Proc. *Image and Multidimensional Digital Signal Processing (IMDSP'98),* Alpbach, Austria, 12-16 July 1998, H. Niemann, H.-P. Seidel, B. Girod (Eds.), Infix Sankt Augustin 1998, pp. 37-40

Incorporating Orientation Attributes in Landmark-based Elastic Medical Image Registration

Mike Fornefett, Karl Rohr, Rainer Sprengel*, and H. Siegfried Stiehl

Universität Hamburg, Fachbereich Informatik, Arbeitsbereich Kognitive Systeme
Vogt-Kölln-Str. 30, D-22527 Hamburg, Germany
Email: fornefett@informatik.uni-hamburg.de

Abstract

We present a new approach to landmark-based elastic medical image registration which allows to incorporate orientation attributes at landmarks. The approach is based on a minimizing functional and can cope with images of arbitrary dimensions, e.g. 2D and 3D images. Constraints due to orientations are incorporated through scalar products between the transformed orientations in the source image and vectors which are perpendicular to the orientations in the target image. For synthetic data sets we show that the structure of a rigid object in an otherwise elastically deformed image can be preserved. The application of our approach to tomographic data sets shows that improvements w.r.t. accuracy can be achieved provided a sufficient number of landmarks is well-distributed over the image.

1 Introduction

To improve the results of landmark-based elastic registration, work in the past has been done on including additional landmark attributes, like orientation. With these approaches the necessity of increasing the number of landmarks can principally be reduced, which is especially important in medical applications.

Bookstein and Green [1] incorporate orientations by approximating them through two landmarks. Mardia et al. [3] use a kriging method to include derivative information. Their interpolation scheme yields an exact solution, but orientation vectors are required to be unit vectors. In this paper, we describe a new approach which i) is based on a minimizing functional and ii) allows to incorporate orientation attributes. As in the approach of Mardia et al. [3], exact orientations at landmarks are incorporated. However, in our case the directional constraints are represented through scalar products and therefore the lengths of the orientation vectors need not to be normalized to unit vectors. Another advantage of our approach is that it covers the full range from interpolation to approximation using a regularization parameter λ. In Sect.2, we give an overview of our approach for the general case of d-dimensional images and in Sect.3, we demonstrate the applicability of our approach for 2D images.

*Now with debis Systemhaus GEI, Hamburg.

2 Our Approach

In our scheme the searched transformation function $\boldsymbol{u} : \mathbb{R}^d \rightarrow \mathbb{R}^d$, where d is the image dimension, minimizes the following functional:

$$\frac{1}{n}\sum_{i=1}^{n}(\mathbf{v}_i - L_i\boldsymbol{u})^2 + \lambda\, J_m^d(\boldsymbol{u}), \qquad (1)$$

which can also be written as:

$$\frac{1}{dn+(d-1)n_\theta}\left(\sum_{i=1}^{n}\left(\mathbf{q}_i - \boldsymbol{u}(\mathbf{p}_i)\right)^2 + \sum_{i=1}^{n_\theta}\sum_{j=1}^{d-1}\left((\mathbf{d}_i{}^T\nabla)\boldsymbol{u}^T(\mathbf{p}_{\theta_i})\,\mathbf{e}_{i,j}^{\perp}\right)^2\right) + \lambda\, J_m^d(\boldsymbol{u}), \qquad (2)$$

where n is the number of pairs of point landmarks $(\mathbf{p}_i, \mathbf{q}_i)$. n_θ is the number of orientations $\mathbf{d}_i$ at locations $\mathbf{p}_{\theta_i}$ in the source image. The vectors $\mathbf{e}_{i,j}^{\perp}, j = 1 \ldots d-1$ are perpendicular to the corresponding orientations $\mathbf{e}_i$ at locations $\mathbf{q}_{\theta_i}$ in the target image. $J_m^d(\boldsymbol{u})$ is the smoothness-related energy term described in [4, 5], where m is the order of derivatives used.

The second term in (2) is a scalar product between $(\mathbf{d}_i{}^T\nabla)\boldsymbol{u}(\mathbf{p}_{\theta_i})$ and the vectors $\mathbf{e}_{i,j}^{\perp}$. $(\mathbf{d}_i{}^T\nabla)\boldsymbol{u}(\mathbf{p}_{\theta_i})$ is the transformed orientation vector of the source image and it is perpendicular to $\mathbf{e}_{i,j}^{\perp}$, the j orthogonal vectors of the orientation vector of the target image, such that its contribution to the functional is zero.

Choosing vectors from the orthogonal space has the advantage that the corresponding scalar product is zero independent of the length of the vectors. Note however, that this holds true only in the case of interpolation but not for approximation. The $d-1$ perpendicular orientations $\mathbf{e}_{i,j}^{\perp}$ to the target vector $\mathbf{e}_i$ constrain the orientation of the transformed source vector $\mathbf{d}_i$ to lie on a line. Accordingly, the number of constraints is lower if an orientation is not constrained w.r.t. a line, but w.r.t. a plane, for example. The landmark pairs $(\mathbf{p}_{\theta_i}, \mathbf{q}_{\theta_i})$ with orientation information may, but need not be a subset of the landmark pairs $(\mathbf{p}_i, \mathbf{q}_i)$.

Application of the spline theorem in [5] yields the following solution:

$$\begin{aligned}\boldsymbol{u}(\mathbf{x}) = &\sum_{k=1}^{M}\sum_{j=1}^{d} a_{k,j}\phi_k(\mathbf{x})\,\boldsymbol{\varepsilon}_j \\ &+ \sum_{i=1}^{n}\sum_{j=1}^{d} w_{1,i,j}U(\mathbf{x}-\mathbf{p}_i)\,\boldsymbol{\varepsilon}_j \\ &- \sum_{i=1}^{n_\theta}\sum_{j=1}^{d-1} w_{2,i,j}(\mathbf{d}_i{}^T\nabla)U(\mathbf{x}-\mathbf{p}_{\theta_i})\,\mathbf{e}_{i,j}^{\perp},\end{aligned} \tag{3}$$

where $\phi_1, \ldots, \phi_M$ are the basis functions of the corresponding null-space of dimension M and $U(\mathbf{x})$ are radial basis functions. Note, that in order to obtain bounded functionals L_i the used function space has to be constrained. As a consequence, we obtain for both cases of 2D and 3D registration incorporating orientations the function $U(\mathbf{x}) = |\mathbf{x}|^3$ as the only possible solution for $m = 2$. The parameters $\mathbf{a} = (a_{1,1}, a_{1,2}, \ldots, a_{1,d}, a_{2,1}, \ldots, a_{M,d})$ and $\mathbf{w} = (w_{1,1,1}, \ldots, w_{1,n,d}, \ldots, w_{2,1,1}, \ldots, w_{2,n_\theta,d-1})$ can be computed as the solution of the following system of linear equations:

$$\begin{aligned}\mathbf{K}\mathbf{w} + \mathbf{P}\mathbf{a} &= \mathbf{v} \\ \mathbf{P}^T\mathbf{w} &= 0,\end{aligned} \tag{4}$$

where $\mathbf{K}$ and $\mathbf{P}$ are matrices consisting of elements of $U(\mathbf{x})$, and derivatives $(\mathbf{d}_i{}^T\nabla)U(\mathbf{x})$, $(\mathbf{d}_i{}^T\nabla)(\mathbf{d}_j{}^T\nabla)U(\mathbf{x})$, $\phi(\mathbf{x})$, and $(\mathbf{d}_i{}^T\nabla)\phi(\mathbf{x})$, respectively. $\mathbf{v}$ is a vector corresponding to the target landmarks as well as zero values due to the scalar product of the orientations.

3 Experimental Results

For the sake of convenience in result display, experiments with 2D synthetic as well as tomographic data sets have been carried out. In medical images it is often important to distinguish between rigid and elastic parts of the image, e.g. rigid parts may be bones while the elastic parts correspond to soft tissue. With our synthetic experiments we have studied whether rigid parts can be mapped onto each other, while the elastic parts deform smoothly inbetween.

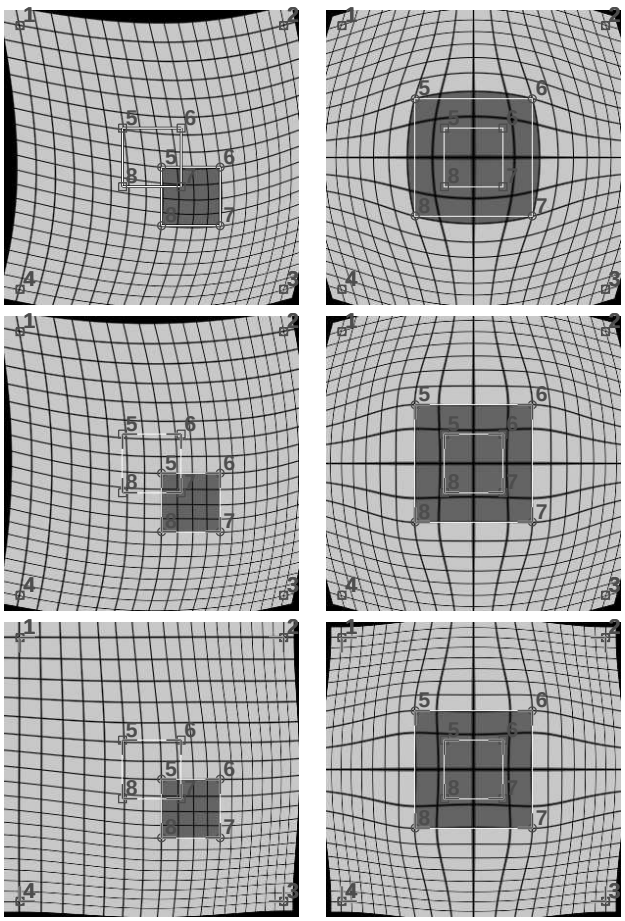

Figure 1: Synthetic data sets. Registration result of a translated (left) and isotropically scaled (right) square. Thin-plate spline registration using only landmarks (first row), with adding two orientations (drawn as grey lines) at each object landmark No.5 to 8 (second row), and with adding two orientations at each of the landmarks No.1 to 8 (last row).

In Fig. 1 a translation of 40 pixels in each direction (left side) and an isotropic scaling of 30 pixels symmetrically in x and y direction (right side) of a square are shown, simulating both shape-preserving object shifts and growth of lesions in medical images, respectively. The outline of the squares both of the source and target image are drawn in white and each of the six images shows the transformed source image. Four image border landmarks (No. 1 to 4) in the corners of the images have been used to fix the whole image and another four object landmarks (No. 5 to 8) have been used at the corners of the square. (See also the caption of Fig. 1.)

In case of translation (left side) we see that without orientation attributes (first row) the gridlines of the elastically transformed rigid part become curved. In contrast, using orientation attributes at the square (second row) the gridlines of the rigid parts remain nearly parallel. Thus rigidity of the square is preserved under translations. Adding orientation attributes at the image border landmarks (third row) weakens the overall deformations at the image border. In case of isotropic scaling (right side) the source structure "grows" out of the border limits of the target structure (first row). Using orientation attributes at the corners of the square instead, the square is preserved (second row). Again, additional orientation attributes at the image border (last row) help to minimize deformations there. Note, that compatible results have been obtained for the registration of 3D images.

In Fig. 2 an example of rotated rigid structures is shown (image size is 181×451 pixels). The five rigid structures simulate a human spine (top left and right) (according to Little et al. [2]). At the bottom of the figure the registration results are represented. We see that registration with landmarks only does not preserve the rigidity of the squares. When using orientation attributes and setting $\lambda = 0$ (interpolation), we get a better registration result. The waviness of the outlines of the squares is reduced. In the last image of the figure we have used the approximation scheme with $\lambda = 100$ and the same orientations as before. In this case we yield the best registration result. The structure of the squares is nearly preserved and the mean distance between the transformed source landmarks and the target landmarks is 0.5 pixels (the maximum is 1.3 pixels).

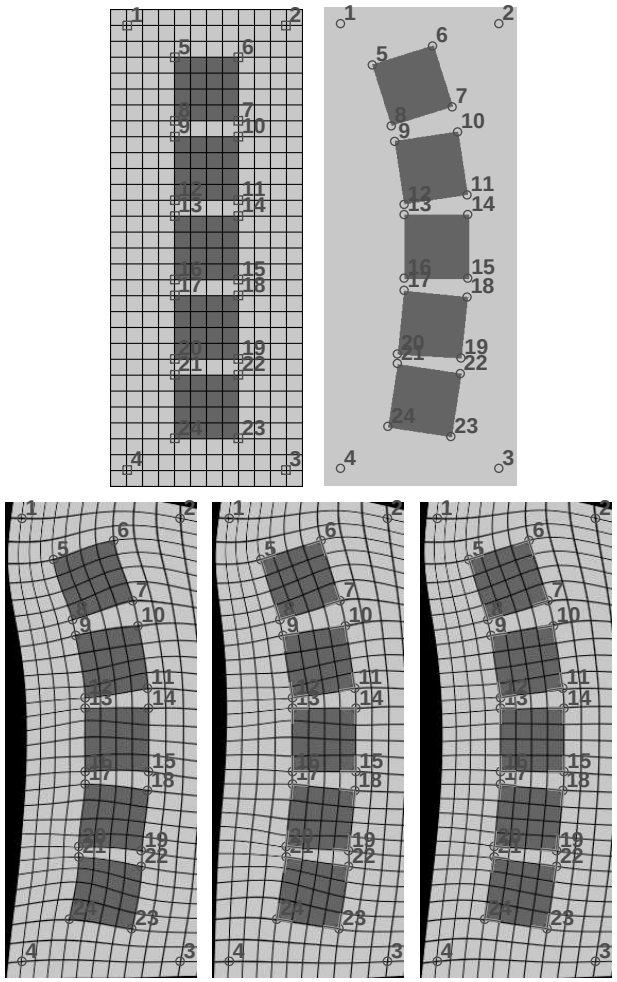

Figure 2: Synthetic data set. Simulating a spine which is bended. First row: Source and target images; second row: registration using thin-plate spline with landmarks only (left), adding two orientations to each object landmark No. 5 to 24 (middle), and using the approximation scheme with $\lambda = 100$ and the same orientations as before (right).

Fig. 3 shows two sagittal slices of two MR images of the brain of two different patients (in the first row is the source and in the second row the target image). We manually specified a number of 13 landmarks. The third row shows the registration result using landmarks only. The white outlines of the target image are overlayed on the transformed source image. Improvement of this result can be achieved if we add further landmarks. However, specifying additional landmarks is often not possible. Therefore, we investigate the incorporation of orientation attributes at landmarks. In the last row we have added one orientation at each of the landmarks No. 1 and 13. As a result we can see that the region between

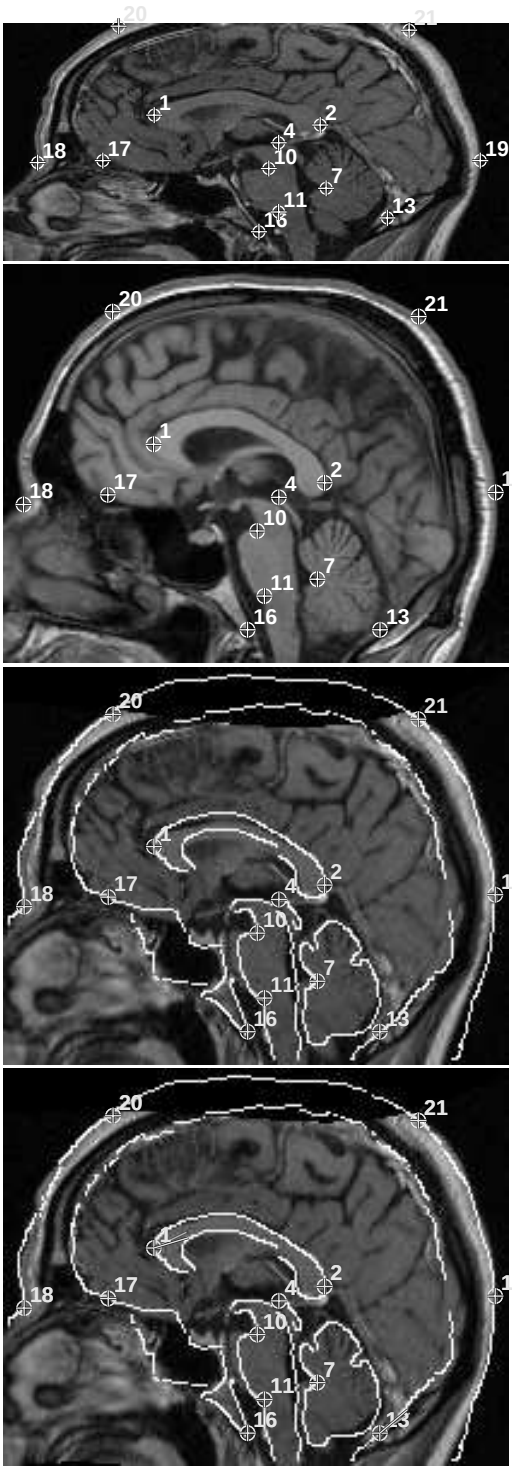

Figure 3: Tomographic data sets. Two MR images of different brains with 13 landmarks, source and target images (first and second row). Third row: thin-plate spline registration using point landmarks only. Last row: thin-plate spline registration using orientations at landmarks No. 1 and 13.

landmarks No. 1 and 2 (at the corpus callosum) is better registered than using landmarks only. However, the incorporation of orientations has also strong global effects, e.g. the region above the corpus callosum is deformed upwards.

4 Summary and Conclusion

We have demonstrated that by incorporating orientations in our elastic registration scheme it is possible to improve the registration accuracy without further adding landmarks. For synthetic images we have demonstrated that rigid structures can be preserved in an otherwise elastically deformed image. Experiments for tomographic data sets have shown that improvements can be obtained, but landmarks should be well-distributed in order to achieve good registration results. A problem is that the incorporation of orientations has strong global effects. Hence, future work will concentrate on how to limit the influence of the orientation constraints.

Acknowledgement

This work has been supported by Philips Research Hamburg, project IMAGINE (Image- and Atlas-Guided Interventions in Neurosurgery).

References

[1] F. L. Bookstein and W. D. K. Green, "A Feature Space for Edgels in Images with Landmarks", *Journal of Mathematical Imaging and Vision*, **3**, pp. 231–261, 1993

[2] J. A. Little, D. L. G. Hill, and D. J. Hawkes, "Deformations Incorporating Rigid Structures", *Computer Vision and Image Understanding*, **66**(2), pp. 223–232, 1997

[3] K. V. Mardia, J. T. Kent, C. R. Goodall, and J. A. Little, "Kriging and splines with derivative information", *Biometrika*, **83**(1), pp. 207–221, 1996

[4] K. Rohr, H. S. Stiehl, R. Sprengel, W. Beil, T. M. Buzug, J. Weese, and M. H. Kuhn, "Point-Based Elastic Registration of Medical Image Data Using Approximating Thin-Plate Splines", *Visualization in Biomedical Computing (VBC'96)*, Lecture Notes in Computer Science (1131), pp. 297–306, Springer, 1996

[5] G. Wahba, "Spline Models for Observational Data", *Society for Industrial and Applied Mathematics*, Philadelphia, Pennsylvania, USA, 1990