Group-wise Feature-based Registration of CT and Ultrasound Images of Spine

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ABSTRACT

Registration of pre-operative CT and freehand intra-operative ultrasound of lumbar spine could aid surgeons in the spinal needle injection which is a common procedure for pain management. Patients are always in a supine position during the CT scan, and in the prone or sitting position during the intervention. This leads to a difference in the spinal curvature between the two imaging modalities, which means a single rigid registration cannot be used for all of the lumbar vertebrae. In this work, a method for group-wise registration of pre-operative CT and intra-operative freehand 2-D ultrasound images of the lumbar spine is presented. The approach utilizes a point-based registration technique based on the unscented Kalman filter, taking as input segmented vertebrae surfaces in both CT and ultrasound data. Ultrasound images are automatically segmented using a dynamic programming approach, while the CT images are semi-automatically segmented using thresholding. Since the curvature of the spine is different between the pre-operative and the intra-operative data, the registration approach is designed to simultaneously align individual groups of points segmented from each vertebra in the two imaging modalities. A biomechanical model is used to constrain the vertebrae transformation parameters during the registration and to ensure convergence. The mean target registration error achieved for individual vertebrae on five spine phantoms generated from CT data of patients, is 2.47 mm with standard deviation of 1.14 mm.

Keywords: UKF-based registration, group-wise registration, ultrasound

1. INTRODUCTION

Percutaneous spinal needle injection is a common procedure for pain management. This procedure is normally guided by fluoroscopic imaging to direct the needle to the targeted injection site, such as a facet joint. To minimize both patient and surgeon exposure to ionizing X-ray radiation and to improve the accuracy of needle targeting, the use of intra-operative ultrasound imaging has been proposed.[1,2] However, interpreting intra-operative ultrasound images is challenging due to overlapping bone segments and the effects of shadowing, especially in the lumbar spine area. It would therefore be desirable to augment the information in ultrasound images with those of another pre-operative imaging modality such as CT or MRI, for enhanced intra-operative guidance.

Many research groups have contributed to registration of ultrasound to CT images of the bones.[1–4] Brendel *et al.* propose a surface to volume registration approach. They extract the visible bone surface, along the direction of the ultrasound imaging probe, from the CT data and register it to the ultrasound image volume. Simplex optimization is used to maximize the average gray level of all ultrasound voxels covered by the segmented bone

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surface points from CT.[4] Recently, the same approach has been applied to the lumbar spine using different evolutionary and gradient-based optimizers.[3]

Penney *et al.* use a volume-to-volume registration scheme where bone probability values are generated from the CT intensity and gradient, and the CT and tracked ultrasound volumes are rigidly registered.[2] Barrat *et al.* manually segment bone surfaces from US images and minimize the distance between these surface points and the segmented CT surface.[1] Using the same approach, they also register a statistical deformation model (SDM) of the femur and pelvis bones to ultrasound.[5]

Surface-based registration has been commonly used in medical image registration. The main challenge in bone surface registration of US to CT is the proper segmentation of ultrasound images. Amin *et al.* use a modified ICP algorithm in order to register the bone surface extracted from CT and ultrasound.[6] Ultrasound points which can be potentially bone surface are extracted and a probability value is assigned to them based on the US intensity, their distance to CT surface and the result of a directional edge filter applied to the ultrasound images. The optimization is done regarding the probability value. Chan *et al.* also use ICP to match corresponding points to the bone surface of femur derived from ultrasound with a statistical bone surface model.[7]

Unscented Kalman Filter(UKF)-based registration has been proposed by Moghari and Abolmaesumi.[8] In this approach, an UKF is applied to estimate the rigid transformation parameters for the registration of two point sets when correspondences are not known. A comparison of UKF- and ICP- based registration of two point sets segmented automatically from CT and ultrasound images of the spine is presented by Talib *et al.*[9] Peterhans *et al.* extend this work to register extracted points from ultrasound to a CT surface. Instead of performing the registration on whole ultrasound and CT points, the registration parameters are updated with each newly acquired ultrasound frame.[10] In addition, using the approach proposed by Penney *et al.*,[1] ultrasound calibration parameters are jointly estimated with the rigid transformation parameters. (Moghari and Abolmaesumi also use a group-wise UKF-based registration approach to globally register multiple 3D point sets collected from fractured bones[11]).

Except the work by Moghari and Abolmaesumi,[11] all the above approaches address a single-body rigid registration problem and do not consider multi-body registration scenarios, where the changes in patient posture exist between pre-operative and intra-operative data such as the case with spine. Our research group has previously proposed several multi-body registration methods.[11,12] Specifically, Gill *et al.* use a group-wise intensity-based method to register vertebrae in CT and ultrasound.[12] Individual rigid transformation parameters are considered for each vertebra. The registration part is an extension of the work done by Wein *et al.*[13] In each iteration of registration, an ultrasound volume is simulated using CT intensity and gradient information. Simulated ultrasound and intra-operative ultrasound images are then registered using the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) optimizer.[3]

In this work we present a group-wise feature-based approach for registration of pre-operative CT and intra-operative freehand 2-D ultrasound images of the lumbar spine. To compensate for the changes in the spine curvature between pre-operative CT and intra-operative ultrasound data, the group-wise UKF-based registration method proposed by Moghari and Abolmaesumi[11] is modified to rigidly and simultaneously register each vertebra using a group-wise registration approach. A biomechanical model is also used to constrain the vertebrae motion during the registration process. The proposed approach is less computationally-intensive than the one by Gill *et al.*[12] and therefore, more suitable for real-time applications. The only drawback of the surface-based registration with respect to a volume-based one is the time consumption on ultrasound segmentation.[12] The drawback can be alleviated by using a fast ultrasound segmentation algorithm such as the one proposed by Foroughi et al.[14]

2. METHODS

Initial experiments were carried out on five lumbar spine phantoms. The phantoms were created by segmenting the surface points of the L1 to L5 vertebrae from the CT data of five patients and generating a 3D physical model of lumbar vertebrae using a Dimension SST 3D printer (Stratasys, Inc., Eden Prairie, MN, USA). The natural curvature of the spine is maintained between the patient CT and the printed model. The printed vertebrae were glued in a plastic container and filled with an agar/geletin mixture. CT-visible fiducial markers were then placed on various locations on the outside of the phantoms container and the phantoms were CT scanned at high

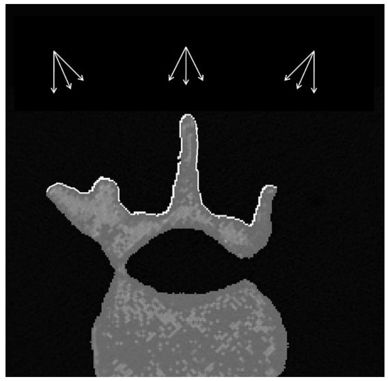


Figure 1: CT surface points are segmented using thresholding. Sound propagation direction are shown by arrows. Segmented points are highlighted.

resolution (0.46 mm × 0.46 mm × 0.625 mm). Prior to collecting a freehand ultrasound scan of the phantoms, the location of the fiducial markers were determined using an optically tracked pointer and a Certus camera system (Northern Digital Inc., Waterloo, Ontario). Ultrasound images of the phantom were then acquired using a Sonix RP ultrasound machine (Ultrasonix Medical Corp., Richmond, Canada) with a linear-array transducer, operating at 6.6 MHz with depth of 5.5 cm. The probe was calibrated using an N-wire US phantom and tracked by the Certus system. The CT data was collected at Kingston General Hospital and the patients provided informed consent to participate in the research.

In our approach, the spine surface was reconstructed from segmented ultrasound frames and the tracking information. Additionally, the CT bone surface was segmented from the volume using thresholding. Surfaces extracted from CT and ultrasound were then registered using the group-wise UKF-based registration.

2.1 Data Preprocessing

Ultrasound frames were first segmented using a dynamic programming approach proposed by Foroughi *et al.*[14] This approach initially enhances the appearance of the bone surface in the ultrasound image using image intensity and shadow information. Next, dynamic programming is employed to minimize a cost function. Existence of the bone in the image and its location is determined in this cost function.

To segment the CT images, the vertebrae surface points that are relevant for the registration, are segmented in a semiautomatic procedure. First, the whole volume is segmented manually to separate vertebra from each other. Then each vertebra is segmented using thresholding. Threshold is chosen manually and points with intensity over threshold are considered to be bone. Segmented points are those bone surface points that lie on the vertebrae. Only the part of the vertebrae surface facing the ultrasound probe are used in the registration process. In our research the ultrasound transducer is moved from dorsal over the spinous processes. Thus, by having an axial slice of the CT volume, the ultrasound beam propagation can be modeled by the posterior-anterior view (Figure 1). To extract all possible visible CT points, several sources of ultrasound are placed in the CT axial slices.

2.2 UKF-based Registration

UKF-based surface registration utilizes Unscented Transform to estimate the registration transformation parameters.[8] The following cost function is minimized during the registration:

$$C_{(R,t)} = \sum_{i=1}^{N} (y_i - Ru_i - t)^T (\Sigma_i)^{-1} (y_i - Ru_i - t). \tag{1}$$

The UKF optimizer is used to find the least squares solution for the rotation matrix R and the translation vector t that minimize the cost function given the following equations:

$$\begin{aligned} x_i &= f(x_{i-1}, n_{i-1}^x) \\ y_i &= h(x_i, n_i^y), \end{aligned} \tag{2}$$

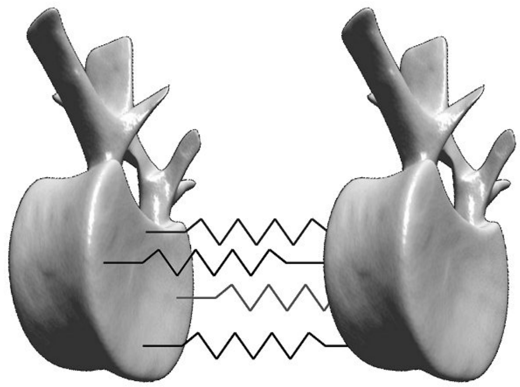


Figure 2: Spring model to constraint the vertebrae motion during the registration process

where f and h are nonlinear functions, y_i is the observation model, and x_i is the state vector. Having the observation vector and noise distributions, the UKF estimates the state vector in a recursive procedure.

The state vector represents the rigid transformation parameters consisting of the Euler angles and translations: $[\alpha, \beta, \gamma, t_x, t_y, t_z]^T$. In the ith iteration of the registration, $u_{1:i}$ and $y_{1:i}$ are used as the moving and fixed point sets, respectively. The function $h(x_i, n_i^y)$, transforms the moving points perturbed by noise n_i^y by the transformation x_i. The observation vector y_i contains the fixed point set. A detailed description of the algorithm can be found in the work of Moghari and Abolmaesumi[8]

2.3 Group-wise Registration

A group-wise UKF-based registration approach has been used by Moghari and Abolmaesumi to globally register multiple 3D point sets collected from fractured bones.[11] Taking a similar approach for the lumbar vertebrae ultrasound to CT registration is reasonable. CT scans of the lumbar spine are usually collected in a supine position whereas spinal interventions are performed in prone or sitting positions. This leads to a difference in the spine curvature between the two different imaging modalities; as such, a single-body rigid registration approach cannot be used for the whole lumbar vertebrae. To overcome this problem, we propose to employ a group-wise UKF-based registration approach.

Assuming, there are n_v vertebrae in the lumbar spine, the main idea is to have individual rigid registration parameters for each vertebra. However, since the motion of adjacent vertebrae are not independent of each other, we employ a biomechanical model based on springs. This model connects neighboring vertebrae to constrain the general spine motion during the registration (Figure 2). The springs obey Hookes law, which states that the force with which the spring pushes back is linearly proportional to the distance from its equilibrium length:

$$F = -k\Delta x \tag{3}$$

To integrate this biomechanical model with the UKF-based registration scheme, the cost function explained in Equation (1) is modified as follows:

$$C_{(R,t)} = \sum_{i=1}^{N} (y_i - Ru_i - t)^T (\Sigma_i)^{-1} (y_i - Ru_i - t) + \sum_{i=1}^{N_s} \omega \Delta s_i \tag{4}$$

where Δs_i stands for the length change of spring i and N_s is the number of springs. The spring constant, ω, is set to be equal for all springs.

Furthermore, the UKF-based registration is modified into a group-wise framework for the lumbar spine. The state vector as suggested by Moghari and Abolmaesumi[11] is extended as follows:

$$\begin{aligned} x &= [t_x^1, t_y^1, t_z^1, \theta_x^1, \theta_y^1, \theta_z^1, \ldots, t_x^{n_v}, t_y^{n_v}, t_z^{n_v}, \theta_x^{n_v}, \theta_y^{n_v}, \theta_z^{n_v}]^T \\ &= [{x_t^1}^T, {x_\theta^1}^T, \ldots, {x_t^{n_v}}^T, {x_\theta^{n_v}}^T]^T. \end{aligned} \tag{5}$$

The spring lengths are computed at each iteration. The current lengths are appended to the estimated observation model. The equilibrium length is also appended to the observation model. It can preserve the cost function explained in Equation (4).

2.4 Outlier Removal

Ultrasound segmentation usually produces many outliers. By including the outliers in registration, the process may converge to a local minimum. Barrat *et al.*[1] suggest an approach to improve registration by removing outliers. In their work, Firstly, a conventional rigid-body registration is performed. Next, outliers are automatically removed by transforming the ultrasound points using the updated registration transformation, and removing 10% of the points furthest from the CT bone surface. Once outliers have been removed, a second rigid-body registration is performed using the remaining ultrasound points. Using a similar approach, after each iteration of the registration, outliers are automatically removed based on their distance to CT surface. Assume $d_{j,k}$ to be the jth moving point distance to its nearest point from the fixed points in iteration k. A weighted average of distances during the registration is taken:

$$\tilde{d}_j = \frac{\sum_{k=1}^{i} w_k \log(d_{j,k})}{\sum_{k=1}^{i} w_k}, \tag{6}$$

where w_k is the weighting factor and is supposed to be higher for higher iterations. In our experiment they are computed using a linear function of k (iteration number). In addition, $\log(d_{j,k})$ shows better result than $d_{j,k}$ itself. In each iteration, the following condition will lead to remove outlier:

$$\text{if } \tilde{d}_j > \log(d_{thr}) \text{ then remove point } j \quad j = 1 \ldots i. \tag{7}$$

3. RESULTS AND DISCUSSION

Registration was performed on a Dell Optiplex GX280, with 3 GHz Intel Pentium 4 CPU and 3 GB RAM. An example of the registration results is shown in Figure 3. To evaluate the registration algorithm, the data collected from each spine phantoms were registered 100 times. The acceptable registration Target Registration Error (TRE)[15] is set to 3 mm; this is deemed as an acceptable accuracy for facet joint interventions.[10] To simulate the difference in spine curvature between CT and ultrasound images, the CT volume for each vertebra were perturbed individually using translation and rotation parameters drawn randomly within ±5 mm and ±5 degrees using a uniform distribution. Another global perturbation was also applied to the CT data to simulate the displacement between pre-operative and intra-operative data. The global transformation includes translation and rotation parameters drawn randomly within ±7 mm and ±7 degrees.

TRE was calculated based on the bounding box of each vertebra. This error represents the worse case scenario since the facet joint, the injection target in this research, is close to the middle of the bounding box and will have lower errors compared to the bounding box. The results for each vertebra and patient can be found in Table 1. Registered vertebrae have a mean TRE of 2.47 mm with standard deviation of 1.4 mm. Table 2 provides the percentage of registration failures in the registration. Cases where TRE is greater than 3 mm are considered as failure. As can be seen in Table 1, the results vary among vertebrae. L3 which is the middle vertebra, is registered with less failure. The extremity vertebrae (L1 and L5) have more failure. This can be explained by their freedom in movement. To compute the TRE for the entire volume, average TRE over the L1 to L5 is calculated. In 12% of cases, the entire volume registration is failed. Results for each vertebra and the entire volume registration are depicted in Figures 3a to 3f. The algorthm is implemented in MATLAB; the mean run time for registration is 14 minutes.

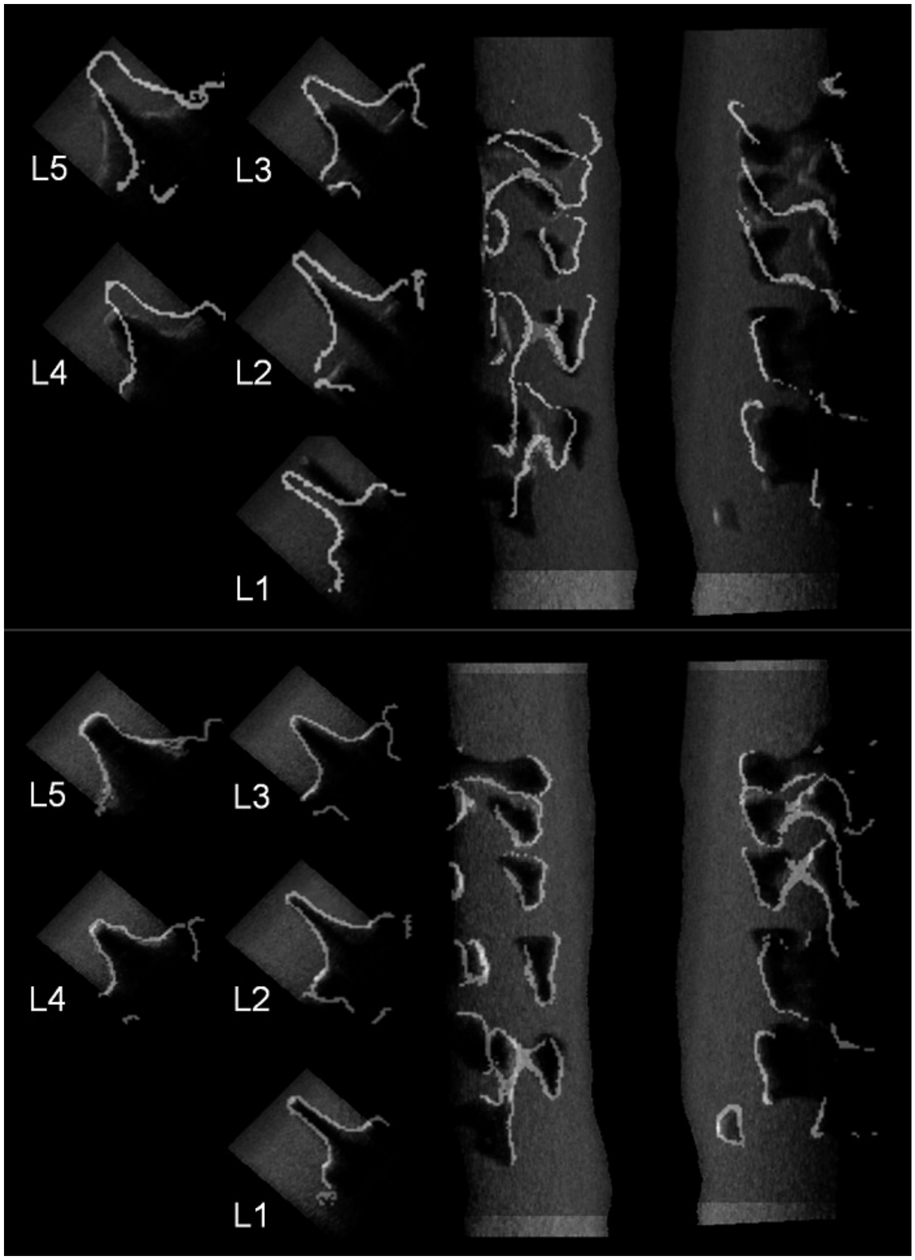
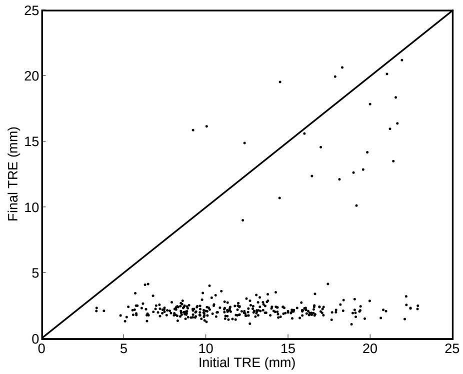
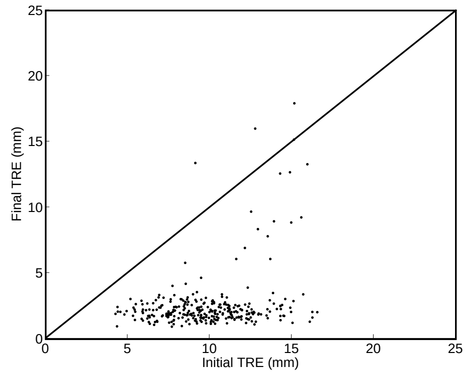


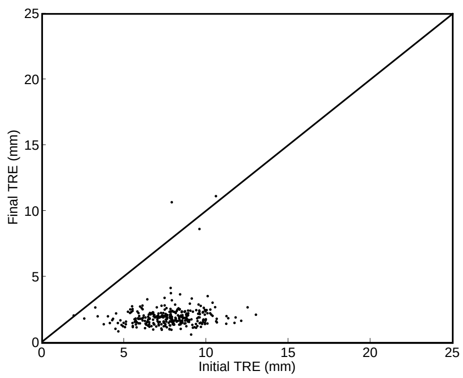
Figure 3: An example of registration: On the top the initial alignment of ultrasound and CT points are depicted. The final alignment after registration is shown at the bottom.



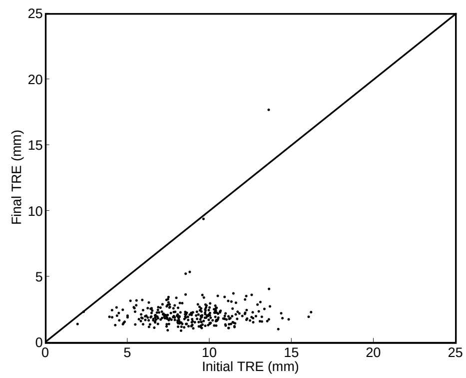
(a) L1 vertebra



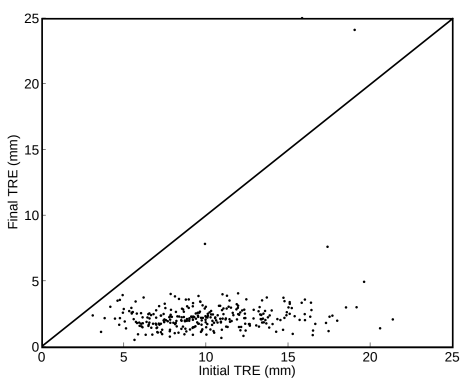
(b) L2 vertebra



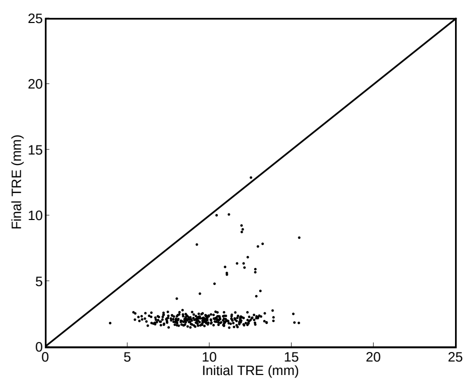
(c) L3 vertebra



(d) L4 vertebra



(e) L5 vertebra



(f) whole body

Figure 4: Results for group-wise registration of three lumbar spine phantoms. The final TRE is plotted against the initial TRE for L1 to L5 in (a) to (e) and for the entire volume in (f).

Table 1: TREs for group-wise registration for 100 registration trials on each phantom. $\mathrm{TRE}_{\mathrm{L}_i}$ are TRE for ith vertebrae. $\mathrm{TRE}_{\mathrm{total}}$ is from averaging over all vertebrae TRE.

Patient	$\mathrm{TRE}_{\mathrm{L}_1}$	$\mathrm{TRE}_{\mathrm{L}_2}$	$\mathrm{TRE}_{\mathrm{L}_3}$	$\mathrm{TRE}_{\mathrm{L}_4}$	$\mathrm{TRE}_{\mathrm{L}_5}$	$\mathrm{TRE}_{\mathrm{Total}}$
1	2.21 ± 0.7	2.08 ± 0.8	1.77 ± 0.5	1.50 ± 0.5	1.73 ± 1.5	1.86 ± 0.4
2	3.03 ± 4.1	2.25 ± 2.2	2.62 ± 1.2	3.28 ± 0.8	4.94 ± 1.1	3.23 ± 2.4
3	2.67 ± 1.9	2.31 ± 1.8	1.88 ± 1.3	1.73 ± 0.6	1.61 ± 0.5	2.04 ± 1.4
4	3.27 ± 4.0	2.33 ± 1.4	1.88 ± 0.4	2.28 ± 0.5	2.83 ± 2.3	2.52 ± 2.2
5	3.58 ± 4.5	2.90 ± 3.0	2.06 ± 0.8	2.37 ± 1.8	2.70 ± 2.3	2.72 ± 2.8
All	2.95 ± 3.4	2.37 ± 2.0	2.04 ± 1.0	2.23 ± 1.1	2.76 ± 2.1	2.47 ± 1.4

Table 2: Failure percentage in group-wise registration. Result are provided from 100 trials on each patient. TREs greater than 3 mm are considered as failure. To compute the whole body registration failure, $\mathrm{TRE}_{\mathrm{E}}$ is considered.

Patient	L1	L2	L3	L4	L5	whole body
1	18%	8%	1%	3%	2%	1%
2	14%	10%	22%	63%	100%	34%
3	8%	9%	4%	4%	2%	4%
4	12%	10%	2%	9%	31%	10%
5	20%	15%	5%	13%	13%	10%
All	14%	10%	7%	18%	30%	12%

4. CONCLUSION AND FUTURE WORK

A group-wise, UKF-based registration is proposed in combination with a biomechanical model, to register CT to ultrasound images of the lumbar spine. Individual transformation parameters are considered for each vertebra, while the biomechanical model is used to constrain the vertebrae motion during registration. The group-wise framework is used to overcome differences in spine curvature between the CT and ultrasound acquisition poses. The proposed algorithm is successfully tested on data collected from five spine phantoms. In each trial the CT volume of each vertebra is individually misaligned within ±5 mm and ±5 degrees. The algorithm is able to register misalignments in individual vertebrae of up to an initial TRE of 9 mm. Although the range capture of our registration algorithm is not improved with respect to similar work done by Gill *et al*,[12] the run time is significantly less.

The ultimate aim of this work is to provide a framework for real-time ultrasound-guided navigation for percutaneous spinal injections. The current methods usually suffer from slowness or less accuracy. Future work will mainly focus on decreasing the run time using parallel processing techniques in graphics hardware.

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