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A total variation based nonrigid image registration by combining parametric and non-parametric transformation models

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ABSTRACT

To overcome the conflict between the global robustness and the local accuracy of dense nonrigid image registration, we propose a union registration approach by combining parametric and non-parametric transformation models. On one hand, to guarantee the robustness, we constrain the displacement field ϕ using a mapping difference metric between the B-spline parametric space Ψ and the non-parametric transformation space Φ. On the other hand, to correct the densely and highly localized geometrical distortions, we introduce a total variation (TV) regularization term for the displacement field ϕ. Accounting for the effect of spatially varying intensity distortions, the residual complexity (RC) is used as the similarity metric. Moreover, to solve the proposed union nonrigid registration, which is a composite convex optimization problem by the smooth ℓ_2 term and the non-smooth ℓ_1 term (TV), we design a two-stage algorithm using split Bregman iteration. Experiments with both synthetic and real images from different domains illustrate that this approach can capture the local details of transformation accurately and effectively while being robust to the spatially varying intensity distortions.

1. Introduction

Image registration aims to geometrically match up two or more images of the same scene, taken at different times, from different viewpoints, or by different sensors, for structure/target localization, difference detection, and many other purposes [1]. It is widely used in medical imaging [2], remote sensing [3], finger print or face recognition [4], image compression [5], video enhancement [6], etc. Existing image registration methods are either feature-based or intensity-based [7]. Because identification and extraction of image features is often a challenging and time-consuming process for feature-based methods [8–10], intensity-based image registration (IBIR) [11,12,14–16], by which the transformation is estimated directly from the observed image intensities of the two images, has received much attention recently.

Most existing IBIR procedures estimate the geometrical transformation or displacement field ϕ globally by optimizing a minimization problem, such as

$$\phi^* = \underset{\phi \in \Phi}{\operatorname{argmin}} D(f, u(\phi)) + R(\phi) \tag{1}$$

where $D(\cdot)$ and $R(\cdot)$ are respectively the distance metric and the regularization term. Φ is a specific transformation space. The entire images f (reference or fixed image) and u (floating or moving image) are involved in the optimization. The choice of transformation model is of great importance for the registration process as it entails an important compromise between computational efficiency and richness of description. It also reflects the class of transformations that are desirable or acceptable, and therefore limits the solution to a large extent.

In the literature, there are two methods to model the transformation field ϕ [17,18]. The first method is parametric, which models ϕ in a parametric space Ψ. The number of parameters corresponds to the degrees of freedom of the transformation model and varies greatly, from six in the case of rigid transformations [18] (including rotation, scaling, translation, and other affine transforms) to tens of thousands when the nonrigid or deformable transformations [19,20] are considered. Rigid transformations are global in nature, thus, they cannot model local geometric differences between images. On the contrary, the parametric nonrigid transformations are capable of locally warping the moving image to align with the fixed image. The second method is non-parametric, which models ϕ directly in the transformation space Φ. The non-parametric image registration has its transformation field directly optimized through the registration process, e.g., the demons algorithm [12,13], the physical model-based methods

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[17,18], the optical flow [21–23]. This type of registration needs an explicit displacement vector for every pixel. When dense nonrigid transformations are considered, the degrees of freedom of the transformation model are tremendous.

Due to the relatively simple computation and other salient properties, the parametric free form deformation (FFD) techniques based on B-spline basis are getting popular to deal with the nonrigid transformation problem in image registration community [11,24–26]. The goal of free-form deformations is to provide a convenient means of modeling arbitrary deformations applied to objects. Rather than being motivated by physical models, the FFD registration is derived from either interpolation theory or approximation theory [27]. In other words, it approximates the underlying displacement field ϕ rather than taking the exact same value. In the classic FFD registration [11], a 2D nonrigid deformation $\phi=[X\ Y]^T$ is parameterized using a set of 2D control points $\psi=[UV]^T$, such that

$$\phi = K\psi, \quad K=\begin{bmatrix} B & 0 \\ 0 & B \end{bmatrix}, \quad \psi \in \Psi \tag{2}$$

where B denotes the matrix of the B-spline basis functions and Ψ is the B-spline parametric space.

One main difficulty of the FFD approach is to cope with the conflict between the global robustness and the local accuracy [28,29]. In [29], Shi et al. referred to the robustness as the ability to recover the deformation in the presence of noise, and the accuracy as the ability to reconstruct the highly localized and potentially discontinuous deformation with as little error as possible. The trade-off between accuracy and robustness stems from the fact that the FFD approach uses a smooth B-spline basis to model the contribution of each control point to the deformation. To model global and smooth deformations a coarse control point grid spacing is typically used. To allow very localized deformations a finer control point spacing is required, however, this can render the FFD registration less robust as the model has far more degrees of freedom which must be optimized. Moreover, the standard smoothness constraints for nonrigid registration methods [11,12,21] assume that the deformation within a neighborhood changes only gradually since the underlying deformation itself is smooth. Combining the implicit smoothness of the B-spline basis and the explicit smoothness constraint in the regularization leads to FFD registration results with smooth deformations.

Compared to the parametric FFD method, the non-parametric registration has a stronger descriptive power for the transformation due to the high degrees of the freedom of transformation space Φ. However, this model enrichment may accompanied by the model's complexity which in turn results in a challenging and computationally demanding inference. Usually, to reduce the risk of being tracked in local minima, a physical model based regularization term for ϕ is needed and a multilevel optimization strategy is used [17,18]. When dense nonrigid deformations are considered, the non-parametric registration has the ability to correct highly localized deformations but lacks the robustness to reconstruct such deformations in the presence of noise.

Many approaches to both parametric and non-parametric nonrigid registration have been proposed that aim to overcome the conflict between robustness and accuracy in estimation of the deformation field ϕ. For parametric FFD registration, some research focussed on the adaptive parameterization of the B-spine control point grid [30,31]. Recently, Shi et al., in [28,29], assumed that the deformation was sparse in the parametric space Ψ and then introduced a sparse regularization term on the basis of the classical FFD registration. The sparse FFD (SFFD) method reduced the conflict between global smoothness and local details of the transformation to some extent, but the assumption of sparsity in SFFD is limited in the scenario without densely localized geometrical distortions. For non-parametric registration approach, in particular the optical flow algorithm, Wedel et al. employed the total variation (TV) regularization to preserve discontinuities in the flow field and applied the robust ℓ_1 norm in the data fidelity term to eliminate outliers [33]. More recently, sparse representation has been proposed to evaluate the patch similarity between two images [34] and to constrain the transformation [35].

In this paper, to overcome the main conflict in the FFD registration, we propose a union nonrigid image registration approach by combining parametric and non-parametric transformation models. On one hand, our approach explicitly takes the implicit smoothness of the B-spline basis as the regularization for the non-parametric registration, which also can be considered as a constraint of the displacement field ϕ using a mapping difference metric between the B-spine parametric space Ψ and the transformation space Φ. It is a strong constraint that guarantees the robustness of the registration result. On the other hand, inspired by the work in [33] and [35], we introduce a total variation (TV) term to describe ϕ in the space of bounded variation (BV), which can preserve the densely and highly localized deformations. In addition, suitable similarity measures are crucial for the intensity-based registration. Considering that real-world images often have spatially varying intensity distortions, which is caused by inhomogeneities from staining, illumination or attenuation [14,32], we adopt the residual complexity (RC) [14] as the similarity metric. Compared to other similarity measures, registration by minimizing the residual complexity is simple in terms of both computational complexity and implementation, and meanwhile produces accurate registration results in problems with spatially varying intensity distortions. Furthermore, to solve the proposed union nonrigid registration, which is a composite convex optimization problem by the smooth ℓ_2 term and the non-smooth ℓ_1 term (TV), we design a two-stage algorithm using split Bregman iteration [36].

Our union registration combines the robustness of the FFD method and the flexibility of the non-parametric method, and outperforms the separate method, the parametric or the non-parametric. Moreover, due to the rapid convergence of split Bregman iteration algorithm in dealing with the TV-based optimization problem, the computation of our two-stage algorithm only needs a few iterations on a fixed level of image resolution after the residual complexity based FFD registration [14], which is more efficient than the FFD-based methods adaptively selecting control point grid spacing [30,31].

The paper is organized as follows. Section 2 describes the proposed registration approach in detail. Experimental results are given in Section 3 to verify our approach and show the performance as compared with other methods, and finally we conclude and discuss the method in Section 4.

2. Proposed method

2.1. The registration model

Consider two images f and $u(\phi)$ to be aligned, assuming the following intensity relationship [14]:

$$f = u(\phi)+s+\eta \tag{3}$$

where $\phi=[XY]^T$ is a 2D deformation field, η is the zero mean Gaussian noise, s is an intensity correction field which accounts for intensity nonstationarities and complex spatially varying intensity distortions in mono-modal settings. Assuming s and ϕ independent, the maximum a posteriori (MAP) approach to estimate s and ϕ is to maximize the probability

$$P(\phi, s|f, u) \propto P(f, u|\phi, s)P(\phi)P(s) \tag{4}$$