Landmark and Intensity-Based Images Elastic Registration Using Hierarchical B-Splines

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ABSTRACT

We present an elastic registration algorithm for the alignment of biological images. Our method combines and extends some of best techniques available in the context of medical imaging. We express the deformation field as a hierarchical B-splines model basing on the information of landmarks. The hierarchical B-splines model allows us to deal with a rich variety of deformations and match two images at increasing levels of detail. We solve the registration problem by minimizing the mutual information between the reference image and the test image. Results using MRI brain data are presented that the degree of matching is higher and the cost of time is less, compared with the algorithm which has not used the concept of hierarchical B-splines.

Keywords: image registration, mutual information, landmark, hierarchical B-splines

1. INTRODUCTION

Image registration is a procedure of finding a correspondence function that maps a test image onto a reference image [1, 2]. It has received considerable attention in the areas of biomedical and computer vision. For instance, in neurosurgery and radiotherapy planning it is important to register images from different modalities, e.g., MR and CT images. According to [3], if the family of correspondence functions is sufficiently general, capable of expressing essentially arbitrary nonlinear relation, we call the registration elastic. There are two main categories of elastic deformation models–nonparametric model [4] and parametric model. Nonparametric methods get a solution by minimizing a scalar criterion. The solution is the deformation model which belongs to a very large and little restrictive functional space. On the other hand, the parametric method represents the deformation by a moderate number of parameters. Specific examples include basis functions by thin-plate splines (TPS) [5, 6], B-splines [7, 8, 9], elastic body splines (EBS) [10], and so on.

Parametric models can also be divided into landmark based method and intensity based method. Previous work on landmark-based elastic registration has concentrated on a) selecting the corresponding landmarks manually or semi automatically and on b) using an interpolating transformation model (e.g., [6, 9, 11]). The registration problems are converted into scattered data approximation problem. The intensity based method, however, can implement an automatic registration. It often takes the sum of squared differences (SSD) [7] and mutual information [12, 13] as the criterion. And the solutions to registration problems are the deformation functions with a set of parameters which minimization the criterion.

The purpose of this paper is to present an algorithm that combines the landmark-based method with the intensity based method, using the hierarchical B-splines. First, we use B-splines to describe both the image and the deformation, and use mutual information as the difference measure criterion according to the multimodalities problems. We adopt the multi-resolution strategy for deformation. Second, we present the idea of semi-automatic registration, targeted to a more robust and precise registration algorithm. We ask an expert to identify a small number of landmarks in both images. The algorithm will calculate the displacement of the landmarks when the registration has finished in some deformation's level. According to this information, the algorithm will mark some regions in which the landmarks' displacements exceed the threshold. Then register these regions in the next deformation's level.

This paper is organized as follow: In Section 2, we discuss the free deformation, the measure criterion and the optimizer related to it. Then a combined registration method based on hierarchical B-splines is presented. In Section 3, we perform an experiment and compare our results to those of other researchers. We conclude in Section 4.

2. PROPOSED METHODOLOGY

2.1 Data Term

The input images are given as two N-dimensional discrete signals $f_r(i)$ and $f_t(i)$, where $i \in I \subset \mathbb{Z}^N$ and I is an N dimensional discrete interval representing the set of all pixel coordinates in the image. We call $f_r(i)$ and $f_t(i)$ reference and test images, respectively. Our goal is to find a geometrically deformed function $g(x; \mu_1, \mu_2, \dots)$, which minimizes the cost function.

We have chosen the negative mutual information as the criterion [13]:

$$S(\mu) = -\sum_{l \in L_T} \sum_{k \in L_R} log_2(\frac{p(l,k;\mu)}{p_T(l;\mu)p_R(k;\mu)}) \qquad (1)$$

where $p(l,k;\mu)$ is the Parzen estimate of the joint

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intensity probability density of the two images. The $p_T(l;\mu)$ and $p_R(k;\mu)$ is the marginal intensity discrete probability of the reference image $f_r(i)$ and the warp test image $f_w(i) = f_t^c(g(x;\mu_1,\mu_2,\dots))$, respectively. The mutual information registration criterion states that the warped test image $f_w(i)$ is correctly aligned with the reference image by the parameter $\hat{\mu}$ for which S is minimal.

2.2 Hierarchical B-splines Deformation Modal

We have considered the deformation function g to be an arbitrary admissible function $\mathbb{R}^N \to \mathbb{R}^N$. Now, we restrict it to a family of functions described by a finite number of parameters $\mu(j)$:

$$g(x) = x + \sum_{j\in J} \mu(j)\beta\left(\frac{x}{h} - j\right) \tag{2}$$

where J is a set of parameter indexes, β_n are the corresponding B-splines basis functions, n is the degree of splines used, and h is the knot spacing of the control points. This transforms a variational problem into a much easier finite dimensional minimization problem, for which numerous optimization algorithms exist. Moreover, the restriction of the family G of all possible functions g can already guarantee some useful properties, such as the regularity of the solution. Note that the addition of x in the above equation makes the set of zero parameters correspond to identity.

The B-splines model has good approximation properties and is fast to evaluate. It is physically plausible, for example cubic splines minimize the 'strain energy' $\|g''\|$ [14]. It can encode all affine transformations, including rigid body motion. Moreover, because of the two-scale B-splines relation, we can exactly represent the warping function from the old coarse space in the new finer space without any loss of information given an integer ratio between scales, when we use multi resolution for the warping function.

We parameterize the warp space by a scale parameter h and denote it V_h. The scale parameter corresponds loosely to the density of the knots or landmarks. By changing h, we can approach a best tradeoff between the cost of the algorithm and the accuracy of the results. Big h yields a global model which has just a few parameters. Such a model is rather constrained, which is equivalent to strong explicit regularization approximatively, but its cost of time is small. On the other hand, a small h gives a local model with many parameters, which generally leads to more complicated optimization. In exchange, a small h generally permits one to approximate any given g in V_h well, because the function space V_h is big. (Arbitrarily small precision can be achieved as $h \to 0$.)

In real situations, the true deformation is not known and not guaranteed to lie in the space where we are looking for it and can therefore never be recovered exactly. However, thanks to the good approximation properties of B-splines, we can reasonably expect that by using a sufficiently small value of h, we can reduce the approximation error to acceptable values.

A major problem of traditional B-splines registration is the selection of the number of B-splines parameters (related to the knot spacing). If we only select a few parameters (big knot spacing), only a rough match can be achieved, because of the small function space. Using a large number of parameters (small knot spacing), the deformation may exhibit local oscillations and prone to local maximization.

In this article, we consider using the concept of hierarchical B-splines [15] to overcome this problem, since our algorithm is adaptive and put more effort in complex regions which cannot be matched by low-level deformation well. Meanwhile, we use the difference between the landmarks of both images to decide in which regions the deformation should be refined and use more parameters.

2.3 Optimization

The criterion is minimized with respect to the coefficients μ_i using a Marquardt-Levenberg like optimizer [12]:

$$\mu^{(k+1)} = \mu^{(k)} - \left(\mathcal{H}S\left(\mu^{(k)}\right)\right)^{-1} \nabla S\left(\mu^{(k)}\right) \tag{3}$$

where $\mathcal{H}S$ is the modified Hessian and ∇S is the gradient.

A remarkable feature of the B-splines model is that the complexity of evaluating the deformation, and the gradient and the Hessian of the criterion, does not depend on the sampling step h, or equivalently, on the number of parameters. This can be seen from the fact that one pixel in the image always contributes to a fixed number of gradient (or Hessian) components.

2.4 Image Representation

We choose to interpolate the image using uniform B-splines:

$$f_t^c(x) = \sum_{i\in I_b \subset \mathbb{Z}^N} b_i \beta_n(x - i) \tag{4}$$

where β_n is a tensor product of centered B-splines of degree n, that is

$$\beta_n(x) = \prod_{k=1}^{N} \beta_n(x_k) \tag{5}$$

with $x = [x_1, \dots x_n]$. In this way, we representing by B-splines coefficients b_i the image initially given by its samples $f_t(i)$.

2.5 Procedure of Our Algorithm

First, we establish a set of landmarks. The landmarks are pairs of corresponding points in the two images, which are manually identified by experts. Because the algorithm will choose the region to be refined according to the landmarks, the landmarks should be located in the complex regions. Now we have a reference point set $\{ p_i | \, i = 0, \dots, n \}$ and a test point set $\{ q_i | \, i = 0, \dots, n \}$.

Second, we register the images in the first level. In this level, the knot spacing is big and the number of parameters is small. The process of registration can be summarized as follows:
Step 1: Initial the deformation function's parameters $\{\mu_i\}$,
Step 2: Deform the test image and calculate the mutual information between the reference image and the warped image,
Step 3: Call the optimizer stated above to change the parameters $\{\mu_i\}$,
Step 4: Repeat the step 2 and 3, until the criterion is minimized.

Now a rough registration has been accomplished quickly. We get the warped image fw and the new position of the landmarks $q'(i)$ in it.

Third, we get the displacement quantities of the landmarks:

$$d(i) = \alpha_i \left\| q'(i) - p(i) \right\| \quad (6)$$

where α_i is the weight of each landmark, and $q'(i)$ is the landmark's position of the warped image. The weigh given by experts is related to the accuracy and importance of the landmark. If $d(i)$ is beyond the threshold we have set, the region around this landmark will be marked to be registered in the next level.

Referring to the panel (*a*) of Fig.1, suppose that we have a knot lattice at one level. After the deformation, if the point q still has large deviation from its reference point, we could suppose that the deformation in this region is not approximated enough to the true deformation. To improve this situation, the B-splines grid close to point q (the shaded region in the left panel) is refined. The refinement is shown in the panel (*b*) of Fig.1, in the region with refined B-splines grid, we will recompute the parameters of deformation. Supposing that the points q_3 and q_4 are close enough to their reference points p_3 and p_4, the grids around them will not be refined. On the other hand, the points q_1 and q_2 are still have large deviation, so the grids around them are refined.

As shown in the bottom row of Fig.1, if the regions of different landmarks are overlapped (panel (*c*)), we combine these regions and keep the combined region rectangular (panel (*d*)). Then register each region respectively following the steps above. We only need to calculate some small regions instead of the whole image.

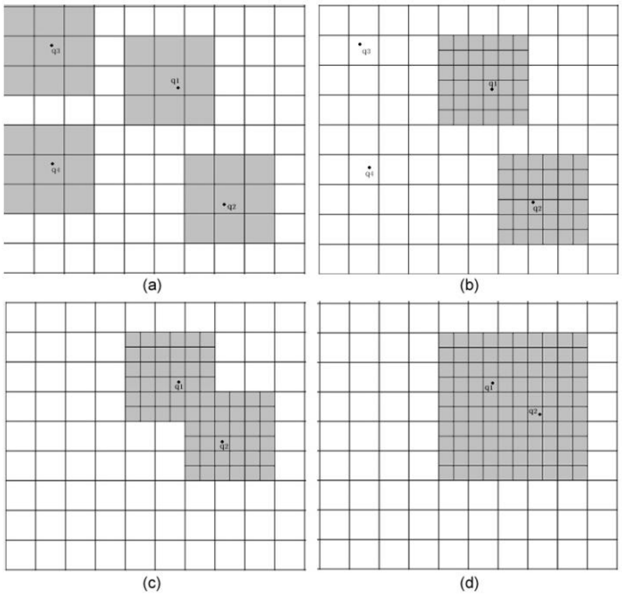

Figure 1: Various situations of hierarchical B-splines refinement.

3. EXPERIMENTS

To show the performance of our proposed algorithm, we consider a typical registration problem: intermodal medical images registration. We use the mutual information as the criterion for the images come from different modalities, and minimize it using a Marquardt-Levenberg like optimizer [12]. Then we compare our results with other ones, which did not adopt the hierarchical B-splines strategy.

Fig.2 shows an example of this hierarchical deformation, we use a pair of biomedical 2-D images coming from different modalities.

The top row of Fig.2, from left to right, are the 256*256 MR-PD test image slices[1], and the 256*256 MR-T2 slice from an atlas[2]. In this example, we get 6 pairs of landmarks from experts, and they are located in the areas where the deformation is complex, as we can see them in the both of test image and reference images. We set the threshold of the landmarks displacement 10, the knot spacing of the first level 64, and the number of level 3.

In the second row, from left to right, are the deformed test image, and the deformed hierarchical B-splines grid. In the bottom row, from left to right, are the superpositions of the two images before and after the registration.

As shown in Fig.2, the B-splines grids are sparse, and

[1] We use a proton density MR image from the visible Human project. http://www.meddean.luc.edu .
[2] Courtesy of Harvard Medical School, http://www.med.harvard.edu/AANLIB/home.html.

only a small region of the image is refined to level 2, and two smaller regions in the former region are refined to level 3. As a result, the cost of time is smaller than the algorithm which refines the whole image.

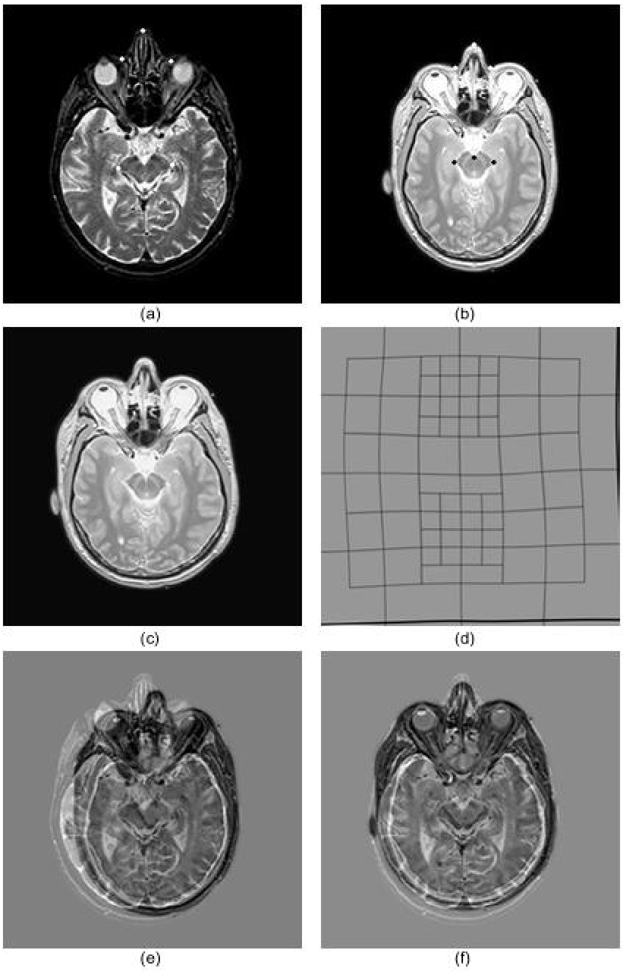

Figure 2: Reference MRI proton density brain slice from the atlas (a). The sample test slice of a corresponding region(b). The warped test image (c). The deformation field of hierarchical B-splines (d). The superposition of the two image (e) before and (f) after the registration.

Table 1 presents the results of the same experiments as before performed with the images of Fig.2, as well as the results of the experiments which use the same methods, including the image represent method, the deformation model, and the optimizer, except the hierarchical B-splines strategy. In table 1, it is clear that the algorithm based on hierarchical B-splines decreases the cost of time a lot, although improves the mutual information a little.

Table 1: The results of our registration algorithm and the traditional one(without hierarchical B-splines)

	Our Algorithm		Tradition Algorithm	
	MI	Time (s)	MI	Time (s)
Initial	0.8875	0.0	0.8875	0.0
Level 1	0.9064	562.1400	0.9064	562.1400
Level 2	0.9962	373.9690	0.9767	866.9840
Level 3	1.0064	16.2100	0.9776	333.2660

4. CONCLUSION AND FUTURE WORK

We have discussed the application of hierarchical B-splines to image registration. This method is proposed based on two kinds of available information, landmarks and intensity. Hierarchical B-splines, in the form of free form deformation, provides a natural way for image registration due to its global-to-local influence, coarse-to-fine matching, and computation efficiency. Furthermore, we applied the algorithm to multi-modalities images to demonstrate the algorithm's speed and accuracy. Compared to the landmark based method, our method depends on the experts less, as it only needs a small number of landmarks. Compared to the intensity-based method, our method's cost of time is much less, as it refines the B-splines grids hierarchically.

However, our algorithm's cost of time is still huge, because of the inefficient optimizer. In addition, the criterion is not perfect. We are currently working on the particle swarm optimization (PSO) and some new criterions, and trying to apply it in the image registration. More results will be reported in the near future.

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