Elastic Medical Image Registration Using Surface Landmarks With Automatic Finding of Correspondences

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Abstract. We propose a novel approach to surface-based elastic image registration which at the same time finds the correspondences between source and target landmarks and determines the global transformation from the source image to the target image. In our approach only the coordinates of the sample points on the surface landmarks are required as free parameters to minimize an energy function. Thus, the number of parameters is kept small in comparison to other approaches which sample the whole image data. The energy function consists of the minimal distance between the transformed source and the target landmarks as well as the bending energy of the transformation. During the optimization procedure, more and more local deformations are allowed. We have investigated the performance of the approach using 2D and 3D synthetic as well as 2D tomographic image data. We found that image registration is achievable even when source and target landmarks differ largely. The registration result can be improved through an increase of the density of sample points. To achieve a better adaption to, e.g., thin dents, we extended our approach for inclusion of predefined landmark correspondences as well as the inverse transformation using sample points on the target landmarks.

Keywords: Elastic Image Registration, Surface Landmarks, Automatic Correspondence Finding

1 Introduction

Registration is an important technique in medical image analysis which yields a transformation from a source image to a target image. Rigid and affine registration methods can only cope with global differences between images. In contrast, elastic or non-rigid methods are required to cope with local differences, which are due to, for example, scanner-induced deformations, movement of the patient, surgical interventions, or anatomical variation.

In this contribution, we propose an approach to elastic registration using surface features (landmarks) which at the same time finds the correspondences between source and target landmarks as well as determines the global transformation from the source image to the target image. The transformation is defined only through a number of corresponding points of the surface landmarks (denoted as sample points) which keeps the number of parameters small. This is different to those approaches which sample the whole image data and where the number of parameters is proportional to the number of control points, e.g. [5, 6]. In comparison to [1, 2, 3], in our approach only sample points of the source landmarks are required and the correspondences between the source and target landmarks are found automatically.

2 Approach

The formal basis of our approach is an energy function $\boldsymbol{h}$ consisting of two terms: a distance term and a bending energy term:

$$\boldsymbol{h}(\mathbf{p}^*, \lambda) = \sum_{\mathrm{j}=1}^{\mathrm{d}} \left[\frac{1}{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{n}} \left(\mathrm{p}^*_{\mathrm{i,j}} - \mathrm{q}^*_{\mathrm{i,j}}(\mathbf{p}^*) \right)^2 + \lambda\, \mathbf{p}_{\mathrm{j}}^{*\mathrm{T}} (\mathbf{L}^{-1})_{\mathrm{n}} \mathbf{p}^*_{\mathrm{j}} \right], \tag{1}$$

where $\mathbf{p}^*$ are the position vectors of the transformed source sample points $\mathbf{p}$, and $\mathbf{q}^*$ are the corresponding vectors of points on the target landmark(s) with smallest Euclidean distance to the transformed source sample points $\mathbf{p}^*$. Note that variables denoted with an asterisk change their value during iteratively minimizing $\boldsymbol{h}$. $(\mathbf{L}^{-1})_{\mathrm{n}}$ is the $n \times n$ upper left sub-matrix of $\mathbf{L}^{-1}$, where n is the number of sample points while $\mathbf{L}$ is the thin-plate spline bending energy [1]. d is the image dimension, e.g., $d = 2$ and $d = 3$ for 2D and 3D images, resp. $\mathbf{q}^*(\mathbf{p}^*)$ can be pre-computed by applying a distance map. The weighting parameter λ determines the relative influence of the bending energy. The sample points $\mathbf{p}_{\mathrm{i}}$ on the source landmarks are determined once and remain fixed. Only the target sample points $\mathbf{q}^*_{\mathrm{i}}$ are allowed to change their positions during the iteration process (as, of course, the *transformed* source sample points $\mathbf{p}^*_{\mathrm{i}}$ do). In 2D, the most simple distribution of sample points on line landmarks is an equidistant distribution, which we used in all our 2D experiments. More sophisticated algorithms may sample the points by a sampling regime being proportional to the curvature of the outline, for example. For the 3D case, we use a meshing algorithm described in [4] to find sample points on surface landmarks.

To circumvent local minima, we start with a large value of λ (e.g., 1000), which leads to a global registration, because affine transformations do not contribute to the bending energy term. Subsequently we reduce λ during the iteration (using an exponential decrease) until a prior defined value λ_{min} (e.g., 0.1) is reached, which determines the allowed "degree of elasticity". As a result of the iterative process, i) the bending energy increases and ii) the transformed source landmarks (i.e. the sample points on the surfaces) more and more adapt to the target landmarks. If $\lambda_{min} = 0$, the source sample points are transformed exactly on the target landmark, which is the interpolation case. For $\lambda_{min} > 0$, the transformed source sample points in general do not exactly lie on the target landmark, which is the case of approximation.

To minimize the non-linear energy function $\boldsymbol{h}$ we apply the numerical scheme of Levenberg-Marquardt using also the gradients of the distance map. After the iteration has stopped, source and iterated (transformed source) sample points serve as input for determining the transformation function $\boldsymbol{u}$ for the whole image based on thin-plate splines (see, e.g., [1]). The transformation fulfills the condition that the source sample points are matched to the iterated sample points while the same bending energy as in (1) is minimized.

3 Experiments

Our approach has been tested using 2D and 3D synthetic as well as 2D tomographic datasets. A 2D synthetic experiment with outline landmarks is shown in Fig. 1. Here, an elliptic object (source, filled with a chess-board pattern) in (a) is registered to a brain outline in (e) using a sample point distance of $d_s = 5$. We obtained the result shown in (c) and (d). At the wavy part at the bottom of the target outline larger errors are present. Using instead a denser sampling ($d_s = 1$) at the bottom only (f), but keeping the sampling distance ($d_s = 5$) in the other parts of the outline landmark, the registration result is rather good ((g) and (h)).

Fig. 2 shows an experiment using 2D tomographic slices from which outlines of two different human vertebrae were extracted. The top row shows the sample points of the source landmark (grey), the iterated sample points (dark), and the

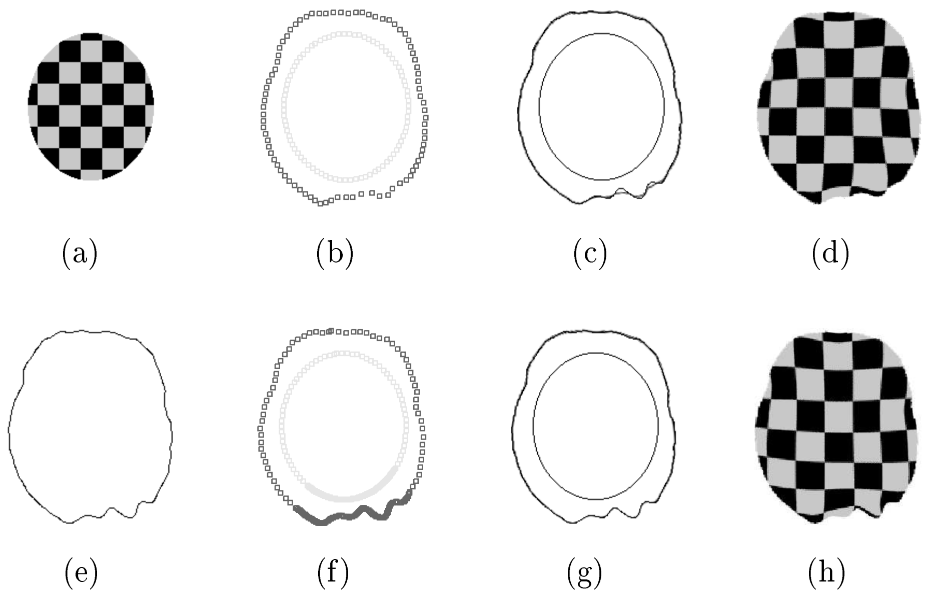
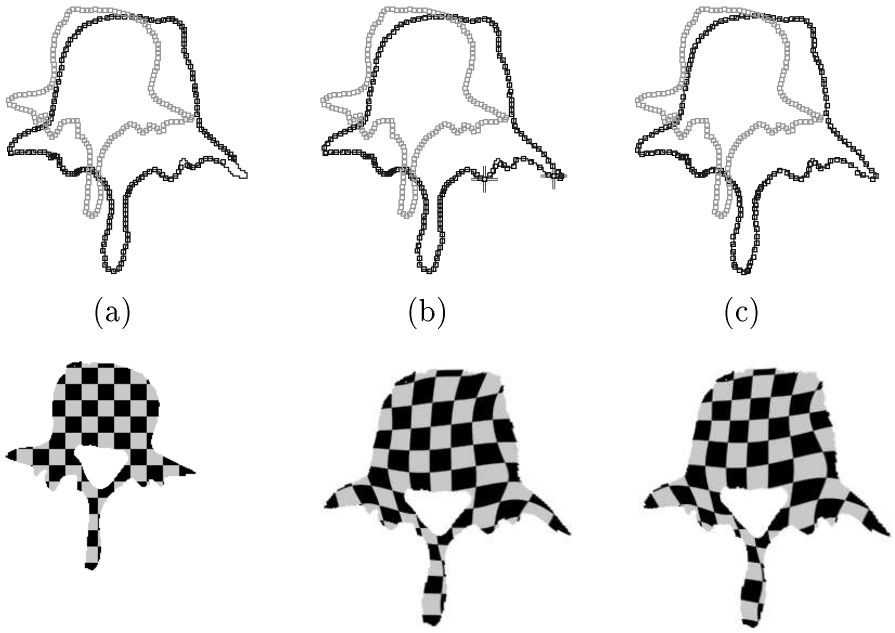


Fig. 1. Registration of an ellipse (a) with a brain outline (e). Sample points and iterated sample points (b), source, target and transformed source landmarks (c), and registration result (d). (f) - (h) same as (b) - (d) but using a different sample point distribution.

Fig. 2. Registration of two different human vertebrae in 2D tomographic images. (a) Results from the original approach, (b) from incorporation of predefined correspondences, and (c) from incorporation of the inverse transformation. (d) represents the source image, and (e), (f) show the registration results of (b), (c), resp.



(a) (b) (c)

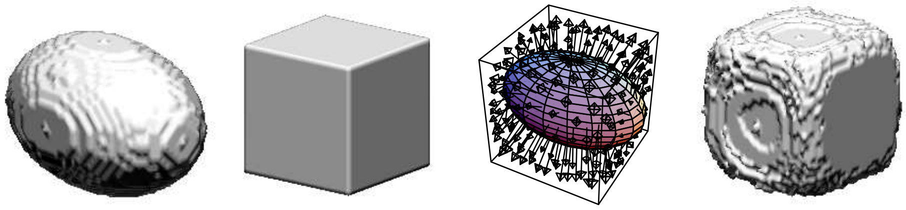
(d) (e) (f)

target landmark (thin black outline, see figure caption). (d) shows the source image filled with a chess-board pattern. In (a) the registration result is shown using a sample point distance of $d_s = 5$ (167 points). Only at the tip of the right processus of the vertebra the registration is locally erroneous. This error can be prevented by interactively incorporating two predefined correspondences, as shown in (b) as two crosses, between the source and target images. As result, the two outlines are well mapped onto each other (see (b) and (e)).

To circumvent the incorporation of predefined correspondences we extended our algorithm by modifying the energy function $\boldsymbol{h}$ in such a way as to include the inverse transformation of sample points of the *target* landmarks. This leads to the results shown in Figs. 2(c) and (f), which are quite similar to those including predefined correspondences ((b) and (e), resp.). Note, however, that this registration result was achieved fully automatically without interactively determining correspondences.

We also tested our algorithm using 3D synthetic images (Fig. 3), where (as an extreme case) an ellipsoid is registered to a cube. (c) shows the calculated correspondences using 271 sample points on the source landmark. The registration result (d) is surprisingly good although the objects are of very different shape.

Fig. 3. 3D experiment with synthetic data: registration of an ellipsoid (a) to a cube (b). Calculated correspondences (c), and registration result (d).



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

4 Summary and Conclusion

We have described a novel approach to elastic registration using surface landmarks. We demonstrated the applicability using 2D as well as 3D image data. The registration result can be improved by increasing the density of the sample points to better adapt to strongly curved structures. It is also possible to incorporate predefined correspondences. As a further improvement, the inclusion of the inverse transformation allows to register tips of anatomical structures fully automatically.

5 Acknowledgement

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References

1. F. L. Bookstein. Visualizing Group Differences in Outline Shape: Methods from Biometrics of Landmark Points. In *Proc. Conf. Visualization in Biomedical Computing (VBC'96),* Hamburg, Germany, volume 1131 of *Lecture Notes in Computer Science*, pp. 405–410, 1996. Springer.
2. M. Gabrani and O. J. Tretiak. Surface-based matching using elastic transformations. *Pattern Recognition*, 32:87–97, 1999.
3. W. D. K. Green. Spline-based deformable models. In *Vision Geometry IV,* San Diego, CA, USA, 9 - 14 July, 1995, 2573, pp. 290–301. SPIE, 1995.
4. N. Krahnstöver and C. Lorenz. Development of a point based shape representation of arbitrary three-dimensional medical objects suitable for statistical shape modeling. In *Medical Imaging: IP, San Diego, CA, USA*, 3661, pp. 620–631. SPIE 1999.
5. G. Subsol, J.-P. Thirion, and N. Ayache. A scheme for automatically building three-dimensional morphometric anatomical atlases: application to a skull atlas. *Medical Image Analysis*, 2(1):37–60, 1998.
6. R. Szeliski and S. Lavallée. Matching 3-D Anatomical Surfaces with Non-Rigid Deformations using Octree-Splines. *International Journal of Computer Vision*, 18(2):171–186, 1996.