



基于快速自由形变的弹性配准算法在放疗CT中的应用

庞皓文,孙小扬

泸州医学院附属医院肿瘤科,四川 泸州 646000

【摘要】介绍了一种基于快速自由形变的弹性配准算法,并将其应用到放疗患者不同分次间的CT图像中,为进一步分析肿瘤及危及器官的变化及累加剂量提供技术支持。通过Matlab软件编写三维全自动弹性配准程序,应用此程序对鼻咽癌放疗患者不同分次时的两组三维CT图像进行仿真实验验证,并与基于传统Lucas-Kanade光流场模型的三维弹性配准相比较。基于快速自由形变的弹性配准算法配准前后对比,最小均方误(MSE)减少了19.8%,相关系数(CC)提高了7.1%;Lucas-Kanade光流场模型算法配准前后对比,MSE减少了37.8%,CC提高10.6%。两种配准方法均取得较好的配准效果,基于传统的Lucas-Kanade光流场模型的三维弹性配准的评价参数好于快速自由形变配准法算法,但快速自由形变配准法算法配准时间只是传统的Lucas-Kanade光流场模型的0.576倍。不过上述两种算法对于细微差别处,仍显得精度不够,如要应用到在线自适应放疗中仍需进一步提高形变的精度与进一步减少配准时间。

【关键词】弹性配准;自由形变;CT;放射治疗

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Application of fast free-form elasticregistration algoritm in radiotherapy CT

PANG Hao-wen, SUN Xiao-yang

Department of Oncology, Affiliated Hospital of Luzhou Medical College, Luzhou 646000, China

Abstract: A fast free-form elastic registration algorithm was presented in this paper, and applied in radiotherapy CT image, providing technical support for further analysis of the changes of tumor and organs at risk, and evaluating cumulative dose during radiotherapy. A 3D fully automatic image elastic registration program was written by matlab software, and applied to do simulated experiment verification for two groups of 3D CT images of patients with NPC, and then compared with 3D elastic registration based on the traditional Lucas-Kanade optical flow model. The comparison between before and after the registration of fast free-form elastic registration algorithm showed that minimum mean square error (MSE) decreased by 19.8%, and that correlation coefficients (CC) increased by 7.1%. For 3D elastic registration based on the traditional Lucas-Kanade optical flow model, MSE decreased by 37.8% and CC increased by 10.6%. Both these two registration methods had achieved good results. Although the evaluation parameter of 3D elastic registration based on Lucas-Kanade mode was a bit better than fast free-form algorithm, the registration time of the latter just was 0.576 times of that of the former. The above two algorithms are not precise enough for subtle, so these algorithms still need to further improve accuracy and reduce registration time in the application to the online adaptive radiotherapy.

Key words: elastic registration; fast free-form algorithm; CT; radiotherapy

前言

放射治疗过程中肿瘤及危及器官的变化贯穿整个放射治疗过程,精确评估个体肿瘤及危及器官变化过程及其累加剂量是放疗热点课题^[1-5]。弹性配准算法为统计这些变化过程提供技术支持,也是放疗四维模型建立的基础^[6-7]。要将弹性配准应用到常规

的放射治疗中,则需要其方法精确、快速且全自动,一些弹性配准方法已经被用于放疗图像中,比如基于样条函数的方法^[8-10]、光流法^[11]等。本文介绍了一种基于快速自由形变的弹性配准算法,并基于Matlab软件编写三维全自动弹性配准程序,成功对鼻咽癌放疗患者不同分次时的两组CT图像进行全自动仿真实验验证。

1 原理与方法

1.1 能量函数的构造

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【作者简介】庞皓文(1981-),男,硕士,工程师,Tel:15892938972,E-mail:279165416@qq.com。

【通信作者】孙小扬,E-mail:sunxy0611@126.com。



设 $v = (x^1, x^2, x^3)$ 为空间三个方向, $M(v)$ 是待配准图像灰度值, $S(v)$ 是参考图像灰度值, 图像弹性形变配准是寻找位移场 $u(v)$, 使配准图像形变后 $M(v+u)$ 与参考图像 $S(v)$ 在某种意义上相似。本研究中应用的能量函数(相似性测度函数)如下公式:

$$\varepsilon(u) = \int_{\Omega} (M(v+u) - S(v))^2 + \lambda \left(\sum_{i=1}^3 \sum_{j=1}^3 \frac{\partial u^i}{\partial x^j} \right)^2 dv \quad (1)$$

$$\hat{u} = \arg \min \varepsilon(u) \quad (2)$$

1.2 变分法

通过变分法, 得到如下欧拉方程:

$$\text{令 } R(v, u) = M(v+u) - S(v)$$

$$\lambda \nabla^2 u - R(v, u) \frac{\partial R(v, u)}{\partial u} = 0 \quad (3)$$

$$\frac{\partial R(v, u)}{\partial u} = \frac{\partial M(v+u)}{\partial u} = \frac{\partial M(z)}{\partial u}|_z=v+u \frac{\partial z}{\partial u} =$$

$$\frac{\partial M(z)}{\partial u}|_z=v+u = \nabla(M)(v+u) = g(v+u) \quad (4)$$

此处, $g(v) = \nabla M(v)$

因此公式(2)可以转换为:

$$\lambda \nabla^2 u - [M(v+u) - S(v)]g(v+u) = 0 \quad (5)$$

1.3 数值实现

1.3.1 有限差分格式 公式(5)为非线性椭圆方程, 我们使用有限差分格式对其进行求解。

让 i, j, k 作为某像素 (x, y, z) 的空间坐标索引, ($i=1, 2, \dots, L_x, j=1, 2, \dots, L_y, k=1, 2, \dots, L_z$), n 表示空间维度($n=1, 2, 3$)。 m 为参数序列($m=1, 2, \dots, N$), N 是图像像素总数。

离散化公式(5), 令

$$L_{m,n} = \lambda \nabla^2(u_{m,n}) - [M(v_m + u_m) - S(v_m)] \\ g_{m,n}(v_m + u_m) \quad (6)$$

$$\nabla^2(u_{m,n}) = \frac{u_{i+1,j,k,n} + u_{i-1,j,k,n} + u_{i,j+1,k,n}}{6} + \\ \frac{u_{i,j-1,k,n} + u_{i,j,k+1,n} + u_{i,j,k-1,n}}{6} - u_{i+1,j,k,n} \quad (7)$$

$$\text{通过牛顿迭代法更新: } u_{m,n}^{new} = u_{m,n}^{old} - \frac{L_{m,n}^{old}}{\frac{\partial L_{m,n}^{old}}{\partial u_{m,n}}} \quad (8)$$

其中

$$\frac{\partial L_{m,n}}{\partial u_{m,n}} = \lambda \frac{\partial(\nabla^2(u_{m,n}))}{\partial u_{m,n}} - \left(\frac{\partial(M(v_m + u_m))}{\partial u_{m,n}} \right) g_{m,n}(v_m + u_m) \\ + \left(\frac{\partial(g_{m,n}(v_m + u_m))}{\partial u_{m,n}} \right) (M(v_m + u_m) - S(v_m)) \quad (9)$$

$$\text{由公式(7)可知: } \frac{\partial(\nabla^2(u_{m,n}))}{\partial u_{m,n}} = -1 \quad (10)$$

$$\text{由公式(4)可知: } \frac{\partial(M(v_m + u_m))}{\partial u_{m,n}} = g_{m,n}(v_m + u_m) \quad (11)$$

$$\text{因此: } \frac{\partial L_{m,n}}{\partial u_{m,n}} = -(\lambda + (g_{m,n}(v_m + u_m))^2) \quad (12)$$

于是公式(9)更新为:

$$u_{m,n}^{new} = u_{m,n}^{old} + \frac{L_{m,n}^{old}}{\lambda + (g_{m,n}(v_m + u_m))^2} \quad (13)$$

1.3.2 快速自由形变配准算法步骤 $n=1, 2, 3; m=1, 2, \dots, N$; 通过公式(7)计算 $\nabla^2(u_{m,n})$; 通过公式(6)计算 $L_{m,n}$; 通过公式(13)更新位移场 $u_{m,n}$; 判断迭代次数如大于设定值迭代终止, $M(v+u_{m,n})$ 为最终的配准图像。配准过程中采用了多分辨策略。

2 结果

作者通过 Matlab 7.6 图像处理工具, 根据上述快速自由形变配准法算法原理编写三维全自动弹性配准程序, 应用此程序对鼻咽癌放疗患者不同分次时的两组 CT 图像进行仿真实验验证, 并与基于传统的 Lucas-Kanade 光流场模型的三维弹性配准相比较^[12]。实验平台为 Intel Core i5-3210M CPU, 2.5 GHz, 4 G 内存。患者 CT 图像断层大小均为 512×512 , 层距为 2.5 mm, 共采集 145 层。实验结果如图 1 所示, 实验参数如表 1 所示。快速自由形变配准算法仿真共用时 375.96 s, 基于 Lucas-Kanade 光流场模型配准仿真共用时 652.69 s。

3 结论

患者放射治疗期间, 由于肿瘤的退缩与运动以及周围正常器官的变化, 或许会使肿瘤及危及器官实际吸收剂量发生较大改变, 因此及时了解这些变化是临床医生十分关心的问题。弹性配准为实际观察这些变化提供了软件支持, 可以用于快速勾画变化后的肿瘤与危及器官以及其累加剂量。我们通过快速自由形变配准法算法原理编写三维弹性配准程序, 应用此程序对鼻咽癌放疗患者不同分次时的两组 CT 图像进行仿真实验验证, 并与基于传统的 Lucas-Kanade 光流场模型的三维弹性配准相比较。从配准前后差分图的比较及表 1 两种算法的评价参数可见, 两种配准方法均取得较好的配准效果, 基于传统 Lucas-Kanade 光流场模型的三维弹性配准的评价参数稍好于快速自由形变配准法算法, 但快速自由形变配准法算法配准时间只是传统的 Lucas-Kanade 光流场模型的 0.576 倍。现今在线自适应放

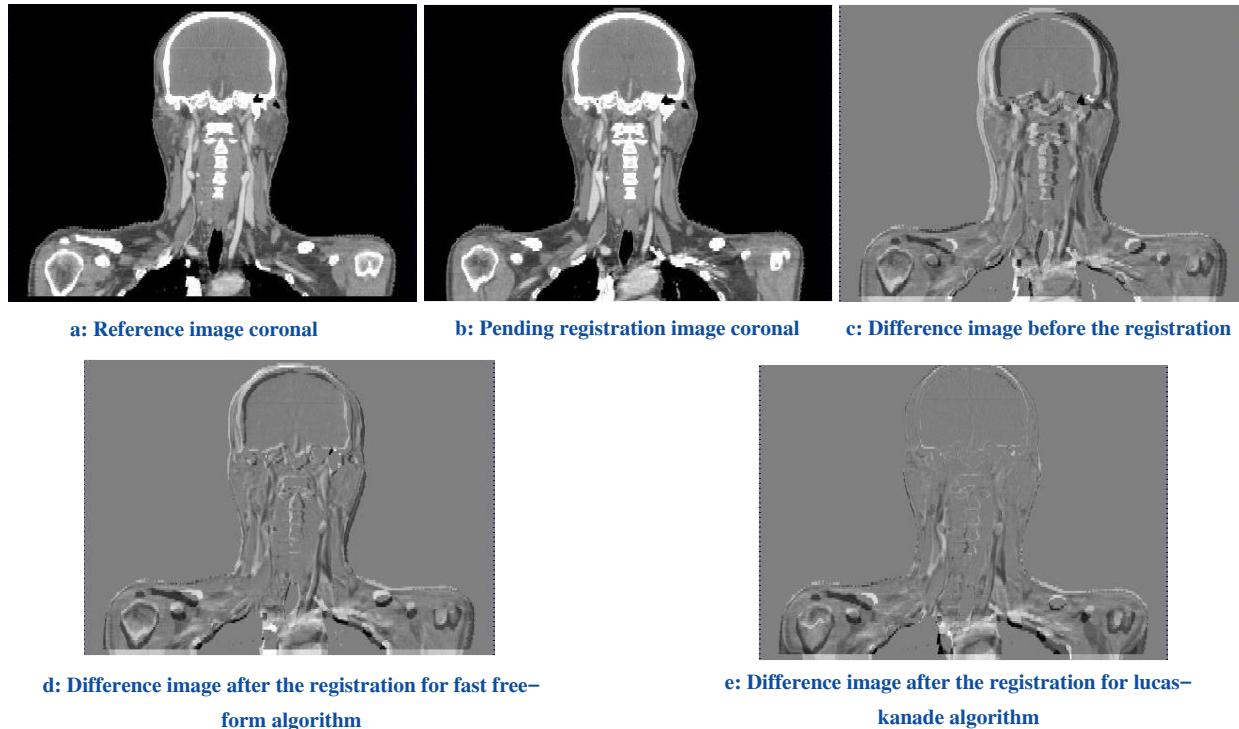


图1 基于快速自由形变配准算法鼻咽癌放疗患者不同分次时的两组CT弹性配准冠状面图

Fig.1 Two treatment images of patients with NPC CT coronal image based on Fast free-form deformable registration algorithm

表1 算法评价参数

Tab.1 Algorithm evaluation parameters

| | Minimum mean square error (MSE) | | | Correlation coefficient (CC) | | |
|----|---------------------------------|---|---|------------------------------|---|---|
| | Before the registration | After the registration for Fast free-form algorithm | After the registration for Lucas-Kanade algorithm | Before the registration | After the registration for Fast free-form algorithm | After the registration for Lucas-Kanade algorithm |
| CT | 248.3 | 199.2 | 154.4 | 0.85 | 0.91 | 0.94 |

疗逐渐取代传统放疗,弹性配准的时间是我们能否实现在线自适应的关键,基于快速自由形变配准法算法的弹性配准在减少时间方面作了有效的探索。但在整个放疗过程中,要获得器官真实的累加剂量,需进一步提高形变的精确性。怎样将时间与精确性二者更好地结合起来,更快更精确地模拟器官运动,是未来研究的方向。

【参考文献】

- [1] Yan D, Jaffray DA, Wong JW, et al. A model to accumulate fractionated dose in a deforming organ[J]. Int J Radiat Oncol Biol Phys, 1999, 44(3): 89-105.
- [2] Noel CE, Santanam L, Olsen JR, et al. An automated method for adaptive radiation therapy for prostate cancer patients using continuous fiducial-based tracking[J]. Phys Med Biol, 2010, 55(1): 65-82.
- [3] Yang D, Chaudhari SR, Goddu SM, et al. Deformation registration of abdominal kilovoltage treatment planning CT and tomotherapy megavoltage CT for treatment adaptation[J]. Med Phys, 2009, 36(2): 329-338.
- [4] Mackie TR, Kapatoes J, Ruchala K, et al. Image guidance for precise conformal radiotherapy[J]. Int J Radiat Oncol Biol Phys, 2003, 56(1): 89-105.
- [5] Brock KK, Lee M, Eccles CL, et al. Deformable registration and dose accumulation to investigate marginal liver cancer recurrences [J]. Int J Radiat Oncol Biol Phys, 2008, 72(1): S538.
- [6] Brock KM, Balter JM, Dawson LA, et al. Deformable registration and dose accumulation to investigate marginal liver cancer recurrences[J]. Med Phys, 2003, 30: 1128-1133.
- [7] Zhang T, Jeraj R, Keller H, et al. Treatment plan optimization incorporating respiratory motion[J]. Med Phys, 2004, 31(6): 1576-1586.
- [8] Ruzena B, Stane K. Multiresolution elastic matching[J]. Comp V G Image Process, 1989, 46(1): 1-21.
- [9] Lucas B, Kanade T. An iterative image registration technique with an application to stereo vision[C]. Proceedings of the 7th International Joint Conference on Artificial Intelligence, 1981: 674-679.
- [10] Dhou S, Motai Y, Hugo GD. Local intensity feature tracking and motion modeling for respiratory signal extraction in cone beam CT projections[J]. IEEE Trans Biomed Eng, 2013, 60(2): 332-342.
- [11] Horn B, Schunck B. Determining optical flow[J]. Artif Intel, 1981, 17(2): 185-203.
- [12] Pang HW, Sun XY. Elastic registration based on optical flow module and its application in clinical radiotherapy[J]. Chin J Med Imaging Technol, 2012, 28(11): 2090-2093.