Biomechanically Constrained Groupwise Statistical Shape Model to Ultrasound Registration of the Lumbar Spine

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Abstract. Spinal needle injections for back pain management are frequently carried out in hospitals and radiological clinics. Currently, these procedures are performed under fluoroscopy or CT guidance in specialized interventional radiology facilities. As an alternative, the use of inexpensive ultrasound image guidance promises to reduce the costs and increase the availability and safety of procedure. We propose to eliminate the need for ionizing radiation by creating a statistical shape model of the lumbar vertebrae and registering it to 3D ultrasound volumes of patient using a groupwise registration algorithm. From a total of 35 patient CT volumes, statistical shape models of the L2, L3 and L4 vertebrae are created, including the mean shapes and principal modes of variation. The statistical shape models are simultaneously registered to the 3D ultrasound by interchangeably optimizing the model parameters and their relative poses. We also use a biomechanical model to constrain the relative motion of the individual vertebra models throughout the registration process. The proposed method was validated on three phantoms with realistic spinal curvatures.

1 Introduction

Facet joint injection, a common percutaneous spinal injection procedure for pain management, requires an experienced physician to deliver the anesthetics to the target area. Contemporary approach to needle guidance with CT and fluoroscopy necessitates specialized facilities often unavailable to patients living in rural areas, and involves X-ray radiation. In contrast to CT and fluoroscopy, ultrasound (US) guidance has been considered, which is an accessible, portable, and non-ionizing imaging modality. For facet joint injections, Watson *et al.* [13] and Klocke *et al.* [9] targeted the L2-L3 and L3-L4 interspaces, a challenging procedure that, if performed inaccurately, damages the spinal cord. The results presented in both papers suggest that US as a mono-modal guidance is inadequate. To address this issue, the combination of US with CT has been proposed in an inter-modality registration framework [5,10,15].

Accurate registration of US and CT images has proven to be a challenging problem because of the low Signal to Noise Ratio (SNR) of US images and the

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presence of artifacts. Hence, most of the existing algorithms preprocess either of the modalities to reduce the artifacts and to increase the similarity between the images. Recently, Wein *et al.* [14] proposed to dynamically simulate US images from CT data using the physical properties of ultrasound. The simulated image is updated throughout the registration process until a correct alignment is achieved between the US and CT.

Many groups have considered Statistical Shape Models (SSMs) [2] as an alternative to preoperative CT scans [1,3]. In this framework, prior knowledge of the anatomy is introduced through the SSM, which removes the need for CT scans. Talib *et al.* [11] investigated the feasibility of US registration to SSMs of the femur. Barratt *et al.* [1] and Foroughi *et al.* [3] built SSMs for the femur and pelvis, which are subsequently repositioned and deformed to fit a cloud of bone surface points extracted from a set of tracked US images. All the above approaches require preprocessing of US data to highlight the location of bone surface. Previously, we demonstrated the feasibility of US registration to SSM of a single vertebra [8] without the need for prior segmentation of US images.

For facet joint injections, using SSMs to guide the intervention is ideal, as normally, preoperative CTs are not available. As facet joints are located at the intersection of two vertebrae, SSM of more than one vertebra has to be registered to US images. In addition, the significant occlusion of adjacent vertebrae in US data makes the single SSM to US registration approach challenging. To alleviate this problem, we propose the first report of the simultaneous registration of multiple vertebrae SSMs to US. The extension of the problem from single SSM [8] to multiple SSMs is nontrivial, as the number of parameters to be optimized grows exponentially with the addition of each SSM. To constrain the possible solutions for the registration problem, we incorporate a biomechanical model of spine motion [4]. In phantom experiments, we demonstrate improved registration results and higher success rates in comparison to the single SSM registration approach [8].

2 Methodology

2.1 CT Data Collection

The CT data were collected at a local hospital under the approval of the Research Ethics Board. A set of CT images, acquired from 38 patients (19 male and 19 female), was used where the L2, L3 and L4 vertebrae were semi-automatically segmented using ITK-Snap [16] and resampled into $120 \times 200 \times 100$ voxels with an isotropic spacing of 0.6 mm. The patient data was divided into two groups: 35 for constructing the SSM (hereafter referred to as training data), and three for validation (two male and one female).

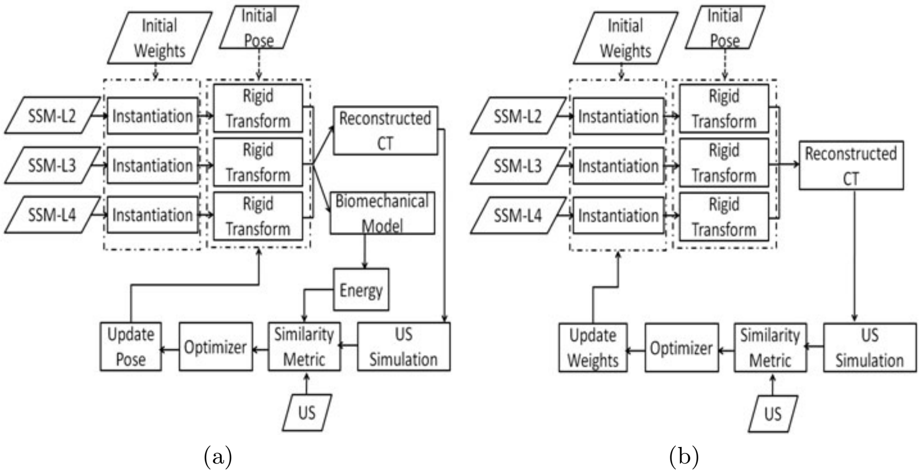

Fig. 1. Detailed description of the (a) rigid and (b) deformable registration blocks for groupwise registration

2.2 Statistical Shape Model Construction

To construct the SSM for each vertebra, we use the approach we have proposed previously [8]. For each SSM, a patient CT volume close to the mean shape of the population is chosen as the template. Each training example is registered to the template by a rigid registration followed by a B-spline deformable registration. With the deformable transformation of all the training examples known with respect to the template, principal component analysis (PCA) is performed to construct the SSM.

Individual vertebra SSMs are used to generate new instances of the population. Each instance is produced by a linear combination of the mean deformation vector, SSM weights, and the eigenvectors of the covariance matrix generated from all the deformation fields. The SSM weights provide a compact description of the transformation needed to deform the mean shape into the shape of the new instance. In our case the first 12 eigenvectors cover 95% of variations in shape for each vertebra.

2.3 Groupwise Registration

This section describes the SSM to US registration method for the L2, L3 and L4 vertebrae. The registration problem is solved in two steps: first rigid and then deformable. At the rigid stage, starting from 18 random initial rigid parameters (six for each vertebra, i.e. the pose) and zero SSM weights, the algorithm solves for the optimal rigid parameters. Subsequently, at the deformable stage, the algorithm finds 36 optimal deformable parameters (12 for each vertebra, i.e. the SSM weights). Using the updated rigid and deformable parameters, the algorithm iterates through the rigid and deformable phases until convergence is achieved. For optimization, Covariance Matrix Adaptation Evolution Strategy (CMA-ES) is used as optimizer because it yields convergence in a irregular search space [15]. Decoupling the problem into rigid and deformable registration phases, not only decreases the complexity of the problem, but also allows for a faster convergence by decreasing the population size of the CMA-ES optimizer.

The rigid registration phase is shown in Figure 1(a). First, we set the initial SSM weights to zero, and generate an instance of each of the L2, L3 and L4 vertebrae. Then, using a random initial rigid transformation, each generated instance is perturbed to an initial pose. After the rigid transformations are applied, the instances are reconstructed into a single volume. For any overlapping voxels, the maximum intensity is selected, thus preserving bone structure. Any gaps in the final volume are filled with a default value approximating the intensity of soft tissue in CT. Then, a ray-casting based ultrasound simulation is applied to the reconstructed volume. Assuming that the Hounsfield units can be related to the acoustic impedance values used to calculate ultrasound transmission and reflection, each ultrasound beam is modelled as a ray passing down the columns of the image [14]. Next, the Linear Correlation of Linear Combination (LC^2) metric is calculated and is fused with a biomechanical model to produce the final similarity measure. This similarity measure is fed to the CMA-ES optimizer until all of rigid parameters converge. A similar approach is employed for the groupwise deformable registration phase, as shown in Figure 1(b). The registration iterates between deformable and rigid phases until the correct pose and shape of the SSMs are found.

2.4 Biomechanical Model

For multiple SSM to US registration, the search space of the parameters to be optimized is relatively large, making convergence to a global minimum challenging. In addition, allowing free motion of the vertebrae during the course of the groupwise registration may result in anatomically unrealistic alignments where the vertebrae are in invalid orientations, colliding or far apart. In order to constrain the space of possible registration outcomes, a biomechanical model [5] is employed. Using a stiffness matrix, this model constrains the vertebrae to a common rotational orientation with no translation perpendicular to the sagittal and coronal planes. The total energy of the system, E, is calculated for all the vertebrae and normalized with respect to the maximum misalignment energy that is generated by 10 mm translation along the axes and 10 degrees about each axis. This normalized energy is incorporated in the computation of the image similarity metric, Biomechanically Constrained Linear Correlation of Linear Combinations ($BCLC^2$):

$$BCLC^2 = LC^2 - \sigma E \tag{1}$$

where σ is a constant that determines the contribution of the biomechanical model. In our case, we used a value of 0.75, previously found to be optimum in terms of registration success rate [5].

3 Experiments and Results

3.1 Ultrasound Data Acquisition

As mentioned in subsection 2.1, we excluded three CT volumes from the patient data for validation. We constructed 3D models of L1 to L5 vertebrae of these patients and printed them using a Cimetrix 3D shape printer (Cimetrix Solutions, Oshawa, ON, Canada). Three spine phantoms were constructed by submerging the models in an agar-gelatine-based gel. A high-resolution CT image ($0.46 \times 0.46 \times 0.625$ mm) and an ultrasound volume were acquired from each phantom from a freehand sweep using a tracked L14-5/38 linear-array transducer and a Sonix RP ultrasound machine (Ultrasonix, Richmond, BC, Canada) operating at 6.6 MHz with an imaging depth of 5.5 cm. Nine fiducial markers, mounted on the exterior of the phantom box, were localized with a tracked pointer and transformed to US space. The CT and ultrasound volumes were aligned using these markers.

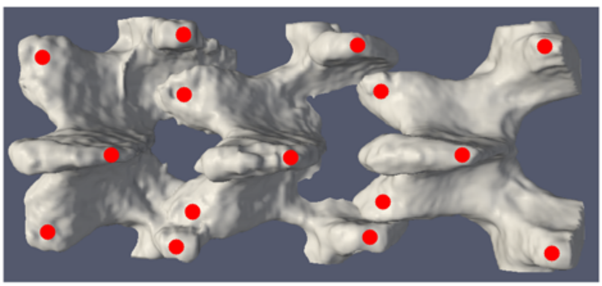

Fig. 2. The red circles mark the position of the surgeon-selected landmarks on the surface of the vertebrae

3.2 Results

The SSMs of the L2, L3 and L4 were brought to an initial pose by a rigid registration between the mean instance and the corresponding phantom CT volume. Then the groupwise SSM to US registration was performed. For each phantom, a total of 30 experiments were performed starting from a random position and orientation about the initial pose. This random perturbation was generated using a uniform distribution in the [0,10] mm translation along each anatomical axis and $[0,10]^\circ$ rotation about each axis.

An expert orthopaedic surgeon was asked to identify 15 anatomical landmarks on the surface of the superior and inferior articular process of each vertebra on the registered SSM, the ultrasound and the corresponding CT volume, as illustrated in Figure 2. The average distance of the five landmarks on the registered SSM and the corresponding CT was chosen as a measure of the final Target Registration Error (TRE), as it was harder for the physician to establish correspondence between the US and the registered SSM. The groupwise registration

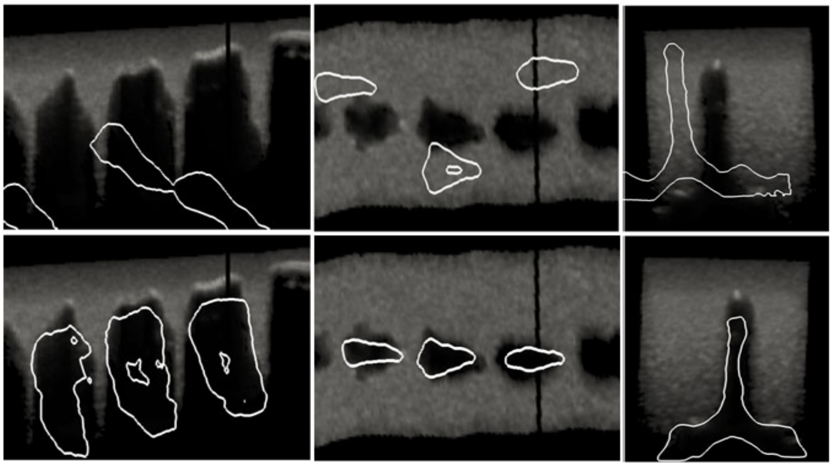

Fig. 3. Transverse (left), coronal (center), and sagittal (right) slices of the original ultrasound volume overlayed with the bone contours of the misaligned (top) and groupwise registered (bottom) SSM volumes

is considered to be successful, only if the final TRE for each vertebra was less than 3.0 mm, a clinically acceptable error tolerance for facet joint injections [5]. The Success Rate (SR), mean, standard deviation and the final TRE for the 30 experiments for each phantom are shown in Table 1. Success rate is defined as the ratio of successful results over the total number of registrations. Individual success rate for each vertebra and also the Group Success Rate (GSR) for all vertebrae are reported. A registration is considered as successful only if the final TRE is less than 3.0 mm for each vertebra. Figure 3 shows the overlay of the registered SSMs of L2, L3 and L4 with the ultrasound volume, prior to and following registration.

Table 1. Results for the SSM to ultrasound groupwise registration

	L2			L3			L4			
Phantom	Mean	STD	SR	Mean	STD	SR	Mean	STD	SR	GSR
1	2.49	0.49	79%	2.56	0.33	82%	2.36	0.43	79%	79%
2	2.40	0.41	70%	2.41	0.29	75%	2.36	0.43	70%	70%
3	2.43	0.36	75%	2.4	0.34	82%	2.56	0.33	75%	75%

As seen in Table 1, the groupwise registration method resulted in an average success rate of 70% with the average TRE below 3 mm for the successful cases. The landmark errors for successful cases were below 3 mm, which is a sufficiently close distance to envelope the nerve sack in the anesthetic agent without endangering the spinal cord. Comparing the results with Khallaghi *et al.* [8] shows that the mean TRE for all vertebrae is well below the threshold of 3 mm, while the overall success rate stays high. This is expected since the neighbouring vertebrae constrain the set of solutions for the registration.

Several factors limit the success rate of the groupwise registration. Due to partial volume occlusion, it is impossible to visualize the superior articular process in ultrasound images. Also, creating an instant of the SSM to capture the sharp corners of the spinous and transverse processes is a challenging task. While the former is intrinsic to ultrasound imaging, the latter can be substantially improved by increasing the number of training images and using a denser grid in the construction of the SSM.

The template CT chosen to create the SSM is from a patient close to the mean shape of the population. This may introduce a bias in SSM towards the template, which may result in larger registration errors when the patient anatomy is far from the template. To avoid this problem, we will consider using unbiased, template-free, techniques to create the SSM in future research [7,12].

The proposed registration method shows promise in the phantom experiments; there are certain challenges to overcome in order to translate it to a clinical setting: 1) The signature of the vertebrae in US images of human is substantially different from the phantom data in terms of the speckle pattern and the visibility of vertebrae surfaces due to the loss of signal and strong reflections caused by surrounding anatomy. Our preliminary results from *ex vivo* experiments on lamb cadavers demonstrate the feasibility of accurate registration between 3D US images and CT data of lumbar spine [4]. Accordingly, we expect that with reasonably accurate initial alignment of the SSM and 3D US, the proposed technique will converge in human data. In other words, the error ranges will be comparable to this study, but the capture range will be limited. A graphical user interface will be required to select corresponding anatomical regions in SSM and US data to obtain the initial alignment. 2) The current runtime for the proposed method is in the order of hours, the bottleneck being the instance generation. By implementing the instantiation on a Graphics Processing Unit (GPU), a significant improvement in runtime is possible [6].

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