An Adaptive Irregular Grid Approach using SIFT Features for Elastic Medical Image Registration

Astrid Franz, Ingwer C. Carlsen and Steffen Renisch

Philips Research Laboratories, P.O. Box 63 05 65, D-22315 Hamburg
Email: astrid.franz@philips.com

Abstract. Elastic image registration is an active field of current research. In contrast to B-spline transformations, defined on a regular grid of control points, we consider physics-based transformations defined on irregular grids. With such control point arrangements, the required non-linear behaviour can be described with less parameters. We combine this transformation model with the SIFT algorithm for identifying prominent image structures that serve well as initial control point positions. Medical applications from different modalities show that with this intelligent control point initialization the number of required control points can be further reduced, which significantly speeds up the registration process.

1 Introduction

Elastic registration of medical images, i.e. finding a non-affine transformation such that corresponding image structures correctly align, is an active field of current research. Accurate image registration is a necessary prerequisite for many diagnostic and therapy planning procedures where complementary information from different images has to be combined. Different registration algorithms have been proposed, but as of yet no generally accepted strategy seems to exist and it is unlikely that a single approach will serve all clinical applications.

One well-established classification scheme of elastic registration methods is their division into parametric and non-parametric methods [1, 2]. Parametric approaches have the advantage of representing the transformation by a moderate number of parameters, but on the other hand limit the transformation freedom. The transformation parameters have to be optimized in order to find that set of parameters yielding optimal similarity of the two images, quantified by a grey-value based similarity measure. Since optimization in a high-dimensional space is computationally expensive, a transformation model has to be found describing the clinical relevant deformations with as few parameters as possible.

A well-known transformation model for elastic image registration are B-splines defined on a regular grid of control points [3, 4]. The registration accuracy for such a transformation strongly depends on the grid resolution, where the use of fine grids results in high computational costs. An alternative is the use of irregular grids of control points with a physics-based transformation model as introduced in [5, 6]. The advantage of such a method is that control points need to be placed only in image regions where they are of significant influence on the registration accuracy. Hence a similar transformation flexibility can be described by fewer parameters than on the basis of a regular control gid. Furthermore, not only the forces applied at the control points, but also the position of the control points can be changed during the optimization process [7, 8]. Hence no prior knowledge is required where to optimally place the control points, which is a great advantage over registration approaches using point landmarks from local image characteristics (see [9] and references therein).

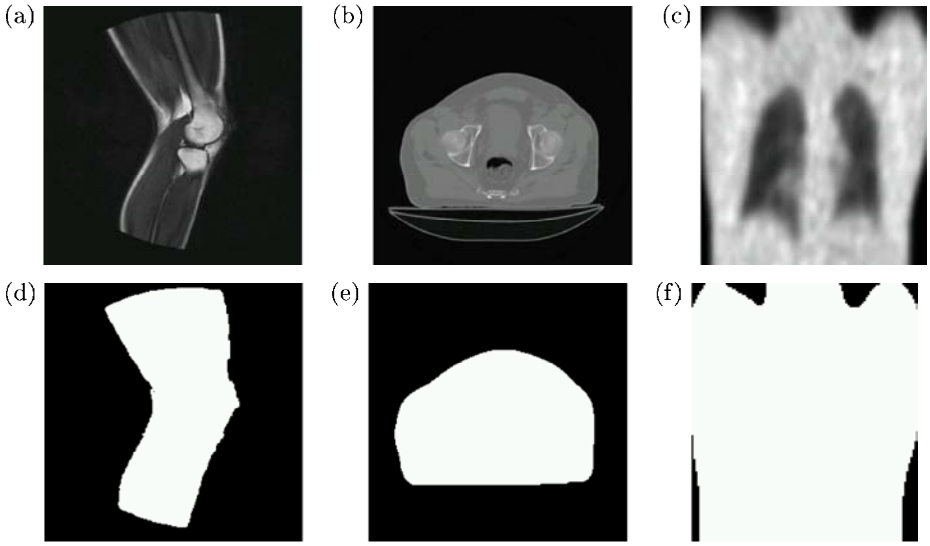
In [7, 8] the number of the control points was fixed, and they where initially placed on a regular grid. A validation investigation of these methods for a set of clinical applications showed that a further reduction of the number of parameters is possible by an iterative placement of the control points [10]. Since global optimization is computationally expensive, the fast derivative-based Levenberg-Marquardt method is used for optimizing the forces as well as the position of the control points, but this optimization strategy is only locally convergent and therefore the registration result depends on the initial placement of the control points. In [10] the control points are initially placed randomly inside the image area, which makes the registration result non-deterministic.

2 Theory and Methodology

Here we propose to use the Scale Invariant Feature Transform (SIFT) algorithm known from panoramic image mosaicing [11] for identifying good initial landmark positions. The SIFT features are geometrically invariant under similarity transforms and invariant under affine changes in intensity. Distinctive SIFT feature points correspond to prominent image structures that serve well as initial control points of relevance and that allow constraining the local optimization to adjust only parameters that have a pronounced influence on improving the image similarity. In contrast to a random control point placement, this results in a deterministic and more robust registration algorithm.

The SIFT algorithm identifies extrema in the scale space, i.e. it measures how long an image structure survives when blurring the image with wider and wider Gaussian kernels. The longer a structure survives the blurring sequence, the more prominent this structure appears in the image. The first control point is then placed at the most prominent SIFT feature. Starting from this control point, the force and the position is optimized by the Levenberg-Marquardt method until optimal similarity between the reference image and the warped floating image is reached. Then this optimal control point configuration is used as starting configuration for the next optimization run, and an additional control point is placed at the next prominent SIFT feature. All control points together are optimized further. The iterative placement of an additional control point at the next prominent SIFT feature is continued as long as a significant improvement of the similarity measure can be reached.

Fig. 1. Application test images: MR image of a joint (a), abdominal CT image (b) and PET transmission image (c), and corresponding regions of interest for computing the displacement error (d-f).



We use the validation strategy introduced in [10] to compare the registration results of the proposed algorithm with previous approaches. We construct a "pseudo" ground truth by applying an artificial, but realistic deformation to a clinical floating image and use this artificially deformed image as reference image further on. After a registration, the resulting transformation can then be compared with the known ground truth, using e.g. the displacement error averaged over a region of interest as quality measure for judging the registration accuracy.

3 Results

We investigated the proposed algorithm of combining the adaptive irregular grid approach with an iterative control point placement based on SIFT features for a range of clinical applications: MR images of freely moving joints for orthopedic investigations, abdominal CT images for adaptive radiation therapy planning, and PET transmission images used for the attenuation correction and registration of independently acquired PET and CT images. The test calculations were carried out for the 2D images shown in fig. 1, but of course the proposed algorithm works equally well in three spatial dimensions.

We constructed a pseudo ground truth by applying a thin plate spline transformation to all three example images, where this transformation was chosen in such a way that the deformed images are in good agreement to real deformed clinical images. Note that the pseudo ground truth transformation was chosen out of another transformation class than that used for subsequent registration.

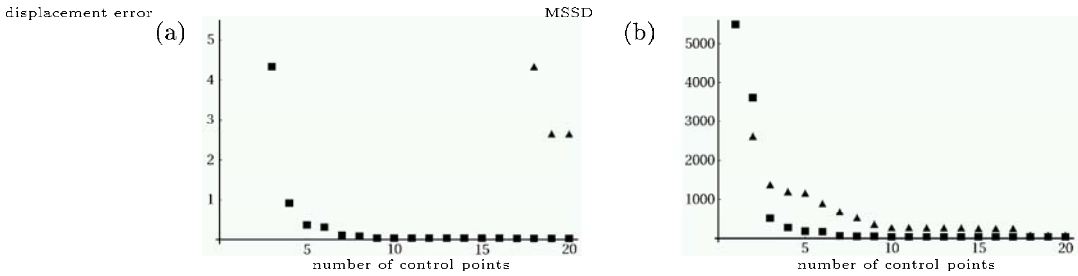


Fig. 2. Displacement error (a) and similarity measure (b) for the MR moving joint application shown in fig. 1a as a function of the number of control points. The control points are initially placed randomly (▲) or at the SIFT feature points (■).

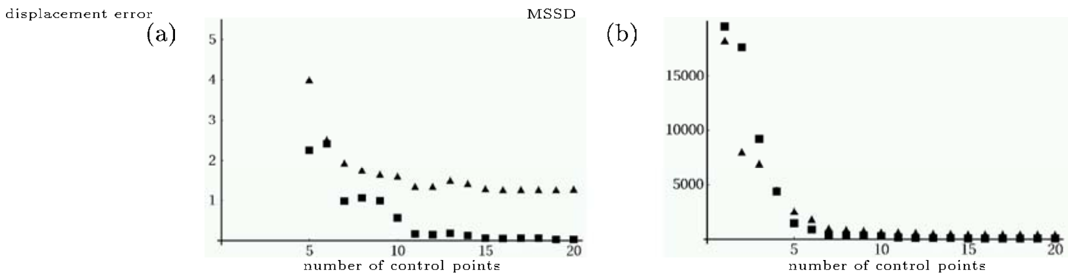


Fig. 3. Displacement error (a) and similarity measure (b) for the radiation therapy planning application shown in fig. 1b as a function of the number of control points. The control points are initially placed randomly (▲) or at the SIFT feature points (■).

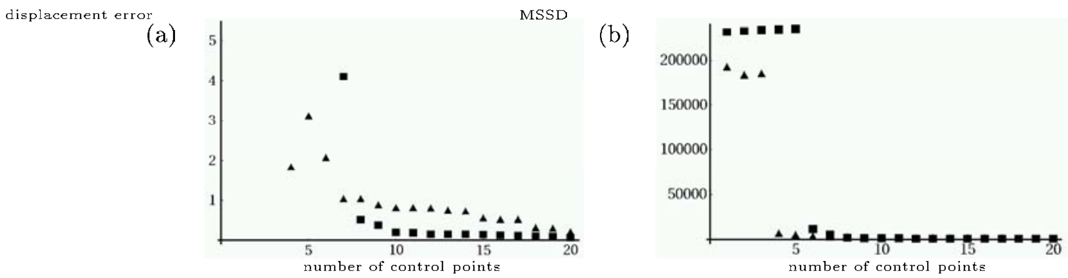


Fig. 4. Displacement error (a) and similarity measure (b) for the PET application shown in fig. 1c as a function of the number of control points. The control points are initially placed randomly (▲) or at the SIFT feature points (■).

In all example applications it turned out that a small number of control points is sufficient to reach an averaged displacement error of less than 1 pixel over the considered region of interest (see figs. 2-4). In comparison, with a random initial control point placement such small displacement errors can not be reached (see figs. 2,3), or they require a much larger number of control points (see fig. 4). Hence, the SIFT feature points are good starting points for the adaptive irregular grid approach to elastic registration.

4 Conclusion and Discussion

The elastic registration algorithm we present here uses the SIFT features known from panoramic stitching for identifying significant image structures for the initial control point placement for adaptive irregular grid transformation models. Contrary to a completely random positioning, it avoids placing control points in areas void of significant grey value structures where their adjustment will hardly change the similarity measure and hence will not efficiently improve image similarity. Furthermore, it makes the registration algorithm deterministic and reproducible, an important aspect for acceptance in the clinical practice. Hence the combination of the adaptive irregular grid transformations and the SIFT features for initial control point placement is a promising approach to elastic medical image registration.

References

1. Rohr K. Landmark-Based Image Analysis: Using Geometry and Intensity Models. Dordrecht: Kluwer; 2001.
2. Modersitzki J. Numerical Methods for Image Registration. Oxford University Press; 2004.
3. Rueckert D, Sonoda LI, Hayes C, et al. Nonrigid registration using free-form deformations: Application to breast MR images. IEEE Trans Med Imaging 1999;18(8):712–721.
4. Kybic J, Unser M. Fast Parametric Elastic Image Registration. IEEE Trans Image Process 2003;12(11):1427–1442.
5. Kohlrausch J, Rohr K, Stiehl S. A new class of elastic body splines for nonrigid registration of medical images. In: Procs BVM; 2001. p. 164–168.
6. Kohlrausch J, Rohr K, Stiehl HS. A New Class of Elastic Body Splines for Nonrigid Registration of Medical Images. J Math Imaging Vision 2005;23(3):253–280.
7. Pekar V, Gladilin E. Deformable Image Registration by Adaptive Gaussian Forces. In: Procs CVAMIA+MMBIA; 2004. p. 317–328.
8. Pekar V, Gladilin E, Rohr K. An Adaptive Irregular Grid Approach for 3-D Deformable Image Registration. Phys Med Biol, in press 2005.
9. Zitová B, Flusser J. Image registration methods: A survey. Image Vis Comput 2003;21(11):977–1000.
10. Franz A, Carlsen IC, Renisch S, et al. Validation of elastic registration algorithms based on adaptive irregular grids for medical applications. In: Procs SPIE Med Imaging: Image Processing; 2006.
11. Brown M, Lowe DG. Recognising Panoramas. In: Procs ICCV; 2003. p. 1218–1225.