f = (f_x, f_y, f_z, f_t)^T$ denotes the partial derivatives of the images and $\mathbf{u} = (u, v, w, 1)^T$ the unknown deformation field between them. To solve this ill-posed problem, an additional regularization term is introduced. The classical global optical flow method uses the quadratic term $\alpha|\nabla \mathbf{u}|^2$ to enforce smoothness of the deformation field, where α serves as a regularisation parameter.

$$E(\mathbf{u}) = \int_\Omega (\mathbf{u}^T(\nabla f \nabla f^T)\mathbf{u} + \alpha|\nabla \mathbf{u}|^2) d\Omega \tag{1}$$

In medical images, a quadratic smoothness term can be too general, as there are naturally occurring discontinuities in both the intensities of images at tissue boundaries, as well as within the motion pattern or deformation fields. To address this complex motion problem, we propose the use of non-quadratic penalisers within the energy functional. Charbonnier et al. [2] proposed the function $\Psi(s^2)$ with its derivative $\Psi'(s^2)$, which allows for a convex penalization and a simple globally convergent solution:

$$\Psi(s^2) = 2\beta^2\sqrt{1+\frac{s^2}{\beta^2}}\,, \; \Psi'(s^2) = \frac{1}{\sqrt{1+\frac{s^2}{\beta^2}}} \tag{2}$$

where β is set to a sufficiently small value 0.001 to obtain a penaliser similar to the L_1 norm. To minimize the energy E and solve for the unknown deformation field $\mathbf{u}$, Euler-Lagrange equations are derived and solved iteratively. Details of the implementation for the optical flow framework can be found in [1].

2.2 Gradient Orientation for Multimodal Image Registration

As stated above, the orientation of gradients can be a useful measure for multimodal image data. Pluim et al. [6] show that it improves accuracy and robustness in rigid image registra-

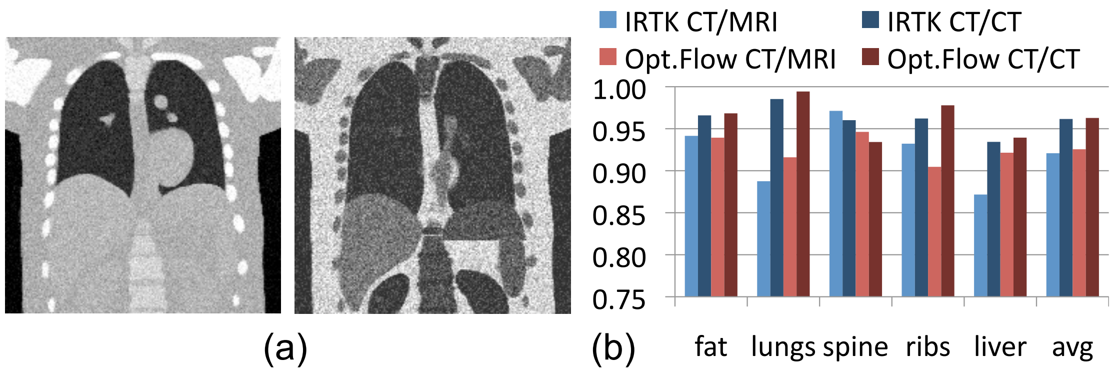

Figure 1: (a) Simulated CT and MRI scans of the NCAT phantom at different respiration levels (5 % added noise). CT at maximum expiration, MRI at maximum inspiration. (b) Quantitative evaluation of segmentation overlaps of 5 regions of interest shows equally good results for IRTK and our new approach, with improvements for lungs and liver.

tion using MI. The angle α_{ij} between two locations i and j in reference and floating image is defined by:

$$\alpha_{ij} = \arccos \frac{\nabla f_i \cdot \nabla f_j}{|\nabla f_i||\nabla f_j|}. \tag{3}$$

Gradients in two images are thought to have either a similar angle or an angle flipped by π depending on image contrast. To account for both, we use a weighting function $w(\alpha) = (\cos(2\alpha)+1)/2$, which favours both small angle differences and angles close to π. An additional challenge in multimodal image matching lies in the fact that tissue boundaries may have gradients in only one of the considered modalities. The angle function is therefore multiplied with the smaller of both local gradient magnitudes, thus the measure M to be maximised becomes $M = \omega(\alpha_{ij})\min(|\nabla f_i|,|\nabla f_j|)$. Derivatives of this measure are approximated by finite differences.

3 Experiments

To evaluate the accuracy and robustness of our new approach we tested it on synthetic and real clinical CT and MRI image sets. For quantitative evaluation, we compared the results for the registration of synthetic multimodal data with a state-of-the-art technique, IRTK[1]. A multi-level setting and optimally chosen smoothing parameters were used to recover larger deformations. We used sums of squared differences (SSD) for single-modal registration, because this cost term is comparable to our approach, and normalised mutual information (NMI) for multi-modal registration.

3.1 Synthetic CT and Multimodality Phantoms

To assess the registration accuracy, we tested and compared the algorithms on synthetic CT data, where a ground truth segmentation is available. We used the NURBS based cardiac

[1]Image Registration Toolkit, http://www.doc.ic.ac.uk/~dr/software/
Another efficient approach for parametric registration: "Dense image registration through MRFS and efficient linear programming" was presented by Glocker et. al. in Medical Image Analysis, 12(6): 731-741, 2008

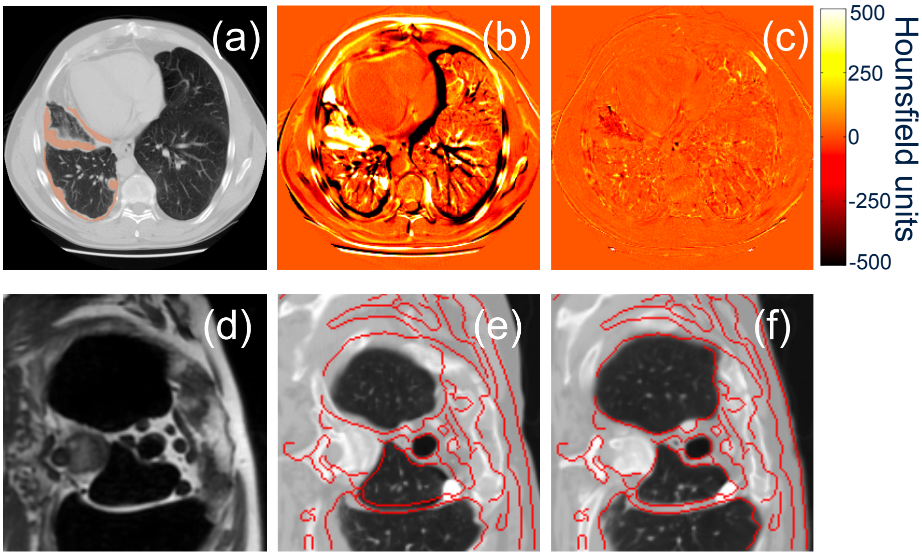

Figure 2: Visual results for single- (top row) and multimodal (bottom row) 3D registration. (a) Axial CT slice with manual segmentation of mesothelioma cancer overlaid in orange (b) Difference to follow-up scan (c) Difference after applying the proposed method. (d) Axial slice of MRI scan (e) Affine registered CT scan with MR contours (f) Non-rigid registration with our approach, showing improved overlap of lungs, bones and body outline.

torso (NCAT) phantom created by Segars [8], which provides a physiologically and physically realistic model of motion of different respiration states and over the cardiac cycle. In total, 30 phantom simulations over one breathing cycle with a maximum diaphragm movement of 20 mm were obtained for a range of body weights (80 – 100 kg), for both CT and MRI intensity labels. The images were additionally distorted by adding normally distributed noise of up 10 % and translation blurring of 1.25 mm. Figure 1 (a) shows exemplary simulations.Labels for regions of interest are provided by the simulation software and were used to calculate the segmentation overlap after registration. The resulting Dice coefficient for both single-modal and multimodal registration are given in Figure 1 (b). Overall, both approaches show equally good results, when compared for the same registration task. The single-modal implementation of our approach outperforms IRTK for all examined labels except for the spine. The increased accuracy around the lung/rib interface strengthens the justification of our non-quadratic regularisation term. The multimodal optical flow approach shows better Dice coefficients than IRTK for liver and lungs and lower results for bones.

3.2 Clinical MRI and CT Registration

To demonstrate the capability of the proposed method, two datasets of clinical images were studied. Pre- and post-treatment CT volumes of patients diagnosed with mesothelioma, an aggressive form of lung cancer, and pairs of CT and MRI volumes of subjects suffering from an empyema. The top row of Figure 2 displays one slice of a post treatment volumetric scan, along with the difference images before and after registration of the pre-treatment scan to the post-treatment scan using our proposed method. The results show a very high agreement with the original slice, in particular for the challenging interface between the rib cage and lung. To demonstrate the suitability of our multimodal extension, we firstly used affine registration to align a CT scan to an MRI of the same patient. Figure 2 (e) shows there is still a large mismatch between the boundaries of organs. We then applied our non-rigid approach, which demonstrates a considerably improved alignment with the target image.

4 Discussion

Non-rigid registration of clinical images can be challenging due to the complex motion pattern between scans, or incomparable intensities when using different modalities. We present a novel fast, robust and accurate technique, which is specifically adapted to align images with large deformations caused by respiratory motion. An extension for multimodal data is given based on the alignment of gradient orientation. This new cost term provides a promising alternative to mutual information based measures, allows for rapid computation and preserves discontinuities in the motion pattern. We show that quantitative evaluation of our extended approach for multimodal data results in similar accuracy compared to a state-of-the-art algorithm (IRTK). Visual results for the clinical CT/CT and CT/MRI application demonstrate the good performance and generalisation of our new approach.

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