Feature Constrained Non-rigid Image Registration

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Abstract

In this paper, we present a novel hybrid algorithm for non–rigid image registration that integrates intensity–based and feature–based methods. An important feature of our method is that the associated optimization problem takes into account the intensity similarity, feature correspondence and smoothness constraints simultaneously. Hence, the resulting registration algorithm yields the appropriate transform that achieves good local feature mapping and global intensity alignment. We demonstrate the application of the algorithm using two different types of features: the landmark and outer surface. However, these two features are treated differently in the algorithm. The landmark correspondences are expressed as interpolation constraints in the optimization problem, so that the landmark pairs in the fixed and the float images are guaranteed to be perfectly matched to each other. For the surface features, we propose a "regularizer" based on the level–set shape representation into the optimization problem. Thus the resulting algorithm is able to enhance the alignment of surface features. We solve the optimization problem in the variational framework, in which the extended Euler–Lagrange equation characterizes the solution. The improvement of the developed algorithm is not limited by image dimension and image modality. Finally, we demonstrate the effectiveness of the proposed algorithm by experimental evaluation using monomodal medical image data.

1 Motivation

Image registration is a very fundamental and crucial technique for computer-aided diagnosis procedures. The motivation of medical image registration arises from the need to combine or compare the images in many clinical processes. However, the images must be appropriately spatially matched before reasonable comparison or combination, since they are often acquired at different time, from different viewing directions or by different image modalities. This task is accomplished by registering images and warping them using a geometric transformation function. In this paper we focus on non–rigid medical image

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registration that is based on deformable models. The rigid approaches are extensively discussed in [ZF03][HBHH01].

Good alignment of shape features and perfect mapping of landmarks are significant for the many medical applications. For the purpose of diagnosis, physicians are more interested in anatomical object matching than solely intensity information matching after registration. There are already some attempts in the literature to design registration schemes which match both of landmark features and intensity information; see, e.g., [Joh02][FM03]. In this paper, we will extend the work of [FM03] to encode the contour feature correspondences. The main contribution of this paper is that the contour correspondences are formulated as a regularizer based on level set functions, which influences the registration to produce more medically reasonable contour feature alignment. And the overall hybrid registration scheme is enabled to register simultaneously intensity information, landmarks and anatomical contour features. The developed algorithm can work in both 2D and 3D registration applications and can register both monomodal and multimodal image data.

2 Method

2.1 Intensity based Registration

In the intensity–based nonrigid registration, two same dimensional images are given, template image $T(x)$ and reference image $R(x)$. For simplification, the intensities of image data have been scaled into $]0,1[$. The mathematical description of registration problem is to find a displacement field $u : \mathbb{R}^d \to \mathbb{R}^d$, such that

$$\mathcal{J}[u] := \mathcal{D}[R,T;u] + \alpha\mathcal{S}[u] = \min \tag{1}$$

The *distance measure* $\mathcal{D}$ indicts the dissimilarity between two volumes. E.g., *sum of squared differences* (SSD) is one of the most popular distance measures for monomodal registration problems. The *regularizer* $\mathcal{S}$ in Eq.(1) is added as the remedy for the arbitrary irregularity of transformation. Here we employ the *curvature regularizer*, which is defined as:

$$\mathcal{S}^{curv}[u] \quad := \quad \frac{1}{2}\sum_{l=1}^{d}\int_{\Omega}(\Delta u_l)^2\, dx \tag{2}$$

2.2 Contour Energy

We assume that the contour features of the desired objects have been extracted from both images before the registration. The contour features are modeled by signed distance function, which is defined as:

$$\Phi(x) = \begin{cases} -D(x,\Gamma) & \text{if } x \in \Omega \\ 0 & \text{if } x \in \partial\Omega = \Gamma \\ +D(x,\Gamma) & \text{if } x \notin \Omega \end{cases}$$

where $D(x, \Gamma)$ denotes the Euclidian distance of position x from the contour Γ. In the registration framework, a *contour feature energy* is defined as

$$\mathcal{E}[u] := \frac{1}{2} \int_{\Omega} (\Phi^T(x - u(x)) - \Phi^R(x))^2 \, dx \qquad (3)$$

The energy $\mathcal{E}$ is integrate into the functional to penalize the mismatch of contour feature.

2.3 Feature Constrained Registration Algorithm

The resulting feature constrainted non-rigid registration can be modeled as,

$$E[u] := \mathcal{D}[R, T; u] + \alpha \mathcal{S}[u] + \beta \mathcal{E}[u] = \min . \qquad (4)$$

If the landmark features are considered, the minimization problem (4) must subjects to the constraints of landmark correspondence. Let the r^j, $t^j \in \mathbb{R}^d, j = 1, ..., m$ denote landmarks on the reference and template respectively. Thus,

$$u(t^j) = d^j = t^j - r^j, \qquad j = 1, ..., m. \qquad (5)$$

The resulting Euler-Lagrange equation of the feature combined registration looks like,

$$f(x, u(x)) + \alpha \Delta u(x) + \beta g(x, u(x)) + \sum_{j=1}^{m} \lambda_j \delta_{t^j}(x) = 0, \qquad x \in \Omega \qquad (6)$$

$$\text{and} \quad \delta_{t^j}[u](x) - d^j = 0, \qquad j = 1, \cdots, m, \qquad (7)$$

where f and g is the first variation of distance measure and contour feature energy. Here the contour feature force g can be computed like,

$$g(x, u(x)) = (\Phi^T(x - u(x)) - \Phi^R(x)) \cdot \nabla \Phi^T(x - u(x)) \qquad (8)$$

For the numerical implementation, we refer to [FM03].

3 Results

3.1 Contour Feature Constrained Registration

This experiment is to demonstrate that the contour feature constrained registration outperforms the common intensity based approach in the aspect of contour feature alignment. The given two objects (Fig.1a, Fig.1b) have obviously different boundary features, which can be specified by manual user interaction or automatic contour extraction techniques. Here, we use active contour segmentation technique to extract the outer contour of the target objects (Fig.1c, Fig.1d). With same parameters and iteration number, the feature constrained one has better contour alignment than the non-constrained one (Fig.1e, Fig.1f). The speed-up can be interpreted that the feature regularization term based on level set contour representation leads the registration to be more sensitive to the matching of correspondent contour feature. And the additional computational cost for the feature constraints is minor in contrast with the non-constrained approach.

Table 1: Performance

	CUR	*FEA*
Iterations	50	50
Time(s)	26.700	29.736
Difference(%)	63.7374	51.1196

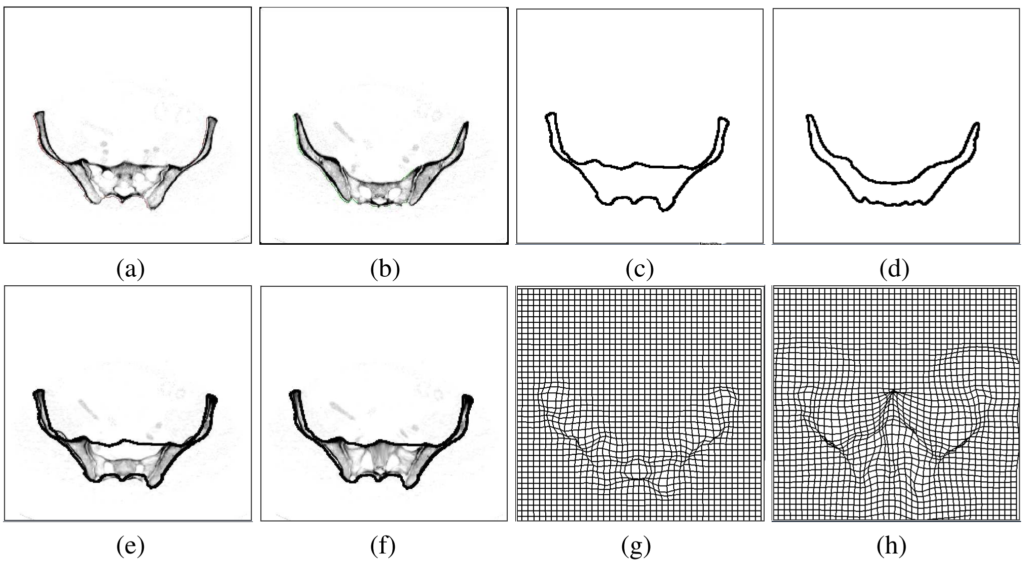

Figure 1: . (a)(b) Reference and template. (c)(d) The outer object boundary in reference and template. (e)(f) The transformed image with and without contour feature constraints. (e)(f) The displacement field of intensity based registration and contour feature constrained registration.

3.2 Monomodel Feature constrained Registration

A monomodel registration applications using feature constraints are presented here. In this example the specified correspondent features may depict the identical anatomical points or boundary, whose alignments are significant in the medical image fusion applications. Because of the respiratory and cardiac motion, there exist a non-rigid deformation between reference and template CT axial slice of the thorax. Three pairs of outstanding feature points are specified manually. One of them is the center of spine and the other two have extreme curvature on the outer surface. Furthermore, the boundaries of heart, which are extracted by automatic segmentation procedure, are also required to be reasonably matched (Fig.2a, Fig.2b). Thought feature combined registration, two images are aligned with satisfactory feature correspondences and the intensity correlation (Fig.2c, Fig.2d).

(a)

(b)

(c)

(d)

Figure 2: Monomodal registration applications. (a) Reference, (b) Template, (c) Target feature alignment (before registration), (d) Feature alignment after the feature constrained registration.

4 Conclusion and Discussion

We have demonstrated a new feature constrained approach in the framework of non-rigid registration. The algorithm was formulated by modifying the functional of the CLD algorithm to emphasize the contour feature correlation. The superiority of the extended algorithm is that it can optionally achieve correspondences of two kinds of anatomical features, namely, landmarks and contour features. However, these two features correspondences are handled in different ways. The landmark-pairs are expected to be perfectly matched. Mathematically, the solution must subject to some interpolation constraints. For the contour feature, we require that the algorithm is more sensitive to this feature correspondence and the sensitivity is tunable. Based on the level set function, we devise a new regularizer to bias the registration toward good object matching.

We compared our experimental result with traditional monomodal and multimodal non-rigid registrations. The featured constrained approach outperforms them on the real medical image data in the aspect of feature correlation. Although all the examples in the paper are 2D registrations, feature constrained registration is a general approach for 2D and 3D registration problem.

For the clinical user, the algorithm provides the possibility that they utilize their knowledge and experience to specify the desired feature correlation automatically or manually, so that they could guide the registration into more anatomically reasonable direction. Therefore, the medical image fusion based on feature constrained approach becomes more reliable than non-biased registration techniques.

However, it requires a lot of further work to optimize the feature constrained registration for clinical workflow. The future work could be, for instance, the precise automatic selection of contours and landmarks, integration of registration with altas based segmentation and extensive clinical evaluation to prove the advantage of the approach.

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