Information Sciences 423 (2018) 66–79

Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

Accelerated nonrigid image registration using improved Levenberg–Marquardt method

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ARTICLE INFO

Article history:
Received 10 April 2017
Revised 18 September 2017
Accepted 20 September 2017
Available online 21 September 2017

Keywords:
Medical image registration
Free-form deformation
B-splines
Levenberg–Marquardt optimization

ABSTRACT

B-splines have been successfully applied to nonrigid image registration and are popular in various applications. They offer a reduced computational overhead because changes in the control points only affect the transformation within a local neighborhood. Optimization is a key stage in image registration. Most optimization methods only use the gradient direction to determine the update step that may be not optimal. A suboptimal update step may result in a large number of iterations, thus significantly increases the computational time or decreases the accuracy of the registration results. Levenberg–Marquardt (L-M) optimization is a superior algorithm that provides more precise steps during the iteration process. However, because of the large number of parameters in nonrigid image registration, the L-M method suffers from high computational complexity. In this paper, a dedicated optimization method is proposed for nonrigid CT image registration based on L-M optimization. A regular L-M step along with an additional L-M step is computed as the optimal vector, which reduces the computation time because the Jacobian matrix is reused for two calculations in every iteration. Besides, the parameters change automatically according to the calculated results in each step to make the method more efficient. In addition, a linear search for the trial step is introduced to enhance performance. Experimental results indicate that the proposed method is effective and efficient.

1. Introduction

Radiological images have been increasingly used in healthcare and medical research. The main medical imaging techniques are structural imaging, which includes computed tomography (CT) and magnetic resonance imaging (MRI), and functional imaging, which includes single photon emission computed tomography (SPECT) and functional magnetic resonance imaging (fMRI). The integration of information from images of different phases or different modalities is of fundamental importance, and this task is mainly performed using image registration. For instance, due to the development of CT technology, the amount of data obtained in clinical CT has increased exponentially and 4D CT scanning has become increasingly popular in medical diagnosis and treatment. In comparison to static images, the sequences obtained from 4D CT scanning data offer additional information about the motion of the imaged organs, which is especially important in lungs [19]. To estimate the

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https://doi.org/10.1016/j.ins.2017.09.059
0020-0255/

motion models of the organs of interest, an accurate and accelerated image registration method is very important and highly necessary.

Image registration is the process of matching two or more partially overlapping images taken, for example, at different times, from different sensors, or from different viewpoints [34]. Typical applications of image registration include motion estimation, atlas construction, atlas-based segmentation, image guidance during interventions and aligning images from multiple subjects in cohort studies [7,23,26]. The goal of image registration is to find the optimal transformation that best aligns the structures of interest in the input images [21]. The main components in image registration are the feature space, transformation, search space, similarity metric, and optimization method. Image registration consists of rigid and nonrigid image registration. Rigid image registration can only simulate transformations such as displacement, scaling, and shear, which are not sufficient to manifest the local deformation of human organs or tissues. Hence, we focus on nonrigid image registration in this study. To date, many image registration methods have been studied. Zuk [35] and Lester [17] divided image registration into spatial transformation, similarity measurement, optimization method, and image interpolation. Petra et al. [10] classified existing image registration methods into those based on the intensity of the region of interest (ROI) and those based on image features.

Feature-based registration methods extract features from a reference image and a target image and seek a deformation field based on the two sets of features. The deformation field of the entire image can then be obtained through interpolation. Feature points are the most widely used feature descriptor. David et al. [18] proposed the scale-invariant feature transform (SIFT) method to extract feature points from an image. Later, the speeded-up robust features (SURF) method accelerated the process by simplifying the Gaussian second-order differential template [3]. Besl et al. [4] proposed the iterative closest point (ICP) method to align the two point sets based on the closest distance rule. ICP is widely used because of its simple structure and low computational complexity. However, it is very sensitive to the initial position of the floating point set, which makes it difficult to align two point sets that are not close. Many modified ICP methods have been proposed to overcome this shortcoming. Soft assignment of correspondences between given two point sets was proposed to establish the fuzzy correspondence matrix before the registration is performed based on the tentative correspondence relations[8]. Myronenko and Song [20] applied Gaussian radial basis functions (GRBF) to estimate the transformation function between two point sets. Moreover, registration methods based on feature curves and feature surfaces have received considerable attention [30].

Intensity-based registration methods are also widely used. These methods are suitable for automatic implementation because they simply take advantage of an image's intensity and omit the processes prior to registration, unlike feature-based registration methods. Of the registration techniques that use image intensity, free-form deformation (FFD) [24], which uses B-splines, has demonstrated its strong potential. Compared with related spline representations such as thin-plate splines or elastic-body splines, B-splines are computationally attractive because any changes in the control points only affect the transformation within a local neighborhood of those points. FFD quickly became popular, and many applications and improvements have been proposed [27,33]. With respect to the transformation model, a concatenated multi-level B-spline transformation model for diffeomorphic registration was proposed in [22]. To align dynamic medical imaging data, atemporal B-spline transformation model was presented in [19]. Nonetheless, the computational cost of FFD is still high, and so an efficient optimization method is necessary. Common optimization methods used in image registration include the steepest descent method, Gauss-Newton method and so on. The steepest descent method converges fast at first, but slows down when the parameters vector is close to the solution set. The Gauss-Newton method exploits not only the first-order but also the second-order differential of objective function to determine the update step, thus provides a more precise search direction. But the existence of areas with constant or nearly constant values in images may result in ill-posed problems which massively increases the iteration number or decreases the accuracy of registration results. Levenberg–Marquardt (L-M) optimization [9] makes a good trade-off between the steepest descent method and the Gauss-Newton method and is able to bypass the reduced rank problem by introducing a matrix $\lambda\mathbf{I}$. In image registration, L-M offers a more precise search direction than the steepest descent method, and requires less computation than the Gauss-Newton method [12,13]. M. Kisaki et al. [15] proposed a new automatic image registration technique for image fusion of head CT (Computed Tomography) and MR (Magnetic resonance) images based on Levenberg–Marquardt algorithm. Klima et al. [16] proposed a robust and fast reconstruction methods based on fitting the statistical shape and intensity model of a femoral bone onto a pair of calibrated X-ray images, which was formulated as a non-linear least squares problem solved by Levenberg–Marquardt optimization. And there have been many works focusing on the applications of L-M method [31,32].

In this paper, we investigate the optimization of image registration based on FFD and introduce an improved L-M method for nonrigid CT lung image registration. In L-M method, the calculation of Jacobian matrix is needed at every iteration. The computational cost becomes very high when L-M is used in image registration. To make the registration more efficient, we take a reuse of the Jacobian matrix at every iteration by introducing an additional step, which is calculated according to the updated residual along with the original Jacobian matrix. A brief pipeline for this method is shown in Fig. 1. The effectiveness is proofed by both the formula demonstration and the experiment results. Moreover, considering the effect of parameters in the method, we take an adaptive strategy for those parameters to ensure the convergence. The experiment results show the significant performance improvement provided by our method.