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Non-rigid image registration with anatomical structure constraint for assessing locoregional therapy of hepatocellular carcinoma

Chunhua Dong[a], Yen-wei Chen[a,b,*], Toshihito Seki[c], Ryosuke Inoguchi[c], Chen-Lun Lin[a], Xian-hua Han[a]

[a] Graduate School of Information Science and Engineering, Ritsumeikan University, Noji-higashi 1-1-1, Kusatsu, Japan
[b] College of Computer Science and Technology, Zhejiang University, Zhejiang, China
[c] Department of Gastroenterology and Hepatology, Kansai Medical University, Osaka, Japan

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ABSTRACT

Purpose: Assessing the treated region with locoregional therapy (LT) provides valuable information for predicting hepatocellular carcinoma (HCC) recurrence. The commonly used of assessment method is inefficient because it only compares two-dimensional CT images manually. In our previous work, we automatically aligned the two CT volumes to evaluate the therapeutic efficiency using registration algorithms. The non-rigid registration is applied to capture local deformation, however, it usually destroys internal structure. Taking these into consideration, this paper proposes a novel non-rigid registration approach for evaluating LT of HCC to maintain the image integrity.
Method: In our registration algorithm, a global affine transformation combined with localized cubic B-spline is used to estimate the significant non-rigid motions of two livers. The proposed method extends a classical non-rigid registration based on mutual information (MI) that uses an anatomical structure term to constrain the local deformation. The energy function can be defined based on the total one associated with the anatomical structure and deformation information. Optimal transformation is obtained by finding the equilibrium state in which the total energy is minimized, indicating that the anatomical landmarks have found their correspondences. Thus, we can use the same transformation to automatically transform the ablative region to the optimal position.
Results: Registration accuracy is evaluated using the clinical data. Improved results are obtained with respect to all criteria in our proposed method (MI-LC) than those in the MI-based non-rigid registration. The landmark distance error (LDE) of MI-LC is decreased by an average of 3.93 mm compared to the case of MI-based registration. Moreover, it could be found regardless of how many landmarks applied in our proposed method, a significant reduction in LDE values using registrations based on MI-LC compared with those based on MI is confirmed.
Conclusion: Our proposed approach can guarantee the continuity, the accuracy and the smoothness of structures by constraining the anatomical features. The results clearly indicate that our method can retain the local deformation of the image. In addition, it assures the anatomical structure stability.

1. Introduction

Locoregional therapy (LT) is a choice for the treatment of hepatocellular carcinoma (HCC). It targets the specific inflicted region of the liver by injecting a higher dose of drugs into the tumor without exposing the rest of the patient's body. This therapy reduces the chances of infection and shortens recovery time. However, in certain situations, tumors cannot be removed clearly with LT. Thus, it is desirable to assess the therapeutic efficiency after treatment of HCC. Currently, the assessment method widely used compares the two-dimensional (2D) CT images (axial, coronal, and sagittal) manually; however, selecting the corresponding slices is a time-consuming process. Hence, in [1], we proposed a three-dimensional (3D) imaging fusion technique that considered a few nearby slices to assess HCC of the treated region before and after LT. This method only performed two factors of transformation: rotation and

* Corresponding author at: Graduate School of Information Science and Engineering, Ritsumeikan University, Noji-higashi 1-1-1, Kusatsu, Japan.
Tel.: +81 77 561 5926.
E-mail addresses: dongchunhua89@gmail.com (C. Dong), chen@is.ritsumei.ac.jp (Y.-w. Chen), sekit@takii.kmu.ac.jp (T. Seki), inokuchr@hirakata.kmu.ac.jp (R. Inoguchi), vrykolakas.rock@gmail.com (C.-L. Lin), hanxhua@fc.ritsumei.ac.jp (X.-h. Han).

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translation, while other factors should also be taken into account. However, the accuracy in determining the location of the ablative region is significantly limited due to manual adjustment.

To resolve these problems, in our previous research [2], we applied an automatic registration method for this application. However, as Archip described in [3] and Lee described in [4], registering soft tissues with rigid registration may result in errors as high as 19–20 mm, due to deformations that may be caused by liver movements such as respiration, variations of position and corporal mass changes over time. To improve detection and characterization in terms of volume and relation with HCC, an accurate non-rigid image registration algorithm is required. Currently, rich literatures on non-rigid registration method have been published [5–14]. It can be summarized as: intensity-based [14–16] (such as B-spline, demons), landmark-based [17,18] (such as thin-plate, ICP) registration method. Meyer et al. [19] proposed a notable registration algorithm based on a thin-plate spline deformation. Due to prohibitive computational complexity of the thin-plate spline warps, the registration was restricted to a very limited number of degrees of freedom. Hence, landmark-based nonrigid registration is not sufficient for most applications, especially the liver registration. Because the number of landmarks for liver which located in the discernible anatomical points is very few that affect the accuracy of registration. In addition, it is a complex task to find the corresponding landmarks. Some studies have presented that intensity-based non-rigid registration methods would be more robust and easier to implement than landmark-based. Intensity-based non-rigid registration, however, poses a number of challenges. It will breaks the internal structure of the organ volume during the intensity-based registration process, and hence results in the loss of anatomical information.

As already explained above, the intensity-based rigid registration is performed to capture the global alignment between images without considering local deformation. The intensity-based non-rigid registration techniques can capture local deformation, which results in a change in the anatomical structure of the volume. However, it is essential that medical images maintain their anatomical structure stability and integrality. Hence, the objective of our work is to provide a new option for non-rigid registration to guarantee the anatomical structure of shape. In this study, we add a landmark penalty term into mutual information (MI) as a new energy function (MI-LC) to constrain the local deformation. If we treated the landmark as an elastic material, from the viewpoint of physics, when the landmarks are not in the optimal positions, the resulting distortion will produce a displacement field. The landmarks in the displacement field carry potential energy. When they move and interact, the total energy associated with them is change. According to the principle of minimum total potential energy, optimal transformation is obtained by reaching the equilibrium state in which the total energy is minimized. Experimental demonstrate our proposed method successfully overcame the disadvantage of intensity-based non-rigid registration.

The rest of this paper is organized as follows: An overview of our registration implementation integrated with the illustration of landmark positions is presented in Section 2. Extensive evaluation of our method is illuminated in Section 3. Section 4 is devoted to the discussion of performance and Section 5 concludes the paper.

2. Materials and methods

2.1. Deformable registration framework.

To evaluate LT of HCC, we need to register the ablative region onto the tumor using registration method. The objective of image registration is to find the optimal transformation parameters $\boldsymbol{\mu}$,

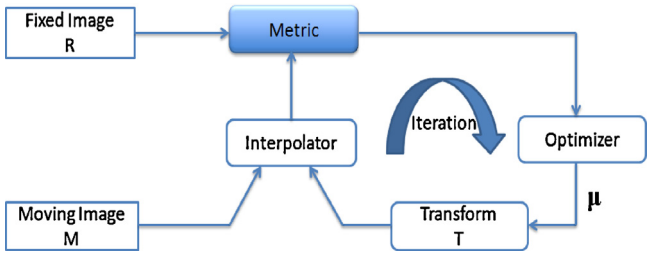

Fig. 1. Deformable registration framework.

which maps every point in the postoperative liver (after LT) which is called the moving image M onto its corresponding point in the preoperative liver (before LT) which is called the fixed image R, so that the similarity function, which measures the difference between M and R can be minimized. Then, it can automatically transform the ablative region to the optimal position using the same transformation parameters.

The input images are given as two 3D discrete signals: the moving image M and the fixed image R with intensities $f_m(\mathbf{x})$ and $f_r(\mathbf{x})$, respectively, where $\mathbf{x} \in I \subset \mathbf{Z}^N$, and I is a 3D discrete interval representing the set of all voxel coordinates in the image. The transformed moving image W can be obtained by using the optimal transformation parameters $\boldsymbol{\mu}$, that can be defined as $f_w(\mathbf{x}) = f_m(\mathbf{x}; \boldsymbol{\mu})$.

Nevertheless the majority of the image registration methods can be viewed as a combination of the four distinctive components: transformation, interpolation, the similarity metric based on cost function, optimization. As shown in Fig. 1, among the four components, the similarity metric based on cost function is the most important significant critical for the registration algorithm, as it defines the goal of optimization and measures how well the transformed moving image W matches the fixed image R. In the following, the non-rigid registration algorithm is described in detail.

2.2. Similarity metric

2.2.1. Conventional cost function

As explained above, we estimate the parameter of transformation by optimizing a cost function (similarity metric) in the processing of registration. In general, the solution to the registration problem can be computed by optimizing the following cost function [14,20,21]:

$$E(\boldsymbol{\mu}) = E_{sim}(R, W) = E_{sim}(f_r, f_m \cdot T(\boldsymbol{\mu})) = E_{sim}(f_r(\mathbf{x}), f_m(\mathbf{x}; \boldsymbol{\mu})) \quad (1)$$

According to the intensity-based registration process, the aim is to minimize/maximize the similarity E_{sim} between the two images. There are several image metrics that are used in voxel similarity-based image registration [5–9]: correlation coefficient, sum of squared differences (SSD), or mutual information (MI). SSD is one of the simplest voxel similarity based cost functions which should be minimized during registration. SSD is based on the strict assumption that the two images only differ from the Gaussian noise, but this is not true for medical images, especially for multi-modal images. Therefore, this method can be only used for mono-modal registration. However, MI [10,11] is the most widely used for medical image similarity measures that no limit to the image content about the modalities (mono-modal and multi-modal). MI can measure the statistical dependence or information redundancy between the image intensities of corresponding voxels in both images, which is assumed to be maximal if the images are registered.

However, the biggest serious drawback of MI is the absence of spatial information [12,14,22,23], due to it's definition being based on Shannon's Entropy, which assumes each pixels is independent