

Part II

Registration

Chapter 6

Introduction

Registration is the process of matching one image to another through translation, rotation and scaling. When two or more image data sets are compared, analyzed or fused, some type of registration is inevitable.

The generation of a realistic 3D knee joint model, relies heavily on the accuracy and precision of the MRI and CT inter-modality registration. Malpositioning of bone and soft-tissue may lead to unrealistic force displacements in the subsequent finite element analysis.

Thus, after introducing the different registration methodologies in chapter 7, an extensive registration accuracy and precision study is presented in chapter 8. Finally in chapter 9 the previously acquired knee joint images are registered and the results discussed.

Chapter 7

Registration Methods

In general there are three registration types: point-based, surface-based, and intensity-based registration. This study primarily uses point-based and intensity-based registration.

Point-based registration was one of the first registration methods available. This method "best fits" a discrete number of points onto a second set of points, by solving the extended orthogonal procrustes problem further describe in subchapter [7.2.2.2](#). This is a non-iterative method based on a relatively small set of points. Therefore, it is a very time- and memory-friendly approach.

Typically this method, uses markers with a high intensity signal in the imaging device. In a later step, these "bright spots", also called fiducial markers, can easily be identified and extracted for use in the point-based registration of the images. Obviously, this method is limited to intra-subject scans, as the positioning of the fiducial markers is crucial for an accurate superimposition of the two images.

Intensity-based registration, on the other hand, is not restricted to a single modality. The underlying principle differs significantly from the point-based registration. Each image voxel contributes to finding the optimal transformation. Therefore, an increased processing time can be expected, but to the benefit of a higher registration accuracy.

For multi-modality registrations (e.g. registrations of CT and MR images), a direct comparison of the gray values in the image is not possible. As MRI and CT measure different tissue properties, their signal intensities (i.e. gray values) for the same tissue types will differ. This problem can be mostly eliminated using mutual information (MI), as explicitly described in subchapter [7.1.1](#).

In subchapter 7.1, the intensity-based registration and its components will be described. Subchapter 7.2.2 focuses on the fabrication of fiducial markers and, finally, the methods involved in point-based registration are presented in subchapter 7.2.2.

7.1 Intensity Based Registration

The intensity-based registration basically consists of four key processing steps, which are executed iteratively until one of the termination conditions is met. Figure 7.1 illustrates the steps involved.

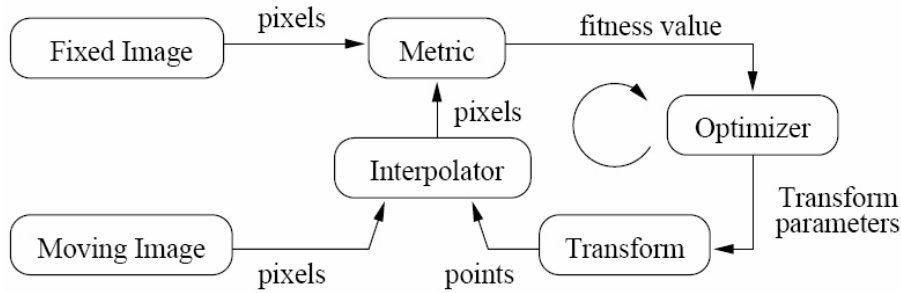


Figure 7.1: Flow chart with all the registration steps.

A fixed and moving image are entered into the loop. The fixed image is used as a reference, while as the moving image is transformed and overlaid on the fixed. This last step is performed by an interpolator which inputs seven transform parameters (i.e. 3 translation, 3 rotation and 1 scaling parameter) and applies them to the moving image. The metric evaluates how well the two images are aligned, and the fitness value is passed on to the optimizer which fine tunes the seven transform parameters. The interpolator again takes the transform values and applies them to the moving image. This loop is repeated until the registration converges or the maximum number of iterations is reached.

Each of these four registration components is explicitly described in the following subchapters.

7.1.1 Metrics

Image registration can also be described as trying to maximize the amount of shared information in two images. The most commonly used measure of information in the imaging field is the Shannon-Wiener [16] entropy H .

$$H = - \sum_i p_i \cdot \log(p_i) \quad (7.1)$$

where $p_1, p_2, \dots, p_i$ is the probability of a set of i symbols. Thus, the entropy will be maximized if all symbols have equal probabilities. Any change in the data that tends to equalize the probabilities of the symbols, increases the entropy.

Image registration attempts to align two images, image A to image B . Equation 7.2 returns the amount of information stored in the combined image AB .

$$H(A, B) = - \sum_a \sum_b p_{AB}(a, b) \cdot \log(p_{AB}(a, b)) \quad (7.2)$$

p_{AB} can be regarded as the joint probability distribution function (PDF) of images A and B . To quicken the registration, joint entropy is not calculated for all intensity values, but for a reduced number of intensity "bins". A common number of bins is 50, therefore the PDF contains 2^{50} by 2^{50} elements. The selected intensity bins are represented by a and b .

7.1.1.1 Mattes Mutual Information

For the registration of multi-modal images (i.e. CT to MR images or vice versa), a direct comparison of intensity values leads to misalignment. As mentioned earlier the intensity values of the same tissue types may differ between modes. One approach to solve this problem was introduced by Mattes.

$$I_M(A, B) = H(A) + H(B) - H(A, B) \quad (7.3)$$

The Mutual information $I_M(A, B)$ qualitatively describes how well one image explains the other, and has a maximum value at the optimal alignment.

7.1.1.2 Normalized Mattes Mutual Information

In overlapping regions with noisy and low intensities, an image transformation can overstate the mutual information given by equation 7.3. To overcome this problem, Maes et al. suggested to joint entropy normalization.

$$I_{NM}(A, B) = \frac{2 \cdot I_M(A, B)}{(H(A) + H(B))} \quad (7.4)$$

7.1.1.3 Viola-Wells Mutual Information

A third option to register inter-modality images is Viola-Wells metric [45], implemented in the SimilarityRegistration application. The Viola-Wells equation is given below.

$$I_{VW}(A, B) = h(A) + h(B) - h(A, B) \quad (7.5)$$

where the entropy is $h(i) \propto -\ln(p(i))$. This metric uses Parzen windows to estimate the probability density distributions $p(i)$ of the overlapping image regions.

The Viola-Wells metric is implemented in a separate application (AppSimilarityRegistrationFloatingPoint described in Appendix I.1.7), as this ITK-function only runs with normalized floating point data. The word-type change from short to float comes with a memory duplication. This may lead to memory shortage on standard workstations (Pentium 4, 3.4GHz, 2GB RAM), for already moderate image sizes.

7.1.2 Optimizer

The optimizer iteratively refines the seven transformation parameters until the optimal image fit is reached. With each iteration, the optimizer calculates the similarity measure based on the previous transform and makes another, hopefully better, estimation of the final transform.

Of numerous implementations, the gradient descent optimizer and the regular step gradient descent optimizer were used. Both methods set the new transformation guess in the direction of the gradient (derivative of the metric function). For the gradient descent optimizer, the transform step length, also known as the learning rate, is constant. On the other hand, the regular step gradient descent optimizer reduces the step length by a factor of two if there is an abrupt change in the gradient vector direction. Such a change usually indicates that the optimal values have been exceeded. The user defined minimum step length is used as a termination condition of the registration and, secondly, defines the accuracy of the final registration.

The biggest challenge for the optimizer is not to get "trapped" in local minima, which may occur due to noise, interpolation artifacts or local matches. To avoid such miss-registrations, very noisy or detailed images are pre-filtered using a Gaussian smoothing filter.

7.1.3 Interpolator

An interpolator effectively transforms the moving image by the transform parameters and adapts it from one image into the coordinates of the second.

Closest-point, B-spline and linear interpolation are only a few of the many possibilities. Moser and Kuhn [31] showed that the linear approach provides the best

trade-off between accuracy and time consumption.

In general, the linear interpolator only takes the neighboring voxels into consideration. It calculates the intensity of the new voxel (f_{new}) as a function of the distance, and gray level, of the intersecting voxels ($f_1, \dots, f_4$) in the moving image (see figure 7.2).

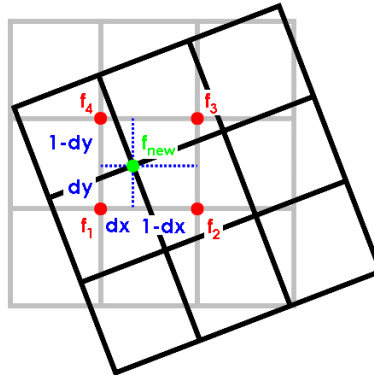


Figure 7.2: Principle of linear interpolation.

7.1.4 Multi-Resolution Registration

The processing time decreases significantly, if registration is first performed on a lower image resolution, followed by increasingly higher resolutions. This method is known under the name multi-resolution registration and was previously included in the registration code by Owoc [33].

Both, the fixed and moving images are scaled down by a factor of 2, 4, 8, ... in each axis direction, depending on the number of multi-resolution levels (see figure 7.3).

As the step size during the first iterations is relatively large, and the registration result inaccurate, it would waste computation time performing these steps on a high resolution level.

For small step lengths, the image resolution increases level by level. More detailed images help to increase the accuracy of the final registration result. However, scaling factors that are too high, will lose too much image information, whereas the registration result on the lowest level of the pyramid gets deteriorated. This mis-registration has to be corrected on a higher and more time-intensive level.

Several studies [27, 32] have shown that multi-resolution registration with a moderate number of 3 levels decreases the computation time by approximately 40%,

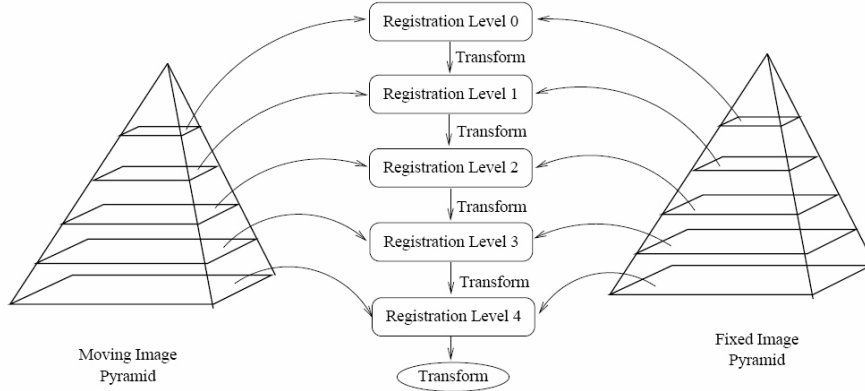


Figure 7.3: Multi-resolution registration pyramid.

returning qualitatively the same or even better registration results.

When the images are downsized, they are simultaneously smoothed due to voxel interpolation. This side-effect additionally helps the optimizer from getting trapped in local minima.

7.2 Fiducial Marker-Based Registration

Unlike image registration procedures that use information contained in the object being registered, the accuracy of fiducial based registration is largely independent of the registration object. This independence arises as the accuracy of the registration is determined, not by any characteristics of the registration object, but by the number, placement, and localization of the fiducial markers.

Especially in multi-modality registration, where the information content of the two images is significantly different, the fiducial markers might even increase the accuracy of the registration.

The fiducial marker manufacturing process and point-based registration algorithms are described in detail in the subchapters [7.2.1](#) to [7.2.2](#).

7.2.1 Fiducial Markers

7.2.1.1 Fabrication

The fiducial markers consist of four basic components: Agarouse gel, Optiray, plastic capillaries, and Parafilm.

First, 4 to 8 plastic capillaries from RAM Scientific [\[36\]](#), are cut to a length of

3.5mm and placed in a glass dish. The fiducials were first manufactured with glass capillaries, however the material properties of glass returned a high intensity signal in the CT scanner, but in the MR scanner, no signal could be detected. In order to prevent position errors in point-based registrations, it is crucial to calculate the centroid from the same volume of interest. Plastic capillaries on the other hand, return a low signal for both, CT and MRI.

In a second step, 5ml de-ionized water is heated to boil. Agarouse powder is added to get a 1% (wt/vol) solution. When the temperature of the solution dropped beneath 60°C, 0.5ml (10% vol/vol) Optiray contrast agent is mixed into the agarouse gel. Mallinckrodt Inc., the manufacturer of Optiray, guarantees that their product remains stable for temperatures below 60°C. Optiray is an iodine based contrast agent which can lead to distortions in the MR scanner due to its magnetic properties. Nevertheless, pre-tests have shown that no image artifacts occurred for Optiray solutions up to 10% (vol/vol).

The mixture, still placed on the hot-plate, is kept at a temperature slightly below 60°C. Approximately 1-2ml of the substrate is drawn into a syringe and immediately injected into the small plastic capillaries in the glass dish. The agarouse gel solidifies at a temperature of 30°C, requiring that the procedure is performed quickly. Care should be taken, to avoid air bubbles inside the plastic capillaries. A trapped air bubble results in a fiducial marker, unreliable for centroid detection in the two different scan methodologies.

The contrast agent filled fiducials are placed in the refrigerator (4°C) for 5 minutes until the solidification process of the agarouse gel is complete.

Afterward, any residual agarouse gel is removed from the cap tube ends. The capillaries are carefully wrapped in small slices of 1.5x1.5mm Parafilm, twisting the film ends (see figure 7.4).

Optiray is responsible for the necessary contrast in CT, where water returns a bright signal in MRI. Agarouse gel was added only to the water/Optiray solution since it turned out to be significantly easier to seal the fiducials, without trapping any air bubbles, if the capillary filling is a solid. Furthermore, the fiducial marker's quality and durability are notably improved.

The fiducials should be stored in the refrigerator when not in use, to prevent them from drying out.

7.2.1.2 Placement

At least three markers are necessary to define a three dimensional space. By adding a 4th marker the registration result can be improved by up to 15% [28].

If the fiducial markers are too small, the partial volume effect becomes high and the centroid of the fiducial may be shifted. A minimum number of 1'000 voxels



Figure 7.4: Fiducial markers wrapped tightly in Parafilm.

inside the fiducial marker is recommended [48]. Though, the general rule of thumb is: "the bigger the better".

To further improve the accuracy and precision of this method, the 4th marker should be placed off-plane and the distance between the fiducials maximized.

If the markers are too close to the region of interest (ROI), the high intensity signal might lead to shadowing effects in the CT scan. On the other hand, if the markers are placed too far apart from the ROI, the image size has to be increased to keep all the fiducials in the catch range. This uses up extra memory and scan time and can also slow the subsequent registration and segmentation processes.

It is best, to attach the fiducial markers on the surface of the sample, in the image corners, slightly off the ROI. This is illustrated by figure 7.5.

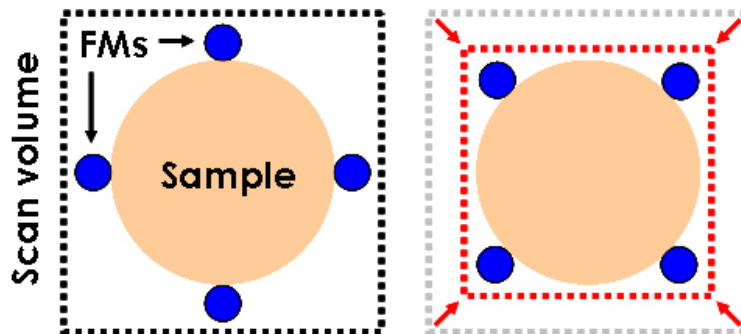


Figure 7.5: On the right the scan volume is only slightly extended, where as on the left, the scan volume is almost doubled.

7.2.2 Fiducial Registration

7.2.2.1 Intensity Weighted Centroid

Each fiducial marker must be reduced to a single point in order to calculate the point-based registration transform. In this case, it makes more sense to evaluate the intensity-weighted centroid of the fiducials. The equations beneath show a slightly adapted approach to the one presented by Wang et al. [47].

$$x_c = \sum_i (I_i \cdot x_i) / \sum_i (I_i) \quad (7.6)$$

$$y_c = \sum_i (I_i \cdot y_i) / \sum_i (I_i) \quad (7.7)$$

$$z_c = \sum_i (I_i \cdot z_i) / \sum_i (I_i) \quad (7.8)$$

The sums are taken over all voxels in the pre-segmented image. The point designated by (x_c, y_c, z_c) is the intensity-weighted centroid of the image. The value I_i is the intensity of voxel i and (x_i, y_i, z_i) are the coordinates of the center of voxel i .

7.2.2.2 Point Based Registration

The point-based registration inputs the previously calculated centroids of the fiducial markers and calculates the seven transformation parameters that minimize the mean square distance between corresponding fiducials in the two images.

The three rotation, three translation and scale factor were determined by solving the extended orthogonal procrustes problem (EOP) [8] first introduced by Schönemann (1966). The difference between the transformed matrix A and the fixed matrix B should be minimized.

$$c \cdot A \cdot R + j \cdot t^T - B = \min \quad (7.9)$$

where j is a unit vector with as many values N as centroids, c is the scale factor, R is the rotation matrix and t the translation vector. A partial derivation for each unknown (R, t, c) and a subsequent single value decomposition $\text{svd}\{\}$, returns the following results.

$$R = U \cdot V^T \quad (7.10)$$

$$c = \frac{\text{tr} \left\{ R^T \cdot A^T \cdot \left(j - \left(\frac{j}{N} \right) \right) \cdot B \right\}}{\text{tr} \left\{ A^T \cdot \left(j - \left(\frac{j}{N} \right) \right) \cdot A \right\}} \quad (7.11)$$

$$t = (B - c \cdot A \cdot R)^T \cdot \frac{j}{N} \quad (7.12)$$

where matrices U and V are single value decomposition components, J is an $N \times N$ unit matrix and $tr \{ \}$ is the trace of the enclosed matrix. The three rotation parameters are evaluated by calculating the versor of R in x, y and z direction.

The fiducial marker related error (FRE), better known as the root mean square (RMS), indicates how well the two sets of points match after the transformation is applied. The lower the value, the better the correlation.

$$FRE = RMS = \sum_{i=1}^N \| (c \cdot R \cdot B(i, :) + t) - A(i, :) \|^2 \quad (7.13)$$

Chapter 8

Accuracy and Precision

As for data acquisition, it is of great interest how accurately and precisely the raw data is registered. The result will provide an additional indication of, how close the final 3D knee joint models the "real" sample.

As mentioned in subchapter [7.2.1](#), fiducial markers are used to simplify the image registration process. To investigate, whether the point-based registration method performs as well as the intensity-weighted registration methods, a series of single- and multi-modal test registrations were made.

8.1 Method

Three CT and MRI scans of the phantom with four fiducial markers were acquired. Due to the phantom's highly defined geometries and rigidity, the images are expected to register almost perfectly with intensity-based registration methods. In this study, the Mattes Mutual Information metric with a linear interpolator, a regular step gradient descent optimizer and a 3-level pyramid registration method with a total of 300 iterations were used to receive the "gold standard" transformation parameters for all images.

For the intensity-based registration, the fiducial markers were excluded by roughly segmenting the CT image with the CUTOUT software [\[40\]](#). This step was necessary to avoid the fiducial markers from influencing the registration result [\[48\]](#).

On the other hand, for point-based registration, the fiducials were cut out and saved as separate AIM files. The FiducialMarkerRegistration application (see Appendix [I.1.8](#)) was specifically implemented to find the centroid of each fiducial and calculate the transformation parameters with the lowest fiducial registration error (*FRE*).

The same steps were repeated for the three MR images as well as the three multi-modal MRI/CT phantom scans.

Especially in multi-modality registrations, the metric value is almost leveled over the whole image area and local minima and maxima strongly influence the registration result. Therefore, the sum of the squared differences s_T of the transform parameters t_i was calculated as a second accuracy and precision reference value.

$$s_T = \sum_{i=1}^7 (t_i - \tilde{t}_i)^2 \quad (8.1)$$

$\tilde{t}_i$ are the transform parameters of the Mattes mutual information based registration with the best metric value.

To further investigate the accuracy and precision of intensity-based registrations, the initial guess parameters of one selected image pair were steadily increased by an offset of 0.002 to 0.032 for each parameter.

A second test registration set identified the changes in accuracy and precision, for transformation parameters randomly changed by an average offset of 0.008 for each initial guess.

An offset of 0.008 is a good approximation of the transformation parameter variation, provided the initial guess is manually evaluated using the "pick point" method implemented in VIS and SHAPE (see Appendix I.2.5).

Two additional implemented metrics (Normalized Mutual Information and Viola-Wells Mutual Information) have also been tested for their registration accuracy and precision. The registration protocol used, can be found on the enclosed DVD.

Unless stated otherwise, the point-based registration transforms were used as an initial guess for the intensity-weighted registrations.

8.2 Results

In tables E.1 and E.2 the difference in metric values and sum of the squared final transform parameters are listed for both, intensity-based Mattes mutual information registration methods and fiducial marker based registration.

The registration result with the best metric value, was subsequently used as the "gold standard" registration, and is shown in figure 8.1. For comparison, the best point-based registration result is depicted in figure 8.2.

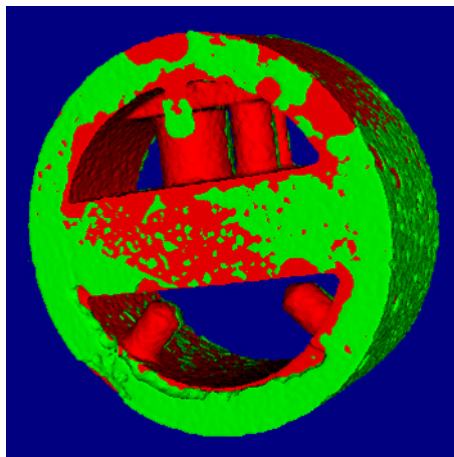


Figure 8.1: "Gold standard" registration based on Mattes mutual information.

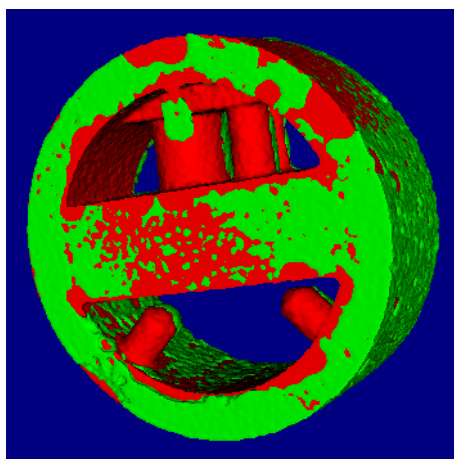


Figure 8.2: Best registration result based on fiducial markers.

In figures 8.3 and 8.4 the accuracy and precision results have been visualized for a better understanding.

Figure 8.5 illustrate the behavior of the Mattes mutual information registration, for an offset that is steadily increased (see also table E.3).

Finally the values for the best transform with the normalized mutual information metric and the Viola-Wells metric are shown in figures figures 8.6 and 8.7.

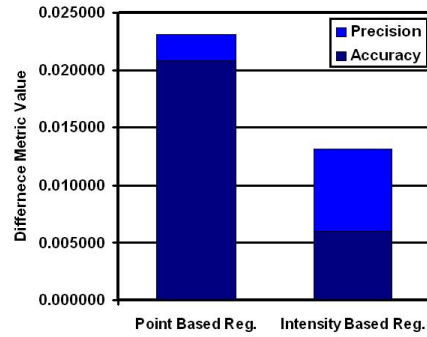


Figure 8.3: Metric value accuracy and precision of the intensity- and fiducial marker-based registration method.

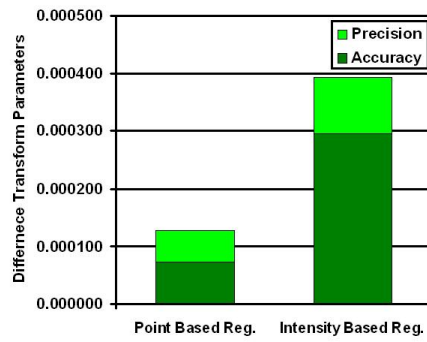


Figure 8.4: Transform parameter accuracy and precision of the intensity- and fiducial marker-based registration method.

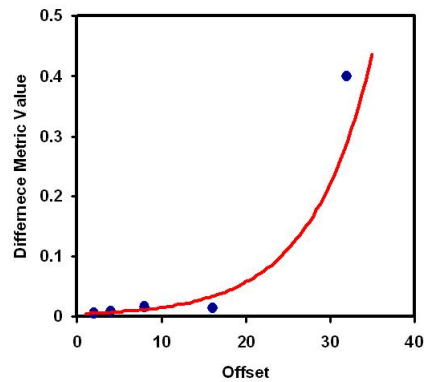


Figure 8.5: Exponential loss of accuracy for an increase in the initial guess offset.

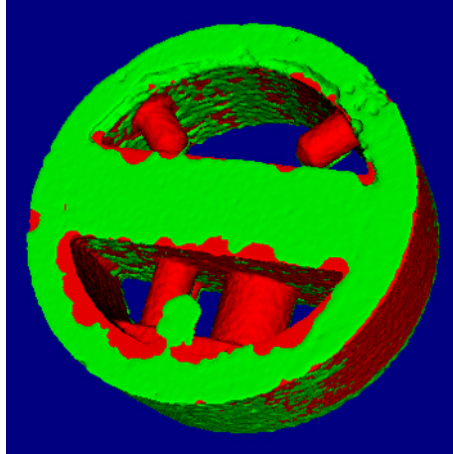


Figure 8.6: Best registration result based on normalized Mattes mutual information.

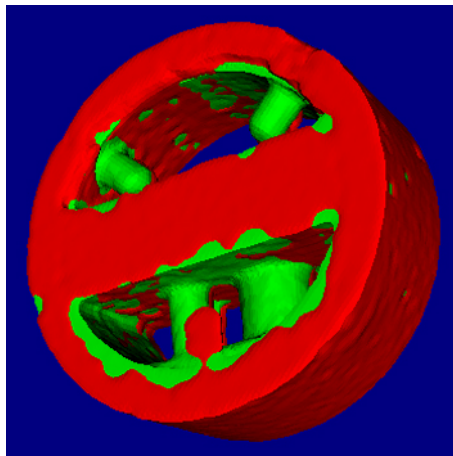


Figure 8.7: Best registration result based on Viola-Wells mutual information.

8.3 Discussion

Based on the metric value results presented in tables E.1 and E.2, intensity based-registration is more accurate than point-based registration. "MRL02_C0002504_INT" was the registration with the best metric value and was used as the "gold standard" transformation throughout the whole accuracy and precision study.

Comparing the transformation parameter accuracy and precision values, the point-based registration lies closer to the "gold standard" value and has the lower variations (see figure 8.4).

This indicates that the intensity-based registration gets easily trapped in local minima where the metric value is close to the "gold standard" value.

Thus, a fiducial marker independent intensity based registration is most probably less accurate and precise than a fiducial marker based registration. However, if the registration result of the point-based registration is used as an initial guess for the intensity-weighted registration method, the final transform parameters can be optimized. A combination of the two methods leads to the best results.

Comparing the intra-modality measures (see table E.4), the almost perfect match of the CT/CT intensity and fiducial marker-based registrations stand out. The potential high performance of the fiducial marker-based registration is again demonstrated with a mean metric difference of 0.69% between the two registration methods.

Slightly larger variations were obtained with the MR images. The reason for this behavior may lie in the lower resolution of the MR scan and in the big distortions, caused by the air/water interface of trapped air bubbles in the phantom. The multi-modal registration may also be negatively influenced by the severe distortions in the MR images.

Due to a noticeable leakage of most of the fiducial markers, the obtained MRI/MRI and CT/MRI point based registration results are less accurate and precise than they could be. The CT scans were hardly effected by this leakage problem, as scan-times were much shorter (25 minutes each) and were acquired the same day as the fiducial markers were made. The MR images were acquired the following morning. Each scan lasted for 65 minutes.

The leakage problem was mostly resolved by using a 1% (wt/vol) agarouse gel instead of pure water. Fiducial markers manufactured as described in subchapter 7.2.1.1 remained leakage free for at least two weeks.

No significant difference is noticeable, if the point-based and intensity-based results are compared visually in figure 8.1 and 8.2.

The main advantages and disadvantages of the fiducial marker based and the intensity-based registration are briefly outlined:

Fiducial marker-based registration

- ⊕ **High speed:** Point-based registration is very fast. An image of 1024x1024x512 voxels is registered in less than 1 minute.
- ⊕ **Memory friendly:** Little memory is required. Therefore large images with a high resolution can be registered without running out of memory.
- ⊕ **Highly accurate and precise:** This is valid as long as all critical preconditions are met (see subchapter 7.2.1).
- ⊖ **Changes:** It is crucial that shape and position of the fiducial do not change during, or between, scans. Any changes lead to miss-registration.
- ⊖ **Compatibility:** For fiducial markers used in multi-modal imaging, all components must be MRI and CT compatible and should return a high intensity signal.
- ⊖ **Applicability:** The fiducial marker based registration is only applicable to intra-subject registrations. Time series or inter-subject registrations cannot be registered with this method.
- ⊖ **Fabrication:** The use of the point based registration requires extra work, to fabricate the fiducials. For experienced users, thirty minutes should be sufficient to manufacture up to 8 fiducial markers. The significant time saved in registration process makes this manufacture worthwhile.

Intensity-based registration

- ⊕ **Highly accurate and precise:** Under the right conditions (registration parameters, initial guess), the intensity based registration returns the most accurate results.
- ⊕ **Applicability:** This method is not limited by modality. The registration is based on image content (intensity values) and therefore always leads to a result.
- ⊖ **Memory intensive:** For images with 128x128x128 voxels a standard PC with 1GB of RAM runs out of memory. In this case, the computer starts memory swapping and the registration time explodes literally.

- ⊖ **Time intensive:** A 3-level Mattes mutual information registration with two data sets of 4MB (MRI) and 12MB (CT) respectively, required 30 minutes. Both data sets were compressed by a factor of 8. Thus, for one single uncompressed registration, a computation time of 4 hours would be needed.

The initial guess of an intensity-based registration is supposed to be as close as possible to the final transform. This not only speeds up the registration time, but also increases the probability of finding the absolute minima. The Mattes MI intra-modality registration with a regular step gradient descent optimizer still converges for an angle offset of 10 degrees, and a position offset of 10% (as experimentally evaluated by R. Göcke [35]). Figure 8.5 shows an exponential registration failure for an absolute offset larger than 0.165% and 0.915 degrees respectively.

Normalized Mattes MI and the Viola-Wells MI registrations are very time consuming methods. Processing times over 3 hours for data sets of 1.5 (MRI) and 12MB (CT) respectively were required for a Pentium 4, 3.4GHz PC with 2GB of RAM.

The MR, as well as the CT image, had to be reduced in size to keep the registration time within a tolerable range. Despite this information loss, figure 8.6 illustrates the high quality of the normalized Mattes MI registration.

The image alignment with the Viola-Wells metric failed in two of the three test registrations. This may be due to the too small number of samples (10%) used in the registration. The sample number is further limited by an upper absolute boundary of 5'000 samples. If the image size on one of the registration levels exceeds 50'000 voxels, the number of samples is kept constant at 5'000. For 5'000 samples, 1 iteration takes approximately 1 minute.

Due to the considerably higher registration times for no visible improvement in the accuracy of the alignment, these two methods are not practical for the registration of 3D multi-modal images.

Chapter 9

Sample Registration

Based on the findings of chapter 8, a fiducial marker registration with additional transform parameter "fine tuning" using the intensity-based Mattes MI method, was thought to be best for aligning the MR and CT knee joint images.

9.1 Method

The first step was to cut out the fiducial markers and save them as separate AIM files. Especially for MR images, the intensity values were relatively unevenly distributed around the fiducials. As the intensity weighted centroid function calculates the center point based on all voxels in the image, the fiducial marker centroid was shifted due to the background distortions. Figure 9.1 (left) illustrates such a center point shift in an MR image.

The images need to be thresholded to eliminate these background distortions. The same filter as for the drilling hole thickness measurements (described in subchapter 4.3.1) has been used. The opening and closing filter removed the final remaining residues in the background.

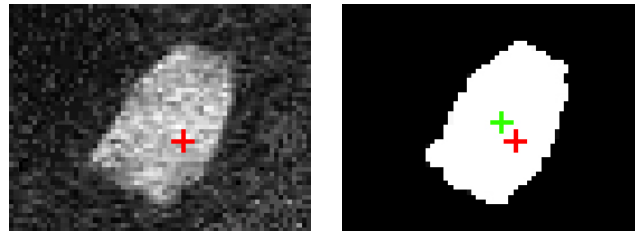


Figure 9.1: Left: Unfiltered sub-image of fiducial marker with centroid shift (red). Right: Filtered sub-image with accurate centroid (green).

The intensity-weighted centroid filter is applied to return an accurate approximation of the fiducial center point as depicted in figure 9.1 (right).

All the following processing steps are identical to the method described in subchapter 8.1.

9.2 Results

Unfortunately, the MRI dataset with contrast agent unfortunately moved during or between the scans. Therefore, neither the point-based nor intensity-based registrations were applicable on the whole image. Figure 9.2 shows the change in angle between the femur and the tibia in the MRI respective to the CT image.

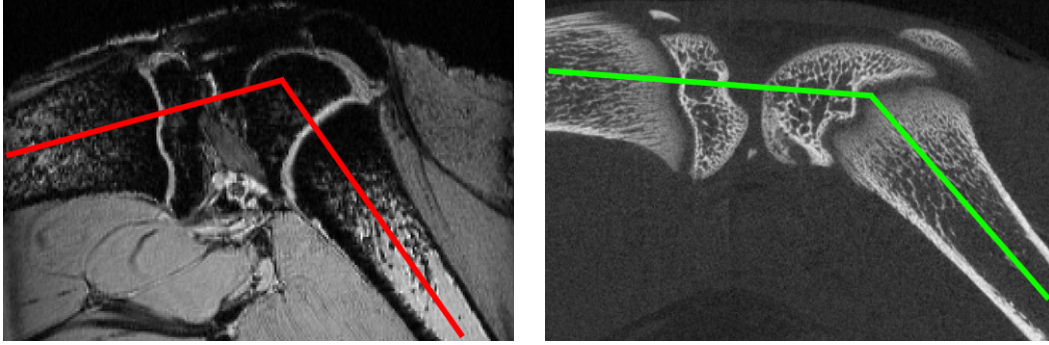


Figure 9.2: Change in angel between MRI (left) and CT (right) scanned knee joint.

As a proof of concept, the MR image without contrast agent was registered to the corresponding CT image. The point-based and intensity-based registration results are illustrated in checkerboard images 9.3 left and right.

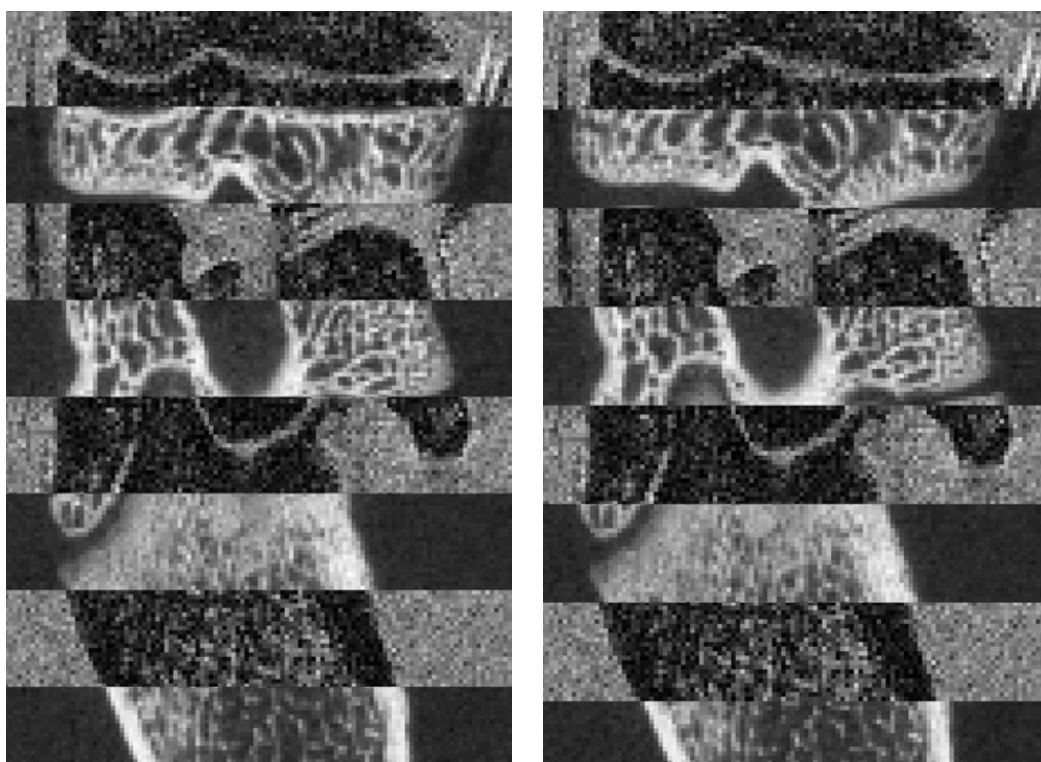


Figure 9.3: Fiducial marker- (left) and intensity-based (right) registered image without MRI contrast agent.

9.3 Discussion

The checkerboard images 9.3 left and right clearly show successful and appropriate multi-modality registration results for both alignment methods.

Unfortunately the contrast agent soaked knee joint moved between the MRI and following CT scan. Consequently, the two data sets could not be registered to one another. The CT image had to be split into an upper and lower half, separating the femur and patella from the tibia and fibula. These two separate CT images could then be accurately registered to the original MRI dataset.

The movement occurred due to a loose fixture of the knee joint in the sample holder. No movement will occur if the sample is wrapped tightly in Parafilm. Though, in this case, the natural shape of the soft-tissue will not be preserved (see figure 9.4). A possible solution to avoid this trade-off will be presented in the Outlook.

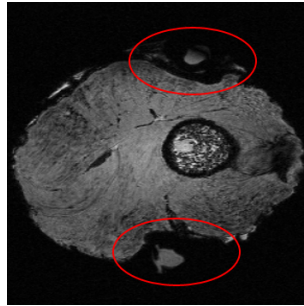


Figure 9.4: MR image with undesirable fiducial marker imprints.

Furthermore, the four fiducial markers left imprints on the surface of the soft-tissue, which negatively influence the natural appearance of the knee muscle structures.

Nevertheless, the fiducial markers were found to be indispensable for multi-modality registration. Without the fiducials, no initial transformation guess can be made. This is due to the partially inversed intensities of the same tissue types in MR and CT images. The pick point functions in VIS and SHAPE can only pick points on an intensity-thresholded marching cube surface. In MR images, muscles are brighter than bone, whereas in CT images, the opposite is true. Therefore, there is no way to visualize the same tissue iso-surfaces in two images of different modalities.