Non-Linear 2D and 3D Registration Using Block-Matching and B-Splines

Heike Hufnagel[1], Xavier Pennec[1], Grégoire Malandain[1], Heinz Handels[2] and Nicholas Ayache[1]

[1]INRIA Sophia Antipolis, Epidaure Project, F-06902 Sophia Antipolis, France
[2]Institut für Medizinische Informatik, Universitätsklinikum Hamburg-Eppendorf, 20246 Hamburg
Email: heike.hufnagel@sophia.inria.fr

Abstract. We developed a non-linear registration technique to align images that feature anatomical variabilities. The algorithm is based on a block-matching technique that identifies a sparse displacement vector field from the iconic features of two images. Subsequently, the displacement vectors are used as sampling points to estimate a parametric non-linear transformation that is represented by a tensor product of B-Splines. The B-Spline transformation estimation approximates the correspondences while minimizing the second order derivatives in the transformation function. The block-matching and the transformation estimation are then iterated in a multiscale framework to improve robustness and accuracy. Experiments on 2D histological slices and 3D MR images show qualitatively good results.

1 Introduction

In this article, we present a registration technique developed to automatically align images that feature anatomical variabilities. We work on anatomical structures that are subject to deformations which are simple locally but complex globally. For instance, we consider the problem of aligning histological slices for 3D reconstruction and analysis. During their preparation process, the slices may undergo geometric distortions, twists, and disruptions. Hence, the sought transformation has to be able to represent complex deformations. In the scale of complexity, we may roughly classify the existing transformation classes as follows: We distinguish rigid or affine transformations that have a very constrained number of degrees of freedom, parameterized deformations that have an arbitrary number of degrees of freedom and deformation fields that define a displacement at every voxel. For our complex deformation, a non-linear function has to be determined and applied. An affine transformation is not sufficient to compensate for local bendings of a gyrus. On the other hand, deformation fields seem to be too elaborate for the considered problem. This led us to choose a *parameterized* transformation. These can be described by e.g. B-Splines, Thin-Plate-Splines, or more general deformable models.

Robustness plays a key role in the algorithm as the transformation could be misled by possible twists or fissures in the slices. Eventually, the algorithm should be applicable also to 3D registration problems of the brain.

In [1] a regularized non-linear transformation estimation based on B-Splines is presented to register local breast motions, and in [2] a B-Spline deformation model for fast elastic multidimensional intensity-based image registration is used and tested successfully on different image types. By varying the number of control points and therewith the number of degrees of freedom in a multiscale scheme, the registration can easily be adapted to the problem at hand. The authors of [3] developed a fast registration algorithm based on 3D radial basis functions of compact support for 2D and 3D inter-patient images. However, the mentioned works did not specifically focus on robustness matters in their algorithms.

To ensure the robustness of the estimation we combine in this paper a B-Spline representation of the transformation with a block-matching algorithm applied to the images. The block-matching scheme proved to be very robust and accurate as shown in [4]. Based on the satisfying results obtained with rigid and affine transformations [5], we believe that the extension to a B-Spline deformation covers well registration problems that require a non-linear approach.

2 Methods

The registration algorithm consists of two principal components that are executed alternately. First, the algorithm finds matches between two images by regarding regional iconic similarities, then, it estimates a global transformation based on these local correspondences. The first component is based on a block-matching technique and works on the iconic features of the two images to identify a sparse displacement vector field. The source image is cut into an ensemble of possibly overlapping blocks. Each block is moved around its equivalent position in the target image in order to find the position where its voxels hold the highest degree of intensity similarity with the voxels of the target image. We use the correlation coefficient as similarity measure so that the intensity distributions of the two images may differ and may spatially vary [6]. Subsequently in the second component, the displacement vectors are used as sampling points to estimate the parametric non-linear transformation T that assigns a corresponding voxel $T(x, y, z)$ in the target image to each voxel at position x, y, z in the source image. We define $T(x, y, z) = (x, y, z) + \boldsymbol{u}_{Bsplines}(x, y, z)$, where $\boldsymbol{u}_{Bsplines}(x, y, z)$ denotes the displacement for the respective voxel. We chose the transformation to be represented by a tensor product of uniform cubic B-Splines (1) as they possess mathematical advantages for that task, in particular local support. They are supported by a control point grid spread over the entire image.

$$\boldsymbol{u}_{Bsplines}(x, y, z) = \sum_{l=0}^{3} \sum_{m=0}^{3} \sum_{n=0}^{3} B_l^x(\alpha) B_m^y(\beta) B_n^z(\gamma) P_{i+l,j+m,k+n}, \qquad (1)$$

where i, j, k are the integer position of the nodes of the control point grid, $P_{i,j,k}$ is a 3D vector of parameters at that node and $B_l^x(\alpha), B_m^y(\beta), B_n^z(\gamma)$ represent the lth (respectively mth and nth) basis functions of the cubic B-Splines. With Δ_x, Δ_y, and Δ_z denoting the spacings of the grid, we define $i = \lfloor \frac{x}{\Delta_x} \rfloor - 1$, $j = \lfloor \frac{y}{\Delta_y} \rfloor - 1$, and $k = \lfloor \frac{z}{\Delta_z} \rfloor - 1$, as well as $\alpha = \frac{x}{\Delta_x} - \lfloor \frac{x}{\Delta_x} \rfloor$, $\beta = \frac{y}{\Delta_y} - \lfloor \frac{y}{\Delta_y} \rfloor$, and $\gamma = \frac{z}{\Delta_z} - \lfloor \frac{z}{\Delta_z} \rfloor$. The algorithm searches the control points that result in the optimal B-Spline approximation. The robustness of the approximation is ensured as we furnish each sampling point with a weight that proportionally depends on the variance in the respective region. Thus, a weighted Least-Squares approach is employed to solve the approximation as described in detail in [7].

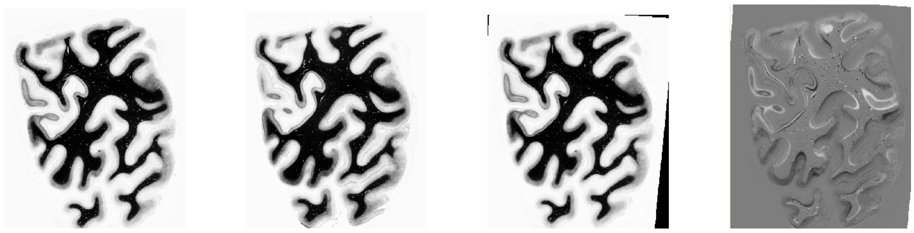
To improve the accuracy and the capture range, the two components are iterated several times and in addition nested in a multiscale concept.

In homogeneous image regions, the number of data may fall below the number of parameters to estimate in which case the data noise influences arbitrarily the estimation. In order to cope with that problem, a smoothing term is integrated in the estimation to smooth undesirable high frequency deformations, see [7]. We optimize $C = C_{similarity} + \lambda C_{regularization}$ where $C_{similarity}$ denotes the sum of the weighted differences between the registered and the target image and $C_{regularization}$ depicts the smoothing term. The parameter λ defines the tradeoff between alignment of the images and smoothness of the transformation. We chose a biharmonic regularization term as it proves to be optimized easily. The minimization of the associated cost function is solved iteratively by the conjugate gradient algorithm which is less sensitive to a non quadratic shape of the criterion than most classical gradient optimization techniques as shown in [8].

3 Experimental Results

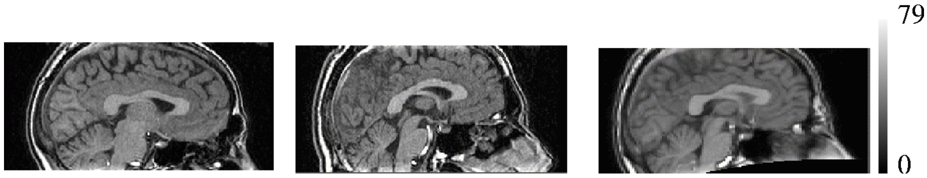
We applied the registration algorithm on different synthetic testing images as well as on images of histological slices of the brain and MR image volumes of the brain. The experimental outputs demonstrate that our non-linear approach yields qualitatively good registration results with respect to the considered applications, see figures 1 and 2. When performing the registration on two consecutive histological slices of size 3000×3000 pixel, a typical parameter setting would be 10 control points per direction, a smoothing term $\lambda = 100$, 3 scale levels (e.g. from 6 to 3 in a 2D quaternaire Gaussian pyramid) and 10 iterations on each level. The calculation on a Pentium III machine (1GHz, 1GB Ram) takes less than 4 minutes and the resulting transformation describes satisfyingly well the local rotations, twists and scalings undergone by the structures without being misled by fissures or holes. For 3D MR images of the brain of two different subjects of size $256 \times 256 \times 152$, a good result demands about 30 iterations and calculation time goes up to several hours. Our algorithm issues a good mapping of the ventricles which is not an easy task ($\lambda = 0.0001$, number of control points per direction equals 20). Moreover, our algorithm achieves a globally correct mapping of the cortexes and the skulls, even if only the main sulci are put into

Fig. 1. Registration of two histological slices. The figure represents the source image a), the target image b), the deformed source image c) and the difference image d) between deformed source image and target image.

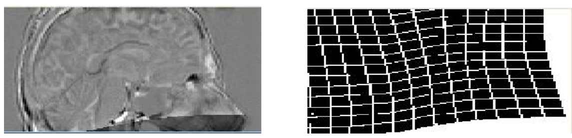


(a) (b) (c) (d)

Fig. 2. Registration of two MR images of the brain. The figure represents the respective sagittal slices. To make the transformation visible, it is applied to a grid as seen in e).



(a) source image (b) target image (c) result image



(e) difference img. (f) deformation grid

good correspondence when we look in more detail. Admittedly, this was expected since a one to one correspondence generally does not exist between the sulci and gyri of two different subjects.

4 Conclusion

Non-linear image registration techniques are designed to find mapping functions for images which feature anatomical variabilities. The non-linear transformation estimation presented in this work is represented by a tensor product of cubic B-Splines that approximates a sparse displacement field, the latter being the result of a block-matching technique applied to the two images in question. The cost function to be minimized consists of the least-squares distances and a smoothing term. The algorithm works satisfyingly well on 2D and 3D images, although the calculation time for 3D images is costly. By varying the number of control points it is possible to modify the degree of detail to be registered, hence, the algorithm is applicable for a great range of different images. However, the respective adaption of the parameters seems to be an heuristic task.

Future work will focus on the acceleration of the transformation estimation. Besides, we need to determine on each multiscale level the optimal number of control points that are used for the B-Spline approximation. Next, by validating the algorithm for various typical clinical applications we want to extensively evaluate the impact of the smoothing term and - according to the results - introduce some methods to automatically adapt it to the considered problem. Last but not least, this registration technique should be carefully evaluated against other non-linear methods, e.g. the algorithm presented in [9] that offer a faster calculation but might be less robust or accurate.

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