AN EFFICIENT LOCALLY AFFINE FRAMEWORK FOR THE REGISTRATION OF ANATOMICAL STRUCTURES

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ABSTRACT

Non-Rigid image registration has been widely developed over the last years. However, many registration techniques do not take into account any a priori information on the structures in the images. We present in this article a general locally affine registration framework, which allows us to register local areas in the images using affine transformations having few degrees of freedom. Thanks to our novel polyaffine framework and Log-Euclidean regularization, we ensure a smooth, coherent and invertible transformation all over the image. Remarkably, this is achieved very efficiently, even in 3D.

We illustrate our method with two applications: bone registration in the lower abdomen area and critical brain structures registration.

1. INTRODUCTION

The registration of medical images is in general a difficult problem. Numerous methods have been devised to address this problem. Rigid and affine transformations are widely used to recover global deformations, e.g. for intra-patient registration. However, they do not cope with local deformations.

Other types of transformations have therefore been developed, called non-rigid. These can be split into two classes. First, parametric transformations can be a linear combination of radial basis functions [1] or B-Splines [2]. These transformations can have an arbitrary number of degrees of freedom. However, defining specific areas having a common behavior can be very complicated. The second class, called dense transformations [3, 4, 5], has the highest number of degrees of freedom, as it defines one displacement vector per voxel. These non-rigid methods can cope with local deformations. However, they may have too many degrees of freedom, resulting in local irregularities in the contours of structures.

We would prefer to use a transformation with few degrees of freedom for each structure. Following this idea, several approaches have already been proposed in the literature. Unfortunately, they either are quite computationally expensive and their use restricted to 2D so far [6, 7], or have been specifically designed for one application as in the case of [8] for the correction of manipulation artifacts in histological slices or of [9] for the registration of articulated structures.

We present in this article an efficient and general framework for locally affine registration. We parameterize our transformations by local affine components, associated to predefined areas. Our framework guarantees an invertible and anatomically consistent transformation, thanks to the use of the Log-Euclidean polyaffine framework and of a Log-Euclidean regularization between affine components [10]. Remarkably, this is achieved very efficiently, even in 3D.

We will first present how to combine local affine transformations to obtain a global transformation and our new regularization scheme. Then, we will focus on qualitative and quantitative results of our method on two applications: bone registration in the lower abdomen area and the segmentation of brain critical structures using atlas-to-subject registration.

2. LOCALLY AFFINE FRAMEWORK

2.1. Locally Affine Transformation

To define locally affine transformations, we proceed as in [11, 7]. Such transformations are parameterized by a finite number N of affine components. Precisely, each component consists of an affine transformation A_i and of a non-negative weight function $w_i(x)$ which models its spatial extension: the influence of the i^{th} component at point x is proportional to $w_i(x)$. Furthermore, we assume that for all x, $\sum_{i=1}^{N} w_i(x) = 1$, i.e. the weights are normalized.

In order to obtain a global transformation from several weighted components, the classical approach to fuse each local behavior, given in [12], simply amounts to averaging the displacements according to the weights:

$$T(x) = \sum_{i=1}^{N} w_i(x) A_i(x). \qquad (1)$$

The transformation obtained using (1) is smooth, but as pointed in [7], this approach has one major drawback: the resulting global transformation is not *invertible* in general. To remedy this, we use the recently proposed *Log-Euclidean polyaffine framework*. See [10] for more details. It basically consists in averaging *infinitesimal* displacements associated to each affine component. The resulting global transformation is obtained by integrating an Ordinary Differential

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Equation (ODE), which can be done in a very efficient way. Log-Euclidean polyaffine transformations are always invertible, and their inverse can also be very efficiently computed.

2.2. Log-Euclidean Regularization

We present here a novel regularization approach, specific to locally affine transformations. For more details, see [10].

The basic idea is to use the 4x4 matrix representation of 3D affine transformation given by *homogeneous coordinates*. Interestingly, whenever the amount of rotation present in an affine transformation A is less than π radians, one can define the *logarithm* of A, simply via the principal logarithm of the matrix representing A. This matrix logarithm is of the form: $\begin{pmatrix} M & v \\ 0 & 0 \end{pmatrix}$, where M is a 3x3 matrix (not necessarily invertible) and v a 3D vector. Conversely, a unique affine transformation is associated to any 4x4 matrix B of the latter form via its *matrix exponential*.

As for diffusion tensors [13], taking the logarithm of affine transformations corresponds to linearizing the (curved) affine group around the identity, while conserving excellent theoretical properties (invariance with respect to inversion in particular). This allows to perform *Euclidean* (i.e. vectorial) operations on affine transformations via their logarithms.

This representation of affine transformations by vectors allows the direct generalization of classical vectorial regularization techniques. For example, one can define a *Log-Euclidean* elastic energy between affine components:

$$Reg(A_i, w_i) = \sum_{i=1}^{N} \sum_{j \neq i} p_{i,j} \| \quad (A_i) - \quad (A_j) \|^2, \qquad (2)$$

where we have $p_{i,j} = \int_\Omega w_i(x).w_j(x)dx / \int_\Omega w_i(x)dx$, which take into account the spatial extensions of the components. Furthermore, one can define a *fluid* energy by regularizing the transformation corrections $\quad A_i$ instead of the affine transformations A_i in (2). In the sequel, $\|.\|$ is set to $\|M\|^2 = \mathrm{Trace}(M.M^T)$ (Frobenius norm).

3. APPLICATIONS

3.1. Registration Algorithm

In our implementation, we chose to have entire areas adopting an affine behavior. Convoluting areas with a gaussian kernel would penalize small areas neighboring large areas. We have therefore implemented the weighting function for each area as a function of the minimal distance to the area: $w_i(x) = 1/(1 + \alpha.\mathrm{dist}(x, \mathrm{area}_i)^2)$. These weights are normalized.

The framework described so far is also independent of how we evaluate each affine component of the transformation. In the following two applications, we choose to optimize all the affine components at the same time using a multiresolution scheme. At each resolution, we perform an alternate optimization between the estimation of the affine components and the regularization of the transformation. The estimation of affine transformation corrections is done using a block-matching algorithm, which uses a correlation coefficient as a similarity measure. The transformation corrections $\quad A_i$ of A_i^{M-1} are estimated at iteration M from the pairings $(x_v, x_v + d_v)$ using a least trimmed squares weighted procedure, which minimizes the following energy:

$$\begin{aligned} E(\quad A_i) \quad = \quad & \sum_v \| \sum_{i=1}^{N} w_i(x_v + d_v) A_i^{M-1}.(x_v + d_v) \\ & - \sum_{i=1}^{N} w_i(x_v) \quad A_i.A_i^{M-1}.x_v \|^2. \end{aligned} \qquad (3)$$

The balance between the regularization and the affine corrections is done by a parameter $\lambda \in [0, 1]$, which acts as a percentage of the mean Frobenius norm of the affine transformation corrections ($\frac{1}{N} \sum_{i=1}^{N} \|log(\quad A_i)\|$).

All the computations are done using the simple displacement averaging method (1). We can indeed assume that the corrections are sufficiently small for the transformation to remain invertible. The Log-Euclidean polyaffine framework is used only at the end of the registration to ensure the invertibility of the final transformation and to compute its inverse.

3.2. Bone Registration in Lower Abdomen Area

We first evaluate the performance of our algorithm in the frame of high-precision radiotherapy planning. The aim is to develop an automatic method for soft-tissue localization in the lower abdomen area, based on CT images. Since soft tissues exhibit, on the one hand, a high variability in shape, size and contrast (e.g. a full or empty bladder) and, on the other hand, a very low contrast on CT images, it is a difficult task to automatically determine their position with accuracy.

We then decide to estimate their position statistically, with respect to a set of landmarks established in more stable surrounding structures showing a better contrast in CT images. For that purpose, we must initially register all the patients' images to a common space. The landmarks we establish are a set of salient points in the pelvic and leg bones. For a feasibility study, we concentrate on two of them that correspond to the centers of mass of the femoral heads. The regions around these points, i.e the femoral heads themselves, are used as affine component localizations in our algorithm.

We present here results of the inter-patient registration process using these anatomical landmarks. All the patients' images are registered with respect to a reference image. The process consists of two stages: a global affine registration is performed using a block-matching algorithm, and then our algorithm is applied. In Figure 1, we see a significant qualitative improvement on the registration result with respect to an affine transformation. Moreover, the information contained in

Fig. 1. **Registration result on the pelvis with femoral heads contours of the reference image superimposed.** On left the reference image, in the middle the floating image after a global affine registration, on right the floating image after using our algorithm.

the images outside the regions used in the registration remains consistent from an anatomical point of view.

We also compare our results with a dense algorithm [4]. Qualitatively, the results are similar. For a more quantitative evaluation of the results, Table 1 shows the norm of the Euclidean distance between the landmarks in the registered images and the corresponding landmarks in reference image.

Patient #	1	2	3	4
Left head (DT)	3.53	1.20	2.51	**4.37**
Left head (MAF)	3.44	1.00	2.11	**3.30**
Right head (DT)	1.11	1.55	1.03	**3.78**
Right head (MAF)	1.33	1.59	0.88	**3.19**

Table 1. **Registration results on femoral head centers.** Distances in millimeters between the expected femoral head centers and those obtained from the registration (locally affine: MAF ; dense transformation: DT).

As we have shown above, the results of our method are at least as good as the results obtained through non-rigid registration. This fact becomes even more evident if we take into account that our algorithm computation time is much lower (3 minutes as opposed to 10 minutes). Moreover, the goal was to place all of the patients' data in a common space while deforming the soft tissues as little as possible. Our method performs the registration based on specific zones and ensures consistent results all over the image. It is then much more adapted to this type of application than a dense transformation solution, which tries to match the entire floating image.

3.3. Brain Structures Segmentation

A second application of our framework is the automatic segmentation of brain critical structures for brain radiotherapy. An accurate segmentation of these structures and of the tumor allows to optimize the irradiation doses received by each structure. The method we follow consists of bringing the patient image onto an anatomical atlas. The atlas is composed of a simulated MRI of the brain and its segmentation done by an expert. The patient image is first globally positioned by an affine registration. The second step is to refine the result locally by using a non-rigid registration algorithm.

The first task to use our algorithm is to define the areas to register. In the following example, we register five critical structures: the cerebellum, the eyes, the optic chiasma and the brainstem. Thanks to our atlas, we can select the areas on which to put affine transformations in a simple manner. For small structures such as the eyes or the chiasma, we simply dilated each related label in the atlas and used it as an area. For bigger structures, like the cerebellum or the brainstem, one affine transformation is not sufficient ; each of these structures is then split arbitrarily into two areas and is therefore handled by two affine transformations.

Having defined the affine areas, we first want to test the contribution of regularization in the registration process. We have therefore run one registration with regularization (with $\lambda_{elas} = 0.3$ and $\lambda_{fluid} = 0.2$) and without regularization.

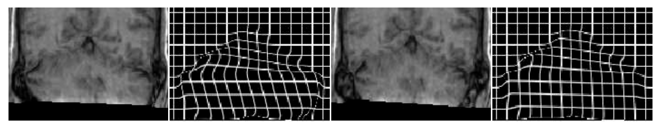

Fig. 2. **Contribution of the regularization in the registration.** From left to right: Patient image registered on the atlas without regularization (image and deformed grid) and with regularization (image and deformed grid).

The results are shown in Figure 2. This example clearly underlines the importance of the regularization. The cerebellum does not have the shape we would expect when not using regularization: there is indeed a lack of coherence between its two components yielding a result which is not consistent from an anatomical point of view. The errors also propagate to the rest of the brain. Our regularization technique solves this problem and provides consistent results all over the brain.

The second series of experiments consists of comparing the results of our algorithm with the algorithm proposed by [5], which computes a dense transformation and allows to use spatial-dependent regularization. The dense method produces quite accurate segmentations (see Figure 3). However, the contours are irregular and in particular the eyes and the chiasma can have a shape that no longer looks like the real structure. The algorithm indeed does not use any prior on the structures present in the brain. As it is only based on a similarity measure, it can result in noisy contours.

The obtained contours are shown on Figure 3. They are much smoother than the ones obtained with a dense registration. They are also more precise, mostly on the brainstem and the eyes. Our framework seems indeed more adapted as it is able to take into account priors on the structures we want to register. The transformation is also, by construction, less sensitive to local minima of the similarity measure. Finally, the

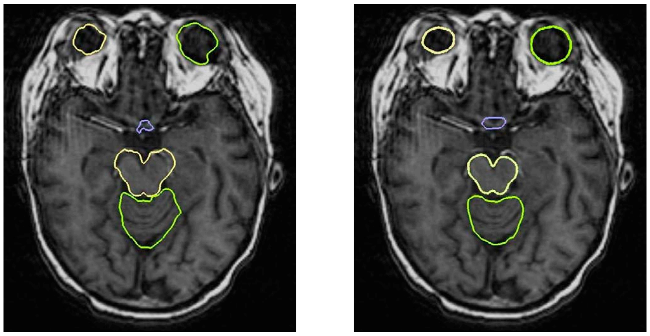

Fig. 3. **Qualitative comparison of the segmentation results on one patient.** From left to right: Contours obtained using a dense transformation and using our new framework.

computation time is faster (10 minutes as opposed to 40 minutes on a 3 GHz computer) than with the dense registration.

4. CONCLUSIONS AND PERSPECTIVES

In this article, we have detailed a new registration framework using locally affine transformations. This framework has shown to be simple, efficient and is fully 3D. Thanks to our novel Log-Euclidean regularization and polyaffine framework, we ensure a smooth and invertible transformation. We have so far used our algorithm on two different applications, for which it is particularly well adapted. Our method show both qualitative and quantitative improvement of the results compared to classical non-rigid dense registration. We have also shown on several examples a consistent behavior of the areas where no affine transformation was defined.

In a near future, we want to go into further quantitative validation, mainly for the brain application using the IBSR database. Another point to look at is the influence of the number and shape of affine components and areas. A measure of the quality of the registration of any area will be a good way to decide whether it should be split or not. Furthermore, we can investigate ways to refine the weight functions, that are fixed in our implementation, depending on the surrounding affine transformations evolution.

Finally, this framework can be used as a link between affine and dense non-rigid registration algorithms. It is indeed not limited to structure registration in atlas-to-subject registration. We could implement a more general registration algorithm by using areas regularly placed on the image and refining them. Our algorithm can also be used as an initialization for dense transformation algorithms like [5].

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