THE ASSESSMENT OF MAGNETIC IMAGERY FOR COMPUTER ASSISTED SPINAL SURGERY

P. M. Tate* **and Dr. M. A. Chapman****
*The University of Calgary, Canada
Department of Geomatics Engineering
ptate@ucalgary.ca
**Ryerson Polytechnic, Canada
Department of Civil Engineering
mchapman@acs.ryerson.ca

KEY WORDS: medical, image registration, accuracy, photogrammetry, segmentation.

ABSTRACT

Introduction: In order to minimize radiation exposure to patients, surgeons are examining the use of magnetic resonance (MR) images for computer assisted spinal surgery. This paper will present a method for assessing the use and accuracy of magnetic resonance imaging (MRI) for computer assisted surgery of the spine. A secondary objective is to compare absolute orientation methods for use in the Iterative Closest Point (ICP) algorithm.
Methods: Titanium screws were placed in a cadaver spine, which was subsequently imaged using MRI, CT, and digital photos. The digital photos were processed using a photogrammetric bundle adjustment to establish ground truth. As a first approximation, registrations were performed using the nine titanium fiducials. A three dimensional model was formed from the CT images using the fully automatic Marching Cubes algorithm. A dense set of surface points were extracted from the surface of the MR after performing a correction for the non-linear attenuation. These images are to be registered using an iterative closest point algorithm. Accuracy is to be assessed using the magnitude and direction of the resulting residuals, as well as visual examination of fused CT and MR images.
Results: Registration using only titanium fiducials gave an RMS error of 2.90 mm for CT-MR registration. Further results on registration using the ICP algorithm are pending.

1 INTRODUCTION

Current production systems use X-ray CT scans for pre-operative planning and guidance of surgical instruments in computer assisted insertion of pedicle screws. The use of these systems has led to a dramatic reduction in misplaced pedicle screws by allowing surgeons to visualize hidden anatomy and track the positions of surgical instruments with precision. CT, however, exposes patients to potentially high levels of harmful radiation that could otherwise be avoided. Furthermore, patients generally undergo MRI scans as part of their diagnostic examinations. If a single scan mode could be used for both diagnosis and guidance of surgical instruments, hospital costs and patient waiting time could be reduced. It is for these reasons that surgeons at the Foothills hospital in Calgary asked us to assist them in examining the potential for MRI in computer assisted surgery of the spine.

The two primary factors limiting the use of MR for computer assisted spinal surgery are the poor radiometric and geometric properties of the images. While MR images soft tissues very well, MR images of bone are poor because bone does not generate any significant signal. Intensity values for bone are not unique across the image and may not even be unique across bone in the image. MR images are also subject to intensity inhomogeneities caused by a loss of signal strength for parts of the anatomy farther away from the detector. These properties make segmentation from bone in MR images problematic. In contrast, bone in CT images corresponds to the highest intensity values in the image with excellent contrast with the surrounding tissue. Thus, fully and semi-automatic threshold based methods work very well (Herring et al., 1998). Furthermore, geometrically, CT images are free of severe spatial distortion. MR images, however, are subject to non-linear distortions from various sources that in many cases cannot be corrected (Sumanaweera et al., 1994).

1.1 Magnetic Resonance image distortions

As mentioned previously, MR images are subject to several forms of geometric distortions, some of which may not be calibrated. Geometric distortions relevant to computer assisted spinal surgery are outlined here. For a complete discussion of causes of distortion see (Sumanaweera et al., 1994). With respect to computer assisted spinal surgery, the most serious errors are resonance offsets caused by chemical shifts and magnetic field inhomogeneities attributed to differences in the magnetic susceptibility of the materials being imaged.

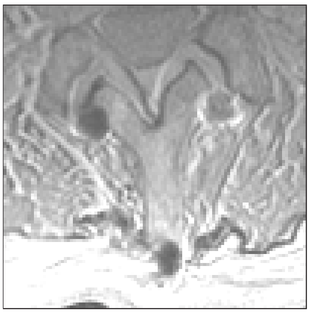

Figure 1: Voids created by titanium fiducials in T_1 MR scan

If 2D MR is used, spatial distortions are more serious as out of plane warping (the "potato chip" effect) and varying slice thickness (the "bow-tie" effect) can cause distortions as large as 2-4 mm. The magnitude of these distortions are relative to the voxel dimensions. By reducing the field of view, these distortions can be proportionally reduced. These distortions are not present in 3D MRI. (Sumanaweera et al., 1994)

Chemical shift artifacts are caused by differences in the way hydrogen is imaged in fat and water. Since hydrogen in water and fat resonate at different frequencies, and MR uses frequency to encode spatial information, MR interprets the frequency shift as a spatial difference causing fat/tissue interfaces to shift from their true locations along the frequency encoding direction of the image. The magnitude of this effect varies with the strength of magnetic field and the read-out bandwidth. Chemical shift artifacts are a serious problem for CASS as fatty areas occur close to the bone (Martel et al., 1998).

Magnetic susceptibility artifacts are also dependent of the shape and material of the object being imaged. Variations in the magnetic susceptibility of different materials causes variations in the magnetic field in the vicinity of that material. The resonant frequency of hydrogen is dependent on the strength of the magnetic field. This will cause a spatial shift in the frequency encoding direction at boundaries between two materials with different magnetic suceptibilities. The effect is greatest where magnetic susceptibility differences are greatest, such as at air/tissue boundaries, and should theoretically be minimal at bone/tissue boundaries. (Sumanaweera et al., 1994)

Correction methods for these distortions have been shown to significantly at improving registration (Dean, 1998), (Maurer et al., 1994), (Martel et al., 1998). However, correction methods suffer from long computation times and an increase of scanning time due to the need to acquire a second scan. Again, these effects are relative to voxel dimensions. Therefore, the absolute magnitude of these errors can be reduced by reducing the field of view.

As magnetic field inhomogeneities manifest themselves only in the frequency encoding (read-out) direction of the image, the direction of the residuals from the resulting registration will be examined in order to determine if the errors are from MR distortion or from other sources (such as errors in segmentation).

1.2 Description of the Data Sets

Prior to scanning, three titanium screws were placed in the spinous and transverse processes of three vertebrae of the lumbar spine to serve as fiducials in the registration process. Unfortunately, the fiducials imaged poorly and could not be localized sufficiently for an accuracy assessment of the MR images. Though titanium in a non-ferrous metal, it does affect the surrounding magnetic field and the titanium screws appear as "voids" in the images (see Figure 1).

Data sets were acquired of the five vertebrae of the lumbar spine from the cadaver using three different imaging devices. CT images were acquired with a General Electric CT scanner. Image resolution was 0.5 x 0.5 x 1 mm. The data set consisted of 82 images enclosing a volume of 256 x 256 x 246 mm. MR images were acquired with a GE Genesis Sigma scanner using T_1 and T_2 weighted 2D MR with a 1.5 Tesla magnetic field, and an image resolution of 0.625 x 0.625 x 3 mm. Each data set consisted of 76 images, enclosing a volume of 160 x 160 x 228 mm. The T_1 weighted data sets used a spin echo imaging sequence, 125 Hz/pixel read-out bandwidth, a flip angle of 90^0, a 9 ms echo time, and a 500 ms repetition time. The T_2 imaging sequence used a 244 Hz/pixel bandwidth, 90^0 flip angle, a 105 ms echo time, and a 5950 ms repetition time.

In addition, digital photos were taken of the spine exposing the nine fiducials using Kodak DCS420 and DC260 digital cameras. These images were processed using a photogrammetric bundle adjustment giving a root mean square (RMS) error of 0.36 mm for the screw head locations.

2 SEGMENTATION

2.1 Surface extraction in CT

The CT images were segmented using the fully automatic Marching Cubes algorithm as implemented by the freely available Visualization Toolkit (VTK) (Schroeder et al., 1992). The output of this algorithm is a triangulated surface. The algorithm uses an intensity value as its only input, and may be subject to partial volume effects due to tissue and bone simultaneously occupying a single voxel (Herring et al., 1998). To the authors knowledge, no comprehensive study has examined the effect on registration accuracy for spinal images.

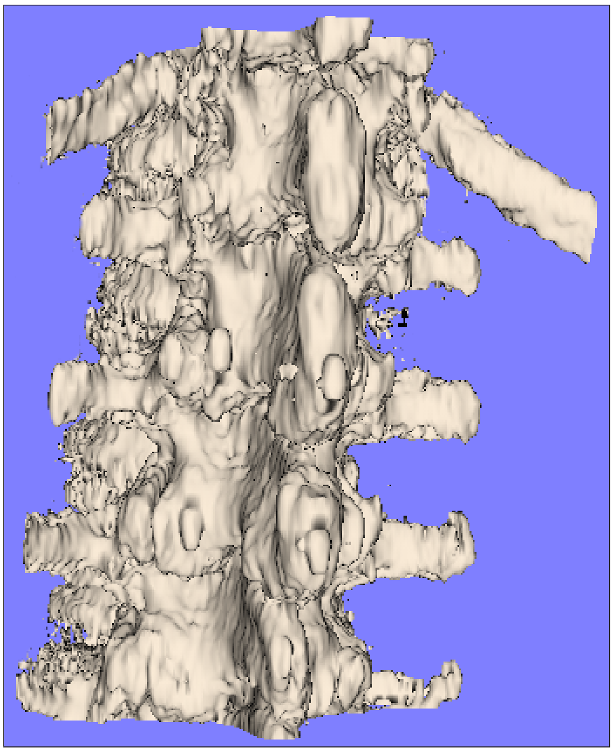

Figure 2: 3D model constructed from CT image Data

2.2 Non-linear attenuation correction in MR

Before a dense set of surface points could be extracted from the MR images, a correction had to be made to remove the non-linear attenuation distortion. The non-linear attenuation distortion is caused by an exponential decrease in signal strength as one moves away from the coil used to detect the magnetic signal. Parts of the anatomy that are closer to the detector generate a stronger signal than those farther away. While high level methods exist to perform this correction (see for example, (Wells et al., 1995)) most algorithms make assumptions about the tissue classes present in the image and require a pre-segmentation step for training the data. For our purposes, a very simple correction was performed to improve edge detection in the images. A scaling factor based on the distance from a horizontal line below the image was used to correct the attenuation:

$$g'(x, y) = S \cdot g(x, y) + y_0 \tag{1}$$

where $g(x, y)$ and $g'(x, y)$ are the original and corrected intensities, S is a scale factor, and y_0 is an offset term representing the line $y = y_0$. The scale and offset parameters were solved for using a least squares model where the minimization function was chosen to be:

$$\Sigma^2 = \| g'(x, y) - G \|^2 \tag{2}$$

where G represents the average intensity in the image. An attempt was made to use a radial distance from a point (x_0, y_0) to eliminate the darkening that appears in the corners of the image (see Figure 3). However the radial model was dominated by the Δx component of the radial distance and, in fact, degraded the image.

2.3 Surface point extraction

After attenuation correction, surface points from the MR images were extracted using an edge detection operator with manual correction.

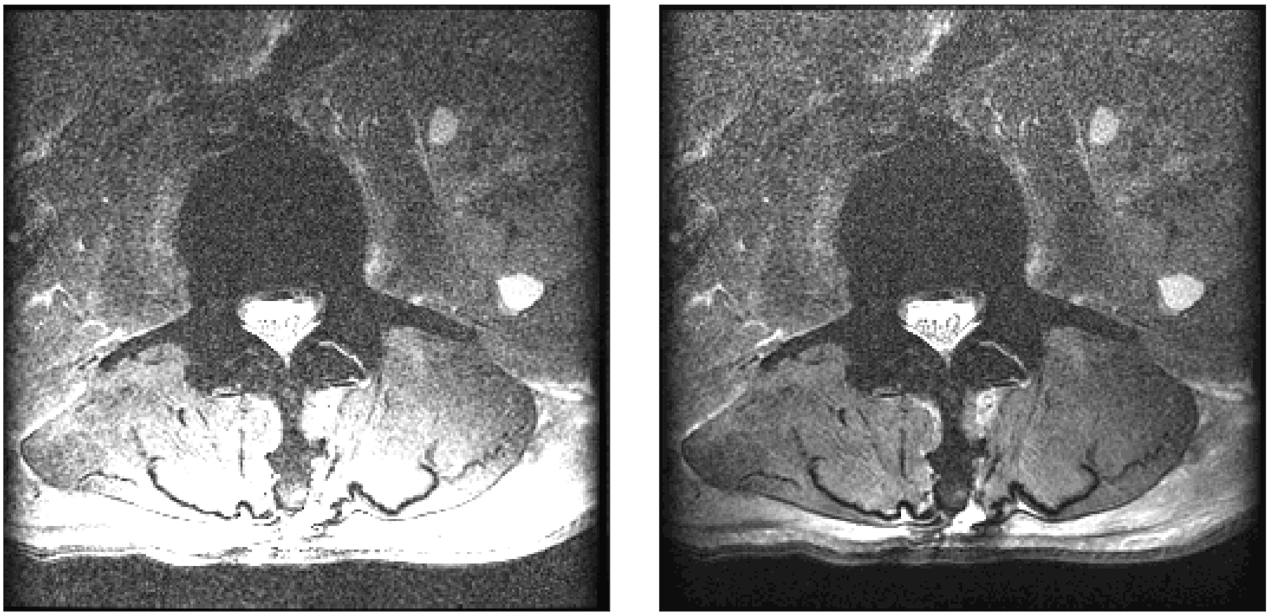

Figure 3: T_2 weighted MR image before and after attenuation correction.

3 REGISTRATION

Registration is the process of determining the spatial alignment between two modalities. Registrations can be extrinsic, based on implanted objects to serve as fiducials, or intrinsic, based solely on information generated by the patient's anatomy.

Initial registrations of the CT-MR, digital photos-CT, and digital photos-MR were performed using the absolute orientation methods described in Section 3.4. Due poor localization of the fiducials in the MR, and movement between different vertebrae between image acquisitions, the fiducials gave only an approximate solution to the registration problem. For a more accurate registration, the images were segmented and registered to one another using an independent implementation of the Iterative Closest Point (ICP) algorithm by Besl and McKay (Besl and McKay, 1992). The ICP algorithm is a popular method for performing surface based registration due to its simplicity, ease of implementation, and potential for optimization (Maintz and Viergever, 1998), (Simon et al., 1995), (Herring and Dawant, 1999).

3.1 Extrinsic registration

As a first approximation, a registration was performed using the nine titanium fiducials. CT-MR, digital photo-CT, and digital photo-MR registrations were performed using the absolute orientation methods described in Section 3.4 (all gave equivalent results). Registration using this method gave a CT-MR registration accuracy of only 2.90 mm, which is insufficient for this application. There are two causes for the large error. First, localization of the fiducials in the MR images were extremely difficult as the titanium screws were imaged poorly in the MR as demonstrated in Figure 1. Second, movement of the vertebrae relative to one another is possible, meaning that a rigid body registration of the three vertebrae is not appropriate. Therefore, a new method based on intrinsic registration of segmented data sets is being used.

3.2 Intrinsic registration

While gray level methods, such as correlation and mutual information methods, appear to be more accurate (Maintz and Viergever, 1998), a surface based registration method was chosen for several reasons. First, gray level methods are generally "full image content" methods (Maintz and Viergever, 1998), using information from outside the region of interest, which may be adversely affected by geometrical distortions (such as at the air/skin boundaries) (van den Elsen et al., 1994). Second, there lacks a gold standard in this study with which to compare our registration results and gray value methods do not give a quantitative indication of registration performance. Surface based methods give the average error, the distance between every point on the model and its corresponding closest point on the surface, as a byproduct of the registration procedure. Third, point matching methods such as the ICP algorithm are used in intra-operative surgical systems to register patients in surgical space to pre-operative models, and we would like to simulate as closely as possible intra-operative conditions. The primary disadvantage of segmentation-based methods is that the registration accuracy is limited to the accuracy of the segmentation step (Maintz and Viergever, 1998).

3.3 The Iterative Closest Point Algorithm

The goal in surface-based registration is to determine the best possible alignment between two corresponding modalities. The ICP algorithm is a general algorithm suitable for determining the pose between data set of many different representations. It works by decomposing one set (the "data") into a point set (unless it is already in point form) and estimates the pose between it and another set (the "model") which may consist of points, lines, polygons, or implicit surfaces. So long as a disparity function can be defined between a data point and a corresponding point on the model surface the solution will always converge to a minimum. This may or may not be the desired global minimum (Besl and McKay, 1992). The terminology "data" and "model" which is used in Besl and McKay's original paper, and comes from the algorithm's initial use in industrial applications. (Besl and McKay, 1992). The ICP algorithm solves the registration problem using the following algorithm:

1. For each data point p_i, find the closest point on the model, p'_i.
2. Compute the absolute orientation.
3. Transform the data points using the parameters found in 2.
4. Repeat until the difference between successive iterations is less than some stopping criteria τ.

The resulting transformation is the product of transformations computed at each iteration. In this study, the "data" set is defined as the set of points extracted from the surface of the vertebrae in the MR images. The "model" set is the triangulated surface extracted from the CT images. The disparity function is, therefore, defined as the shortest distance between a 3-D point and a triangle. In order to minimize the chance that the solution will fall into a local minimum, the parameters derived from the extrinsic registration are used as an initial approximate in the registration process. Because of the likelihood of motion between vertebrae, registration will be performed on individual vertebrae.

3.3.1 Finding the closest points. The most computationally expensive part of the algorithm is finding the corresponding closest points. While many optimizations are possible (Simon et al., 1995), only an improved search criteria to speed up computation time was used. Several useful properties of the model set can be used to our advantage. First, find the closest triangle vertex on the model surface. The triangle containing the closest point will be on a surface adjacent to this point (this is not strictly true, in degenerate cases this may not be the actual closest point, it has been demonstrated that this technique is valid 99.5% of the time and does not affect registration accuracy (Maurer et al., 1996)). The triangles adjacent to this vertex are then searched for the closest corresponding point.

3.4 Absolute orientation

The problem of estimating the pose between two corresponding 3-D point sets is called the "absolute orientation" problem in photogrammetry. The absolute orientation is the rigid body transformation (rotations and translations) that relates the positions in the data set to their corresponding positions in the model set. In this study, four different algorithms, each giving equivalent solutions were used and tested to determine the most appropriate for use with the ICP algorithm. Space precludes a complete discussion of the solutions and their derivations, interested readers are referred to the papers in question. Three closed form solutions were used. Horn's method (Horn et al., 1988) finds the best fit 3x3 orthonormal rotation matrix by decomposing the cross-correlation matrix of the two center of gravity reduced point sets into an orthogonal matrix and a positive definitive symmetric matrix (US reduction). The best fit orthonormal matrix is the transpose of the orthogonal matrix (U^t). A similar method derived by (Arun et al., 1987) using a singular value decomposition (SVD) of the cross-correlation matrix in Section 3.4.3. Both methods may give a reflection if the data is severely corrupted or coplanar. A third closed form method using unit quaternions to represent rotations was tested (Horn, 1987). The method uses eigenvalue/eigenvector decomposition of a 4x4 symmetric matrix to solve for the absolute orientation. Finally, an iterative solution was tested. The iterative solution used is the Space-M method (Blais, 1979). The method is typical of iterative methods familiar to photogrammetrists, based on the linearized least-squares solution of rotation. The method is very stable, however it may require many iterations to converge if an initial approximate is not provided. For small angles, the solution will often converge in one iteration.

While closed form solutions are desirable in many cases, computation time in the ICP algorithm could be reduced if the iterative solution converges in one or two iterations. In later iterations of the ICP algorithm, very slight refinements are made to the pose estimation.

3.4.1 Computing the absolute orientation. While iterative methods for computing the absolute orientation should be well known to most photogrmmetrists, the closed form solution using singular value decomposition is presented here without proof (Arun et al., 1987).

Given two 3-D point sets, $\{p, p'\}$, where p_i and p'_i are 3x1 columns vectors representing points in the data and model sets, we wish to estimate the rigid body transformation parameters between the two 3D point sets:

$$p'_i = Rp_i + T \tag{3}$$

We seek a solution for the 3x3 orthonormal rotation matrix R and the 3x1 translation vector T that minimizes:

$$\Sigma^2 = \sum_{i=1}^{N} \parallel p'_i - (Rp_i + T) \parallel^2 \tag{4}$$

3.4.2 Centroids of Measurements. By reducing the point sets to their centroids, we can decouple rotation and translation components:

$$r_i = p_i - \bar{p} \qquad \text{and} \qquad r'_i = p'_i - \bar{p}'$$

where $\bar{p}$ and $\bar{p}'$ represent the mean of point sets $\{p\}$ and $\{p'\}$ respectively. Now the least squares error function to minimize is dependent solely on the rotation R:

$$\Sigma^2 = \sum_{i=1}^{N} \parallel r'_i - (Rr_i) \parallel^2 \tag{5}$$

The optimal translation T is found by:

$$T = \bar{p}' - R\bar{p} \tag{6}$$

3.4.3 Singular Value Decomposition. The closed form solution of the rotation by singular value decomposition is presented here without proof. Calculate the cross-covariance matrix:

$$C = \sum_{i=1}^{N} r_i (r'_i)^t \tag{7}$$

where C is a square, positive semi-definite matrix. Find the SVD of C:

$$C = UDV^t \tag{8}$$

where U and V are 3x3 orthogonal matrices and D is a diagonal matrix with non-zero elements. The optimal rotation is given by:

$$R = VU^t \tag{9}$$

As noted in Section 3.4, both the SVD solution and Horn's method can give a reflection in degenerate cases. This has not been a problem in this study.

4 RESULTS

Final results are pending, however preliminary results based on registration of the titanium fiducials are presented in Table 1.

Modality	**RMS (mm)**
CT-MR	2.90
Digital Photos-CT	0.72
Digital Photos-MR	2.54

Table 1: Results from extrinsic registration of titanium fiducials.

Using the absolute orientation parameters derived from the CT-MR registration using the titanium fiducials, the MR images were resliced using a nearest neighbor interpolation. Contours were extracting from the CT images using the intensity of bone as the threshold value and overlain on the MR images to produce a fused (Figure 4).

Figure 4: MR image overlain with boundary extracted from CT.

5 DISCUSSION

In a previous study, Martel et al. performed phantom and cadaver studies to assess the suitability of using MRI for computer assisted surgery of the spine (Martel et al., 1998). They imaged a series of cadavers using CT, 2D and 3D MR, and performed image to patient registration using a 3D localizer. In their study they concluded that 2D MR images were not sufficiently accurate for computer assisted surgery of the spine. However, 3D MR images acquired using what they call a FLASH (Fast Low Angle SHot) imaging sequence generated images of sufficient accuracy.

Our study differs from theirs in several important ways. The resolution of our 2D MR images is higher than theirs (0.625 x 0.625 x 3 mm as opposed to 1 x 1 x 3 mm). Since the magnitude of chemical shift artifacts and magnetic field inhomogeneities are dependent on the resolution of the images, higher resolution images might be sufficiently accurate for computer assisted surgery of the spine. Their study used an extrinsic marker based system for registration with fiducials placed along the length of the spine while this study focuses on using anatomical fiducials.

6 ACKNOWLEDGEMENTS

We are grateful for the generous financial support for this project provided by the Whitaker Foundation and the NCE-GEOIDE network. The authors would also like to thank Dr. Richard Hu, Dr. Stephan J. Du Plessis and Dominic Young, our partners at Foothills Hospital in Calgary for their assistance in this project.

REFERENCES

Arun, K. S., Huang, T. S. and Blostein, S. D., 1987. Least-squares fitting of two 3-D point sets. IEEE Transactions on Pattern Analysis and Machine Intelligence 9(5), pp. 698–700.

Besl, P. J. and McKay, N. D., 1992. A method for registration of 3-D shapes. IEEE Transactions on Pattern Analysis and Machine Intelligence 14(2), pp. 239–256.

Blais, J. A. R., 1979. Least-squares block adjustment of stereoscopic models and error analysis. Technical Report 30001, The University of Calgary.

Dean, D., 1998. Validation of object-induced MR distortion correction for frameless stereotactic neurosurgery. IEEE Transactions on Medical Imaging 17(5), pp. 810–816.

Herring, J. L. and Dawant, B. M., 1999. Automatic identification of a particular vertebrae in the spinal column using surface-based registration. In: C. Taylor and A. Colchester (eds), Medical Image Computing and Computer-Assisted Intervention ’99 : Second International Conference, Lecture Notes in Computer Science, Vol. 1679, Springer-Verlag, pp. 613–620.

Herring, J. L., Dawant, B. M., Maurer, Jr, C. R., Muratore, D. M., Galloway, R. L. and Fitzpatrick, J. M., 1998. Surface-based registration of CT images to physical space for image-guided surgery of the spine: A sensitivity study. IEEE Transactions on Medical Imaging 17(5), pp. 743–752.

Horn, B., Hilden, H. M. and Negahdaripour, S., 1988. Closed form solution of absolute orientation using orthonormal matrices. Journal of the Optical Society America 5(7), pp. 1127–1135.

Horn, B. K. P., 1987. Closed form solution of absolute orientation using unit quaternions. Journal of the Optical Society of America 4(4), pp. 629–642.

Maintz, J. B. A. and Viergever, M. A., 1998. A survey of medical image registration. Medical Image Analysis 2(1), pp. 1–36.

Martel, A. L., Heid, O., Slomczykowski, M., Kerslake, R. and Nolte, L., 1998. Assessment of 3-dimensional magnetic resonance imaging fast low angle shot images for computer assisted spinal surgery. Computer Assisted Surgery 3, pp. 40–44.

Maurer, Jr, C. R., Aboutanos, G. B., Dawant, B. M., Gadamsetty, S., Margolin, R. A., Maciunas, R. J. and Fitzpatrick, J. M., 1994. Effect of geometrical distortion correction in MR on image registration accuracy. In: M. H. Loew (ed.), Medical Imaging 1994: Image Processing, Vol. 2167, SPIE, pp. 200–213.

Maurer, Jr, C. R., Aboutanos, G. B., Dawant, B. M., Maciunas, R. J. and Fitzpatrick, J. M., 1996. Registration of 3-D images using weighted geometrical features. IEEE Transactions on Medical Imaging 15(5), pp. 836–849.

Schroeder, W., Martin, K. and Lorensen, B., 1992. The Visualization Toolkit: An Object-Oriented Approach To 3D Graphics. Second edn, Prentice Hall.

Simon, D. A., Herbert, M. and Kanade, T., 1995. Techniques for fast and accurate intra-surgical registration. Journal of Image Guided Surgery 1(1), pp. 17–29.

Sumanaweera, T. S., Adler, Jr, J. R., Napel, S. and Glover, G. H., 1994. Characterization of spatial distortion in magnetic resonance imaging and its implication for stereotactic surgery. Neurosurgery 35(4), pp. 696–704.

van den Elsen, P. A., Pol, E.-J. D., Sumanaweera, T. S., Helmer, P. F., Napel, S. and Adler, J. R., 1994. Grey value correlation techniques used for automatic matching of CT and MR brain and spine images. In: R. A. Robb (ed.), Visualization in Biomedical Computing, Vol. 2359, SPIE, pp. 227–237.

Wells, W. M., Grimson, W. E. L., Kikinis, R. and Jolesz, F. A., 1995. Adaptive segmentation of MRI data. In: N. Ayache (ed.), Computer Vision, Virtual Reality and Robotics in Medicine - First International Conference, Lecture Notes in Computer Science, Vol. 905, Springer-Verlag, pp. 59–69.