Image Registration for CT and intra-operative ultrasound data of the liver

Nils Papenberg[1], Thomas Lange[2], Jan Modersitzki[1], Peter M. Schlag[2], Bernd Fischer[1]

[1] Institute of Mathematics, University of Lübeck
Wallstraße 40, 23560 Lübeck, Germany
[2] Charitè - Universitätsmedizin Berlin, Department of Surgery and Surgical Oncology
Lindenberger Weg 80, 13125 Berlin, Germany

Abstract

The paper is concerned with image registration algorithms for the alignment of computer tomography (CT) and 3D-ultrasound (US) images of the liver. The necessity of registration arises from the surgeon's request to benefit from the planning data during surgery. The goal is to align the planning data, derived from pre-operative CT-images, with the current US-images of the liver acquired during the surgery. The registration task is complicated by the fact, that the images are of a different modality, that the US-images are severely corrupted by noise, and that the surgeon is looking for a fast and robust scheme. To guide and support the registration, additional pairs of corresponding landmarks are prepared. We will present two different approaches for registration. The first one is based on the pure alignment of the landmarks using thin plate splines. It has been successfully applied in various applications and is now transmitted to liver surgery. In the second approach, we mix a volumetric distance measure with the landmark interpolation constraints. In particular, we investigate the promising normalized gradient field distance measure. We use data from actual liver surgery to illustrate the applicability and the characteristics of both approaches. It turns out that both approaches are suitable for the registration of multi-modal images of the liver.

Keywords: image registration, normalized gradient field, landmark registration, parametric transformation, liver surgery

1 Introduction

In liver surgery one major task is the resection of tumors. Typically, this task leaves the surgeon with a dilemma: remove all tumor tissue while sparing a sufficient amount of the patient's liver. With modern computed tomography (CT) and magnetic resonance imaging (MRI) the precise individual anatomy and the location of the tumor in relation to vascular structures can be imaged. From this imaging 3D models of the relevant structures and individual vascular territories can be computed [31], which are the basis of modern planning systems for liver surgery. These systems offer the surgeon the possibility to perform a detailed risk analysis and to define optimal individual resection plans [15]. The goal is to preserve as much of the liver volume as possible to improve convalescence of the patient. The importance and clinical use of such 3D planning systems is increasing.

Medical Imaging 2008: Visualization, Image-guided Procedures, and Modeling, edited by
Michael I. Miga, Kevin Robert Cleary, Proc. of SPIE Vol. 6918, 691808, (2008)
1605-7422/08/$18 · doi: 10.1117/12.770105

The precise transfer of the preoperative plan to the patient in the operating room (OR) is a challenging task. During surgery the location of the tumor and relevant vessels is hidden underneath the liver surface and the location of the virtual resection line can only be estimated. Intraoperative navigation systems support the surgeon by visualizing the spatial relation of surgical instruments to anatomical structures, which are not directly visible. For liver surgery such navigation systems are under development and clinical approval. They are based on either intraoperative liver surface information acquired by a range scanner [7] or intraoperative 2D [4] or 3D ultrasound [2, 3].

To use the preoperative planning data in an ultrasound-based navigation system the necessity of non-rigid registration comes up. The goal is to find a transformation, such that the transformed CT-volume matches the current intraoperative US-volume.

In the literature one may find only a few publications regarding CT/MR-ultrasound registration. Some rigid methods have been reported, which are either intensity- [27, 32] or feature-based [24, 23]. Usually the liver vessels are used as features, because they are identifiable in CT/MRI and ultrasound data, in particular in power doppler ultrasound. Extensions of such vessel-based approaches to non-rigid transformations are reported in [17, 16, 26, 25]. The extraction of the vessels from the intraoperative ultrasound data constitutes a bottleneck of these attempts, as this task is hardly to be accomplished in a robust, fast and reliable fashion. Hybrid approaches [1], which fit preoperatively extracted features directly to the intensities of intraoperative image data are an alternative. Often features are already available by the planning software like vessel models in liver surgery. Hybrid methods are also extendable to non-rigid transformations [18].

One way of looking at hybrid methods, is their ability to incorporate user and/or a priori knowledge about anatomical structures of the underlying tissue. A priori knowledge induces constraints on the registration problem. Applying constraints reduces the level of non-uniqueness of a registration task and thus generates more reliable transformations. The incorporation of constraints is a very recent and challenging topic in image registration. Typical examples for incorporation of a priori knowledge are masks indicating lesions or anatomical structures [14, 30], volume preservation [28, 11, 13] and local rigidity constraints [19, 33, 22].

Another kind of constraints are user-defined corresponding landmark pairs. In our application these landmarks are set pre-operatively in the planning data and intra-operatively in the US-data by the surgeon. Pure non-rigid landmark registration has already been applied to MRI-ultrasound registration [10]. Usually thin-plate splines (TPS) [5, 29, 21] are used as transformation model for the non-rigid landmark registration.

To supplement a nonparametric intensity-based registration scheme [21] by landmarks a constraint optimization problem may be formulated [9]. Another approach is an alternating optimization of a distance measure and a spline based landmark registration with coupled displacement fields [35].

In this paper we follow a different strategy. A suitable term is added to the registration functional which penalizes distances between corresponding landmarks, which may be seen as a so-called soft constraint. It is the goal of this note to devise and discuss first steps for the solution of the resulting challenging registration problem.

2 Methods

In this section we present two approaches to solve the registration problem associated with a given US-volume R and CT-volume T. We assume that $M \in \mathbb{N}$ pairs of corresponding anatomical landmarks $r_j \in R, t_j \in T$, $j = 1, \ldots, M$, in both data sets are given. The wanted displacement field is denoted by $y : \mathbb{R}^3 \to \mathbb{R}^3$.

The first approach is based on a direct matching of the landmarks using thin plate splines. The use of landmarks within the registration of ultrasound images is quite popular [20, 6, 8, 10]. The underlying mathematics is outlined in [21, 29]. To set up notation, let us briefly introduce the problem to be solved. One is interested in obtaining a smooth function, measured by the global smoothness measure

$$\mathcal{S}^{\mathrm{LM}}[y] = \int (\partial_{11}y)^2 + (\partial_{22}y)^2 + (\partial_{33}y)^2 + 2\left((\partial_{12}y)^2 + (\partial_{13}y)^2 + (\partial_{23}y)^2\right) dx.$$

Adding the landmark conditions, i.e. $y(r_j) = t_j$, as so-called hard constraints, one ends up with the constraint optimization problem

$$J[y] = S^{\mathrm{LM}}[y] \to \min \quad \text{s. t.} \quad \{y(r_j) - t_j = 0,\, j = 1, \dots, M\}.$$

The solution of this problem is analytically known and turns out to be a linear combination of thin plate splines. It is worth noticing that the actual computation of the optimal y boils down to the solution of a linear system of the size of the number of chosen landmarks. Therefore, the scheme is computationally very attractive. To our best knowledge, the scheme has not been applied to the special situation of liver data (i. e. vessel structures). Of course, the performance of any landmark based procedure highly depends on a proper choice of landmarks, as images are replaced by just a few outstanding points. The determination of landmarks in US-data is a tricky problem. Only the bifurcation points of large vessels, like the portal vein, may be selected with high assurance. That is, the 'save landmarks' are located in the interior of the liver and consequently the computed deformation has to be closely examined in the exterior parts. Outcomes in this direction will be presented in the result section.

As a second approach we introduce an algorithms that combines the landmark correspondence with the intensity value information from the US- and the CT-images. To measure the volumetric distance of the multimodal images, we choose the so-called *normalized gradient field* introduced in [12] which may be seen as an enhancement of [34]:

$$\mathcal{D}^{\mathrm{NF}}[y; T, R] = \int_{\Omega} \|\nabla_n R \times \nabla_n T(y)\|^2 \, dx,$$

where $\times$ denotes the outer or cross product of vectors and $\nabla_n R$ and $\nabla_n T(y)$ the normalized gradient of R and $T(y)$, i.e. $\nabla_n R = \nabla R / \|\nabla R\|$. The term $\mathcal{D}^{\mathrm{NF}}$ may be interpreted as a measure that quantifies pointwise the area of the rectangle spanned by the normalized gradients. The quantity $\nabla_n R \times \nabla_n T(y)$ reaches its maximum when $\nabla_n R$ and $\nabla_n T(y)$ are perpendicular and is zero when both vectors are linear dependend. That is, the smaller $\mathcal{D}^{\mathrm{NF}}[y; T, R]$, the better R and $T(y)$ match.

We combine the measure $\mathcal{D}^{\mathrm{NF}}$ with a penalizer which forces the deformation field y to fulfill the landmark conditions (i.e. $y(r_j) = t_j$) as good as possible, which is related to the approach of Fischer and Modersitzki [9]. The penalizer looks like

$$\mathcal{P}[y] = \sum_{j=1}^{M} \|\delta_{r_j} \star y - t_j\|^2, \tag{1}$$

where the somewhat awkward formulation as convolution with a delta distribution allows one to formulate the penalizer as a function of y, with $\delta_{r_j} \star y - t_j$ is equal to $y(r_j) - t_j$. The resulting overall functional looks like

$$\mathcal{J}[y] = \mathcal{D}^{\mathrm{NF}}[y; T, R] + \beta \mathcal{P}[y], \tag{2}$$

where β controls the influence of the penalizer. The actual choice of β depends on the size of the trust region of the chosen landmarks.
In this paper, we restrict y to the set of affine linear mappings, i.e. for each point $x = (x_1, x_2, x_3)^\top$, the deformation may be written as

$$y = \begin{pmatrix} \gamma_1 & \gamma_2 & \gamma_3 \\ \gamma_5 & \gamma_6 & \gamma_7 \\ \gamma_9 & \gamma_{10} & \gamma_{11} \end{pmatrix} x + \begin{pmatrix} \gamma_4 \\ \gamma_8 \\ \gamma_{12}, \end{pmatrix}$$

the thought after function $\mathbf{y} = \mathbf{y}(\gamma)$ is a linear combination of rotation, shear, translation and scaling. To solve the minimization problem (2) we use the promising discretize-optimize approach, which allows for fast Newton-like optimization schemes. The idea to interpolate the given images by differentiable functions, e.g. B-splines, then to discretize the resulting continuous optimization problem with respect to any desired resolution and finally to solve the resulting discrete optimization problem. Here, the discrete version of the normalized gradient field is easily to identify. We briefly outline the discretization of the penalty term. Due to its linearity with respect to y the discretization of $\mathcal{P}$ is straightforward. Let $\mathbf{y}$ be the evaluation of y on a discrete grid, then we can specify a vector c_j with

$$c_j^\top \mathbf{y} = t_j.$$

Here, the coefficients of c_j are given by the weights of the coordinates of r_j using an arbitrary interpolation scheme. Collecting the vectors c_j for all given landmarks row-wise within the matrix C the discrete formulation of the penalizer reads

$$P(\mathbf{y}) = \|C\mathbf{y} - t\|^2,$$

where t contains the landmarks' coordinates of the template image. This function is differentiable with respect to $\mathbf{y}$, i.e. $d_\mathbf{y} P = C^\top(C\mathbf{y} - t)$ and $d^2_\mathbf{y} P = C^\top C$. The derivatives with respect to the parameter γ is calculated via the chain rule.

This approach allows the usage of a multiresolution strategy, since the resolution of the discrete penalizer depends only on the grid size of $\mathbf{y}$. For each resolution only the interpolation weights, i.e. the coefficients of C, have to be evaluated. The special usage of nodal grids to discretize the transformation $\mathbf{y}$ bewares of boundary artifacts.

The minimization of the discrete, nonlinear objective function is performed by a Gauss-Newton scheme. Supplemented by a clever multiresolution strategy, this scheme allows for a fast and robust optimization strategy. We start the whole scheme by an affine linear pre-registration based solely on the landmark information.

3 Results

In this section we demonstrate the applicability of the introduced methods using real-life data from liver surgery. The data is acquired before and during surgery at the Department of Surgery and Surgical Oncology, Charitè Berlin, Germany. For better visualization we illustrate only the segmented portal vessel system in both data-sets using standard segmentation algorithms of Amira (see http://www.amiravis.com). The landmarks are determined by an clinical expert.

The set of data consists of a CT-scan of the liver with a ROI of size $171 \times 166 \times 96$ and a 3D US-scan of the ROI of size $146 \times 136 \times 161$, both a B-mode scan and a power doppler scan were measured. The locations of the landmarks in the ultrasound volume are presented in Figure 1(a). In (b) both vessel system were visualized after rigid alignment of the two datasets. This image can be seen as a benchmark for the comparison of the results of the registration algorithms, which are presentetd in 1(c)-(e). Part (c) documents the outcome of the thin plate spline registration. One may notice a clear compression of the CT-vessels in upright direction that matches the vessel systems in the interior of the volume very well. As foreseen above, the exterior vessels, like the beginning of the portal vein in the upper right of the image, do not mach very well. Figure 1(d),(e) show the results of the second approach with a affine linear model of y. Here we used the ultrasound power doppler data. Image (d) is just illustrating the landmark-based pre-alignment, whereas (e) clearly shows that the combined approach is superior to the plain landmark based approach, in particular for the portal vein. The overall value of $\mathcal{J}$ is minimized to about 11% compared to its starting value, i.e. the one obtained from the landmark registration.

4 Conclusion and Outlook

In this paper we present registration algorithms for the alignment of US- and CT-data of the liver. The first one is based on a conventional landmark based technique. In contrast, the second combined approach is entirely new, both on the theoretical and the practical side. It combines the landmark penalizer with the normalized gradient field distance measure. The initial test runs on 3D-real life data turned out to be very promising and most likely outperform alternative approaches. The presented results open the door towards a fast and reliable alignment of planning information with the actual intra-operative view of the liver and thereby providing a better navigation for the surgeon and hopefully a better convalescence of the patient.

This paper can be considered as a first step of transferring the theoretical well understood image registration algorithms to liver surgery. Next items will be the replacement of the affine linear model of the deformation by a non-parametric approach like elastic-matching (see e.g. [21]). Due to the physical properties of the elastic registration methods, the actual deformation of the liver during surgery can be approximated and estimated more realistically. In [9], Fischer and Modersitzki, demonstrate the combination of non-parametric registration algorithms with landmark registration, where the estimated displacement fulfills the landmarks condition. We will apply these methods to the special case of liver surgery. As a third step we will test different distance measures like mutual information, which is standard measure for multi-modal images, like CT and US. This way, we expect to improve upon the registration quality.

References

[1] S.R. Aylward, J.Jomier, S. Weeks, and E. Bullitt. Registration and analysis of vascular images. *Int J Comput Vision*, 55(2-3):123–138, 2003.

[2] S. Beller, M. Hünerbein, S. Eulenstein, T. Lange, and PM Schlag. Feasibility of navigated resection of liver tumors using multiplanar visualization of intraoperative 3d ultrasound data. *Annals of Surgery*, 246(2):288–294, 2007.

[3] S. Beller, M. Hünerbein, T. Lange, S. Eulenstein, B. Gebauer, and P.M. Schlag. Image-guided surgery of liver metastases by 3d ultrasound - based optoelectronic navigation. *Brit J Surg*, 94(7):866–875, 2007.

[4] M. Birth, M. Kleemann, P. Hildebrand, and H.P. Bruch. Intraoperative online navigation of dissection of the hepatical tissue - a new dimension in liver surgery. In *CARS*, pages 770–774, 2004.

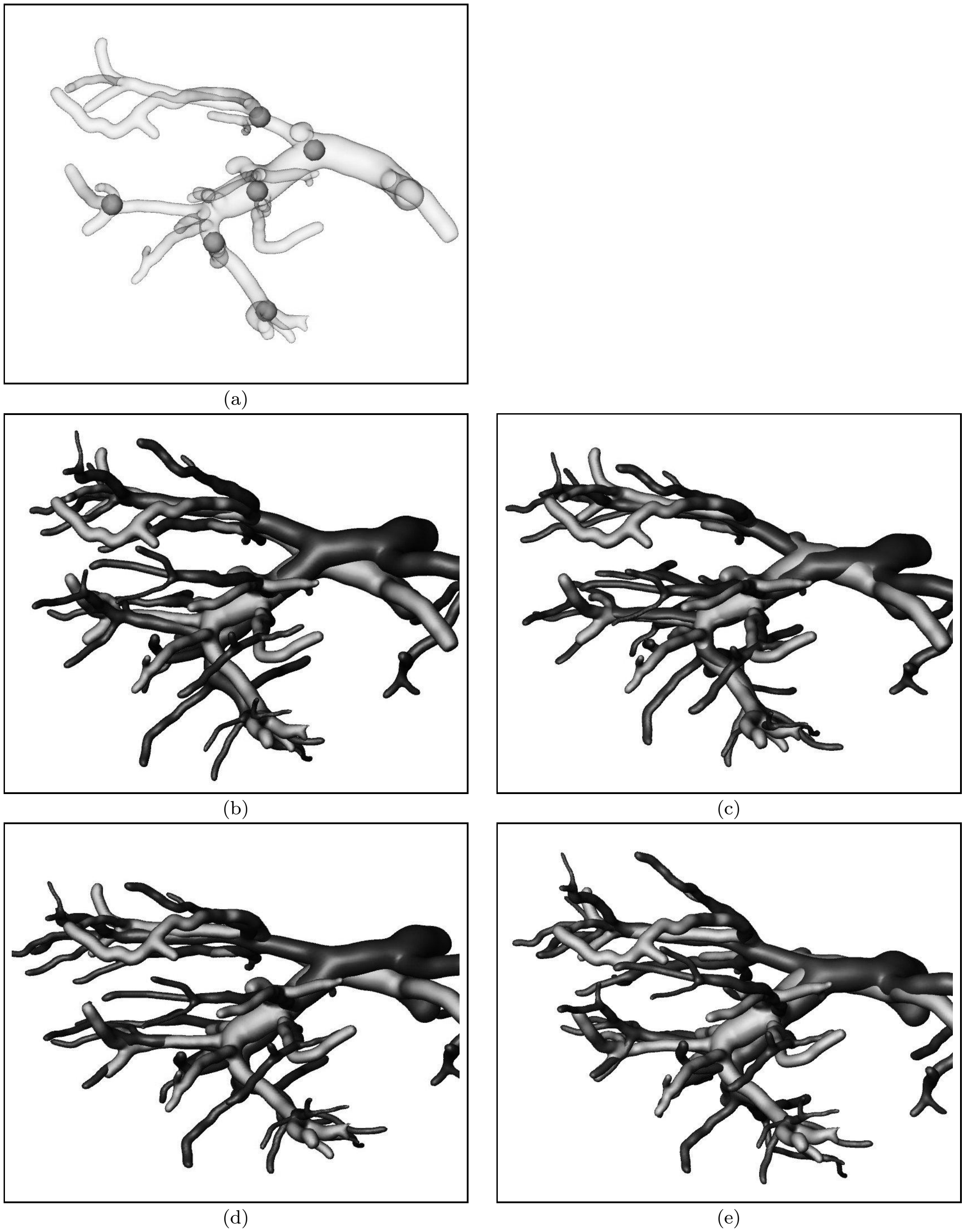

Figure 1: Ultrasound vessels are bright; CT vessels are dark: (a) positions of the landmarks marked with bubbles; (b) after rigid alignment; (c) after landmark registration with thin plate splines; (d) after the pre-registration for the combined approach; (e) after combined registration

[5] F.L. Bookstein. Principal warps: Thin-plate splines and the decomposition of deformations. *IEEE Trans. on Pattern Anal. and Mach. Intell.*, 11(6):567–585, 1989.

[6] D. M. Cash, T. K. Sinha, W. C. Chapman, H. Terawaki, M. I. Miga, and R. L. Galloway, Jr. Incorporation of a laser range scanner into an image-guided surgical system. In R. L. Galloway, Jr., editor, *Medical Imaging 2003: Visualization, Image-Guided Procedures, and Display*, volume 5029, pages 269–280, May 2003.

[7] D.M. Cash, M.I. Miga, S.C. Glasgow, B.M. Dawant, L.W. Clements, Z. Cao, R.L. Galloway, and W.C. Chapman. Concepts and preliminary data toward the realization of image-guided liver surgery. *J Gastrointest Surg*, 11(7):844–859, 2007.

[8] P. W. de Bruin, F. M. Vos, F. H. Post, A. M. Vossepoel, and S. de Blok. Interactive matching of ultrasound and MRI for visualization during resection of myomata. In S. K. Mun, editor, *Medical Imaging 2002: Visualization, Image-Guided Procedures, and Display*, volume 4681, pages 77–84, May 2002.

[9] B. Fischer and J. Modersitzki. Combining landmark and intensity driven registrations. *PAMM*, 3:32–35, 2003.

[10] D. G. Gobbi, R. M. Comeau, and T. M. Peters. Ultrasound/mri overlay with image warping for neurosurgery. In *MICCAI '00: Proceedings of the Third International Conference on Medical Image Computing and Computer-Assisted Intervention*, pages 106–114, London, UK, 2000. Springer-Verlag.

[11] E Haber and J Modersitzki. Numerical solutions of volume preserving image registration. *Inverse Problems*, 20:1621–1638, 2004.

[12] E. Haber and J. Modersitzki. Intensity gradient based registration and fusion of multi-modal images. In C Barillot, DR Haynor, and P Hellier, editors, *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2006*, volume 3216, pages 591–598. Springer LNCS, 2006.

[13] E. Haber and J. Modersitzki. Image registration with guaranteed displacement regularity. *International Journal of Computer Vision*, 71:361–372, 2007.

[14] S. Henn, L. Hömke, and K. Witsch. Lesion preserving image registration with applications to human brains. In *Pattern Recognition, 26th DAGM Symposium*, volume 3175 of *Lecture Notes in Computer Science*, pages 143–154, 2004.

[15] H. Lang, A. Radtke, M. Hindennach, T. Schroeder, N. R. Fruhauf, M. Malago, H. Bourquain, H. O. Peitgen, K. J. Oldhafer, and C. E. Broelsch. Impact of virtual tumor resection and computer-assisted risk analysis on operation planning and intraoperative strategy in major hepatic resection. *Arch. Surg*, 140(7):629–638, 2005.

[16] T Lange, S Eulenstein, M Hünerbein, H Lamecker, and PM Schlag. Augmenting intraoperative 3d ultrasound with preoperative models for navigation in liver surgery. In C. Barillot, DR Haynor, and P Hellier, editors, *Medical Image Computing and Computer-Assisted Intervention*, volume 3217 of *LNCS*, pages 534–541. Springer, 2004.

[17] T. Lange, S. Eulenstein, M. Hünerbein, and P.M. Schlag. Vessel-based non-rigid registration of MR/CT and 3d ultrasound for navigation in liver surgery. *Comput Aided Surg*, 8(5):228–240, 2003.

[18] T Lange, H Lamecker, M Hünerbein, S Eulenstein, S Beller, and PM Schlag. A distance measure for non-rigid registration of geometrical models to intensity data. In H Lemke and et al., editors, *CARS*, volume 2 (Supple 1) of *International Journal of Computer Assisted Radiology and Surgery*, pages 204–206. Springer, 2007.

[19] D Loeckx, F Maes, D Vandermeulen, and P Suetens. Nonrigid image registration using free-form deformations with local rigidity constraint. In *Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, volume 3216 of *LNCS*, pages 639–646. Springer, 2004.

[20] K. E. Lunn, A. Hartov, F. E. Kennedy, M. I. Miga, D. W. Roberts, L. A. Platenik, and K. D. Paulsen. 3D ultrasound as sparse data for intraoperative brain deformation model. In M. F. Insana and K. K. Shung;, editors, *Medical Imaging 2001: Ultrasonic Imaging and Signal Processing*, volume 4325, pages 326–332, May 2001.

[21] J. Modersitzki. *Numerical Methods for Image Registration*. Oxford University Press Series, 2004.

[22] J Modersitzki. Image registration with local rigidity constraints. In *Bildverarbeitung für die Medizin*, pages 444–448, 2007.

[23] G. P. Penney, J. M. Blackall, M. S. Hamady, T. Sabharwal, A. Adam, and D. J. Hawkes. Registration of freehand 3d ultrasound and magnetic resonance liver images. *Med. Image Anal.*, 8(1):81–91, 2004.

[24] B.C. Porter, D.J. Rubens, J.G. Strang, J. Smith, S. Totterman, and K.J. Parker. Three-dimensional registration and fusion of ultrasound and mri using major vessels as fiducial markers. *IEEE Trans Med Imaging*, 20(4):354–359, 2001.

[25] I Reinertsen, M Descoteaux, K Siddiqi, and DL Collins. Validation of vessel-based registration for correction of brain shift. *Medical Image Analysis*, 11(4):374–388, 2007.

[26] I Reinertsen, F Lindseth, G Unsgaard, and DL Collins. Clinical validation of vessel-based registration for correction of brain-shift. *Medical Image Analysis*, In Press, 2007.

[27] A. Roche, X. Pennec, G. Malandain, and N. Ayache. Rigid registration of 3-d ultrasound with mr images: A new approach combining intensity and gradient information. *IEEE Trans Med Imaging*, 20(10):1038–1049, 2001.

[28] T. Rohlfing, Jr. C. R. Maurer, D. A. Bluemke, and M. A. Jacobs. Volume-preserving nonrigid registration of mr breast images using free-form deformation with an incompressibility constraint. *IEEE Trans Med Imaging*, 22(6):730–741, 2003.

[29] K. Rohr. *Landmark-Based Image Analysis*. Springer, 2001.

[30] H. Schuhmacher, A. Franz, and B. Fischer. Weighted medical image registration with automatic mask generation. In JM Reinhardt and JPW Pluim, editors, *SPIE Medical Imaging 2006: Image Processing*, volume 6144, pages 740–747, 2006.

[31] D. Selle, B. Preim, A. Schenk, and H. O. Peitgen. Analysis of vasculature for liver surgical planning. *IEEE Trans Med Imaging*, 21(11):1344–1357, 2002.

[32] P. J. Slomka, J. Mandel, D. Downey, and A. Fenster. Evaluation of voxel-based registration of 3-d power doppler ultrasound and 3-d magnetic resonance angiographic images of carotid arteries. *Ultrasound Med. Biol.*, 27(7):945–955, 2001.

[33] M Staring, S Klein, and JPW Pluim. Nonrigid registration using a rigidity constraint. In *SPIE Medical Imaging 2006: Image Processing*, volume 6144, pages 355–364, 2006.

[34] S. Wirtz, N. Papenberg, B. Fischer, and O. Schmitt. Robust and staining-invariant elastic registration of a series of images from histologic slices. In *Proc. of SPIE Vol. 5747 Medical Imaging 2005*, volume 5747, pages 1256–1262, 2005.

[35] Stefan Wörz and Karl Rohr. Hybrid spline-based elastic image registration using analytic solutions of the navier equation. In *Bildverarbeitung für die Medizin (BVM)*, Informatik Aktuell, pages 151–155. Springer, 2007.